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Research article

Optimizing sentiment analysis of Nigerian 2023 presidential election using two-stage residual long short term memory

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ABSTRACT

Sentiment analysis is the process of recognizing positive or negative attitudes in text. This technique makes use of computational linguistics, text analysis, and natural language processing. The 2023 presidential election in Nigeria is a significant event for the country, as it will determine the leader of the nation for the next four years. As such, it is important to understand the sentiment of the public towards the different candidates. In this research, we aimed to understand the sentiment of the public towards the three main candidates in the 2023 presidential election in Nigeria, Atiku, Tinubu, and Obi, by conducting a sentiment analysis on tweets related to the candidates. We used the long short-term memory (LSTM), peephole long short term memory (PLSTM), and two-stage residual long short-term memory (TSRLSTM) models to classify tweets as positive, neutral, or negative. Our dataset consisted of a large number of tweets that were pre-processed to remove noise and irrelevant information. Results showed that TSRLSTM performed excellently well in classifying the tweets and in identifying the sentiment towards each candidate individually. Our findings provide valuable insights into the public's opinion on the candidates and their campaign strategies, which can be useful for researchers, political analysts, and decision-makers. Our study highlights the importance of sentiment analysis in understanding public opinion and its potential applications in the field of political science.

1. Introduction

Social media data, particularly Twitter data [1,2], has been utilized for monitoring and forecasting elections. Social media platforms like Twitter provide a vast amount of real-time data that can be used to analyze public opinion [3] and sentiment towards political candidates [4] and parties. Researchers have used a variety of methods, such as sentiment analysis [5], natural language processing [6], and machine learning [7] to analyze Twitter data and make predictions about election outcomes. Twitter data has been used in a variety of ways for election monitoring and prediction [8]. For example, researchers have used sentiment analysis to understand how the public feels about different candidates, which can provide insights into their popularity and the issues that are most important to voters. Researchers have also used Twitter data to track the spread of misinformation and disinformation during elections,

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which is an important concern for election integrity. Additionally, Twitter data has been used to predict election outcomes by analyzing the activity and sentiment of tweets related to different candidates. Studies have found that the volume and sentiment of tweets can be used to predict the results of both primary and general elections with a high degree of accuracy. Machine learning [9] and deep learning [10] models have been used effectively in sentiment analysis tasks. Machine learning models are simpler and can be trained on smaller datasets, while deep learning models are more complex and require large amounts of data to train, but they can often achieve better performance. Machine learning models such as support vector machines (SVM) [11], Naive Bayes [12], random forest [13], and logistic regression [14] are commonly used in sentiment analysis.

These models are trained on labeled data, where the text is pre-labeled as positive, negative, or neutral. The models learn to identify patterns and features in the text that correspond to the different sentiments. Once trained, these models can be used to classify new text as positive, negative, or neutral. Deep learning models such as recurrent neural networks (RNNs) [15] and convolutional neural networks (CNNs) [16] are also commonly used in sentiment analysis. These models may discover intricate patterns and correlations in the data since they were trained on vast volumes of textual data. RNNs are particularly useful in sentiment analysis tasks as they can process sequential data like text, taking into account the context of the words in a sentence. CNNs are also effective in sentiment analysis as they can learn features in the text, regardless of the order in which they appear.

In this research, we propose a new method for sentiment analysis of political figures in the 2023 presidential election in Nigeria. Our main contributions are as follows:

1. A two-stage residual long short term memory (TSRLSTM) model for sentiment analysis that is able to achieve state-of-the-art performance on a dataset of tweets about Atiku, Tinubu, and Obi was proposed in this work. Our model outperforms traditional long-short-term memory (LSTM) models as well as other deep learning models such as Peephole Long Short-Term Memory (PLSTM).
2. A new dataset of tweets specifically related to the 2023 presidential election in Nigeria, which includes a diverse set of tweets from various sources and languages, was created.
3. This is the first study to perform sentiment analysis on political figures in the 2023 presidential election in Nigeria, which provides valuable insights into public opinion on these figures.
4. The proposed approach compared the performance of several existing methods, including traditional long short term memory (LSTM) models and peephole long short term memory (PLSTM) models. Two-stage residual long short term memory (TSRLSTM) model consistently outperforms these methods in terms of accuracy, precision, recall, and F1-score.
5. An in-depth analysis of the results was done. This provided insights into the strengths and limitations of our model. We also investigate the factors that affect the model's performance, such as the quantity of tweets, the source, and the language of the tweets.

In summary, this research presents a new method for sentiment analysis of political figures in the 2023 presidential election in Nigeria. Two-stage residual long short term memory (TSRLSTM) model outperforms existing methods and provides valuable insights into public opinion. Our new dataset and tool can be used for sentiment analysis on similar datasets or tasks in the future.

2. Related works

In recent years, there have been several studies on sentiment analysis of political individuals and parties using social media data. The most pertinent studies on sentiment analysis of political leaders and parties on social media platforms are reviewed in this section.

An investigation of political homophily among Twitter users during the 2016 American presidential election was conducted by Ref. [17]. From August 2016 to November 2016, they gathered 4.9 million tweets from 18,450 people and their network of contacts. Regarding their feelings toward Donald Trump and Hillary Clinton, they established six user classifications. The results demonstrated that in all of the situations examined, homophily existed among negative users, Trump supporters, and Hillary supporters. They also discovered that reciprocal connections, comparable utterances, and multiplex linkages all raise the homophily level. By examining 7.6 million tweets sent between October 31 and November 9, 2020, the authors [18] are able to discern how the general public feels about the candidates running for president of the United States in 2020. In order to initially identify tweets and user accounts, they employ a new strategy. They are able to see how each presidential candidate is seen across a variety of user and tweet groupings, including available tweets and accounts, that were visible, removed, suspended, or unreachable. They contrast the sentiment scores determined for these groups and offer important details about the variations. According to their findings, tweets that were removed after election day were more friendly to Joe Biden, whereas those that were deleted before election day were more favorable to Donald Trump. Additionally, older Twitter accounts posted more supportive messages about Joe Biden.

In order to forecast the outcome of the Indonesian presidential election, the authors [19] utilized tweets from Jokowi and Prabowo, as well as tweets from important hashtags for sentiment analysis, collected between March and July 2018. The authors develop an algorithm and a technique to identify significant information, the most popular terms, train the model, and forecast the polarity of the sentiment. The experimental results, which were generated using the R language, demonstrate that Jokowi is now predicted to win the election. This forecast result corresponds to four survey institutes in Indonesia, which demonstrated that our technique has generated accurate prediction outcomes. The authors of [20] utilized a basic classifier and a semi-supervised method to analyze sentiment in both English and Tagalog tweets. They utilized the tweets from the hotly disputed election between the son of the former president and dictator of the Philippines and the country's departing vice president in the Philippines, where social media was a major part of both candidates' campaigns. These tweets were processed, annotated, and trained to categorize tweets in English and Tagalog into three polarities: positive, neutral, and negative using NLP approaches. The accuracy of 84.83% obtained using the self-training with multinomial Nave Bayes as the basis classifier and 30% unlabeled data outperformed earlier research utilizing Twitter data from the Philippines. Machine learning was utilized in a study by Ref. [21] to extract the political feelings from it. The analysis of Twitter user emotions toward the major national political parties running in the 2019 Indian general elections takes place concurrently with the extraction of tweets related to those elections. The classification model based on feelings is then developed to forecast the tendency for tweets to infer election results. The classification model is created using the long short term memory (LSTM), which is then compared to traditional machine learning models.

In order to identify their sentiment polarity, the author of [22] used lexicon-based and supervised machine learning (ML) approaches to conduct sentiment analysis on election-related postings from Nairaland, a social network aimed at Nigerians. Between January 1 and February 22, 2019, they gathered 118,421 posts. Three lexicon-based classifiers and five ML-based classifiers were put into use, and their performance were compared. The sentiment polarity of postings is then calculated using the classifier that performs the best. To learn more about the public's perceptions of each candidate, they also conducted theme analysis on both positive and negative posts. The independent national electoral commission's findings were highly correlated with the final election results (INEC). In Ref. [23], the ascension and inauguration addresses of Nigerian heads of state and presidents from 1960 to 2019 were utilized as textual data in the authors' research. They were isolated and subjected to text-mining analysis. Latent dirichlet allocation (LDA) was used to cluster text data according to their thematic content, and a similarity matrix and heatmap were used to analyze the speech cohesiveness between these addresses. The inauguration addresses of Obasanjo in 2003 and Buhari in 1983 had the greatest and lowest average sentiment scores, respectively. The emotion score for the ascension/inauguration speeches revealed that civil presidents displayed more joy, hope, and optimism in their inaugural addresses than did military heads of state.

3. Methodology

3.1. Dataset

Social media plays an important role in our lives by connecting us with others, providing access to information, and giving us a platform to express ourselves. It enables us to connect with friends and family, regardless of geographical distance. Social media also allows us to access a wide range of information and news, as well as participate in online communities and movements. Additionally, it provides a platform for individuals to share their thoughts, ideas, and creativity, and to connect with like-minded people. However, it is also important to be aware of the potential negative effects of excessive social media use, such as addiction, loss of privacy, and the spread of misinformation. Twitter has grown in popularity as a tool for political campaigns and elections. It enables candidates to communicate with people in real time, express their message, and respond to current events. Twitter allows politicians to bypass traditional media gatekeepers and communicate directly with voters. It has also become a key tool for voter mobilization, as campaigns can use Twitter to reach out to potential supporters and encourage them to vote. Additionally, Twitter can be used by campaigns to quickly respond to opposition attacks, correct inaccuracies in the press, and shape the narrative around their campaign. Twitter also allows for greater citizen engagement in the political process. It provides a platform for ordinary citizens to follow the campaign, engage with candidates, and become informed about issues. Additionally, Twitter provides a valuable source of information for journalists and researchers studying the election. The dataset employed in this analysis was sourced from Twitter, contained a total of 20000 rows each for the three major contemporary political parties in the 2023 election in Nigeria which are Peter Obi of the labour party (LP), Tinubu of the all progressives congress (APC) and Atiku of the people's democratic party (PDP). We used the open-source intelligence tool Twitter Intelligence Tool (TWINT) to scrape Twitter data and obtain a sentiment dataset for our analysis. TWINT allowed us to gather information on tweets, user profiles, and hashtags without using the official Twitter API, making it a valuable tool for our research. Here are some of the reasons why TWINT is important:

- Gathering information: TWINT allows users to gather information from Twitter that may not be available through other sources. This can include tweets, user profiles, and hashtags.
- Investigative purposes: TWINT can be used by investigators to gather information on specific individuals or groups. It can help identify connections between individuals and can provide valuable insights into their activities.
- Security: TWINT can be used for security purposes to monitor conversations and identify potential threats. It can also be used to track the spread of misinformation or disinformation.
- Marketing: TWINT can be used by businesses to gather information on their target audience and to monitor their brand reputation on Twitter. It can help businesses understand their customers better and improve their marketing strategies.
- Open-source: TWINT is an open-source tool, which means that anyone can use and modify it for their purposes. This makes it a flexible tool that can be customized to meet specific needs.

