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Sentiment Analysis of Nigerian Students' Tweets on Education: A Data Mining Approach

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Abstract

The paper is aimed at investigating data mining technologies by acquiring tweets from Nigerian University students on Twitter on how they feel about the current state of the Nigerian university system. The study for this paper was conducted in a way that the tweet data collected using the Twitter Application was pre-processed before being translated from text to vector representation using a feature extraction technique such Bag-of-Words. In the paper, the proposed sentiment analysis architecture was designed using UML and the Naïve Bayes classifier (NBC) approach, which is a simple but effective classifier to determine the polarity of the education dataset, was applied to compute the probabilities of the classes. Furthermore, Naïve Bayes classifier polarized the tweets' wording as negative or positive for polarity. Based on our investigation, the experiment revealed after data cleaning that 4016 of the total data obtained were utilized. Also, Positive attitudes accounted for 40.56%, while negative sentiments accounted for 59.44% of the total data having divided the dataset into 70:30 training and testing ratio, with the Naïve Bayes classifier being taught on the training set and its performance being evaluated on the test set. Because the models were trained on unbalanced data, we employed more relevant evaluation metrics such as precision, recall, F1-score, and balanced accuracy for model evaluation. The classifier's prediction accuracy, misclassification error rate, recall, precision, and f1-score were 63 %, 37%, 63%, 62%, and 62% respectively. All of the analyses were completed using the Python programming language and the Natural Language Tool Kit packages. Finally, the outcome of this prediction is the highest likelihood class. These forecasts can be used by Nigerian Government to improve the educational system and assist students to receive a better education.

Keywords: Sentiment analysis; Naïve Bayes; Education; Students; Polarity; Twitter.

1. Introduction

Improving the quality of students' education, as well as education in general, has always been a goal that educational institutions have pursued.

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Efforts have been undertaken to understand and improve students' learning experiences in a variety of ways. Therefore, this study investigated the development of sentiment analysis or opinion mining system for determining the feedback of students about Nigerian education in the context of improving the sector. The current educational system is a landscape that is constantly enriched by a large amount of data generated daily in various formats, much of which hides useful and valuable information [1].

In today's world, there is a vast amount of data shared on social media all over the world from which data analysts leverage from to access views of users on various topics of interest and; hence predict business and social outcomes like stock return, product sales, the political outcome of elections [2,3,4] and others. Social media are defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content" [5]. Consequently, the gathering and evaluation of real-time user-generated content help to acquire important insights about a specific demand, which is critical for decision-making [6]. One of the major aspects in which these leveraged data is used is in the analysis of opinions popularly known as "Sentiment Analysis".

Sentiment analysis, also referred to as opinion mining, subjectivity analysis and appraisal extraction is described as a process that automates the mining of opinions, views, attitudes and emotions from the text, tweets, speech and database sources through Natural Language Processing (NLP) [7]. Sentiment analysis makes use of computational techniques to study peoples' emotions and opinions on given topics shared in form of text data. The concept of sentiment analysis is to study a group of text data to understand the opinion or sentiment expressed by the text. This is usually achieved by identifying the sentiment within the text(s) and representing them with a value that is positive or negative, known as polarity. From the sign of the polarity, the overall sentiment is often deduced as positive, neutral or negative. Sentiment analysis has a major impression on texts which hold some form of emotion, or dispositions.

Although sentiment analysis (SA) and opinion mining (OM) appear to be the same thing, there is a distinction: the former relates to discovering sentiment words and phrases that express feelings, whilst the latter refers to extracting and analyzing people's opinions for a certain entity. For this study, both strategies are considered interchangeable. One's attitude toward a target thing is represented by the sentiment/opinion polarity, which can be positive, negative, or neutral. Emotions, on the other hand, are one's expressed feelings about a certain topic. Several hypotheses about emotion detection and classification have been established since the 1960s.

One of the major benefits of sentiment analysis and opinion mining approaches is the ability to find and extract hidden "pearls" from a sea of educational data. Students' feelings and opinions are an important source of information not only for examining students' attitudes about a course, topic, or teacher but also for modifying policies and institutions to improve their performance [1].

Sentiment analysis has been widely used in a variety of fields in the previous decade, including business, social media, and education. In addition, the previous systematic reviews focused on techniques, methods, and domains in various fields [8, 9] or specific areas such as Marketing, education, health, and tourism [8, 9,10, 11,12]. The usage of sentiment analysis is rising due to the increasing amount of online published data; hence

Higher Education (HE) must use automatic techniques to acquire a deep understanding of this online data. However, it remains problematic, particularly in the education area/sector, where dealing with and processing students' thoughts is a difficult task due to the nature of the language used by students and the vast volume of information. For instance, analyze the students' online opinions and behaviours to have a complete vision of the quality of the services and address some aspects that may affect their education [13].

Nonetheless, several studies of the literature illustrate the current state of sentiment analysis application in this sector from various perspectives and settings. However, there is little or no systematic overview of the research and results of using natural language processing (NLP), deep learning (DL), and machine learning (ML) solutions for sentiment analysis in the education domain in the body of literature. In addition, education in Nigeria is beset by a slew of problems that have harmed its quality. As a result, students have gone to social media to express their dissatisfaction with Nigeria's educational system. Sentiment Analysis has been used on a variety of datasets, including customer comments on a particular product or service, political views on various politicians, and so on. However, there has rarely been any research conducted on a dataset of Nigerian students to determine their overall attitudes regarding education in Nigeria.

Studies have also shown that students' feedback for the evaluation of teaching and learning enhances the delivery of quality education. There has been a series of manual methods such as polling and audience response used to analyze the text (opinion) submitted by students. However, the existing approach, which is manual methods, used for the evaluation of students' opinions has been adjudged to be inefficient. In contrast, scholars and several researchers have developed an interest in formulating models that will analyze the opinion received from students accurately to polarize results. As a social media platform, Twitter makes it easier to freely share personal thoughts, making it a useful tool for Opinion Mining and Sentiment Analysis. Consequently, public debates on Twitter based on ideas regarding higher education institution (HEI) topics and events can generate a substantial volume of real-time data in informal settings, which can be leveraged to gain helpful insights into the HEI environment.

Opinions play a very important role in development and decision- making. Therefore, insights gotten from this study, are expected to play an important role in the development and enhancement of the Nigerian educational sector. Also, to get very accurate polarity, a robust model would be developed which can be trained using other datasets. However, researchers and other Institutional officials, have yet to look into this unstructured data. Therefore, the need for a computational model that will analyze the opinion given by students and polarize the result for decision-making emerges in the context of mining and evaluation university informal remarks is therefore required, hence this study.

In today's digital era, academic Higher Educational Institutions (HEI) or higher institutions of learning get a significant number of comments, opinions and critiques daily via popular social media platforms. Recent US research, for example, examined and deconstructed the rising adoption rates of various key social media platforms in US higher education institutions [6]. In this regard, United States (USA) and other nations' higher education institutions including Nigeria currently have official accounts on the most popular social media platforms, including Facebook, Twitter, and YouTube on their official university website, they even provide an icon connection to these social networks. For instance, Figure 1 shows that 85.8% of USA HEIs have Twitter accounts, implying that many US Twitter users maybe writing a large number of Tweets in the context of HEIs. As a result, gathering and analyzing such Tweets of informal utterances is essential to infer some academic institutes' significant ideas. In this way, such observations piqued our interest and provided the impetus for us to perform this study. Based on the foregoing, Twitter social media platform is chosen because of its vast source of subjective text material that reflects public mood with more quick responses than a traditional web blog.

