ORIGINAL RESEARCH

Analyzing sentiments towards E-Levy policy implementation in Ghana using twitter data

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Abstract A newly proposed or implemented government policy often encounters challenges. Ghanaian citizens have always look down negatively upon their government's policies, hence those are rarely appreciated. This paper ponders over the Ghanaian government's proposal of electronic levy on mobile money transactions which was announced in the 2022 budget on November 17, 2021. We have scrutinized this governmental policy through the ordinary citizen's perspective using lexicon-based sentiment analysis on Twitter data. Lexicons are collections of words that express specific emotions, and deals with interpreting emotions like happiness, frustration, anger, and sadness. Twitter, serving as a means for people to share their views, provides enormous user generated content, beneficial for research purposes. We collected e-levy specific Twitter data in five phases, namely; policy introduction, popularity, discussion, feeble, and debate phases. The policy introduction phase recorded the least volume of data containing 1400 tweets, among which our sentiment analyzer classifies 8.93% as positive, 89.29% as neutral, and 1.78% as negative. The debate phase recorded the highest amount of data containing 18.423 tweets, among which 24.43% tweets are classified as positive, 59.29% as neutral, and 16.28% as negative. An analysis on the entire data containing 38,771 tweets reports 25.50% positive, 59.02% neutral, and 15.48% negative tweets. Our study determines that people are not largely unhappy established by the stable positive sentiment percentage, however, there is a high neutral score in all the phases.

Keywords E-Levy · Policies · Sentiment analysis · Taxation · Natural language processing · Twitter data

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1 Introduction

"Taxation is the price we pay for living in a civilized society"—says Justice Oliver Wendel Holmes, the U. S. Supreme Court Justice. The history of taxation in Ghana dates to the colonial era. During World War II, the British colonial authority-initiated taxation in Ghana, in September 1943, called the Gold Coast [1]. Several attempts had been made previously; for instance, in April 1852, the poll tax ordinance was passed under the then-Governor Major Hill to earn money to support the growing expense of the British administration [2]. The Income Tax Ordinance (No.27) of 1943 was thus the first Income Tax Law, however, they were unsuccessful. Taxation is taking a different swift with the advent of technology and is

now electronically charged, which is termed as E-Levy. Technology over the years has altered our daily lives and the way the world runs. Multi-functional devices built upon modern technology, such as QR codes, E-Zwich, and smartphones have made transactions feasibly quicker. The Electronic Transaction Levy (also known as the E-Levy) is a tax levied on the transactions conducted over electronic or digital platforms. The government of Ghana has proposed an electronic levy on all mobile transactions. It is a new tax on fundamental transactions related to digital payments and electronic platform transactions that the government proposed in the 2022 Budget. A charge of 1.75% will apply to all electronic transactions that are more than GH¢100 per day.

With the advent of social media, people resort to sharing their opinions and interacting with peers, thus generating vast volumes of social media content. Numerous high-profile people and other citizens in the country have reacted on the issues of E-Levy, making it a widely discussed topic on Twitter. Sentiment analysis, often known as opinion mining, is an approach to natural language processing (NLP) that determines the emotional tone behind a body of text [3]. Sentiment Analysis (SA) and Opinion Mining (OM) are used interchangeably. Sentiment Analysis detects and analyzes the sentiment represented in a document, whereas Opinion Mining extracts and analyzes people's opinions on a subject. As a result, SA's purpose is to find people with strong beliefs, figure out what they are saying, and then characterize their polarity. Sentiment analysis is concerned with a text's polarity (positive, negative, or neutral), but it may also detect specific moods and emotions (angry, joyful, sad, etc.), urgency (urgent, not urgent), and even intents (interested versus not interested). Sentiments are expressed in different types, such as.

- Fine-grained Sentiment Analysis: Graded Sentiment is used to understand ratings. The ratings are based on how satisfied a person shows interest and/or dissatisfaction towards a policy;
- Emotion detection: Emotion detection sentiment analysis deals with interpreting emotions like happiness, frustration, anger, and sadness. Emotion detection systems frequently employ lexicons, which are collections of words that express specific emotions;
- Aspect-Based Sentiment Analysis: It assists in determining which conversation components are being discussed. It considers the whole sentence or text;
- Intent Analysis: The intent analysis can assist figure out whether a customer is looking to buy anything or is just looking around. If a customer is willing to make a purchase, monitor them, and market to them;
- Multilingual Sentiment Analysis: detect the language in texts automatically with a language classifier, then train

a custom sentiment analysis model to classify texts in language choice.

When these fundamental notions are combined, they form a powerful tool for evaluating millions of brand dialogues with human-level accuracy. Sentiments have been shared on various mainstream tabloids and social media through posts, comments, and reactions. People shared their opinions on the mammoth anti-government protest in the 1995 dubbed "Kume Preko," literally translated as "kill me now" demo. This protest was held to express displeasure at the Jerry John Rawlings' government's introduced Value Added Tax (VAT) idea and the untold economic hardships experienced by Ghanaians at the time [4]; all these were sentiments.

Sentiment Analysis is a term that refers to the application of Natural Language Processing (NLP), text analysis, and computational linguistics to determine a speaker's or writer's opinion toward a particular issue [5]. It aids in determining whether a text expresses good, negative, or neutral thoughts. Sentiment analysis is one of the most popular research topics in Natural Language Processing. Opinion mining, recommender systems, and event detection are a few of sentiment analysis's scientific and commercial applications [6]. Ghana had approximately eight million social media users as of January 2021, according to Statista.com. Twitter and other social media platforms play a crucial part in expressing thoughts (sentiments) about an event, likewise Ghanaian people have expressed their feelings on the proposed E-Levy. Anguish, as well as pleasure, can be used to indicate rejection or approval of specific regulations. Therefore, there is a need to conduct sentiment analysis on the proposed E-Levy introduced by the government of Ghana. The two primary strategies for sentiment analysis are lexicon-based and machine-learning-based approaches. Multidisciplinary theoretical knowledge, such as statistics and algorithm complexity, is merged into computer-based machine technology, enhancing artificial intelligence's functional capabilities.

The primary goal of this study is to use lexicon-based sentiment analysis to form a fair judgment of people's sentiments in response to the E-Levy government policy.

This article focuses on presenting an exploratory analysis on Twitter data to present the Ghanaian population's sentiments towards the new e-levy policy. The article aims to understand how the general public feels and reacts in response to this new government policy. We do not propose a machine learning or deep learning-based method in this article, which however is our task for the future work. Since the dataset in unannotated, the proposition of a supervised machine learning or deep learning approach is not feasible. We further aim to annotate the collected dataset and present robust algorithms to perform the sentiment classification task. The strength of this article lies in the results and observations derived using the sentiment analyzer tool. The

methodology used in this paper is lexicon-based that uses python library for Textblob to extract the sentiment polarities on the collected Twitter data.

This form of unsupervised exploratory analysis shall help understanding people's opinion and analyzing governmental policies through people's perspective. This shall also allow to assess the impact of user sentiments on government policies. This study proposes a sentiment analysis concept to understand users' reaction to the proposed E-Levy policy by the government. With the increased usage of social media in the recent times, user sentiment analysis is an impressive tool to understand the emotions of a target audience. This paper shall guide governments, state agencies, and industries to make informed decisions to strategically propose, announce and impose policies.