3.2. Text processing

Text processing is the process of manipulating and analyzing text data. It is a crucial step in many natural language processing (NLP) tasks, such as text classification, sentiment analysis, and language translation. Text processing can be done using various techniques, such as regular expressions, natural language processing libraries, and machine learning models. The first stage is the preprocessing of the tweets obtained from Twitter database. There are various ways of deleting any unnecessary text from the data, which resulted in text preprocessing that is faster and less difficult in terms of time. The tweets were cleaned up using the following:

- Remove Unicode strings

Removing Unicode characters from text is important in text processing because some Unicode characters may not be supported by certain systems or software and can cause issues with text encoding and display. Additionally, certain Unicode characters may not be relevant to the task at hand, and removing them can improve the efficiency and accuracy of text processing algorithms. It's also important to remove Unicode characters that can introduce noise or bias in text classification and NLP tasks.

- Remove RT and replace with blanks

Removing the "RT" (retweet) prefix from text in text processing is important because it helps to prevent the duplication of information and reduce the noise in the text data. The "RT" prefix is used to indicate that a tweet is a retweet of another tweet, and it is not useful information for most text processing tasks. Removing it and replacing it with blank spaces can help improve the efficiency and accuracy of text processing algorithms and deep learning models. Additionally, by replacing "RT" with blanks, it would prevent the text data from being skewed towards the tweets that are retweeted. This could be beneficial in the case of text classification, sentiment analysis, and other NLP tasks where the context is important.

- Convert any url to "URL"

Converting URLs (Uniform Resource Locators) to the token "URL" in text processing is important because it helps to reduce the noise in the text data. URLs can be very long and often contain irrelevant information for most text processing tasks. Converting them to the token "URL" can help to improve the efficiency and accuracy of text processing algorithms and machine learning models by reducing the dimensionality of the data. Additionally, converting URLs to "URL" can also help to protect users' privacy. URLs may contain sensitive information such as login credentials, personal information, etc, and converting them to "URL" can help prevent such information from being exposed.

- Replace any "@username" to "user"

Replacing "@username" with the token "user" in text processing is important because it helps reduce noise in the text data. "@username" is used to mention or tag other users on social media platforms such as Twitter. These mentions are not relevant to most text processing tasks and can cause bias in the results. By replacing "@username" with the token "user", it helps to improve the efficiency and accuracy of text processing algorithms and machine learning models by reducing the dimensionality of the data. Additionally, it can also help to protect users' privacy by removing specific usernames from the text data.

- Remove additional white spaces

Removing additional white spaces in text processing is important because it helps to improve the efficiency and accuracy of text processing algorithms and machine learning models. Extra white spaces can cause issues with text encoding and display, and can also affect the performance of text processing algorithms. Additionally, extra white spaces can also make the text data difficult to read and understand for humans and can cause issues when trying to extract specific information from the text. Removing them can make the text data more consistent and structured, which can help improve the readability and usability of the text data.

- Remove hashtags in front of words

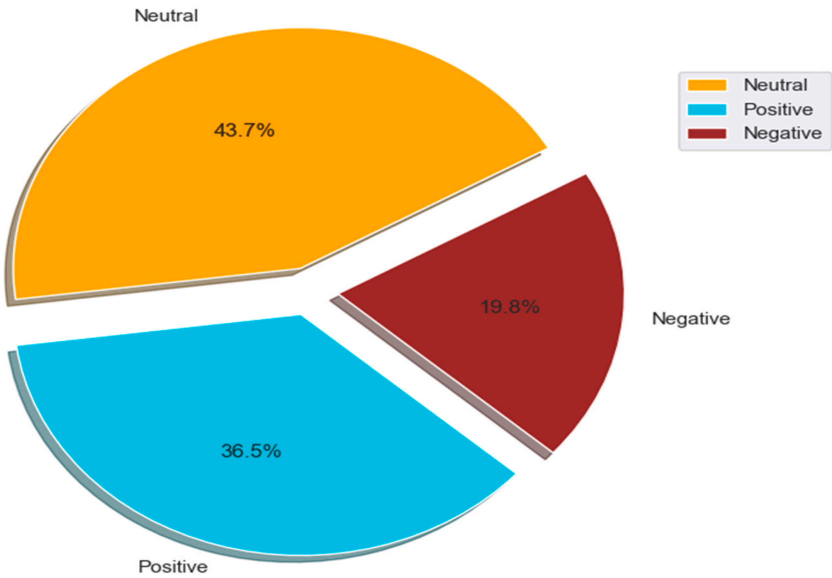
Removing hashtags in front of words in text processing is important because it helps reduce the noise in the text data. Hashtags are used to categorize and label tweets on social media platforms like Twitter, but they are not always relevant to the task at hand. Removing hashtags can help improve the efficiency and accuracy of text processing algorithms and machine learning models by reducing the dimensionality of the data. Additionally, hashtags can also introduce bias in text classification, sentiment analysis, and other NLP tasks. Removing them can help improve the accuracy of the results by eliminating the potential bias caused by the hashtags.

- Remove numbers, multiple exclamation marks, multiple question marks

Removing numbers, multiple exclamation marks, and multiple question marks in text processing is important because they can introduce noise and bias into the text data. Numbers can be irrelevant to the task at hand; multiple exclamation marks or question marks can indicate sentiment but they can also indicate a typo or a joke and not real sentiment. Removing them can help to improve the efficiency and accuracy of text processing algorithms and machine learning models by reducing the dimensionality of the data. It can also help to improve the readability of the text data for humans.

- Remove emotions

Removing emotions (such as emoticons and emojis) in text processing is important because they can introduce noise and bias into the text data. Emotions are often used to express sentiment, but they can also be irrelevant to the task at hand and can introduce bias in



ig. 1. Pie Chart of Positive, Negative and Neutral tweets for Atiku.

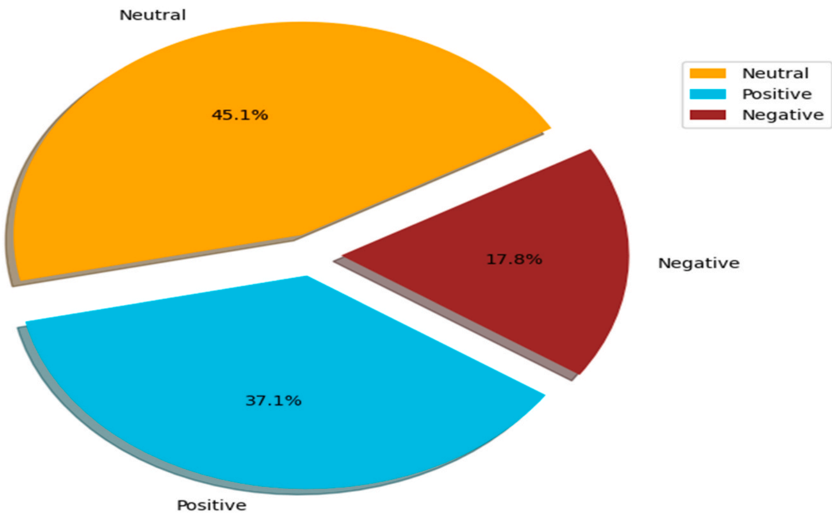


Fig. 2. Pie Chart of Positive, Negative and Neutral tweets for Obi.

text classification, sentiment analysis, and other NLP tasks.

- Change to lower case

Converting text to lowercase in text processing is important because it helps to improve the efficiency and accuracy of text processing algorithms and machine learning models. This is because many text processing algorithms and machine learning models are case-sensitive, and converting the text to lowercase can help reduce the dimensionality of the data and make the text data more consistent.

3.3. *Classification of the tweets*

The next stage is classifying tweets into positive, neutral, and negative categories using a tool like TextBlob. TextBlob is a Python text processing toolkit that is built on top of the NLTK library. As a result, it provides a simple API for fundamental natural language processing (NLP) activities including part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more. It is important in text processing because it help to automatically determine the sentiment of the tweets. By classifying

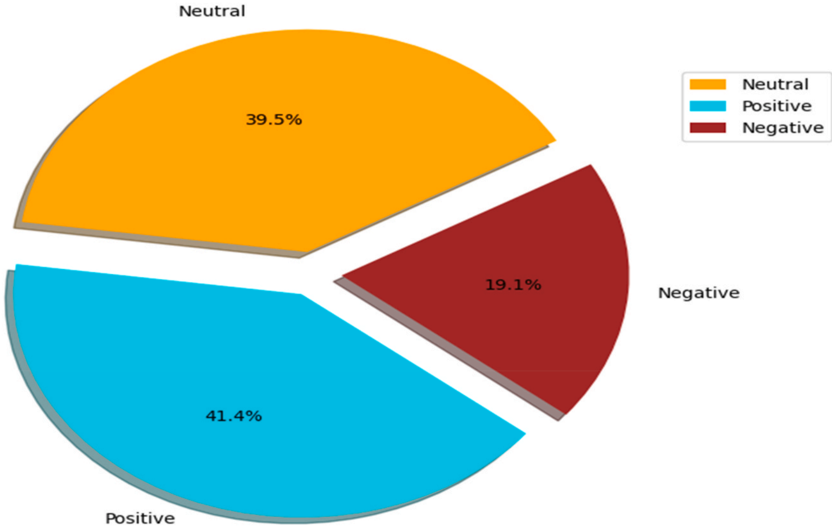


Fig. 3. Pie Chart of Positive, Negative and Neutral tweets for Tinubu.

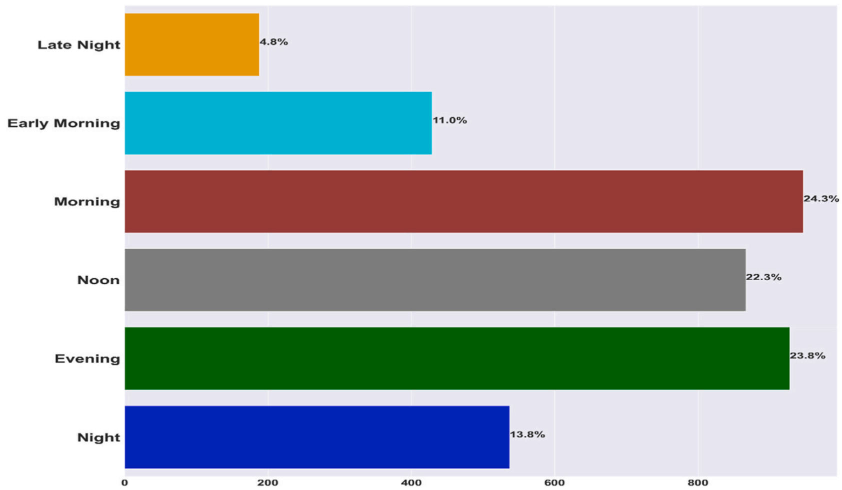


Fig. 4. Bar Chart for the time frequency of Negative tweets for Atiku.

tweets into positive, neutral, and negative categories, it will enable us to identify patterns, trends and insights in the data.