Twitter, amongst other social media network, has been the most widely used social media platform for sharing texts data about a particular topic or matter. Opinions matter in decision making. As a result, many companies and organizations such as; Apple, Amazon, etc. usually seek an opinion from their customers on their products or services in other to upgrade products or services to fit the customers' needs. Furthermore, due to its freely available API, the vast amount of available data is easier to collect and crawl [15/14,16/15]. Twitter, on the other hand, allows users to share their thoughts, opinions, and feelings on a variety of topics, fostering lively debate and discourse on social, political, and economic issues, as well as, more recently, educational issues. As a result, Twitter is seeing a flurry of new Sentiment Analysis research as an important source for opinion data in several domains.

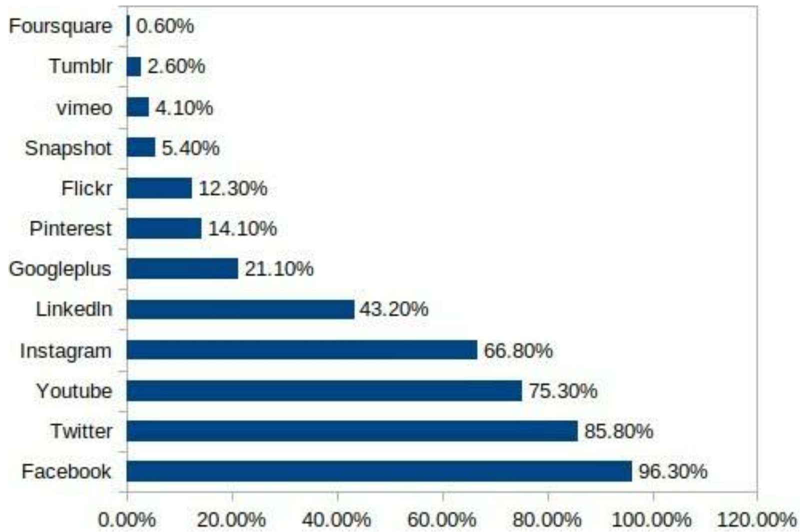

Figure 1: Relative proportion of all US higher education institutions with an official account for each social network

Reference [16] opined that Sentiment Analysis is presently one of the most popular expanding fields of research in Computer Science, which coincides with the growing popularity of microblogging platforms. It's used to automatically extract and comprehend hidden sentiment in text written by people to communicate their thoughts and feelings. The majority of Sentiment Analysis work on the Twitter microblogging platform has focused on movie and product reviews [5,17,18], with less emphasis on reviews and informal opinions regarding HEIs such as universities and colleges.

Nevertheless, sentiment analysis can be performed on individual words, sentences, or documents. However, due to the high volume of papers, manual sentiment processing is not feasible. As a result, automated data processing is required. Natural language processing is used to analyze sentiment from text-based, phrase or document-level corpora (NLP). Therefore, the paper aims to design and implement a sentiment or opinion analysis model to evaluate the opinion of Nigerian students as feedback from teaching and learning in Nigerian tertiary institutions. To successfully achieve the aim of the study, the specific objectives are to examine the existing models and systems, design the opinion mining model, implement the designed model and evaluate the performance of the system.

In many developing nations like Fuji and the Korean Republic, the government is using sentiment analysis to improve their present state of the education system. The government has taken many decisions in the educational sector for various parameters such as the extracting opinions of students regarding higher studies, the kind of environment required in the educational institution, teaching quality and overall performance in academics [19].

Decision making has so far been the significance of researching people's opinions. By carrying out such research, insights are gained into what people want, and how they feel about a certain topic, product or situation. This can be likened to the review section on various e-commerce platforms such as Amazon, and eBay where individuals are urged to leave their opinion on how they feel about the product or service hence considering these opinions, they can upgrade or update their product or service to suit the user's needs. Likewise, this study gives insight into the sentimental state of the underlying population and thus aids decisions making. Also, in studying other opinion mining models, comparisons are made and a more accurate model would be established.

In addition, investigating tweet sentiments at the university level might reveal important information about various responses and reactions connected to the entire academic, institutional, and social experience among Twitter users in that subject. As a result, officials in educational institutions can use the findings of this study to make critical decisions about how to improve the overall quality of teaching and learning, as well as how to improve students' college experiences in terms of social support and on-campus amenities.

Moreover, Students, teachers, staff, and alumni are increasingly using social media platforms like Twitter regularly to make informal statements (comments, opinions and thoughts) about their universities and university education. As a result of this reality, mining and analyzing such opinions is critical in a variety of ways. For starters, it acts as a performance monitoring method for obtaining a high-level overview of the university situation. As a result, from an institutional standpoint, the study will assist in the decision-making process for further improvement and plan adjustments. Second, people rely on such research to help them decide whether or not to enroll in a particular university or class. Hence, educational environments must be used to their greatest potential for public opinion to be heard [1] in such a way that this information can be used to understand the benefits of SA in HE institutions and its potential to improve institutions' quality and evaluate the teaching process and teachers' performance.

This study covers mostly university students in Nigeria. The fact that there is no actual method for filtering tweets of just students in Nigeria has led to the use of keyword parameters like; “students”, “education”, “university”, “lectures” “lecturers” etc. to acquire only tweets across the Nigerian geographical region using Nigeria’s latitude and longitude points on the map. With this, it is assumed that 90% of data acquired would be that of university students in Nigeria. Also, the population is internet users who have written tweets about university education in Nigeria. The period covered is from 2019 to 2020.

Also, the content of the study relates to the mining of emotions and opinions from Online Forums, Blogs and Twitter. However, the study is limited to information diffusion texts through Twitter on educational institutions in Nigeria as a case study. The study will be limited to analyzing the texts (student feedback) submitted by Nigerian students, extracting and polarizing the result. As much as sentiment analysis (SA) is concerned through the use of NLP, Natural Language Processing (NLP) techniques require text data, where these text data need to match with a certain dictionary. Most users on social media tend to create these strings of text whichever way they want to. While some do this because of a lack of proper education, others see it as a trend to follow and a rule for social media messaging/texting. In some cases, these abbreviated words are contrary to the production rule for the strings in English Language and therefore will not be understood by the computer. The use of an abbreviated form of texting like "5yn" instead of "fine" can be problematic as the word "fine" indicates positivity but would eventually be removed during the data cleaning stage as it does not have any meaning in the English language. Also, some words when used in context might portray an emotion that is in contrast to the word. For example, "these sneakers are mad!" in context, "mad" is positive

The rest of the paper is organized as follows. Section 2 provides some background information on sentiment analysis and related works that focused on or employed educational textual data. Section 3 is dedicated to the methodology of search strategy adopted, data collection, cleaning and processing the data as well as the building the proposed classifier model. Section 4 contains the experimental results of the model and a discussion of the result of the experimental phase. Finally, in Section 5, we provided a conclusion and introduce a further improvement of the research topic.

2. Literature Review

Sentiment analysis is a task that focuses on detecting polarity and recognizing emotion toward a person, a topic, or an event. The purpose of sentiment analysis, in general, is to find people's opinions, identify the sentiments they express and categorize them as positive, negative, or neutral. Sentiment analysis systems utilize natural language processing (NLP) and machine learning (ML) techniques to find, retrieve, and synthesize information and opinions from large amounts of textual data [20]. Sentiment analysis, which is the technique of identifying sentiment words and phrases that express emotions, has recently gotten a lot of study attention, particularly in the education sector and massive open online courses (MOOCs) in particular [21,22].