The remainder of the paper is structured as follows: Sect. 2 examines the literature of related studies. The methodology and dataset are explained in Sect. 3. Section 4 analyzes the methodology's results and limitations, followed by the conclusion in Sect. 5.

2 Literature review

To buttress our research with solid backgrounds, we reviewed the existing literature related to the study. Singh et al. [5] considered the Indian government's policy of the demonetization of high-denomination money, which went into effect at midnight on November 8, 2016. Their study used sentiment analysis on Twitter to examine this policy from the standpoint of the average citizen. In another study by Manguri et al. [6], they used the Tweepy library to extract Twitter data, and performed sentiment analysis operation using Python's TextBlob library. Chowdary et al. [7] used the POS-N-gram tokenization technique to extract word tokens for identifying sentiments or opinions in key utterances (tweets) related to the Indian GST (Goods and Service Tax) policy. Their research aimed to increase the sentiment classification accuracy by using the least number of phrases possible. Kaurav et al. [8] underlined the concerns and focus of NEP (National Education Policy) 2020. The authors used qualitative data analysis methodologies and computer-assisted qualitative data analysis software to understand crucial areas of concentration in policy texts. Balakrishnan et al. [9] discussed a strategy in which a stream of tweets from the Twitter microblogging site was pre-processed and classified as positive, negative, or irrelevant based on their emotional content; it examined the performance of several classifying algorithms in such cases based on their precision and recall. Abeywardena [10] aimed to learn more about public attitudes toward OER (Open Educational Resources) and MOOCs (Massive Open Online Courses) and their complementary functions using a text mining approach.

Pagolu et al. [11] investigated the link between the stock market movements of a firm and related sentiments using sentiment analysis and supervised machine learning concepts on tweets retrieved from Twitter. Pokharel [12] took tweets from twelve countries into account which were collected between March 11 and 31, 2020, and were somehow related to COVID-19. The researcher looked at how people in other countries dealt with the problem. In another related work by Zhanga et al. [13] the authors used a sampling of Twitter data to uncover the fundamental factors of carbon tax discussions to cluster tweets based on phrases that indicate people's attitudes. They used bisecting k-means algorithm and correspondence analysis for the task. Sharma et al. [14], during the campaigning season for general state elections in 2016, performed data (text) mining on 42,235 tweets collected over a month that referenced five national political parties in India. They analyzed how Twitter users felt about each of the Indian political parties in consideration. A sentiment analysis design was presented in a study [15] that used tweets to categorize consumers' perspectives into good and negative categories, portrayed in a pie chart and an HTML website. Over a period spanning the outbreak of the SARS-COV-2 pandemic, [16] analyzed whether everyday news and tweets from CEOs have an impact on stock market performance. They also identified whether traditional news sources and tweets from the heads of states have an impact on the benchmark indexes of major world economies.

3 Methodology

Our strategy assumes that people use social media platforms to express their feelings, opinions, attitudes, and sentiments. These emotions and thoughts are communicated through short sentences that include terms and words that represent their hidden beliefs and attitudes about laws, concepts, and other topics. The language and words employed to symbolize the hidden driving forces of people's views about the electronic levy are considered in this scenario. Figure 1 depicts the workflow of the sentiment analysis task performed in this study. We first identified a specific hashtag in the sample of collected tweets. The hashtag '#elevy' was used as the search term on the microblogging website Twitter. We collected the tweets containing the hashtag using Python's snscrape library. Next, the collected data was pre-processed turning raw data into a format that computers and machine learning can understand and evaluate [17]. The preprocessing steps included text cleaning, stemming and lemmatization, and stopword removal. After preprocessing, we performed text feature representation and selection, selecting the most robust qualities that reflect a text and could be utilized to successfully and efficiently forecast the sentiment class of the text [18–25]. We have employed the bag of
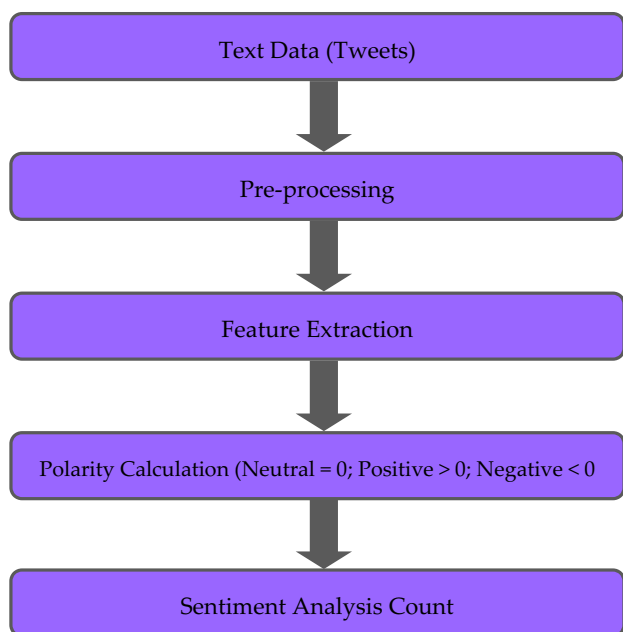
Fig. 1 Sentiment analysis workflow of the study

words technique, which collects words or properties from a sentence, document, website, or other sources, and then classifies them according to their frequency of use. The polarity of each tweet is computed to determine the sentiment in each data sample. The collected data is divided into five different categories: phase 1, phase 2, phase 3, phase 4, and phase 5. The phases were deemed necessary for our study to ascertain the real sentiments of the citizens from when the e-levy policy was first announced in parliament to when it gained

traction in the mainstream and on social media. Finally, we compare the user sentiments in each of these phases.

3.1 Data collection

Ghana had over 16 million internet users as of January 2022, up from 15.70 million in 2021 and 14.76 million in 2020 [26]. Figure 2 depicts the internet usage trend in Ghana. The country had approximately eight million social media users as of January 2021 [26]. Figure 3 shows platform-specific social media usage in Ghana. In this study, we consider Twitter data which represents 36.2% of the social media users in Ghana. Table 1 shows sample tweets used in this study.