3.3.1. Using tokenizer

Using a tokenizer in text processing is important because it helps to break down a piece of text into smaller, more manageable units called tokens. Tokens are the basic building blocks of text data, and they can be words, phrases, or even individual characters. Tokenization is a crucial step in text processing and natural language processing (NLP) as it allows for further analysis and manipulation of the text data. A tokenizer can help to improve the efficiency and accuracy of text processing algorithms and machine learning models by breaking down the text data into smaller, more manageable units. Tokens can be used as input for various NLP tasks such as text classification, sentiment analysis, language translation, text generation, and more. In this study, the maximum number of words is set at 1000 while the maximum sequence length is set at 200. Since, the tweets have a limit of 280 words per individual.

3.3.2. Padding of sequence of tweets

The pad_sequence function in python is used to pad or truncate sequences to a specific length, which can be set as a parameter. Setting the padding to "post" ensures that any additional padding is added to the end of the sequence, which helps to preserve the original structure of the text data. Setting the truncating to "post" ensures that any truncation happens at the end of the sequence, which helps to preserve the most important information of the text. Using the pad_sequence function in Python, specifically when setting padding to "post" and truncating to "post" is important in text processing because it helps to standardize the length of sequences of text data. This is often necessary when working with neural networks, which require input data to be of a fixed length. By

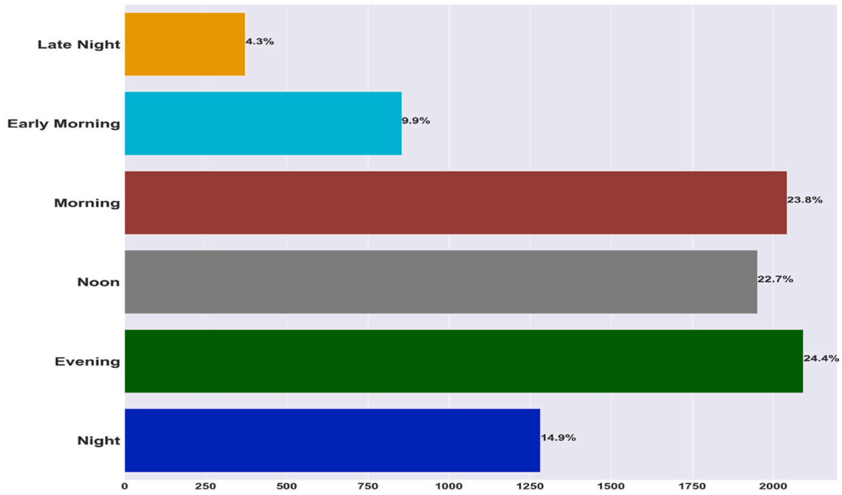


Fig. 5. Bar Chart for the time frequency of Neutral tweets for Atiku.

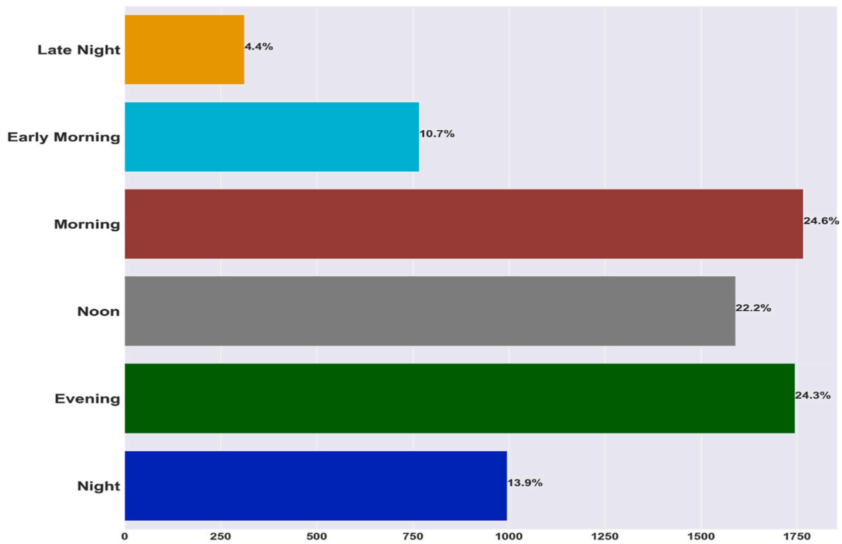


Fig. 6. Bar Chart for the time frequency of Positive tweets for Atiku.

standardizing the length of sequences of text data, it helps to improve the efficiency and accuracy of text processing algorithms and deep learning models. It also makes it possible to train models on variable length input which is a common problem in NLP tasks.

3.4. Proposed model

3.4.1. Long short term memory (LSTM)

In this study, the Long Short Term Memory (LSTM) [24] model for text processing is defines as follows: The model starts by adding an Embedding layer, which is used to convert the input text data into a dense vector representation. The Embedding layer is initialized with a maximum number of words set at 1000, an embedding dimension set at 100, and an input length set at 280. After the Embedding layer, the model includes several layers of LSTM, which is a type of recurrent neural network (RNN) that is commonly used in text processing and natural language processing (NLP) tasks. LSTM are able to handle the problem of vanishing gradients in RNN by using gates to control the flow of information. The first LSTM layer has 64 units, and it is followed by a dense layer with 64 neurons, another LSTM layer with 32 units, and another dense layer with 32 neurons. The model also includes a maxPooling1D layer, which is used to down-sample the input data, and a dropout layer with a dropout rate of 0.5, which is used to prevent overfitting by randomly dropping a certain proportion of the neurons during training. Then, the model includes another LSTM layer with 16 units, another maxPooling1D layer with a pool size of 5, another dense layer with 16 neurons, and another dense layer with 8 neurons. The model also includes a dropout layer with a dropout rate of 0.4, another batch-normalization layer, which is used to normalize the input data, and a

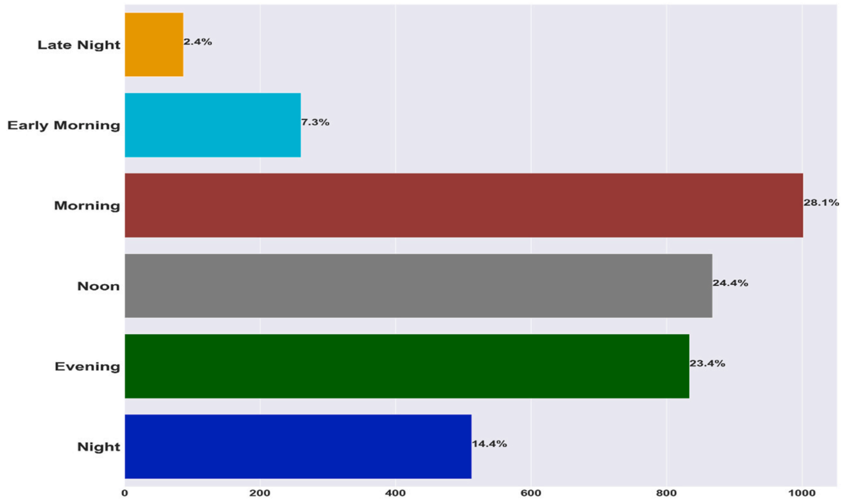


Fig. 7. Bar Chart for the time frequency of Negative tweets for Obi.

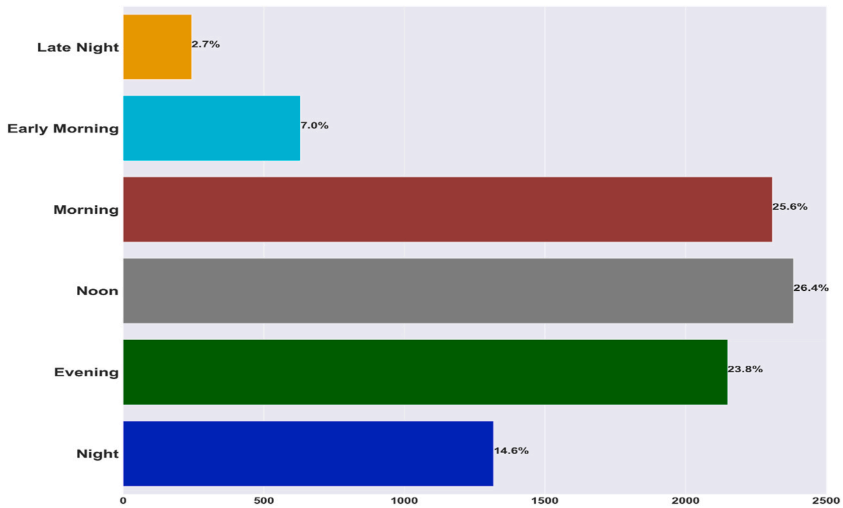


Fig. 8. Bar Chart for the time frequency of Neutral tweets for Obi.

flatten layer which is used to flatten the input data. Finally, the model includes a dense layer with 8 neurons and an output layer with 3 neurons, which are used to classify the text data into positive, neutral and negative categories. The activation function used in the output layer is 'softmax' which is commonly used for multi-class classification. The LSTM can be expressed as depicted in equations (1)–(5):

$$g_t = \gamma\left(P_g.[e_{t-1}, i_t] + q_g\right) \tag{1}$$

$$b_t = \gamma(P_b.[e_{t-1}, i_t] + q_b) \tag{2}$$

$$r_t = tanh(P_r.[e_{t-1}, i_t] + q_r) \tag{3}$$

$$c_t = \gamma(P_c.[e_{t-1}, i_t] + q_c) \tag{4}$$

$$e_t = c_t \times \tanh\ (r_t) \tag{5}$$

where g_t is the forget gate, b_t is input gate, r_t is cell gate, c_t is the output gate, e_t is the hidden state, P_g, P_b, P_r, P_c are the weight.