Sentiment analysis is a technique that can extract the most important information for the user from plain text data. This prompted a rise in the study in the fields of opinion mining and sentiment analysis, to develop algorithms that can evaluate text spans or user reviews automatically and extract information that is most relevant to the user. However, there have been several papers written on sentiment analysis for the domain of blogs and product reviews, politics, movies, [23]. In addition, Sentiment analysis has been widely used for diverse reasons in a variety of application fields, particularly in business and social networks. Product and service evaluations, financial markets, customer relationship management, marketing strategies and research [17,18,19] are only a few examples of well-known sentiment analysis business applications. In terms of social network applications, the most typical use of sentiment analysis is to track a brand's reputation on Twitter or Facebook [20] and to investigate people's reactions to a crisis; for example, COVID-19 [21]. Another prominent application sector is politics [22,23] where sentiment analysis can help candidates running for political office with their election campaigns.

Sentiment analysis techniques are divided into three categories namely Machine Learning (ML), lexicon-based (LB) and hybrid (HB) approaches [19, 24]. Machine Learning methods can be supervised or unsupervised, and they employ conventional machine learning algorithms as well as linguistic features to classify opinions into positive or negative sentiment. A list of words or phrases that convey positive or negative polarity information is referred to as the Lexicon-based approach. The lexicon-based approach is more understandable and can be easily implemented in contrast to the machine learning approach. However, limited to the requirement involving humans in the process of text analysis as illustrated in Figure 2. While the hybrid approach combines both machine learning and lexicon-based methods.

Much study has been done on user sentiment analysis, which mostly judges the polarities of user evaluations. Sentiment analysis is frequently used in this research at one of three levels: document-level, phrase level (aspect), or attribute (sentence) level. According to the literature review, two types of methodologies, machine learning and semantic orientation, are relevant in sentiment analysis [25]. Sentiments by analyzing the entire document that is being treated as a single entity, However, the results generated at the document-level are not always relevant. The Sentence-level analysis, which is performed on the sentence is aimed at determining the polarity of sentences rather than the full document, therefore it is more fine-grained. While the Aspect-level sentiment analysis focuses on recognizing features or attributes stated in reviews and classifying users' feelings about them. [26, 27, 1].

Sentiment Analysis is a branch of research in the text mining industry that is still evolving [28]. The majority of text analytics systems attempt to classify a document after proper training and comparing positive and negative classifiers. Sentiment Analysis is a classification issue in this context, to categorize documents into two groups (positive and negative). The authors of Thumbs up! Sentiment Classification using Machine Learning [29] demonstrated that three of the most commonly used machine learning techniques (Naïve Bayes, Maximum Entropy Classifiers, and Support Vector Machines (SVM)) perform differently in sentiment analysis problems than in simple topic classification problems. An emotion lexicon is also utilized in several techniques to assess whether words/phrases have a positive connotation or negative meaning.

Nevertheless, [29] elaborated and presented a meaningful piece of work based on traditional topic classification approaches. The proposed approach described by the authors tries to see if a chosen group of machine learning algorithms can yield positive results when sentiment analysis is viewed as document topic analysis with two topics: positive and negative. However, [29] findings for studies revealed that the Naïve Bayes, Maximum Entropy, and Support Vector Machine methods produced a surprisingly comparable result to other solutions, ranging from 71% to 85% depending on the method and test datasets. [30] proposed the use of a neural network to learn an effective model of sentiment classification. The authors compared their work with a Support Vector Machine model using the multi-thematic Amazon corpus. However, the experiment result shows identical performance.

Moreso, because of commercial challenges, the discipline of sentiment analysis is wide and growing rapidly. [7] compiled a fairly comprehensive state of the art in 2008, focusing on the applications and problems of sentiment analysis. The authors discussed the approaches utilized to solve each sentiment analysis task. The authors addressed the challenge encountered in search engines. In an attempt to achieve the goal, the authors employed an unsupervised machine learning technique to re-rank the search engine result when queries are issued using a document-level type. The result from the study revealed that the method used performed comparably to the pre-encoded linguistic knowledge used. Furthermore, both methods produced an improved result when implemented by the yahoo search engine.

[31] investigated the character and organization of web forums and e-learning blogs using sentiment analysis. They have 1,000 positive and 1,000 negative writings in their corpus. Using the Information Gain feature [24] on hybrid classifier Hidden Markov Models [25] and SVM, they were able to attain the best results. [12] proposed methods for gathering student input. On NB and SVM classifiers, they used features including word presence and frequency, n-grams, part-of-speech, grammar, and negation.

2.1. Related Work

In the education arena, sentiment analysis and opinion mining have recently gained a lot of study attention [20]. Unlike the above-mentioned domains of business or social networks, which focus on a single stakeholder, education sentiment analysis research considers a variety of stakeholders, including teachers/instructors, students/learners, decision-makers, and institutions. By assessing learners' attitudes and behaviour regarding courses, platforms, institutions, and teachers, sentiment analysis is primarily used to improve teaching, management, and evaluation.

[32] employed data mining with natural language processing to obtain the chunks of knowledge from large volume of student feedback dataset on faculty performance with the aim of comparing two well-known association rule mining and sequential pattern mining algorithms namely Apriori and Generalized Sequential Pattern (GSP) mining in the background of extracting common features and opinion words. Student feedback data was crawled, pre-process, tagged, and converted in tri-model data files. The two algorithms are then applied on prepared data using WEKA version 3.7.10 to extract the rules. Testing files are subjected to mined rules in order to extract common features and opinion words. Results from evaluations indicate that GSP is a more valuable tool than Apriori for textual data mining. Dhanalakshmi et. al. [33] applied SA on students' feedback and implemented the model using Rapid Miner tool to classify the comments into positive and negative classes.

With the help of text mining and sentiment analysis, Leong and his colleagues [34] gathered SMS input from students. The authors looked into the missing words and typos as well. Based on the concepts established for each category, each input has been categorized. Each comment has the option of belonging to none, one, or many categories. For the hybrid approach SVM and HMM developed by Jagtap and Dhotre [35] was employed to analyze the sentiment of teacher evaluations.

Altrabsheh and his colleagues [12] analysis's of student comments was based on data they gathered from social media sites like Twitter. They not only recognized the positive and negative emotions that students were experiencing, but also some more complex feelings. Positive emotions like confidence and enthusiasm are taken into consideration, as well as negative emotions like confusion, boredom, and irritability. A few methods have emerged as superior performers in sentiment analysis, including Naive Bayes (NB), Max Entropy (MaxEnt), and Support Vector Machines (SVM).

Sultana and his colleagues (2018)[36] proposed a Deep Learning model-based approach to perform sentiment analysis on educational data to improve the quality of teaching by giving positive or negative sentiments. The data was obtained from the Kalboard 360 dataset and trained by several classifiers like MLP, SVM, DTREE, simple logistics, multiclass classifier, K-star, Bayes network and Random Forest. The trained model was implement using WEKA. The result obtained was validated using 10-fold cross validation and evaluated using the accuracy, Root mean Square Error, specificity, sensitivity and the ROC area curve. In addition, the result obtained from the comparison of the models revealed that SVM and MLP-Deep learning method performed better when compared to the other classifiers in terms of performance metrics used to evaluate the system.