To gather Twitter data, we used snscrape, a python library to scrape tweets without requiring a personal API (Application Programming Interface). Snscrape returns thousands of tweets in seconds, and its extensive search features allow highly customizable searches. We filtered the tweets using the hashtag #elevy in all the tweets posted between November 17, 2021, and January 31, 2022. We filtered Ghana as the targeted country because the electronic levy tax on mobile transactions was specific to the residents of Ghana. During the first phase from November 17, 2021 to November 30, 2021, 1400 tweets were collected. This could be referred as the 'Policy Introduction' phase. This was when the policy was first announced in the parliament by the Ghanian finance minister. The mainstream media started discussing the policy and gaining citizens' attention. This phase recorded the least recorded data, attributable to the policy's novelty. The second phase recorded 4554 tweets between December 01, 2021

Fig. 2 Internet usage trends in Ghana from 2017 to 2022 (Source: [26])
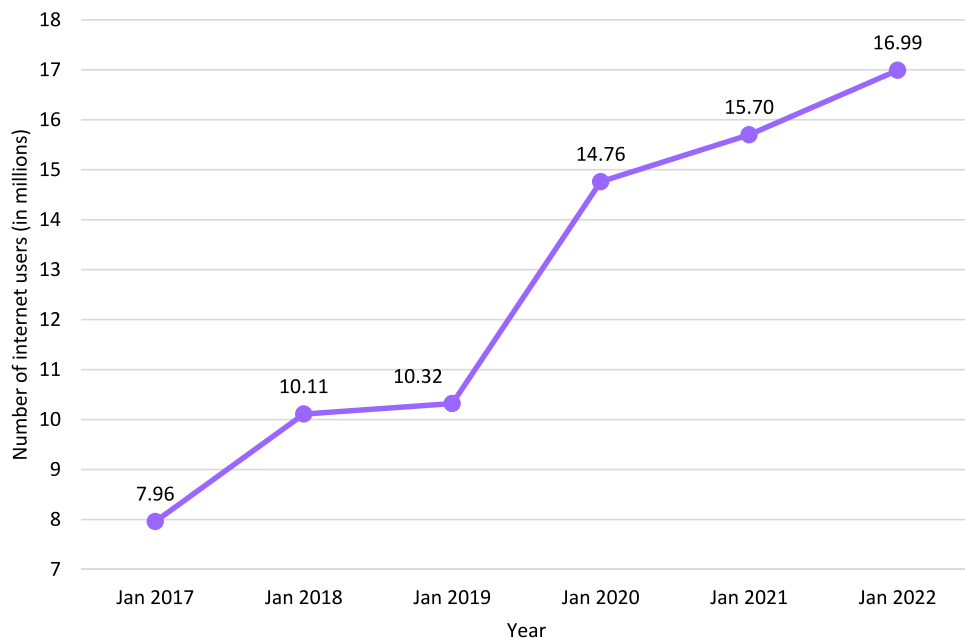
Fig. 3 Social media trends in Ghana based on platforms (Source: [26])
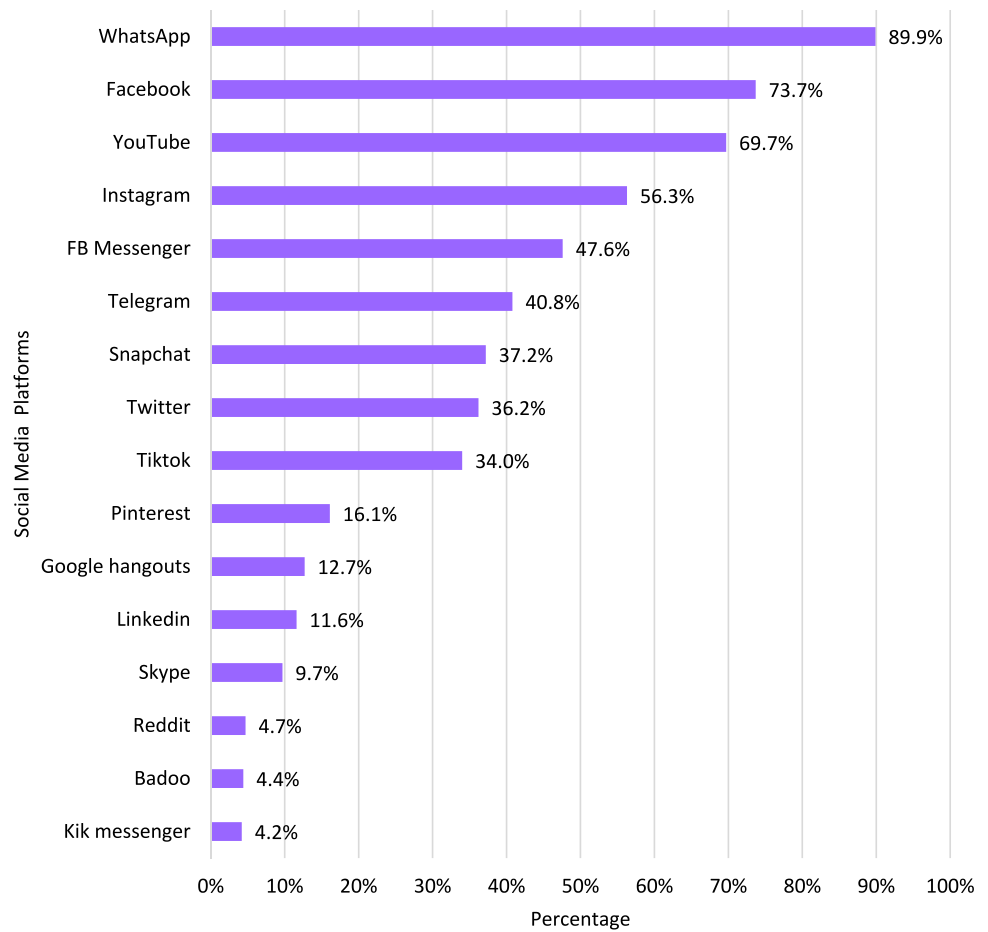
Table 1 Sample tweets used in the study

Tweets
E-Levy: Where we've gotten to, borrowing is not an option; taxing is the way. But the question is, can we trust government to make good use of our taxes?—Hassan Ayariga \n\n#OneOnOne
Showboy @NAkufoAddo, please increase the E-Levy and add internet tax too. \n\nThey've enough money to moan on Spaces
The e-levy is the most long-term approach to improve public budgets. â€ " John\xa0Boadu https://t.co/HGX5iOOgXz'
'Please find another way to tax and forget about this E-Levy. 3nfa https://t.co/oUoEVJlwES'
'NPP clutching at straws now. the â€œyÉ›te sika so no…â€ ein this? ein be the E-Levy no? https://t.co/OoY7jI8APN'

and December 14, 2021. The data collected in phase 2 increased due to the popularity the policy gained since its announcement, thus named as the 'Popularity Phase'. The topic was widely discussed in the media and on social media. The third data collection phase, named as the 'Discussion Phase', dates from December 15, 2021 to December 30, 2021 with a total of 7679 tweets. The minority and majority caucuses met to discuss whether the electronic levy tax should be accepted, and more people were aware of the policy. Both sides engaged in a heated argument, and Ghanaians voiced their opinions and feelings about the policy. Furthermore, the fourth and fifth phases were from December 31, 2021, to January 15, 2022, and January 16, 2022 to January 31, 2022, with a total tweet of 1,701 and 18,423, respectively. Our research shows that due to the Christmas holiday, there was little discussion about the policy in phase 4, thus named as the 'Feeble Phase' when the people's attention got drawn away from the electronic tax. Phase 5, the 'Debate Phase', recorded the highest amount of data. The issue was debated in the

2204

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214

Table 2 2-Week interval tweet collection

Phase	Date interval	Total tweets
Phase 1 – Policy Introduction Phase	17/11/2021 – 30/11/2021	1,400
Phase 2 – Popularity Phase	01/12/2021 – 14/12/2021	4,554
Phase 3 – Discussion Phase	15/12/2021 – 30/12/2021	7,679
Phase 4 – Feeble Phase	31/12/2021 – 15/01/2022	1,701
Phase 5 – Debate Phase	16/01/2022 – 31/01/2022	18,423
Total	17/11/2021 – 31/01/2022	33,757

parliament, and public opinion was expressed on both traditional and social media. A total of 33,757 tweets were used for our analysis. The two-week interval tweet collection is shown in Table 2. The tweets were scraped using the Python snscrape package, and the codes were executed on the Google Colab platform.