3.4.2. Peephole long short term memory (PLSTM)

The peephole long short term memory (PLSTM) [25] model starts by adding an Input layer, which is used to specify the shape of the

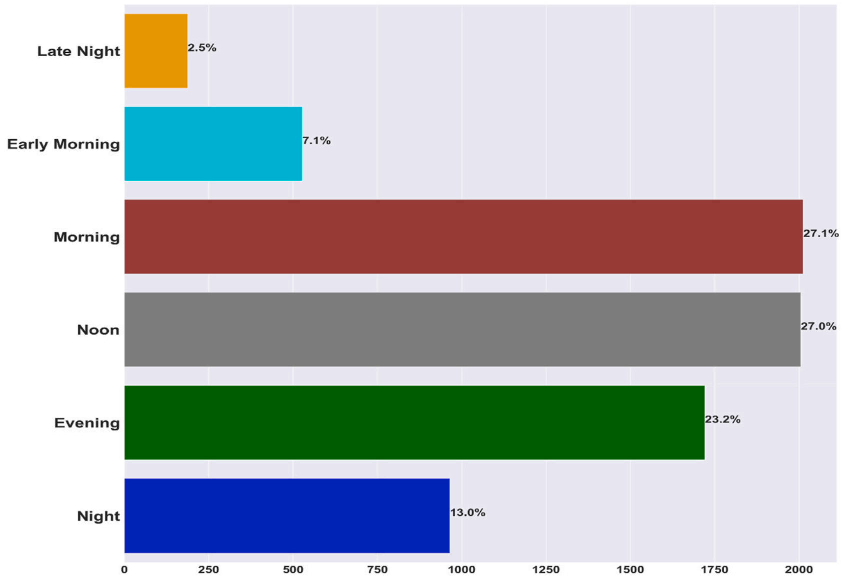


Fig. 9. Bar Chart for the time frequency of Positive tweets for Obi.

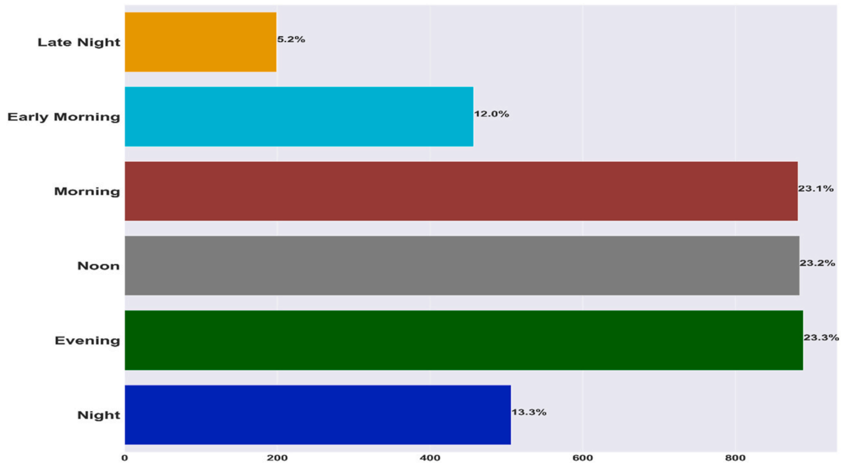


Fig. 10. Bar Chart for the time frequency of Negative tweets for Tinubu.

input data. The input data shape is given by a tuple set at 280, which represents the maximum length of the sequence of text data. The model then includes an embedding layer, which is used to convert the input text data into a dense vector representation. The embedding layer is initialized with a maximum number of words set at 1000, an embedding dimension set at 100, and an input length set at 280. After the embedding layer, the model includes a dropout layer with a dropout rate of 0.2, which is used to prevent overfitting by randomly dropping a certain proportion of the neurons during training. The model then includes a PeepholeLSTMCell layer, which is a type of LSTM cell that is used in recurrent neural networks (RNN). It uses peephole connections to allow the LSTM cell to access previous hidden states and output gates. After the PeepholeLSTMCell layer, the model includes a Dense layer with 64 neurons and an activation function 'relu' and another dense layer with 3 neurons. The activation function used in the output layer is 'softmax' which is commonly used for multi-class classification. The PLSTM differs from the standard LSTM in that it accepts the memory content of the preceding cell, r_{t-1} as an extra parameter in addition to the traditional LSTM's inputs, whereas the classic LSTM does not take r_{t-1} as input. The PLSTM can expressed as expressed in equations (6)–(10):

$$g_t = \gamma\left(P_g.[e_{t-1}, i_t] + q_g\right) \tag{6}$$

$$b_t = \gamma(P_b.[e_{t-1}, i_t] + q_b) \tag{7}$$

$$r_t = g_t r_{t-1} + b_t \, tanh(P_r.[e_{t-1}, i_t] + q_r) \tag{8}$$

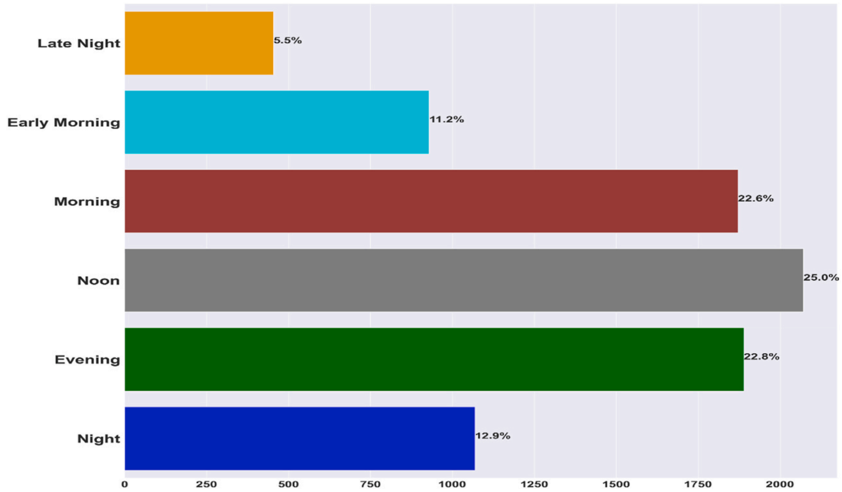


Fig. 11. Bar Chart for the time frequency of Positive tweets for Tinubu.

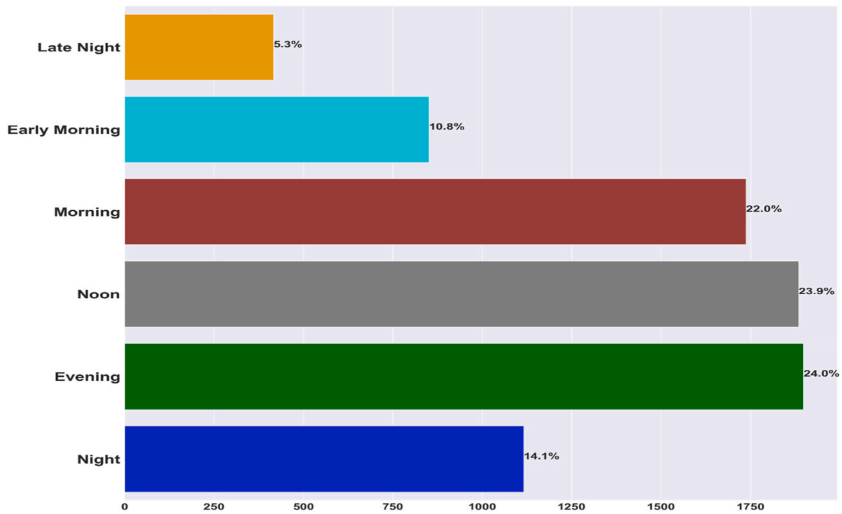


Fig. 12. Bar Chart for the time frequency of Neutral tweets for Tinubu.

$$c_t = \gamma(P_c.[e_{t-1}, i_t] + q_c) \tag{9}$$

$$e_t = c_t \times \tanh\,(r_t) \tag{10}$$

where g_t is the forget gate, b_t is input gate, r_t is cell gate, c_t is the output gate, e_t is the hidden state, P_g, P_b, P_r, P_c are the weight.

3.4.3. Two-stage residual long short term memory (TSRLSTM)

Two-stage residual long short term memory (TSRLSTM) consisting of two different stages with three add connection in each stage. The first stage starts by defining an input layer with the shape of the input data set to 280. The model then includes an embedding layer, which is used to convert the input text data into a dense vector representation. The embedding layer is initialized with a maximum number of words set at 1000 and an embedding dimension set at 32 and input length set at 280. The model then includes two LSTM layers with different numbers of units (64, 32), which are used to process the input data. Each LSTM layer has the argument return_sequences = True, which means that the LSTM layer returns the full sequences of outputs. Then the model includes add layers, which are used to add the output of the previous LSTM layer to the output of the current LSTM layer. This allows the model to take into account the previous output when processing the current input. Immediately after the first add layers, the model then includes two LSTM layers with different numbers of units (64, 64), which are used to process the input data. Each LSTM layer has the argument return_sequences = True, which means that the LSTM layer returns the full sequences of outputs. Then the model includes the second Add layers, which are used to add the output of the previous LSTM layer to the output of the current LSTM layer. This allows the model

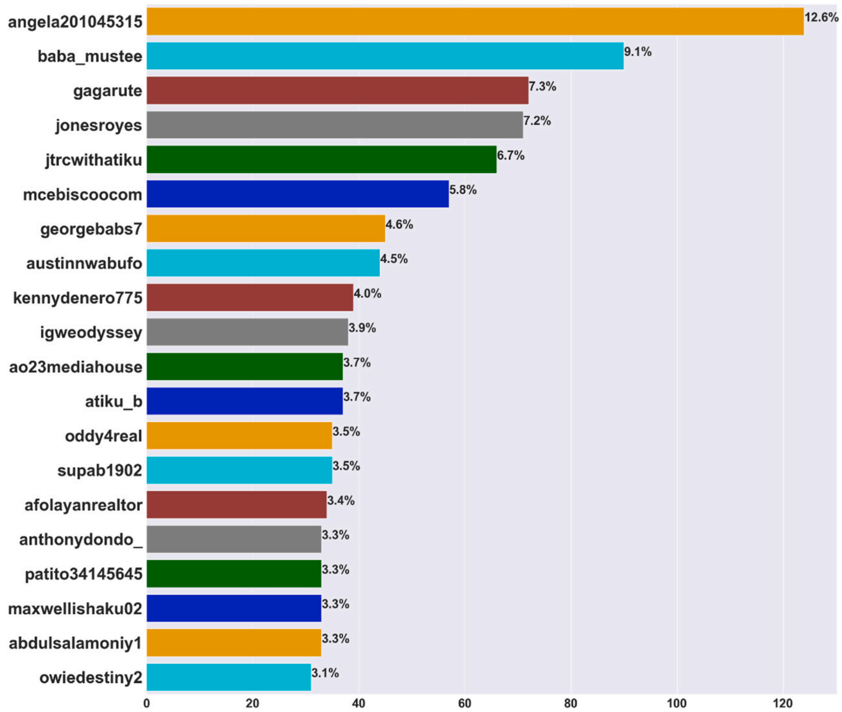


Fig. 13. Top twenty Frequency Tweets for Atiku.