The majority of studies in the HE setting used SA methodologies to evaluate universities' performance, courses, teacher performance, teaching quality, and university rank, or to develop models for enhancing HE institutions' teaching quality. For example, [37] employed SA to look into students' perceptions of teacher performance, and they discovered that social mining can be used to solve the problem of analyzing teacher assessment feedback. The presented approach suggests the computation of sentiment score to classify the feedback as either positive, negative, or neutral conducted using KNIME. Similarly, the performance of the SA was measured using accuracy, recall, precision, and *F*-measure which were calculated and the results were found to be very positive. In addition, the best performance was for positive sentiments as it had the highest recall and precision rates. The paper also demonstrated that the sentiment score is comparable to aggregated Likert scale-based score. The study made use of confusion matrix, which helps in understanding the applicability of the presented approach. Findings revealed shows that there were 1028 positive feedbacks in our data set and 1002 were classified correctly. Similar to that, 94 out of 176 unfavorable comments were correctly identified, 29 out of 30 neutral feedbacks (a mix of positive and negative feedback) were accurately assessed, and just one was labeled as negative. Thus, the proposed approach was able to achieve an accuracy of 91.2%.

Reference [12/11] used SA and opinion mining to create a teacher performance evaluation tool that might assist identify teachers' strengths and weaknesses based on positive and negative feedback from students. In the study, the author applied four SA model and chose the best for automatic analysis of opinion at four aspects: preprocessing, features, machine learning techniques and the use of the neutral class. Moreover, the author employed 10-fold cross validation (recall, precision, F1-score and accuracy) to measure the performance of the SA model. The result showed that the highest result for the four aspects is Support Vector Machines (SVM) with the highest level of pre-processing, unigrams and no neutral class with an accuracy of 95% and SVM at 88%. However, the result of using the Naïve bayes gave a relatively low accuracy.

Reference [38] used SA to investigate students' textual instructor evaluations. The findings of the study revealed that categorizing students' input could improve the teaching and annual evaluation procedure quality. Furthermore, some earlier studies employed SA to assess higher education institutions. Reference [39], for example, used SA to compare university rankings from the institution with graduate students' social media posts and comments on social media sites like Twitter using the Twitter Application Programming Interface from 2014 to 2015. This is the same method through which [40,41] obtained their data for sentiment analysis in different domains. The author classified sentiment expressions into positive and non-positive. 16,488 twitter data was obtained using the API, preprocessed and its features was extracted using n-gram method of feature extraction. Furthermore, the annotated data set was classified using three models: NB, SVM, and Maximum Entropy. Moreover, the SA system was implemented using Python programming Language giving an accuracy of 73.6%. Furthermore, Reference [36] employed SA to evaluate Twitter data (about 16488 tweets) as a source of data for evaluating university performance using Natural Language Processing Techniques (NLP). The findings of such an analysis, according to this study, can be used to justify university rankings that have been criticized for measuring essential indicators. In the study, the data collected from the Twitter platform was classified using Support Vector Machine and Naïve Bayes (NB) classifier algorithms. Reference [37] applied SA techniques like StanfordCoreNLP to help students identify the right HE institution. The output of the study produced a system that extracts review data from social media sites like Twitter and Facebook and applied sentiment analysis techniques to assign a rating to an institution based on the value obtained. [9] also conducted a study utilizing NLP to evaluate overseas students' online reviews of the HE institutions using a social platform.

Furthermore, [38,10,42] employed lexicon-based SA to identify students' positive and negative opinions for predicting teacher performance and evaluating the quality of the teaching process. In their approach, any teacher's opinion level score is automatically extracted and evaluated from students' feedback comments. The students' feedback opinions were automatically classified into a strongly positive, moderately positive, strongly negative, moderately negative, weakly negative, weakly positive, or neutral category based on two lexicons. Similarly, Reference [12] used SA methods to analyze students' feedback to identify their positive or negative feelings towards the teaching process. Likewise, the author used SA to automatically model students' feedback using SVM. Maximum Entropy and NB SVM and NB were shown to be the most effective models for modelling students' feedback. However, NB can be a decent solution for non-regular training classes, which can be useful when the neutral class has insufficient data.

Reference [43] gave a comprehensive systematic literature review on Sentiment Analysis in Educational Domain. The review was aimed at identifying the approaches and digital educational resources used in sentiment analysis as well as to identify the major benefits of using sentiment analysis in the education domain, which includes the improvement of the teaching-learning process and students' performance, as well as the decrease in course menace. In an attempt to achieve the aim of the study, the researcher argued that several authors consider sentiment analysis to be a viable alternative for improving the learning process in an e-learning environment because it allows for the analysis of students' opinions to better understand their viewpoint take more effective and well-targeted actions. The authors employed the supervised method of Naïve Bayes (NB). The results revealed that Naïve Bayes is the most used technique for sentiment analysis and that forums of MOOCs and social networks are the most used digital education resources to collect data needed to perform the sentiment analysis process. Finally, some of the main benefits of using sentiment analysis in the education domain are the improvement of the teaching-learning process and students' performance, as well as the reduction in course menace, as well as the reduction in course menace.

Reference [44] developed a sentiment discovery and analysis (SDA) framework for multimodal fusions. Instead of focusing on text, audio, and visual data like some other authors did, the authors offered a comprehensive description of available and existing approaches for sentiment discovery, as well as the outcomes produced, in an attempt to cover all aspects of sentiment analysis of educational content systematically, with an emphasis on textual information only.

Reference [45] sought to analyze SA scholarly literature on education data and to identify future study opportunities in this area, where educational information is organized logically in a single location. From about 41 relevant research publications, the authors focused on the education field in greater depth, including the development of sentiment analysis systems, the research of learner-related themes, and the evaluation of teachers' teaching effectiveness, among other things. In the result obtained with regards to the comparison, the researchers filtered 612 research articles from various journals and conferences to perform a scientific literature review analysis. At the end of the screening procedure, the authors included 92 of the most relevant and high-quality scientific publications published between 2015 and 2020 in their study.

Reference [46] addressed the challenge of getting feedback from education. the explored the using data mining technologies to assess people's feelings (positive or negative) on the Federal Government of Nigeria (FGN) under President Muhammadu Buhari's administration (PMB). The Naïve Bayes (NB) classifier was used to classify numerous tweets into positive and negative attitudes. The findings revealed that the proportions of positive and negative sentiments were 45.2% and 54.8%, respectively, showing a more unfavourable viewpoint.

Reference [47] worked on classifying students' input using a natural language processing and machine learning technique to address the issue in teaching and learning. In an attempt to achieve the aim of improving teaching and learning, The authors proposed and designed a sentiment Analysis architecture. The proposed system examined student responses from course surveys and web sources to determine sentiment polarity, the types of emotions expressed, and pleasure satisfaction versus discontent dissatisfaction. The authors collected a data corpus consisting of students' feedback about a Coursera course from the learning portals (*coursera.org)* and the University Student Response System (SRS) the data has 4000 comments and 1700 other opinions after the completion of the course. The data obtained were pre-processed and the NRC emotion Lexicon algorithm was employed to classify the words into positive, negative opinions as well as other emotions. The results from the data visualization show that the positive emotions expressed by the student sought to weigh the negative emotions. In addition, the system was evaluated and validated through the ratings observed from the comment and students survey and comments obtained from the SRS on a 100 scale.

Reference [47, 48] in their studies opined that each domain in HE employs a certain number of SA techniques or applications. SVM and NB were the most often employed techniques/approaches in HE. As depicted in the paper authored by [47], these sentiment analysis techniques were employed in a variety of research and areas, followed by NLP, K-Nearest neighbour (KNN), and Lexicon-based SA, each with three applications. Multi-layer Perceptron (MLP), Stochastic Gradient Decent, sentiment classifier, VADER, StanfordCoreNLP, LDA, Maximum Entropy, social media mining, a Knime process, and the Opinion Finder tool were among the other techniques. On the other hand, the most popular SA platforms in the HE context are social media platforms like Twitter and Facebook, as well as discussion forums with 30%, 21%, and 19% usage respectively. Other platforms, such as e-learning, google forms, private datasets, and other social media websites have 9%,16%, and 5% usage respectively were used in specific sectors like course evaluation and performance feedback.