3.2 Data pre-processing

Data pre-processing involves cleaning and preparing the text for classification [41–43]. Noise and uninformative sections such as HTML tags, scripts, and ads are common in online writings [27]. We decreased the text noise to help increase the classifier's performance and speed up the classification process, allowing for real-time sentiment analysis. The terms or phrases (features) that represent the positive or negative opinion most strongly are extracted. The following steps are used in our pre-processing approach: online text cleaning, white space removal, expanding abbreviations/contractions, stemming, stop words removal, negation handling, and finally, the feature selection filtering stage. The pre-processed stage is described by Eq. 1 below:

$$Y_{ij} = TX_{ik} \tag{1}$$

such that:

(i) Y_{ij} preserves the "valuable information" in X_{ik},
(ii) Y_{ij} eliminates at least one of the problems in X_{ik}
(iii) Y_{ij} is more useful than X_{ik}.

In the above relation, i = 1,... n where n = number of objects, j = 1,... m where m = number of features after pre-processing, k = 1,... l where l = number of attributes/features before preprocessing, and in general, m ≠ l.

3.3 Feature selection

Feature selection is also known as variable selection or attribute selection. The automatic selection of attributes

in the data is performed to identify and remove data's unneeded, irrelevant, and redundant attributes. We employ the Term Frequency—Inverse Document Frequency method to select the desired features. Equation 2 below shows the feature selection;

$$TF - IDF = FF * log(DF) \tag{2}$$

where N indicates the number of documents, and DF is the number of documents that contain the feature. FP takes the value 0 or 1 based on the feature absent/presence in the document.

3.4 Polarity calculation

Sentiment Analysis (SA) is a widely discussed task in Natural Language Processing (NLP). There are a variety of approaches for determining the state of sentiment (positive or negative feeling) in a text [6]. After the data collection, pre-processing and feature extraction steps, we calculate the sentiment polarity to check the data's neutral, positive and negative counts, as in Eq. 3. We use lexicon-based sentiment analysis technique that involves the usage of the TextBlob library in the Python environment.

$$f_m = \{f(posScore), iff(posScore) \leq f(negScore) \\ - f(negScore), otherwise \tag{3}$$

where f_m computes the absolute maximum of the two scores. It is worth noting that f(negScore) is always positive by construction. The negative sign is imposed to obtain a final prior polarity that ranges from -1 to 1. Lastly, decisions are made/conducted where the analysis is plotted in the phase of sentiment polarity and subjectivity. To categorize the tweets according to their sentiments, the tweets with a polarity score greater than zero are classified as positive, those with a polarity score less than zero are classified as negative and the rest are classified as neutral.

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214

2205

4 Results and findings

In this section, the results and findings of the paper are presented. It provides an in-depth analysis of various sentiment analyzed on the available data. The sentiment analysis results are categorized into three polarities: Positive, Negative, and Neutral. Both Textblob and Vader produce same results and hence a common result is presented in the further sections. The study outcomes with their associated word clouds are presented below.

4.1 The policy introduction phase

The first data was collected from November 17, 2021, to November 30, 2021, when the E-Levy was first announced in parliament. A total of 1400 tweets were collected. Figures 4 and 5 represent the sentiment analysis classification and word count, respectively.

Phase 1 recorded a total of 1400 tweets from when it was announced on November 17, 2021, to November 30, 2021. Out of the total, 1250 (89.29%) tweets were neutral tweets, while 125 (8.93%) and 25 (1.78%) tweets were positive and negative tweets. This was when the policy was first announced in parliament. The discussion on traditional and social media gained traction, and people shared their sentiments. The positivity rate was quite substantial, meaning people were not unhappy about the tax; however, the neutral point was higher. The neutrality signifies that people did not clearly understand how the policy works. The country's literacy rate is presently at 69.8%,

Fig. 4 Sentiment analysis score for phase 1

Fig. 5 Word count score for phase 1

2206

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214

according to the Ghana Statistical Service's 2021 Population and Housing Census report [28]. However, education and awareness as to how the policy works is needed, particularly for those that may draw deductions. Words like "elevy," "budget," and "government" were used in several tweets. These are due to people's desire to understand the proposed electronic levy tax.

4.2 The popularity phase

The second phase was when the public had become aware or heard much of the E-Levy policy. From December 1, 2021 to December 14, 2021, 4554 tweets were collected. Figures 6 and 7 represent the sentiment analysis classification and word count for the second phase.

It can be observed that the data increased during the second phase. Out of the total tweets, 4500 (98.81%) were neutral, 38 (0.83%) were positive, and 16 (0.36%) were negative. The positive score increased, i.e., people were not unhappy about the policy. However, understanding of how the policy works was still required in this phase. Words like "elevy," "government," "money," "budget," "momo", and "minority" were mentioned most during this phase. People were concerned about the impact of this policy on the economy, the budget, mobile money (momo), and income creation.