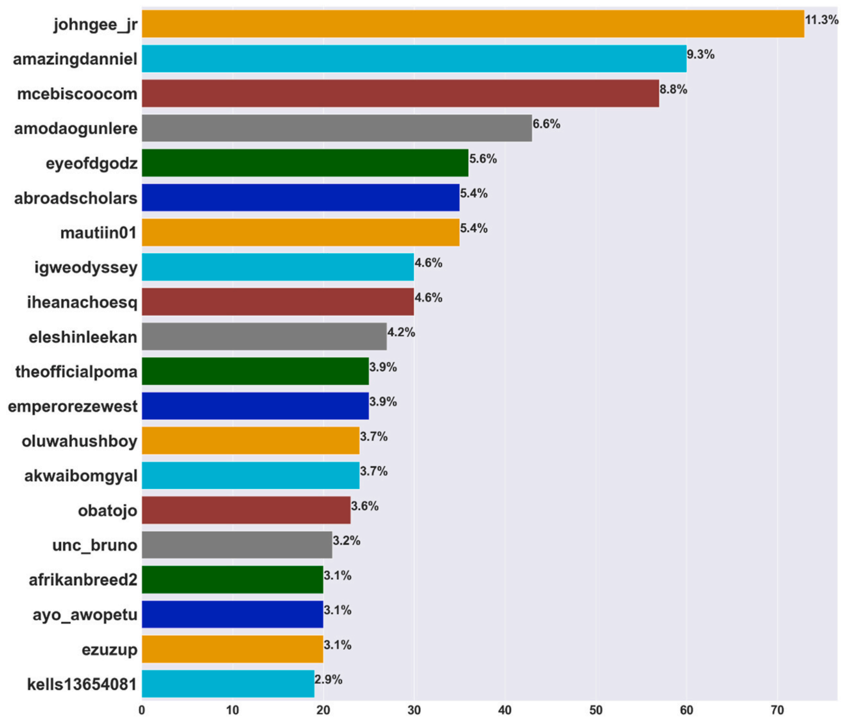


Fig. 14. Top twenty Frequency Tweets for Obi.

to take into account the previous output when processing the current input. After the second Add layers, the model then includes two LSTM layers with different numbers of units (64, 64), which are used to process the input data. Each LSTM layer has the argument return_sequences = True. Then the model includes the third Add layers, which are used to add the output of the previous LSTM layer to

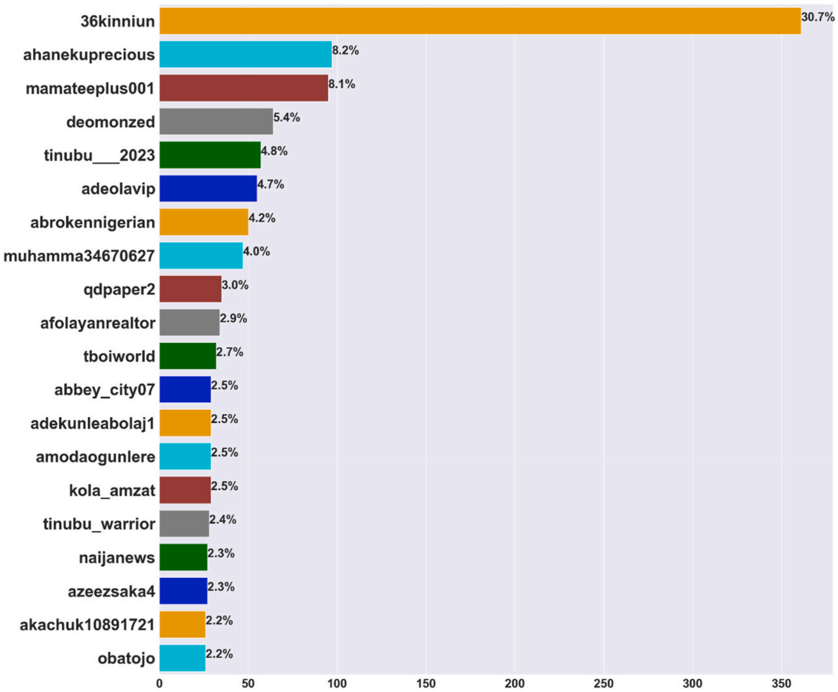


Fig. 15. Top twenty Frequency Tweets for Tinubu.

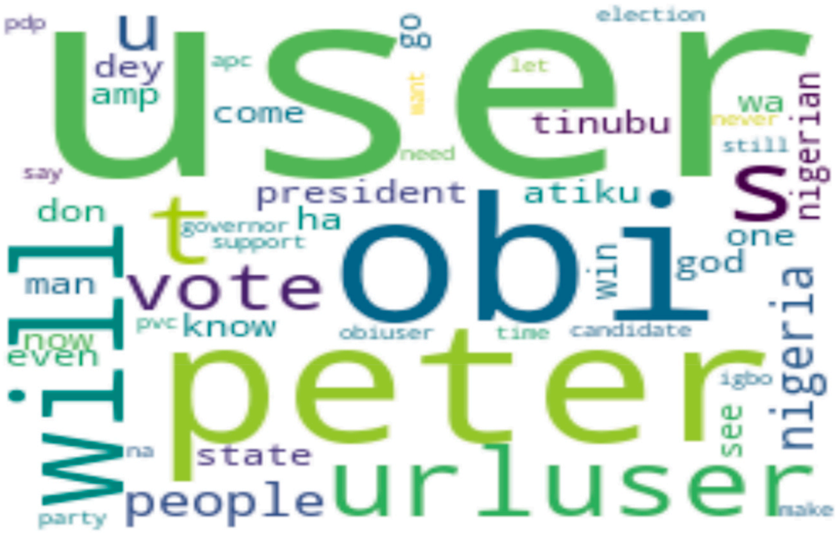


Fig. 16. Trends of Obi tweets.

the output of the current LSTM layer. This allows the model to take into account the previous output when processing the current input.

The second stage starts by including an embedding layer, which is used to convert the input text data into a dense vector representation. The embedding layer is initialized with a maximum number of words set at 1000 and an embedding dimension set at 32 and input length set at 280. The model then includes two LSTM layers with different numbers of units (32, 32), which are used to process the input data. Each LSTM layer has the argument return_sequences = True, which means that the LSTM layer returns the full sequences of outputs. Then the model includes add layers, which are used to add the output of the previous LSTM layer to the output of the current LSTM layer. This allows the model to take into account the previous output when processing the current input. Immediately after the first add layers, the model then includes two LSTM layers with different numbers of units (32, 32), which are used to process the input data. Each LSTM layer has the argument return_sequences = True, which means that the LSTM layer returns the full sequences of outputs. Then the model includes the second add layers, which are used to add the output of the previous LSTM layer to the

Fig. 17. Trends of Atiku tweets.

Fig. 18. Trends of Tinubu tweets.

Table 1
Classification report of LSTM, PLSTM, TSRLSTM for atiku.

Candidates	Algorithm	Classes	Precision	Recall	F1-Score
ATIKU	LSTM	Negative	0.00	0.00	0.00
		Neutral	0.87	0.61	0.72
		Positive	0.51	0.94	0.66
	PLSTM	Negative	0.00	0.00	0.00
		Neutral	0.43	1.00	0.60
		Positive	0.00	0.00	0.00
	TSRLSTM	Negative	0.37	0.04	0.07
		Neutral	0.77	0.91	0.83
		Positive	0.67	0.85	0.75

output of the current LSTM layer. This allows the model to take into account the previous output when processing the current input. After the second add layers, the model then includes two LSTM layers with different numbers of units (64, 64), which are used to process the input data. Each LSTM layer has the argument return_sequences = True. Then the model includes the third add layers,

Table 2
Classification report of LSTM, PLSTM, TSRLSTM for obi.

Candidates	Algorithm	Classes	Precision	Recall	F1-Score
OBI	LSTM	Negative	0.00	0.00	0.00
		Neutral	0.75	0.88	0.81
		Positive	0.65	0.81	0.72
	PLSTM	Negative	0.00	0.00	0.00
		Neutral	0.75	0.88	0.81
		Positive	0.65	0.81	0.72
	TSRLSTM	Negative	0.60	0.29	0.39
		Neutral	0.72	0.96	0.82
		Positive	0.85	0.71	0.77

Table 3
Classification report of LSTM, PLSTM, TSRLSTM for tinubu.

Candidates	Algorithm	Classes	Precision	Recall	F1-Score
TINUBU	LSTM	Negative	0.00	0.00	0.00
		Neutral	0.92	0.21	0.34
		Positive	0.43	0.98	0.60
	PLSTM	Negative	0.00	0.00	0.00
		Neutral	0.00	0.00	0.00
		Positive	0.39	1.00	0.57
	TSRLSTM	Negative	0.34	0.09	0.14
		Neutral	0.73	0.91	0.81
		Positive	0.72	0.80	0.76

Table 4
Performance accuracy of LSTM, PLSTM, TSRLSTM for atiku.

Candidate	Algorithm	Training(%)	Test(%)
ATIKU	LSTM	60.99	61.46
	PLSTM	43.80	42.96
	TSRLSTM	73.02	71.12

Table 5
Performance accuracy of LSTM, PLSTM, TSRLSTM for obi.

Candidate	Algorithm	Training(%)	Test(%)
OBI	LSTM	70.57	70.33
	PLSTM	44.58	45.95
	TSRLSTM	75.52	74.73

Table 6
Performance accuracy of LSTM, PLSTM, TSRLSTM for tinubu.

Candidate	Algorithm	Training(%)	Test(%)
TINUBU	LSTM	50.04	47.23
	PLSTM	41.63	39.38
	TSRLSTM	72.47	70.16

Table 7
Performance loss of LSTM, PLSTM, TSRLSTM for atiku.

Candidate	Algorithm	Training	Test
ATIKU	LSTM	0.8508	0.8538
	PLSTM	1.0520	1.0538
	TSRLSTM	0.6330	0.6580

Table 8
Performance loss of LSTM, PLSTM, TSRLSTM for obi.

Candidate	Algorithm	Training	Test
Obi	LSTM	0.7274	0.7352
	PLSTM	1.0403	1.0311
	TSRLSTM	0.6299	0.6547

Table 9
Performance loss of LSTM, PLSTM, TSRLSTM for tinubu.