Other studies used SA to propose new approaches and frameworks to model students' comments according to a specific issue or problem or improve teaching quality in HE context. For instance, [49] conducted a study for examining the sentiment polarity from students' views and for modelling students' emotions (Anxiety, Amused, Confused, Enthused, Excited, Bored, Frustrated, etc.) using machine learning techniques such as a sentiment classifier, NB, and SVM based on the big data frameworks. In the same vein, [24] applied different ML methods such as SVM, Multinomial Naive Bayes, Random Forest, Multilayer Perceptron Classifier, and Stochastic Gradient Descent to propose SA model for improving the quality of teaching in HE institutions. The study effectively examined different SA models to find the appropriate model for analyzing students' classroom feedback. The study emphasized that social media websites such as Twitter and Facebook could be used as a valuable source of information and opinion mining related to students' education learning activities.

3. Methodology

3.1. Searching Techniques

According to the systematic mapping process, the conduct of search involves identifying the search string. In this study, the fact that there is no actual method for filtering tweets of just students in Nigeria led to the use of keyword parameters like; “students”, “education”, “university”, “lectures” “lecturers” etc. to acquire only tweets across the Nigerian geographical region using Nigeria’s latitude and longitude points on the map. The steps of the methodology used in this study are depicted in Figure 2. In the first step, we gathered Twitter data and discussed the tweet collection process that resulted in the data for this project. As part of the second stage, we cleaned up the data that was collected. This process is discussed in detail in section 3.2. The third stage is to analyze the data collected and preprocessed. Subsequently, we do exploratory and sentiment analyses of the tweets' texts for data analysis.

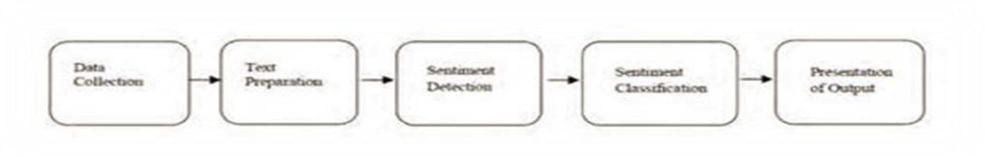

Figure 2: Methodology Step

3.2. Data Collection

This section presents information about the Nigerian University Education, Universities and its students' comments and the Twitter social network and its features. The method of collecting the education Twitter data is discussed in the following subsection.

3.2.1. Twitter

Twitter is a microblogging social network that was established in 2006 by Jack Dorsey, Biz Stone, Noah Glass and Even Williams [50]. The social network allows users to communicate messages, links to external websites, photos, and videos with other users who have subscribed to the service. In addition, Twitter serves as a platform where people can freely express their thoughts, feelings, issues and also state beliefs and opinions [51]. In comparison to typical blogs, messages submitted on microblogs are brief. blogging becomes micro simply by reducing blogging to its fundamental essentials and expressing the heart of the message and communicating the necessary as rapidly as possible in real-time, Twitter's messages were limited to 140 characters in 2016 [52]. Other microblogging platforms include Tumblr, FourSquare, Google+, LinkedIn, Skype, Facebook, etc. of which Twitter is the most popular, having begun in 2006 and attracting a vast number of users.

The data in form of tweets for this study came from Nigerian Student tweets on Twitter (a well-known social media platform) on the Nigerian Educational Sector about how they feel about the current state of Nigerian universities students, education or workers. The sample data of tweets collected is illustrated in Figure 3. A total of 4016 tweets i.e., comments that are in an unstructured form full of noise and unwanted information were received or scrapped online using the Twitter API and some Python Programming Language Libraries and packages, of which all were used after data cleaning. The twitter text data file contains two columns (Content and Sentiment) and about 4000+ rows of twitter data. To acquire this data, the Python libraries “snscrape”, “pandas” and “itertools” were used. The location variable "loc" was created and assigned the value of the geographical coordination of Nigeria. This "loc" variable as well as search keywords and number of tweets were then passed as an argument into the iterator module. The scraped tweets were added to a data frame using “pandas” library and saved as a .csv file.

3.3. Preprocessing Data

The Preprocessing was accomplished on the word-based data in two ways as shown in Figure 2. The first method involves the use of a tweet-preprocessor and a Python-based preprocessing package for tweet data cleaning (removal of stop words, punctuation, hashtags, hyperlinks, username (@) to prepare the data for further analysis). Second, to make the process of matching words in student comments easier, characters are changed to lower case using the “Swapcase” function in Python Language before the tokenization of the tweets. To make the data cleaning process more streamlined, a data cleaning pipeline (function) was created. The function removed punctuations, joined all the data as a string, converted the texts to lowercase and removed stop words such as after, etc. This was done to prepare the dataset for tokenization.

	@NASENIHQ @SenBoroffice https://t.co/0YSnEDbZLe
100	The future of education in the entire northern Nigeria is in complete mess, lack of motivation from the teachers, zero commitment from the government to invest in the education sector.
101	#Climate conflict, has been huge blow for #Education in Northern #Nigeria. #Climate Conflict has kept many children out of #class for more than years. It is painful to see a #girlchild begging on the street, you know
102	@GuardianNigeria You're benefit all you life in government you education an you health an you wealth and family all benefit with govt of Nigeria over fifty's year's ago be care with world and time help citizens of Ni
103	@TundeTASH The reason I vow never to be a Teacher in Nigeria despite my Education background
104	@comark Education in Nigeria is suspect Lai Mohammed quote😂😂😂😂😂😂.
105	@Gasbytweet @woye1 If you cn at list let go of your love for this current government and put Nigeria first, u will understand putting this huge amount of money into EDUCATION, HEALTH, AGRICULTURE AND INFA
106	NLC in Yobe kicks against 10% deduction from workers salaries to boost education https://t.co/l9lWFqttCH #Nigeria #NigeriaNews https://t.co/Bk2hQ51Lue
107	NLC in Yobe kicks against 10% deduction from workers salaries to boost education https://t.co/0WZKuAGLO8
108	NLC in Yobe kicks against 10% deduction from workers salaries to boost education https://t.co/bNBOqktPnC
109	I've been sick for the last couple of days, and I mostly spent my time hallucinating/thinking about how to fix the education system in Nigeria. The people teaching are mostly people who didn't get other jobs/proper education so they are teaching these kids rubbish.
	She was raised in Northern Nigeria where she had her primary and secondary education between 1940 and 1952 in Kano.

Figure 3: Screenshot of Sample data collected from Twitter social media Network

3.4. Feature Extraction

Feature extraction is an important step in information mining which is aimed at reducing the noise and dimensionality of the data. This process is called feature extraction (or vectorization), which is otherwise called tokenization. Here, the phase involves the conversion of the cleaned collected tweets text data into a list of words using Scikit-learn's Count Vectorizer to a vector of term/token counts. The Count Vectorizer provided a simple way to both tokenize the collection of cleaned text data and build a vocabulary of known words, known as a bag of words. Here, in practical terms, the word order was ignored and the frequency of words in the text was taken into consideration and processed using n-grams, particularly unigram. In step 4, a manually defined function was written to double-check the tweet preparation and re-move any undesirable tweets such as retweets. This is to ensure that the data obtained has been cleaned properly. The results of the preprocessed tweets are stored in the .csv file which provides data storage into columns of variables and rows of observations as shown in Figure 4.