4.3 The discussion phase

During the third phase from December 15, 2021, to December 30, 2021, 7679 tweets were gathered. During this period,
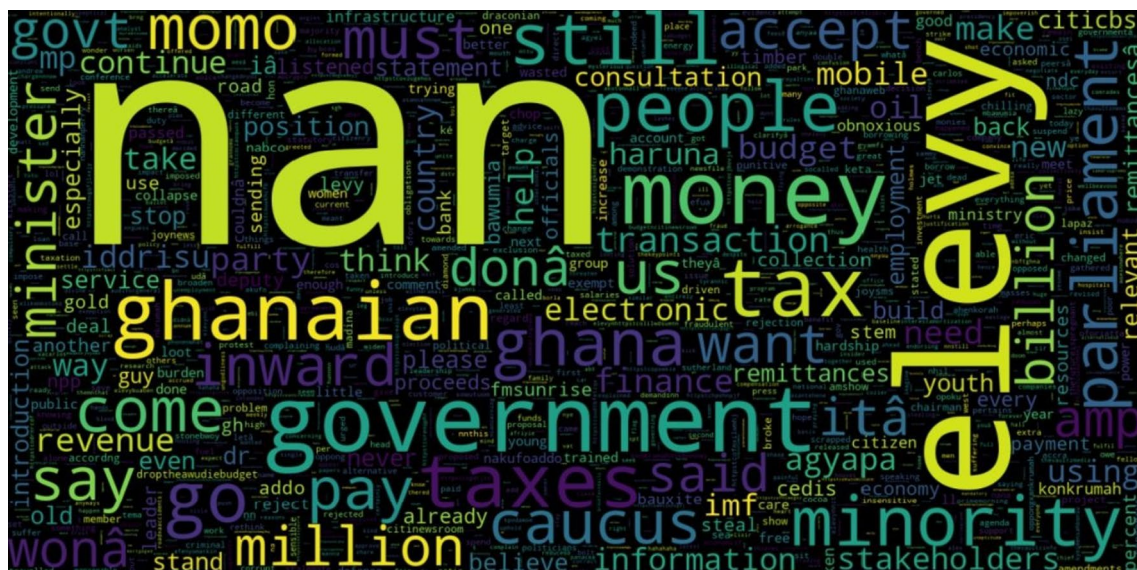
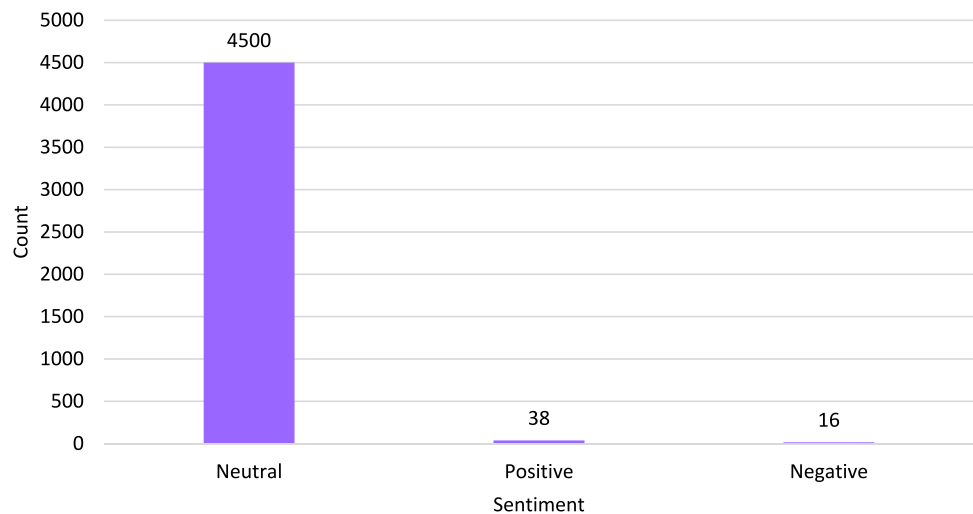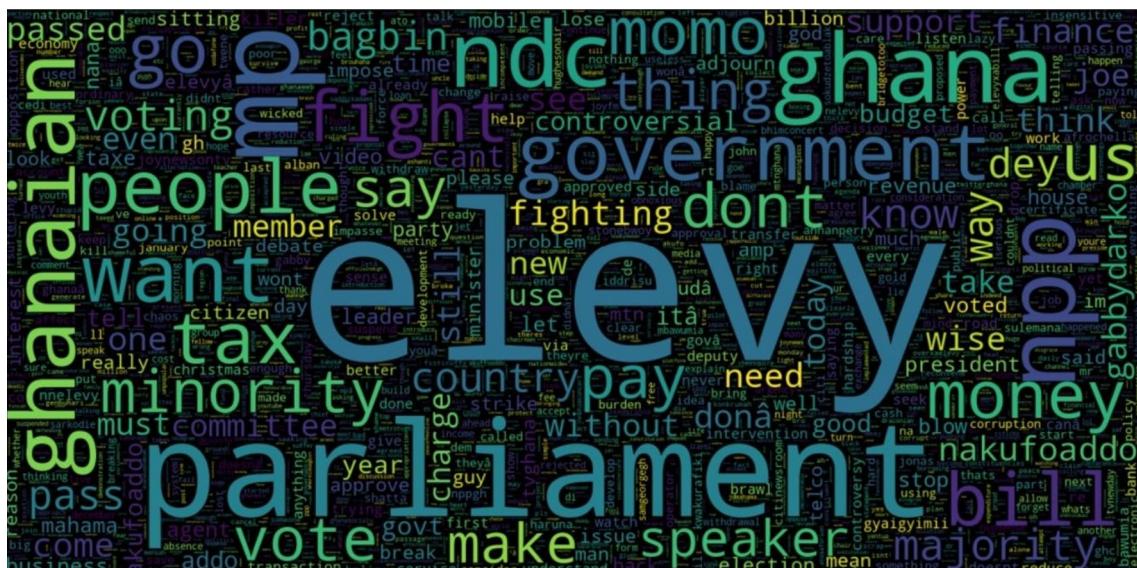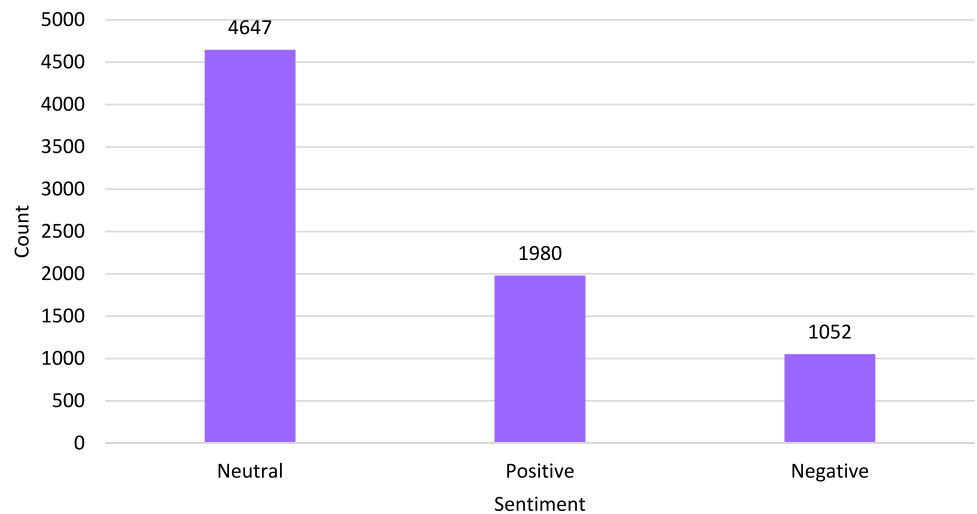**Fig. 6** Sentiment analysis score for phase 2