Candidate	Algorithm	Training	Test
TINUBU	LSTM	1.0649	1.1076
	PLSTM	1.0475	1.0541
	TSRLSTM	0.6541	0.6964

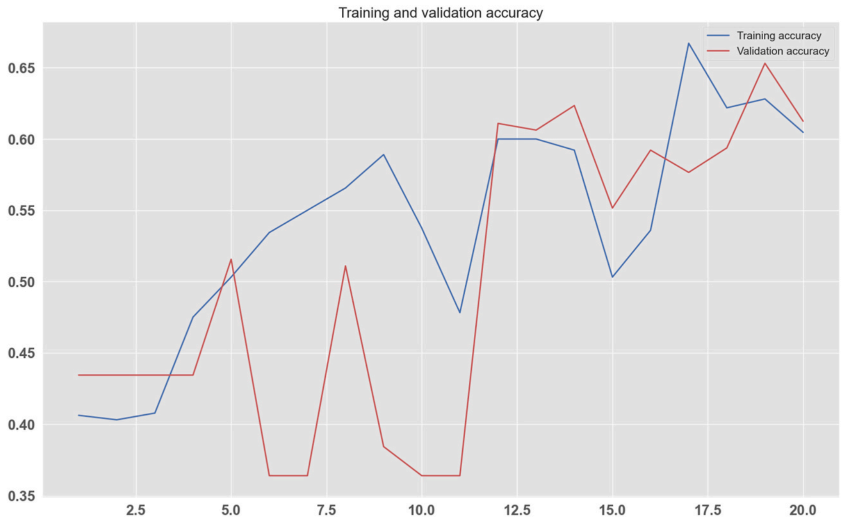


Fig. 19. Training and Validation accuracy of LSTM for Atiku.

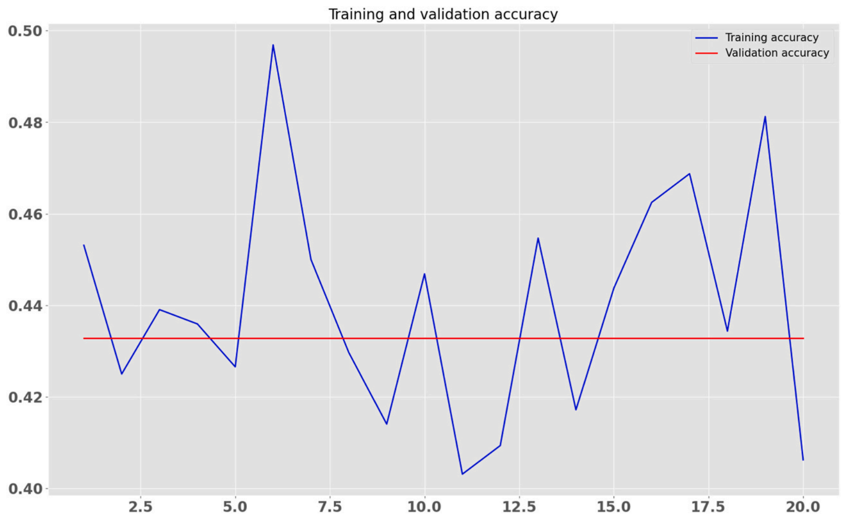


Fig. 20. Training and Validation accuracy of PLSTM for Atiku.

Fig. 21. Training and Validation accuracy of TSRLSTM for Atiku.

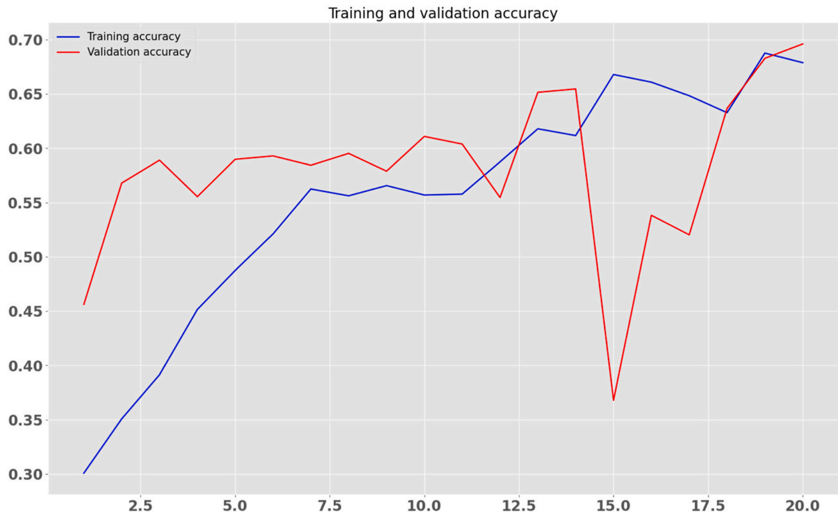


Fig. 22. Training and Validation accuracy of LSTM for Obi.

which are used to add the output of the previous LSTM layer to the output of the current LSTM layer. This allows the model to take into account the previous output when processing the current input.

Then the model includes a concatenate layer which is used to concatenate the output of two previous LSTM layers such as the first and second stage, a maxpooling1D layer which is used to down-sample the input data, a flatten layer which is used to flatten the input data, and a dense layer with 32 neurons and an activation function 'relu'. Finally, the model includes an output layer with 3 neurons, which is used to classify the text data into positive, neutral and negative categories. The activation function used in the output layer is 'softmax' which is commonly used for multi-class classification.

4. Results and discussion

In this study, we trained a Long Short Term Memory (LSTM), Peephole Long Short Term Memory (PLSTM), Two-Stage Residual Long Short-Term Memory (TSRLSTM) model for sentiment analysis of tweets related to the 2023 presidential candidates Atiku, Tinubu, and Obi in Nigeria. We used a dataset of 20,000 tweets each for the candidates that were collected from various social media platforms. The dataset was preprocessed to remove irrelevant information and noise. Sentiment analysis is important in the election because it can provide valuable insights into the level of support and opposition for each candidate among the electorate. By analyzing the sentiment of social media posts, news articles, and other forms of online content, it's possible to gain a better understanding of how people feel about the candidates, their policies, and their chances of winning. This information can be used by political campaigns,

Fig. 23. Training and Validation accuracy of PLSTM for Obi.

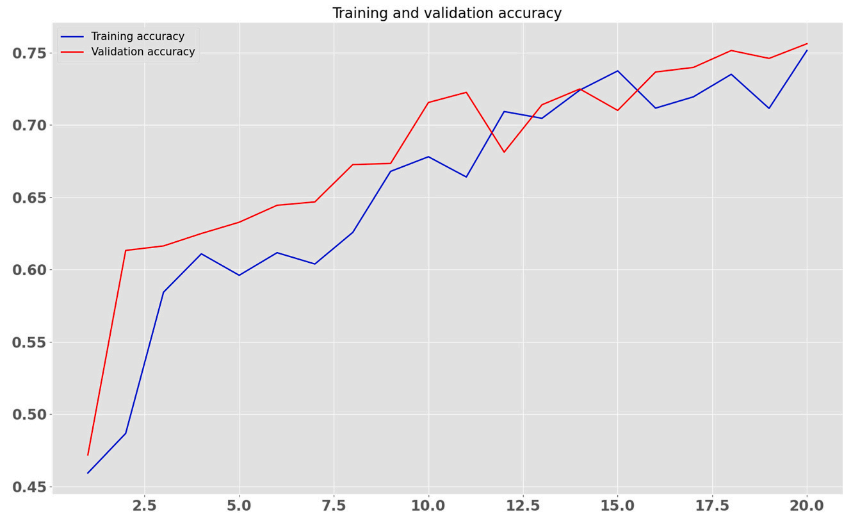


Fig. 24. Training and Validation accuracy of TSRLSTM for Obi.

pollsters, and other stakeholders to make more informed decisions about how to communicate with voters, allocate resources, and develop strategies for winning the election. Sentiment analysis can also be used to identify key issues that are important to voters and track changes in public opinion over time. This can help campaigns to understand the issues that are resonating with voters and address them in a more effective way. Additionally, sentiment analysis can also help identify patterns of misinformation, false claims, and propaganda that might be used by candidates or other groups to influence the electorate. However, sentiment analysis is important in the election because it can provide valuable insights into public opinion, help identify key issues and track changes in public opinion over time, and detect patterns of misinformation and propaganda that might be used to influence the electorate. Fig. 1 is the pie chart of Positive, Negative and Neutral tweets for Atiku. The results of the sentiment analysis showed that Atiku has the highest percentage of neutral tweets at 43.7% followed by positive tweets at 36.5% and negative tweets at 19.8%. Fig. 2 is the pie chart of Positive, Negative and Neutral tweets for Obi. The results of the sentiment analysis showed that Obi has the highest percentage of neutral tweets at 45.1% followed by positive tweets at 37.1% and negative tweets at 17.8%.

Fig. 3 is the pie chart of Positive, Negative and Neutral tweets for Tinubu. The results of the sentiment analysis showed that Tinubu has the highest percentage of positive tweets at 41.4% followed by neutral tweets at 39.5% and negative tweets at 19.1%. The overall results of the sentiment analysis show that Tinubu had the highest percentage of positive tweets, indicating that he has a relatively high level of support among social media users. On the other hand, Obi had the highest percentage of neutral tweets, which could mean that there is a relatively high level of uncertainty or lack of opinion among social media users regarding his candidacy. However, Atiku had the highest percentage of negative tweets, indicating that he has a relatively high level of opposition among social media users. It's

Fig. 25. Training and Validation accuracy of LSTM for Tinubu.

Fig. 26. Training and Validation accuracy of PLSTM for Tinubu.

worth noting that the data used for this analysis is based on tweets that were collected from social media platforms and might not be representative of the entire population. Fig. 4 is the bar chart for the time frequency of Negative tweets for Atiku. The highest percentage of Negative tweets was in the morning with 24.3% followed by evening with 23.8%. This shows that most negative sentiment in the tweets are expressed in the morning. Fig. 5 is the bar chart for the time frequency of Neutral tweets for Atiku. The highest percentage of Neutral tweets was in the evening with 24.4% followed by morning with 23.8%. This demonstrates that the majority of neutral tweets are sent in the evening. Fig. 6 is the bar chart for the time frequency of positive tweets for Atiku. The highest percentage of positive tweets was in the morning with 24.6% followed by evening with 24.3%. This shows that most positive sentiment in the tweets are in the morning.

Fig. 7 is the bar chart for the time frequency of Negative tweets for Obi. The highest percentage of Negative tweets was in morning with 28.1% followed by noon with 24.4 This demonstrates that the majority of negative tweets about Obi are sent in the morning. Fig. 8 displays the time frequency of neutral tweets for Obi which indicates that people tweet more at noon with 26.4% followed by morning with 25.6%. Fig. 9 is the bar chart for the time frequency of Positive tweets for Obi which indicates that people tweet more in the morning with 27.1% followed by noon with 27.0%. Fig. 10 is the bar chart for the time frequency of Negative tweets for Tinubu which indicates that people tweeting in the morning, noon and evening are within the range of 23.1–23.3%. Fig. 11 is the bar chart for the time frequency of positive tweets for Tinubu which indicates that people tweet more in the noon with 25.0% followed by 22.8% in the evening. Fig. 12 is the bar chart for the time frequency of Neutral tweets for Tinubu which indicates that people tweet within the range of 23.9% and 24.0% in both evening and noon.