	Content
0	seriously he's kai education in nigeria is ha...
1	tech of crypto holders in kenya nigeria south...
2	amen i cant wait for that day that nigeria e...
3	nigeria no get dream abegnigerians in nigeria...
4	good work in azerbaijan education should ...
...	...
4011	recommended inter alia that nigeria should est...
4012	no international media want to report this cr...
4013	there is no way you can expect me not to s...
4014	the educated ones they don't even teach us a...
4015	just removed nigeria hand from fire and put i...

4016 rows × 1 columns

Figure 4: Preview of Dataset after cleaning.

3.5. Experiment Tool

In this study, tools such as Wordnet and Naïve Bayes Classifier (NBC) were used on the dataset. Given the probabilistic characteristic of Naïve Bayes, each training sentence is vectorized by the trained Naïve Bayes classifier through the calculation of the posterior probability value for each existing. Finally, the model is evaluated by a set of testing data. To test the classification ability of the model, several evaluation measures (such as precision, recall, F1 Score Sensitivity and Specificity) are adopted. For the classification phase, a document (d) and class (c) depicted by the Naïve Bayes theory is given in (1).

$$P(A|B) = \frac{\left(P(X|C)P\middle|(C)\right)}{P(C)} \qquad (1)$$

Here, *P(x|c)* is the probability of x given that c is True, *P(c)* and *P(x)* is the independent probabilities of c and x, *P(c|x)* is the Posterior probability, *P(x|c)* is the Likelihood, *P(c)* is the Prior probability, *P(x)* is the Marginal probability. Thus, the NBC can be represented by the relation:

$$C * argMax * c\ P(x \middle| c) \qquad (2)$$

3.5.1. Exploratory Data Analysis (EDA)

The EDA approach was employed to analyze the total number of tweets collected after the preprocessing process to summarize their main features with data visualization. The EDA is an important step before the sentiment analysis or building the model to identify the various insights that will be later needed. A variety of strategies are employed here to gain a deeper understanding of the dataset in question. Understanding a dataset can refer to a variety of things, including but not limited to extracting important variables and discarding useless variables, identifying outliers, missing values, or human error, understanding the relationship(s), or lack thereof, between variables, and, finally, maximizing our insights into a dataset while minimizing potential error that may occur later in the process. After preprocessing and feature selection phases, the sample data are more precise for use in building the classification model.

In addition, different classifiers (such as SVM, NB and Maximum Entropy) are used to create the model during the classification step. However, this study only focused on using Naïve Bayes to classify the sentence collected from social media. Naïve Bayes (NB) was used as the classifier because of its simplicity and good performance in document and text classification. Naïve Bayes classifier is the simplest instance of a probabilistic classifier. With the supervised training, the preprocessed data were randomly split into 70:30 ratio for training and testing parts respectively, it can classify the new text data into their right categories, according to the highest posterior probability. For the model to be trained, the dataset would be labelled (annotated) using an online web tool called Label Studio, where the tweets are identified as positive (1) and negative (0).

3.6. Proposed Sentiment Analysis Model

By doing sentiment analysis of Nigerian students' input in terms of Nigerian higher Education institution satisfaction, the proposed SA model as depicted in Figure 5 helps to improve teaching and learning. The system classifies feelings into two categories: positive and negative, from which satisfaction and discontent are calculated. The system architecture includes the following major components: data collecting, data preprocessing, sentiment and emotion detection, satisfaction and dissatisfaction computation, and data visualization. Data preprocessing and sentiment classification are performed by the system. Sentiment analysis of education tweets involves understanding the attitudes, opinions, views and emotions from tweets using Natural Language Processing (NLP) techniques. Here, the sentiment analysis carried out involves subjectivity and polarity. Polarity is a sentiment analysis that determines if a tweet expression gives a positive or a negative opinion. This helps to determine the attitude of Twitter users towards a topic under review or discussion through the sentiment of textual information. On the other hand, subjectivity is a sentiment analysis that classifies a text as opinionated or not opinionated. Terms such as adjectives, adverbs and some groups of verbs and nouns are used in this study to identify a subjective opinion. Words like these are incorporated into a feature vector and they can represent the proximity of a word to a similar word, this is a good way to detect subjectivity in a document. Hence, subjectivity analysis is the classification of sentences as subjective opinions or objective facts. Thus, sentences that are not subjective are discarded, and only those that contain subjective text are kept for further analysis. To facilitate the analysis of student feedback about Nigerian University education performance, the developed SA system has a data-visualization component that creates sentiment and emotion word clouds as well as line graphs of changes in sentiments and emotions over time. Visualizing the data on a histogram is another way to gain insight into the dataset. Pandas and Seaborn was used to visualize the dataset and the diagrams of the histogram are shown in Figure 6 and Figure 7 respectively.

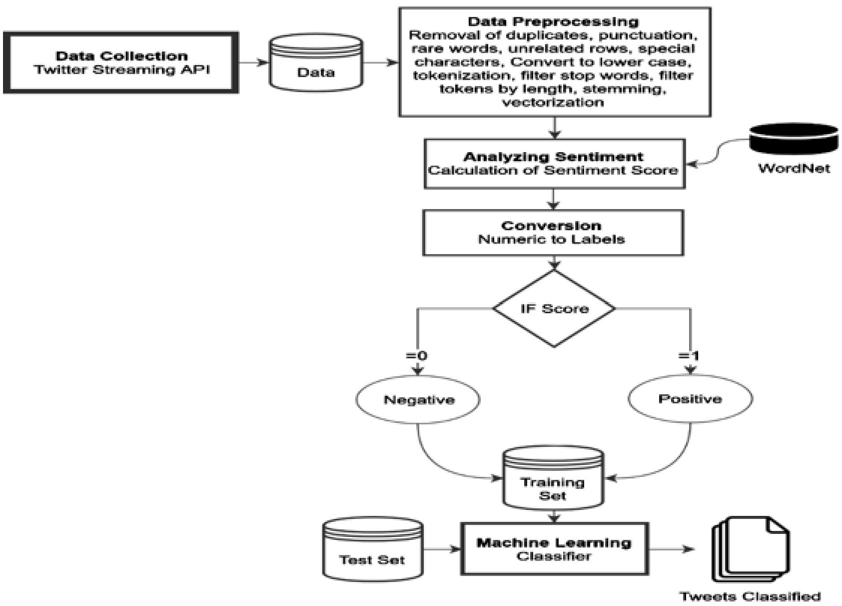

Figure 5: Proposed sentiment analysis (SA) architecture.

4. Result and Discussion

4.1. Data Analysis and Result

The outcomes of the experiments are presented in this section, which are based on the research objectives posed in the introduction. While we employed sentiment analysis to investigate student's attitudes toward Nigerian Education and University system, as well as whether or not such attitudes are subjective, an exploratory data analysis was performed to give quantitative insights on the Twitter dataset collected for better interpretation and understanding of student's opinion regarding the university education system in Nigeria. Government and HEI can use this analysis to give ideas to check so that they can take better decisions for the students and the quality of education can be improved.

Moreover, the goal of this study is to classify the given specified experimental dataset into two (2) categories (i.e., positive and negative) correctly. In the data generation phase, tweets including "The future of education in entire Northern Nigeria is in complete mess" are generated. Similarly, the tweets search was restricted to cover mostly university students' comments in Nigeria from 2019 to 2020. A snapshot of the sampled dataset from the Twitter social media network is presented in Figure 3.