Fig. 7 Word count score for phase 2

Fig. 8 Sentiment analysis score for phase 3

Fig. 9 Word count score for phase 3

the bill was called before the parliament to be considered. The sentiment analysis classification and word cloud are represented in Figs. 8 and 9.
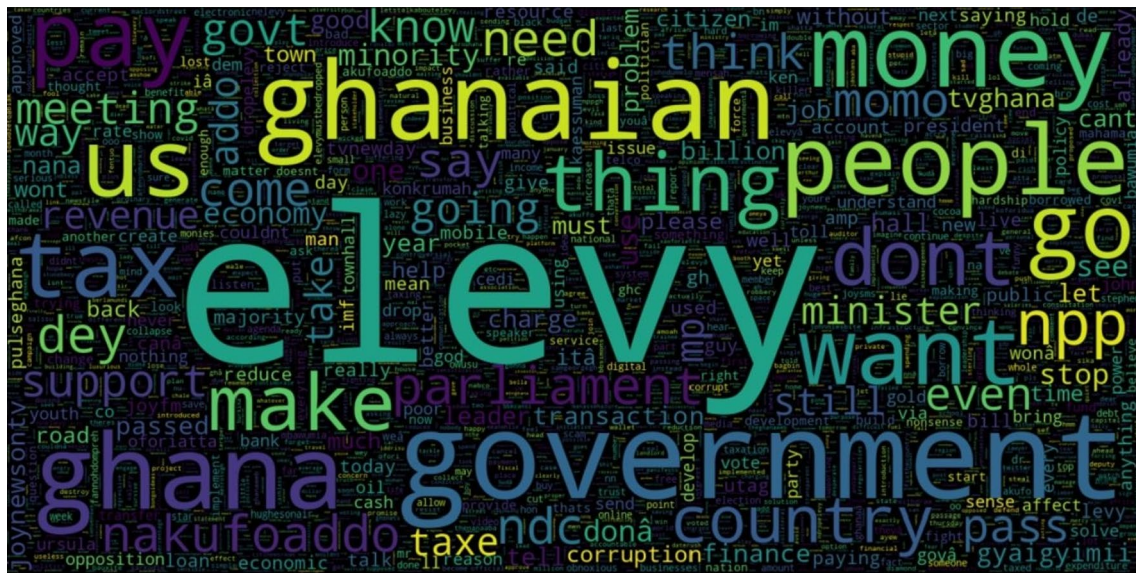
From the results in Phase 3, 4647 (60.52%) tweets were neutral. 1980 (25.79%) tweets and 1052 (13.69%) tweets were positive and negative, respectively. There was an increase in positive tweets, which can be attributed to the controversies the policy garnered in the mainstream media after the brouhaha in parliament. People began to comprehend how the policy worked, but it was not enough to make a clear decision because most people understood how it worked. The words like "elevy," "parliament," "momo," and "fight" were frequently used. When the bill was called for

consideration, the minority and majority caucuses in parliament had a scuffle, which was not a pleasant scene.

4.4 The feeble phase

Between December 31, 2021, to January 15, 2022, 1701 total tweets were collected in phase 4, with Figs. 10 and 11 depicting the sentiment analysis classification and the word cloud. During this period, the parliament was in recess, and the issue of E-Levy was not prevalent in the mainstream media, primarily due to the Christmas and New Year festivities. Positive tweets were 400 (23.52%), negative tweets were 200 (11.5%), and 1101 (64.73%) tweets were neutral.

2208

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214

Fig. 10 Sentiment analysis score for phase 4

Fig. 11 Word count score for phase 4

Fig. 12 Sentiment analysis score for phase 5

Fig. 13 Word count score for phase 5

There was a slight drop in the count of positive tweets compared to the third phase. Though the e-levy policy was addressed, it was not well received because most people were engaged in celebrating Christmas.

4.5 The debate phase

The fifth phase recorded a total of 18,423 tweets. This took place between January 16, 2022, and January 31, 2022. Figures 12 and 13 represent the sentiment analysis classification and the word cloud, respectively.

From the analysis, 10,923 (59.29%) tweets were neutral, 4500 (24.43%) tweets were positive, and 3000 (16.28%) tweets were negative. It can be seen from the analysis that enormous data was collected during the fifth phase with the highest positivity. During this period, parliament recalled the policy to be discussed, and the government also held town hall meetings to explain how the policy works to the general public. Words like "elevy," "money," "people," and "country" are very frequently used. People began to wonder what impact it would have on the economy, the regular citizen, and economic opportunities.

Figure 14 below represents the trend in the number of tweets recorded in each phase graphically. Table 3 shows the results of the analysis.

### 4.6 Sentiment analysis on entire dataset

In order to determine the efficacy of our model and check for possible biases, we performed sentiment analysis on collective data from the five phases (38,771 tweets) collected from November 17, 2021, to January 31, 2022. The sentiment analysis classification and the word cloud is depicted in Figs. 15 and 16. According to Fig. 15, 9,887 (25.50%), 6,000 (15.48%), and 22,884 (59.02%) tweets were positive, negative and neutral, respectively. The words like "elevy," "pay," "momo," and "government" were used frequently. The citizens mainly asked what the implications would have on small businesses, such as mobile money businesses and individuals. The favorable attitude improves as the dataset grows, indicating that individuals are not upset with the tax and that more education and awareness will produce positive consequences.

4.7 Evaluation of various machine learning and deep learning models on the total data

We evaluated the performance of a variety of machine learning models and deep learning models on the full dataset for a proper comparative analysis. In machine learning frameworks, we evaluated the performance of Support Vector Machine [29], Naïve Bayes [30], Random Forest [31], Logistic Regression [32] and XGBoost [33] models. Each model was optimized using GridSearch for a variety of parameter settings. In deep learning architectures, we evaluated the performance of CNN [34], LSTM [35], CNN-LSTM [36], Attention-BiLSTM [37], Very Deep CNNs [38], BERT [39], Electra [23] and AlBERT [40]. Each model was optimized using early stopping on the validation set accuracy. Our

2210

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214

Fig. 14 Graphical representation of the tweet trends
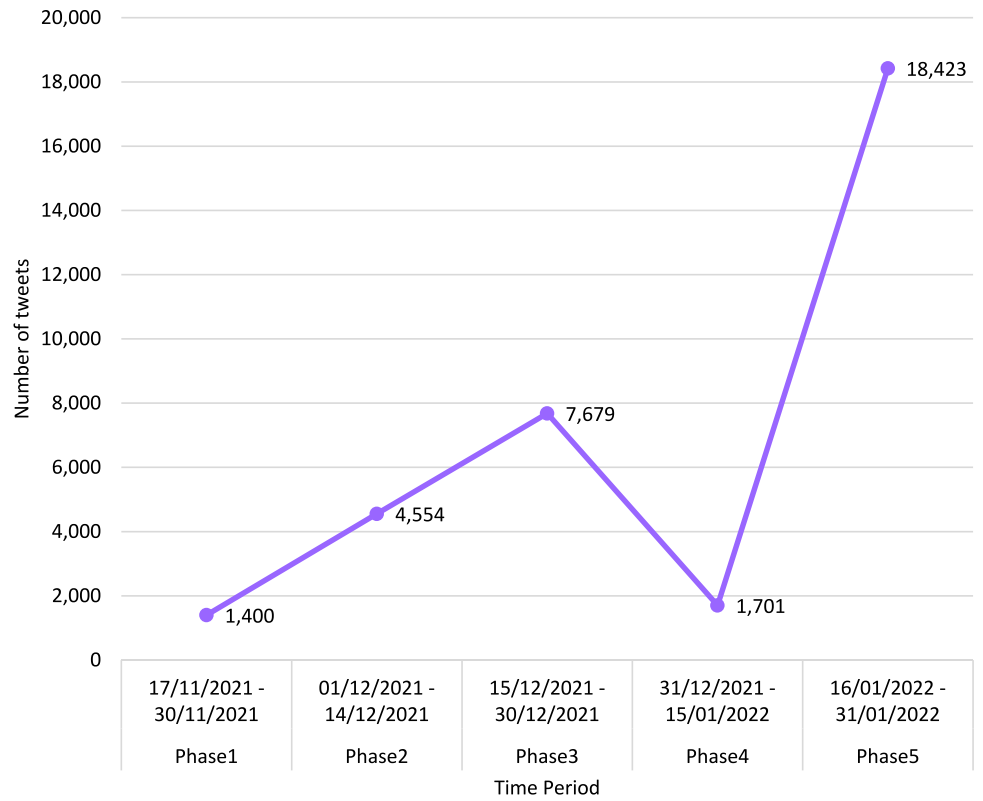
Table 3 Analysis of the phases