Fig. 27. Training and Validation accuracy of TSRLSTM for Tinubu.

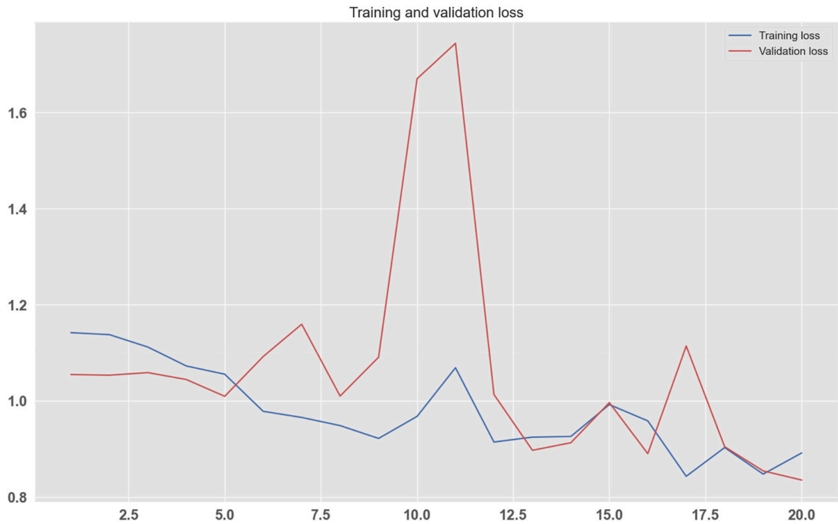


Fig. 28. Training and Validation loss of LSTM for Atiku.

Fig. 13 is the top twenty frequency tweets for Atiku, which indicates that the highest percentage of tweets for Atiku is from angela201045315 with 12.6% followed by baba_mustee with 9.5% and third the most tweets is from gagarute with 7.3%. Fig. 14 is the top twenty frequency tweets for Obi which indicates that the highest percentage of tweets for Obi is from johngee_ji with 11.3% followed by amazingdaniel with 9.3% and the third most tweets are from mcebiscoocom with 8.8%. Fig. 15 is the top twenty frequency tweets for Tinubu which indicates that the highest percentage of tweets for Tinubu is from 36kinnium with 30.7% followed by ahanekuprecious with 8.2% and the third most tweets are from mamateephis001 with 8.1%. A word cloud is a graphical depiction of the terms that appear the most often in a text or dataset. It is a popular tool in text analysis and is used to swiftly find the most essential words and topics in a given text. Typically, a word cloud is generated by counting the frequency of each word in a text or dataset and then displaying the words in a size proportional to their frequency. Terms that are often used are generally printed in larger font sizes, whereas words that are less commonly used are displayed in smaller font sizes. The words are also arranged in a way that makes it easy to identify patterns and trends in the data.

Fig. 16 displays the trends of Obi tweets which shows obi, peter, user, vote was the most frequency word in the Obi tweets. Fig. 17 display the trends of Atiku tweets, which show that atiku, wike, user, obi, tinubu, win were the most frequent words in the Atiku tweets.

The words “tinubu,” “user,” “atiku,” “vote,” “state,” and “lagos” were the most frequently used in Tinubu tweets, as shown in Fig. 18. A classification report for sentiment analysis provides several metrics that can be used to evaluate the performance of a sentiment analysis model. These metrics include precision, recall, and F1-score for each class (positive, neutral, negative). A high

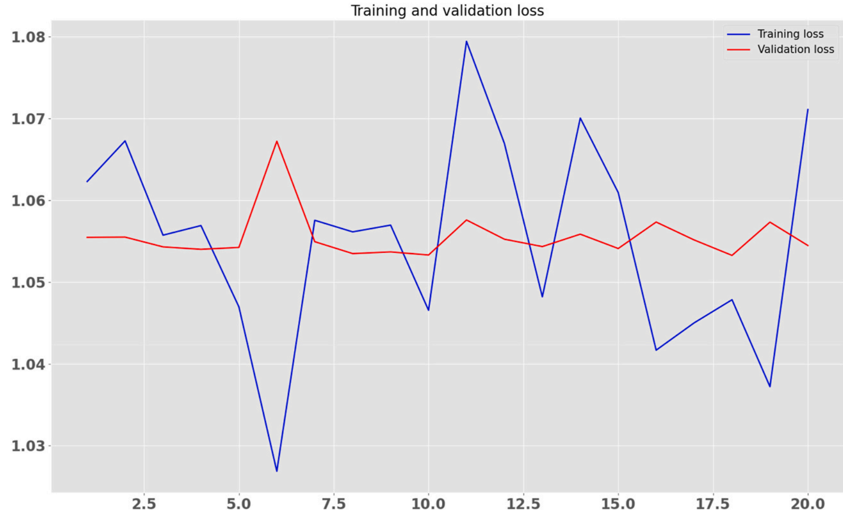


Fig. 29. Training and Validation loss of PLSTM for Atiku.

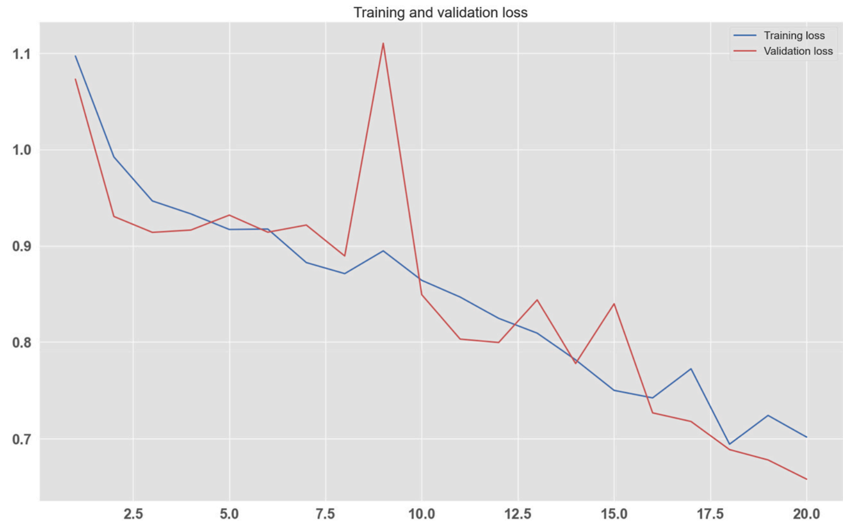


Fig. 30. Training and Validation loss of TSRLSTM for Atiku.

precision indicates that the model is effective at recognizing positive instances while ignoring negative instances. A high recall indicates that the model is effective at detecting all positive instances. A high F1-score means that the model has a good balance between precision and recall. Table 1 display the classification report of LSTM, PLSTM, TSRLSTM for Atiku candidate in the presidential election. A precision, recall and f1-score of 0 in Negative and Positive class of LSTM and PLSTM shows that the model fails to identify the two classes. A precision of 0.87 indicates that the model is correctly identifying more than half of the instances that it predicts as neutral in the LSTM. A precision of 0.37, 0.77, 0.67 in the TSRLSTM shows that the model is able to identify the class when compared to other model. Table 2 display the classification report of LSTM, PLSTM, TSRLSTM for Obi candidate in the presidential election. A precision, recall and f1-score of 0 in Negative class of both LSTM and PLSTM shows that the model fails to identify the negative class. A precision of 0.60, 0.72, 0.85 in the TSRLSTM shows that the model is able to identify the class when compared to other model. Table 3 display the classification report of LSTM, PLSTM, TSRLSTM for Tinubu candidate in the presidential election. A precision, recall and f1-score of 0 in Negative class of LSTM and PLSTM shows that the model fails to identify the neutral class. A precision of 0.92 indicates that the model is correctly identifying 92% of the instances that it predicts as neutral in the LSTM. A precision of 0.34, 0.73, 0.72 in the TSRLSTM shows that the model is able to identify the class when compared to other model. Table 4 is the performance accuracy of LSTM, PLSTM, TSRLSTM for Atiku which indicates that TSRLSTM model achieved an overall accuracy of 73% on the training set while overall accuracy of 71% on the test set. The TSRLSTM model performed well in identifying positive, neutral and negative sentiment in the tweets. Table 5 is the performance accuracy of LSTM, PLSTM, TSRLSTM for Obi which indicates that TSRLSTM model achieved an overall accuracy of 76% on the training set while overall accuracy of 75% on the test set. The TSRLSTM model performed well in

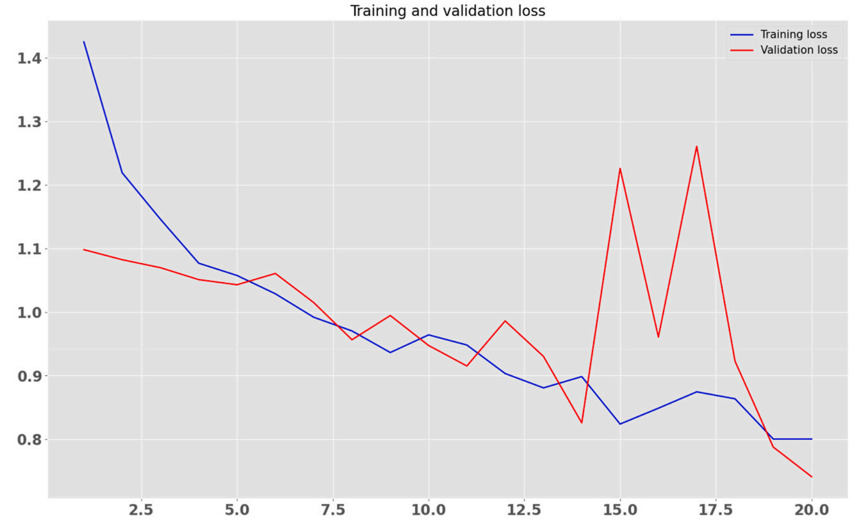


Fig. 31. Training and Validation loss of LSTM for Obi.