4.2. Exploratory Data Analysis

To carry out EDA, the dataset is first split into two (2) parts. One, a set of positive tweets, and the other is a set of negative tweets. The positive tweet data frame is stored with a variable "positive" while the negative tweet data frame is stored with the variable "negative". Sns, a module in the seaborn library is used to first check the dataset for omitted tweets label i.e., tweets with no label. In this case, there was no omitted tweets label. The NBC model was trained for sentiment analysis with a training database labelled with sentiments positive and negative. In addition, the sentiment classifier model labels the tweet with sentiment.

The NBC was developed or built on the training data after the preprocessing stages and feature extraction processes were completed on the input tweets. To facilitate analysis of student opinion feedback about Nigerian University education performance, the developed SA system has a form of descriptive measure of data presentation, word cloud data-visualization component that describes textual data in terms of how frequent some words occur in a sentence and creates sentiment and emotion word clouds, as well as line graphs of changes in sentiments in this study, was built and the result is as shown in Figure 6 and Figure 7. Visualizing the data on a histogram is another way to gain insight into the dataset. Pandas and Seaborn was used to visualize the dataset in different approaches for sentiment analysis as illustrated below in the figures shown. Also, a graphical display of the polarity of the sentiments expressed by Nigerian Students is depicted by the bar chart of the number of positive and negative tweets in Figure 6 while Figure 7 shows the histogram chart of the dataset plot using SNS in Seaborn. Figure. 8 shows a graphical representation of students' tweet with word cloud software which combines keywords and presents them in graphical form.

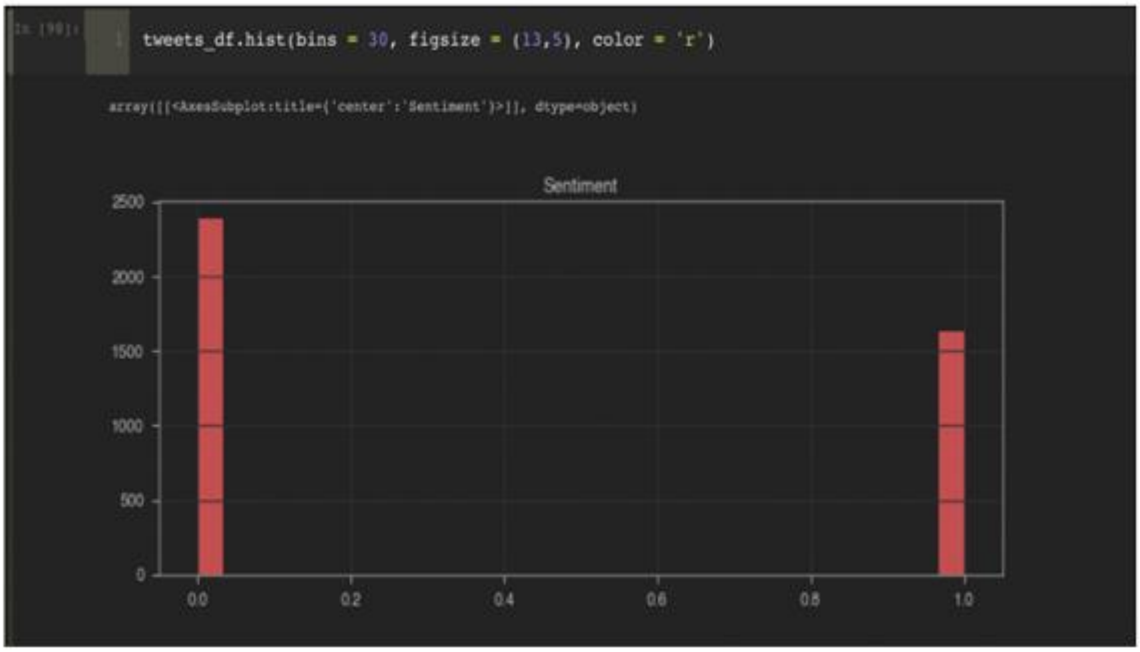

Figure 6: Bar plot of classification of tweets by emotion using Pandas

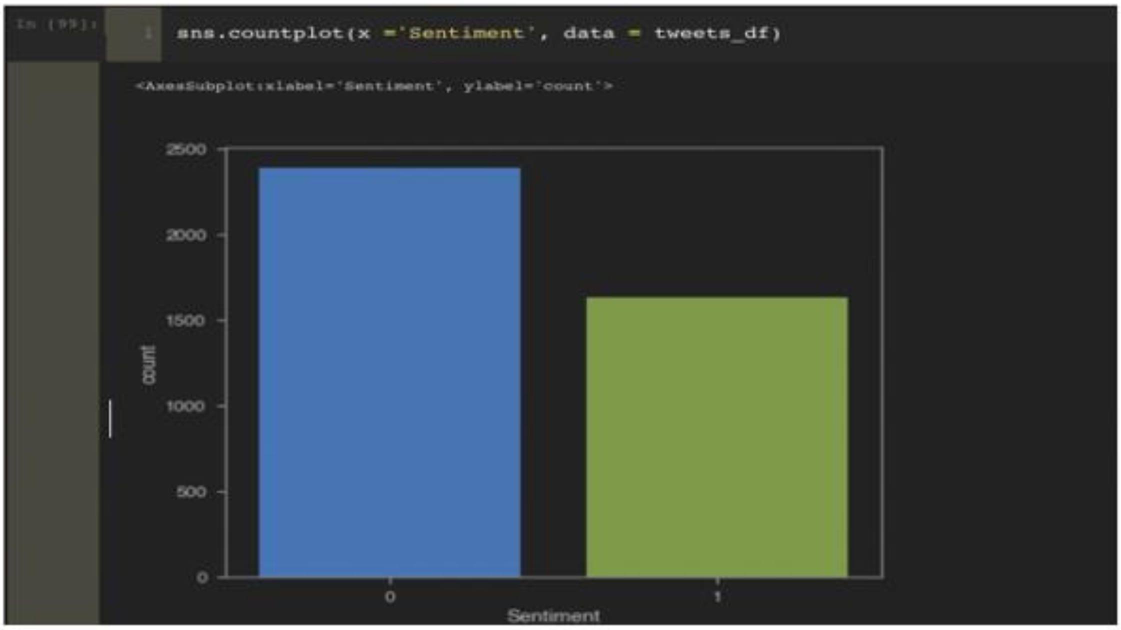

Figure 7: Histogram of the dataset plot using SNS in Seaborn

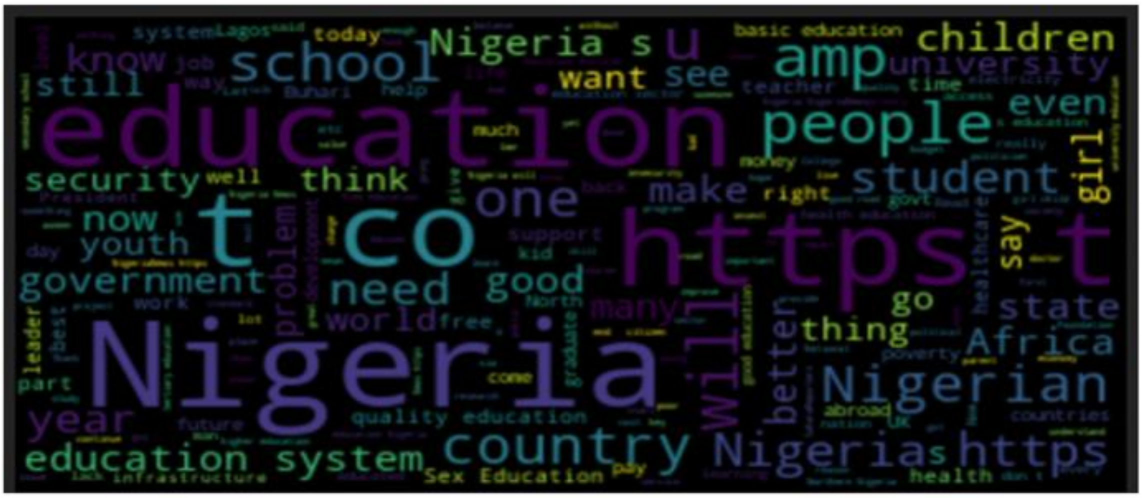

Figure 8: Word Cloud Representation of Student Opinion.