Phase	Date	Pos	%	Neu	%	Neg	%	Total
Phase 1	17/11/2021 – 30/11/2021	125	8.93	1,250	89.29	25	1.78	1,400
Phase 2	01/12/2021 – 14/12/2021	38	0.83	4,500	98.81	15	0.36	4,554
Phase 3	15/12/2021 – 30/12/2021	1,980	25.79	4,647	60.52	1,052	13.69	7,679
Phase 4	31/12/2021 – 15/01/2022	400	23.52	1,101	64.73	200	11.75	1,701
Phase 5	16/01/2022 – 31/01/2022	4,500	24.43	10,923	59.29	3,000	16.28	18,423
Total	17/11/2021 – 31/01/2022	7,043		22,421		4,293		33,757

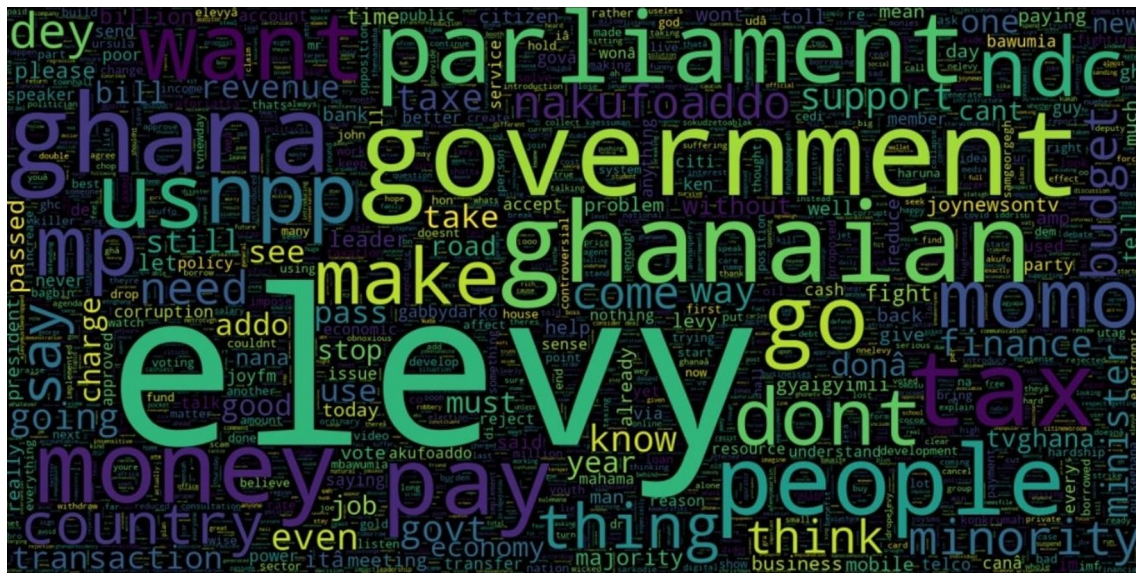**Fig. 15** Sentiment analysis score for full dataset
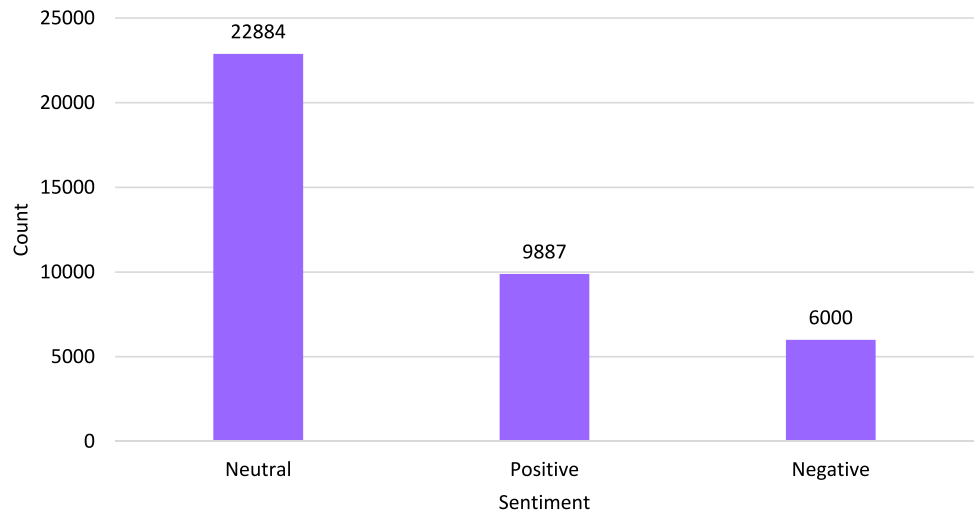
Fig. 16 Word count score for full dataset

Table 4 Performance evaluation of various machine learning and deep learning models

| Model	Accuracy	Precision	Recall	F1-score
SVM	0.921	0.899	0.873	0.885
Naive Bayes	0.707	0.829	0.482	0.501
Random Forest	0.743	0.83	0.548	0.589
Logistic Regression	0.906	0.867	0.856	0.861
XGBoost	0.746	0.822	0.553	0.595
CNN	0.886	0.838	0.898	0.857
LSTM	0.928	0.903	0.886	0.894
CNN-LSTM	0.949	0.922	0.928	0.924
Attention-BiLSTM	0.938	0.905	0.899	0.901
VDCNN Depth 2	0.941	0.911	0.917	0.914
BERT	**0.972**	**0.957**	**0.963**	**0.96**
Electra	0.951	0.924	0.94	0.932
AlBERT	0.966	0.947	0.958	0.952

Bold indicates the best-performing model

results are illustrated in Table 4 and pictorially represented in Fig. 17.