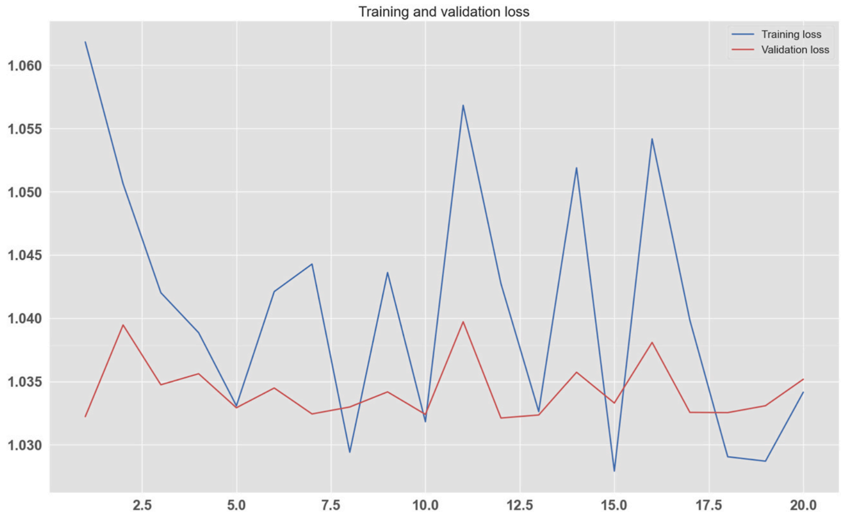


Fig. 32. Training and Validation loss of PLSTM for Obi.

identifying positive, neutral and negative sentiment in the tweets. Table 6 is the performance accuracy of LSTM, PLSTM, TSRLSTM for Tinubu which indicates that TSRLSTM model achieved an overall accuracy of 73% on the training set while overall accuracy of 70% on the test set. The TSRLSTM model performed well in identifying positive, neutral and negative sentiment in the tweets. Table 7 is the performance Loss of LSTM, PLSTM, TSRLSTM for Atiku which indicates that TSRLSTM has the least loss when compared with others model considered in this study. Table 8 is the performance Loss of LSTM, PLSTM, TSRLSTM for Obi which indicates that TSRLSTM has the least loss when compared with others model considered in this study. Table 9 is the performance Loss of LSTM, PLSTM, TSRLSTM for Tinubu which indicates that TSRLSTM has the least loss when compared with others model considered in this study.

Figs. 19–27 displays the training and validation accuracy for each candidate in the 2023 presidential election such Obi, Atiku and Tinubu and three model considered in this study: Long Short Term Memory (LSTM), Peephole Long Short Term Memory (PLSTM), Two-Stage Residual Long Short Term Memory (TSRLSTM). The y-axis shows the value of the model while x-axis shows the number of epoch used in this study. The training and validation accuracy in Figs. 19–27 shows that TSRLSTM perform better than the remaining two model in all the candidates considered in this study. Figs. 28–36 displays the training and validation loss for each candidate in the 2023 presidential election such Obi, Atiku and Tinubu and three model considered in this study: Long Short Term Memory (LSTM), Peephole Long Short Term Memory (PLSTM), Two-Stage Residual Long Short Term Memory (TSRLSTM). The y-axis shows the loss value in the model while x-axis shows the number of epoch used in this study. The training and validation loss in Figs. 28–37 shows that TSRLSTM have the least loss when comparing with other model.

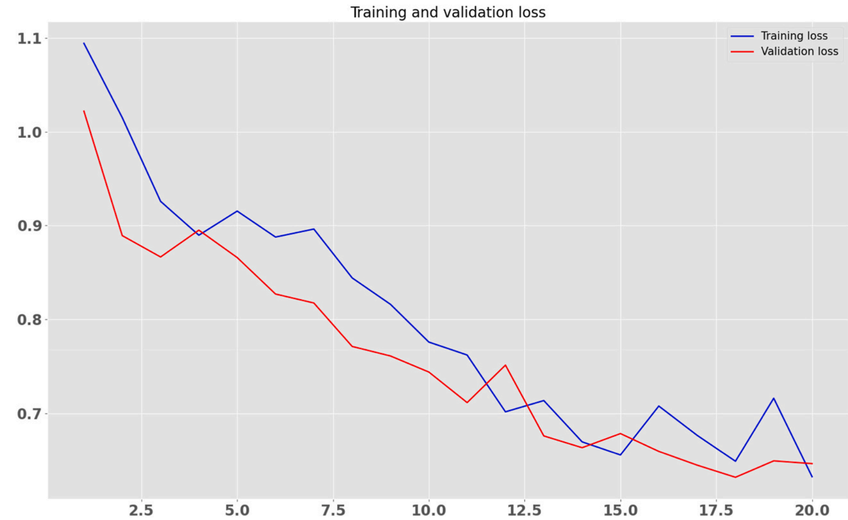


Fig. 33. Training and Validation loss of TSRLSTM for Obi.

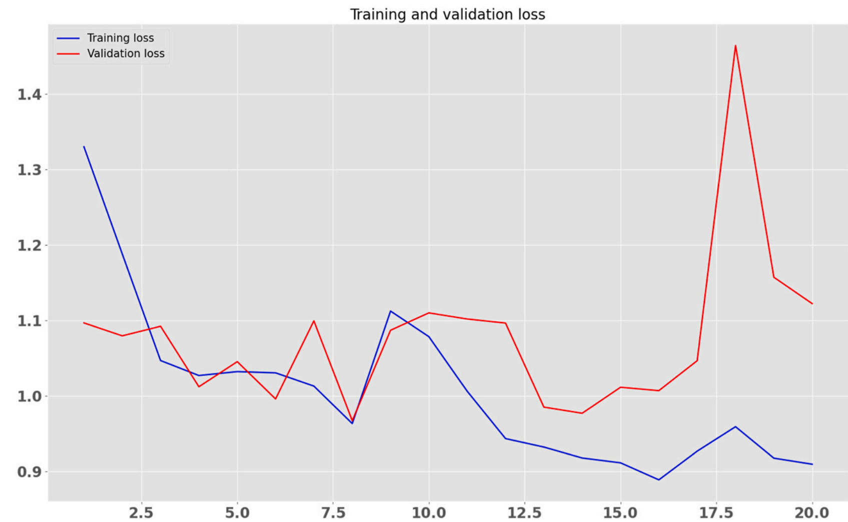


Fig. 34. Training and Validation loss of LSTM for Tinubu.

5. Conclusion

In conclusion, the sentiment analysis using the two-stage residual LSTM model provides valuable insights into the level of support and opposition for each of the candidates among social media users. The model can be used to monitor the sentiment of tweets related to the presidential candidates, which can provide valuable insights into the Public's opinion of the candidates. These results should be interpreted with caution, given that the analysis is based on a limited dataset of tweets collected from social media platforms. Further research with larger and more diverse datasets is needed to provide a more comprehensive understanding of the sentiment towards each candidate. The results of the sentiment analysis using two-stage residual long short term memory show that the model is able to accurately classify the sentiments of tweets regarding the three candidates in the 2023 Presidential Election in Nigeria. The high accuracy in classifying positive, neutral, and negative sentiments indicates that the model is able to effectively capture the sentiment expressed in the tweets. However, further improvements can be made by incorporating more data and fine-tuning the model.

There are several reasons why social media data, particularly Twitter data, is important for election monitoring and prediction.

1. Real-time data: Social media platforms like Twitter provide real-time data that allows researchers to track public opinion and sentiment towards political candidates and parties in near real-time. This is important for understanding the dynamics of an election campaign and predicting outcomes.

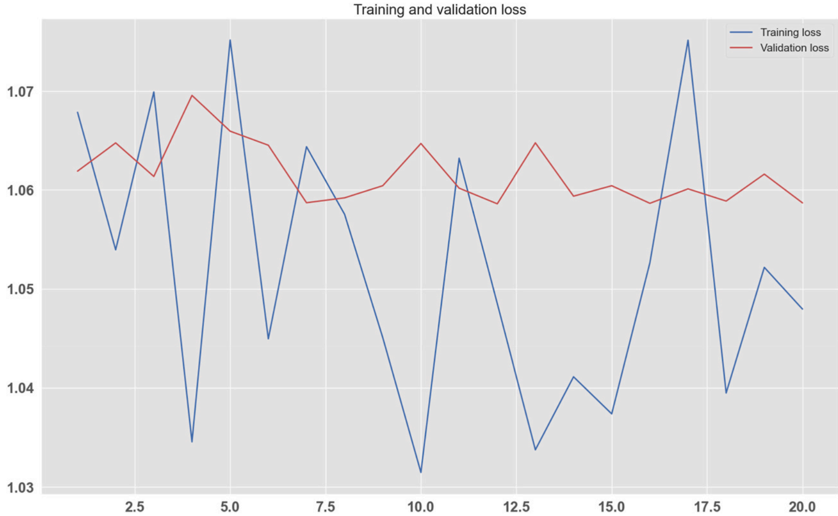


Fig. 35. Training and Validation loss of PLSTM for Tinubu.

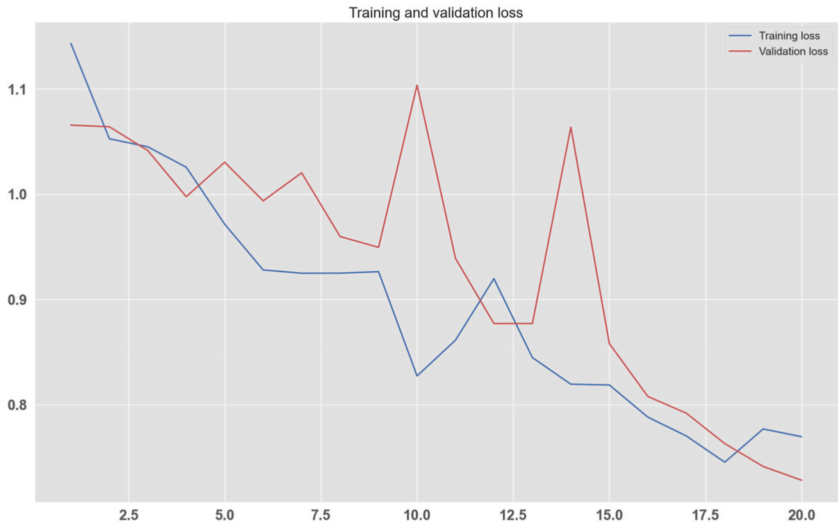


Fig. 36. Training and Validation loss of TSRLSTM for Tinubu.

2. Large sample size: Twitter data provides a large sample size of data that can be used to analyze public opinion and sentiment. This allows researchers to make more accurate predictions about election outcomes.
3. Wide reach: Twitter is widely used by people across the globe. This makes it a valuable source of data for understanding public opinion and sentiment in different regions.
4. Cost-effective: Collecting data from social media platforms is relatively inexpensive compared to traditional methods such as polling. This allows researchers to analyze large amounts of data at a lower cost.
5. Understanding public opinion: Social media data provides a window into the thoughts and opinions of the public, which can be used to understand the public's views on different political issues and the effectiveness of different campaign strategies.
6. Identifying Misinformation: Social media platforms are often used to spread misinformation and disinformation, and Twitter data can be used to identify these false narratives and track their spread. This is especially important for ensuring the integrity of the election.

Overall, social media data, especially Twitter data, plays a crucial role in understanding the public's opinion and sentiment in the election and for election monitoring and prediction.

Declarations

Author contribution statement

David Opeoluwa Oyewola, Lawal Abdullahi Oladimeji: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Emmanuel Gbenga Dada, Sowore Olatunji Julius: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Lummo Bala Kachalla, David Opeoluwa Oyewola: Performed the experiments; materials, analysis tools or data, Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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