4.3. Confusion Matrix

The confusion matrix (CM) helps us to handle data imbalances, that is, if the number of observations has many differences, we can also see the miss-classified data present. The CM is calculated from the top-left diagonal to the right diagonal. That is, where the actual label and the predicted label meet each other. a confusion matrix is created by tabulating the performance of any classifier, The CM graph depicts the relationship between successfully anticipated and incorrectly predicted reviews. The number of positive education tweets that are successfully predicted by the classifier is represented by True Positive (TP), whereas the number of positive education tweets that are incorrectly predicted by the classifier is represented by False Positive (FP). Similarly, TN (True Negative) refers to the number of negative reviews that the classifier properly predicted, whereas FN (False Negative) refers to the number of negative reviews that the classifier incorrectly classified as positive.

Table 1: Table showing the confusion matrix for Naïve Bayes (NB) Classifier

Predicted values	Actual values	
	Positive (*1*)	Negative (*0*)
Positive *(1)*	530	190
Negative *(0)*	260	230

Nevertheless, classification accuracy is one of the evaluation metrics by which the performance of the developed SA model is measured. The accuracy is the total number of correct predictions divided by the total number of predictions made for a dataset. Other metrics include precision, recall and f1 score. Precision is a metric that measures how many correct positive forecasts have been made. As a result, precision estimates the accuracy of the minority class. The ratio of accurately predicted positive instances divided by the total number of positive examples predicted is used to compute it. Precision is determined as the number of true positives divided by the total number of true positives and false positives in a two-class unbalanced classification issue. While recall is a statistic that measures the number of correct positive predictions made out of all possible positive predictions, as determined by the formulas in equations 3 and 4. Similarly, the F1-score allows one to integrate precision and recall into a single metric that incorporates both attributes of the model as given by the formula in equation 5. While the classification accuracy is calculated because it gives a single measure used to summarize the developed SA model performance. The performance evaluation parameters obtained for Naïve Bayes Classifier (NBC) is shown in Table 2.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1\_Score = 2 * \frac{Prcision * Recall}{Precision + Recall} \tag{5}$$

In the case of the Naïve Bayes binary classifier employed in this study, this would be the amount of true/false positive/negative. Based on those numbers, we calculated some values that explain the performance of the developed model.

Table 2: Table showing results of performance evaluation parameters obtained for Naïve Bayes Classifier (NBC)

Polarity	Precision	Recall	F1-score
Positive (1)	0.54	0.47	0.50
Negative (0)	0.67	0.73	0.70
Accuracy			0.63
Maximum Avg	0.61	0.60	0.60
Weighted Avg	0.62	0.63	0.63

4.4. Discussion

Based on the objectives of performing sentiment analysis on HEI in Nigeria. Twitter data was extracted using Twitter API (web scrapping) using snscrape. Keywords related to education, Nigerian university and higher education institutions were used for keywords streaming and retrieving the feedback from Twitter in English language only while regular expression is used for preprocessing and Matplotlib, Natural Language Toolkit (NLTK), Seaborn and word cloud are used for analysis and visualization. The tweets data obtained from Twitter was used to analyze sentiments expressed by Nigerian students about HEI in Nigeria. At the end of the analysis, it was discovered that about 1629 (40.56%) of the students' sentiments were positive towards the state of Nigerian Higher education institutions, particularly universities while about 2387 (59.44%) of the sentiments were negative. The result is in consonance to the study of [12/11,41/], who in their separate study applied machine learning algorithm including Naïve bayes to determine the performance competencies of teachers and compare ranks among universities respectively using Sentiment analysis. Similarly, the present study is in tandem with the method by which Pak and Parouk, Bifet and Frank, Amusa extracted their data. Moreover, the Twitter data extracted was not automatically annotated but manually showing some level of reduced accuracy of the model.

The Naïve Bayes Classifier has proven to be very efficient in text and data mining as illustrated by the outcome of this study. Results of classification of various sentiments as expressed by Nigerian University students showed that the NBC has an average prediction /classification accuracy of 63%. Also, the estimated average precision, recall and F1-score were 62%, 63% and 62% respectively, which justified the goodness of the NB model for text mining. This is similar to the result obtained in [12/11,41/], that gives a low accuracy when compared to other machine learning a model used in performing sentiment analysis. Though the accuracy obtained in [41/,47/] is higher than the accuracy of the sentiment analysis of the present study because of the large amount of data size used in the Sentiment analysis.

The word cloud visualization is an excellent way to communicate the findings. For this present study, the built-in Python package of Seaborn and word cloud visualization feature have been used. The word cloud representation of the model developed as shown in Figure 8 revealed that among other things, the words that kept creeping into students' thoughts on Nigerian HEI were issues that make it right, education, basic education, proper funding, jobs etc. However, the result is not surprising because the issue of basic education and proper funding of Nigerian Universities, for instance, has generated a lot of controversies during past and present governments. Ironically, many Nigerians including Nigerian students are very curious and seriously yearning to experience the better education promised amidst the several challenges facing the government.

5. Conclusion

Researchers in the educational domain have been interested in sentiment analysis facilitated by NLP, machine learning, and deep learning approaches in the recent decade to examine students' attitudes, opinions, and behaviour towards numerous teaching aspects. In this context, we provided an analysis of the related literature. It was also noted that the adoption of the emerging area of data mining sentiment analysis has great potential. In this paper, the application of a data mining technique, particularly Naïve Bayes methodology was employed to identify and classify the opinions of Nigerian students on the state of university education in Nigeria. The procedure consists of four steps which include the generation of related tweets, extraction of sentiment terms or words, building the classification model and evaluation of the classifier. The Naïve Bayes Classifier has proven to be very efficient in text and data mining as illustrated by the outcome in this study. Results of classification of various sentiments as expressed by Nigerian University students showed that the NBC has an average prediction /classification accuracy of 63%. Also, the estimated average precision, recall and F1-score were respectively, which justified the goodness of the NB model for text mining. From the result obtained in this study, it can be deduced that more Nigerian students were having a negative opinion about the current state of Nigerian HEI (Universities) though some still have a considerable good opinion about it.

Nevertheless, there is rarely any research that has contributed to this domain. Due to the limited availability of data in this domain, there is a limitation of labelled training data for building machine learning classifiers as such classifiers usually perform better when fed with a large amount of data. Despite these limitations, the model has achieved 66.04% accuracy using the Naïve Bayes classifier. Furthermore, more data can be collected in the future to increase the training set so that machine learning classifiers can offer even better accuracy. Finally, instead of using WordNet dictionary for analyzing sentiments, other approaches can be used such as SentiWordNet and other automated methods. In the future study, the efficiency of other classification methods like SVM, Maximum Entropy and K-Nearest neighbour for data mining shall be examined and their performance shall be compared.

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