4.8 Discussion

Based on the results of our analysis, the driving factors of the Ghanaian people's attitudes toward the implementation of the e-levy can be categorized into three: positive, neutral, and negative. Positive refers to the section of the populace who are in support of the proposed e-levy. Neutral means the people do or do not understand the proposed e-levy (neither in support nor against) and how it works, while negative are people strongly against the proposed e-levy. Individuals around the globe support policies that minimize their expenses and maximize their benefits. For this study, we categorized our dataset into five phases to ascertain the real sentiments of the people using the Twitter data. The first phase recorded the least amount of data, and the highest recorded twitter data was phase five. In phase 1, the positivity rate was quite substantial, meaning people were not unhappy about the tax; however, the neutral point was higher. The neutrality signifies that people did not clearly understand how the policy works. In the second phase, the positive score increased; that is, people are not unhappy about the policy; however, understanding how the policy works is still needed. There was an increase in the positive tweet count during the third phase. This can be attributed to the controversies the policy garnered in the mainstream media after the brouhaha in parliament. People began to comprehend how the policy worked, but it was not enough to make a clear decision because most people understood how it worked. In addition, there was a slight drop in the positive tweet count compared to the third phase. Though the e-levy policy was addressed, it was not well received because people celebrated Christmas. During the fifth phase period, parliament recalled the policy to be discussed, and the government also held town hall meetings to explain how the policy works to

2212

Int. j. inf. tecnol. (April 2024) 16(4):2199–2214
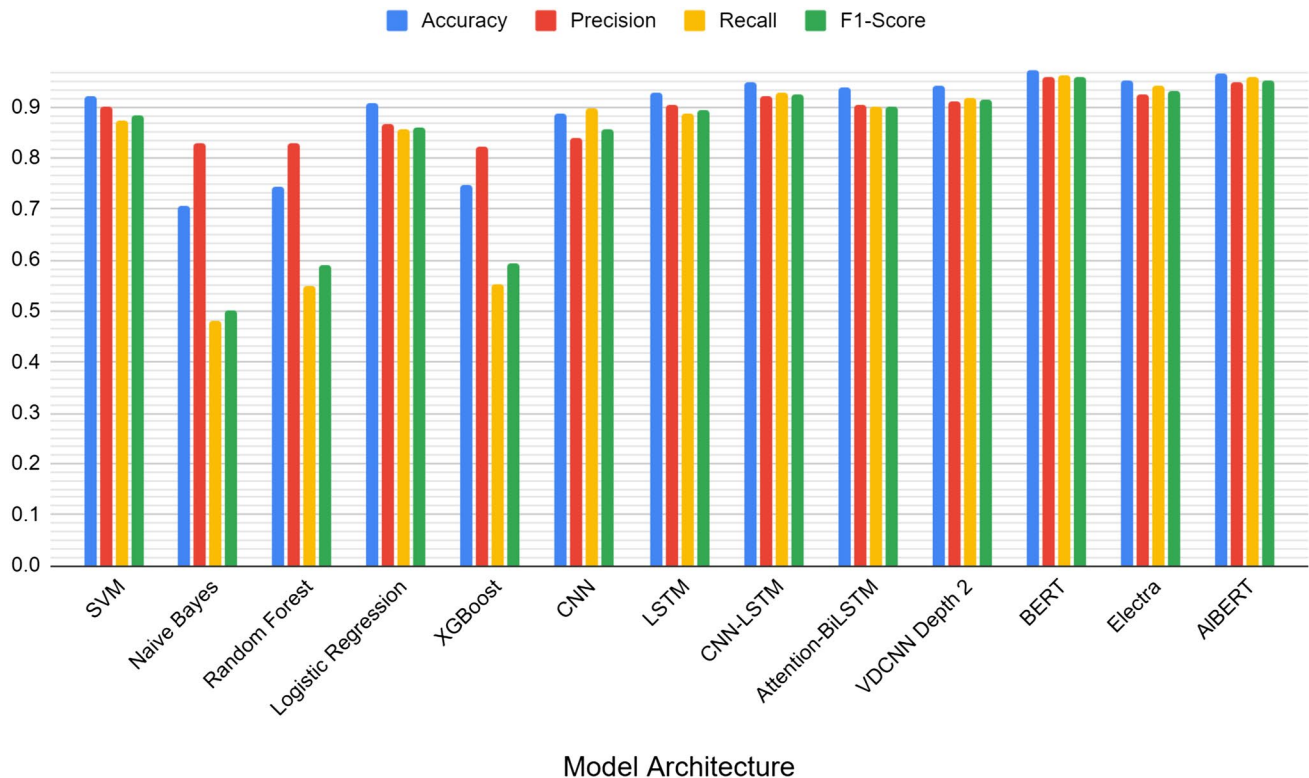
Fig. 17 Bar graph for the performance results obtained for various ML and DL models

the general public. Moreover, a complete dataset analysis was also conducted to prevent any possible biases in the data collection. The analysis shows that the number of positives increases steadily whenever the total amount of data increases in each phase. From this study, it can be observed that a large portion of the populace shares neutral sentiments; that is, they can be a category of people who are informed of the policy and yet remains neutral or have not clearly understood (neutral) how the e-levy policy works. We urge that town hall meetings be organized nationally, with local dialects as the medium of communication, for the government to earn citizens' support. The government is keen to generate homegrown revenue for development, hence, the introduction of the electronic levy tax to generate revenue. We strongly believe that, when the proposed e-levy policy is understood, the more positive the sentiments to support the policy. The novelty of this study brings to bear the introduction of a novel electronic levy which is rare in Africa, and introduced by the government of Ghana. In existing studies, researches such as Singh et al. [5] considered the Indian government's policy of the demonetization of high-denomination money, and Kaurav et al. [8] underlined the concerns and focus of NEP (National Education Policy). This study focuses on a

novel policy that the Ghanaian populace has never heard of. The vast amount of information gathered on Twitter focuses on taxes.

5 Conclusion

With the announcement and implementation of new government policies, there are always some positive and negative repercussions. A typical example is the proposed E-Levy policy to charge 1.75% on mobile transactions. The goal of this study was to use sentiment analysis to assess the impact of the proposed e-levy policy. Our research found that a considerable percentage of Ghanaians were neither delighted nor unhappy (neutral) with the policy because the average person had little or no awareness of the policy. Eventually, as the policy gained popularity on mainstream and social media, the positive sentiments of the people increased steadily.

The complete data analysis led us to conclude that, in broader terms, a large number of Ghana people are neutral on the proposed policy with little difference in positive and negative. Based on those mentioned above, we suggest the government take a critical look at the policy before

its implementation. This is to curb the possible drop in mobile transactions to sabotage our vision as a cashless country. The government should increase its town hall meetings with communication in the local dialects for easy understanding.

This study uses data collected from the microblogging site Twitter; however, a more significant portion of social media users in Ghana is on Facebook. It is challenging to access data from Facebook due to the platform's privacy concerns and API restrictions. Through proper means, fellow researchers can indulge into analyzing user emotions better by extracting data from other social media applications. Robust machine learning and deep learning models can be employed to perform sentiment analysis to generate some decision generation systems in the future. Future research can also use hybrid and ensembles of various machine learning algorithms, as well as quantum learning machines, thanks to the development of even higher algorithms.

Presently, the study involves and is limited to exploratory analysis of sentiments about the policy implementation. The authors have planned to perform labeling the data in order to perform supervised sentiment classification using machine learning and deep learning algorithms.

Declarations

Conflict of interest The authors declare no conflict of interest.

Appendix A

See Table 5

Table 5 Definition of used symbols used in the study

Symbol	Definition
QR code	Quick response code
E-Zwich	Electronic switches
E-levy	Electronic levy
Kume preko	Kill me now
@	Location or institution of an email receipient
\n	Newline
#	Hashtags used in the tweets
â€œyÉ›te	Yete: a local dialect literally translated "we sit on"
â€	Noaa: a local dialect meaning "is that all"
Nan	Nana: the name of the current president of Ghana

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