Journal of Informatics and
Web Engineering

Vol. 3 No. 2 (June 2024) eISSN: 2821-370X

Sentiment Analysis in Social Media: A Case Study of Hike in University School Fees in Selected Nigerian Universities

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Abstract- Faced with escalating operational costs and government disinvestment, Nigerian public universities are implementing tuition fee increases to maintain institutional functionality. This necessary fiscal measure comes in the wake of 2022 industrial action, which exacerbated pre-existing financial strain through extended work stoppages and potentially higher costs associated with resuming activities, while leaving unaddressed the longstanding demands of academics for improved welfare and working conditions. The court-mandated resumption of academic activities without resolution of these core issues further strained university finances, leading to a significant increase in tuition fees. Using VADER, this study investigated social media sentiments related to the increase in university school fees at Usmanu Danfodiyo University, Sokoto, and the University of Maiduguri. The results revealed that students' sentiments regarding the rise in tuition fees at the two universities were largely neutral, with 4.6% positive sentiment, 7.9% negative sentiment, and 87.5% neutral sentiment identified for Usmanu Danfodiyo University, Sokoto. In contrast, the University of Maiduguri had 0% positive sentiment, 19.8% negative sentiment, and 80.2% neutral sentiment. The study recommends seeking feedback through surveys or student leaders and offering scholarships to indigent students to address fee hike concerns at the two universities. While VADER is designed to handle social media textual data, few misclassifications of sentiments were noted and discussed.

Keywords—Nigerian universities, School fees, Hike, Social media, Vader

Received: 21 December 2023; Accepted: 22 February 2024; Published: 16 June 2024

I. INTRODUCTION

Nigerian universities have been facing various challenges which include inadequate infrastructure, limited funding, and a shortage of teaching staff, resulting in low-quality outputs, a poor state of infrastructure, diminished international competitiveness, and consequently, the need to seek strategies for reconstructing, restructuring, and rebuilding the system to respond favorably to novel development challenges [1]. These problems have contributed to the rising cost of education as universities are now seeking alternative ways to fund the system, which is simply by overcharging their students.

Hike in university school fess in Nigerian universities has generated various reactions from students on Facebook and Twitter. The rise in fees follows the eight-month 2022 industrial action between the Academic Staff Union of Universities (ASUU) and the government. "ASUU, formed in 1978 as a successor to the National Association of University Teachers established in 1965, represents academic staff in both federal and state universities in Nigeria" [2]. "The trade union often embarks on various industrial actions to advocate for improvements in their welfare, teaching and research facilities, and university autonomy" [3]. The high cost of

Journal of Informatics and Web Engineering
https://doi.org/10.33093/jiwe.2024.3.2.7

Published by MMU Press. URL: https://journals.mmupress.com/jiwe

school fees is the result of a lack of funding by the government, and students have taken to social media to express their sentiments over the high tuition fees. Sudden surge in Usmanu Danfodiyo University Sokoto and University of Maiduguri school fees has become a topic of discussion among their students on Facebook and Twitter. Usmanu Danfodiyo University Sokoto increased its school fees from between N36,400.00 and N73,900.00 to between N51,050.00 and N111,800.00 (Source: Released university's fee schedules) while University of Maiduguri increased its own from between N29,830.00 and about N74,000.00 to about N100,000.00 to N252,500.00 [4]. However, the position of their students on the issue, and the effective strategies that the two universities can adopt to address sentiments surrounding hike in school fees on social media remain unexplored. Therefore, this research sets out to fill this gap.

Sentiment analysis "considers the computational treatment of subjective information contained in text" [5]. Understanding public opinion, for example, empowers institutions to make data-driven, strategic choices [6]; analyzing customers' sentiment through sentiment analysis can guide product development decisions such as customers' needs and preferences. Similarly, political campaigns can leverage sentiment analysis to refine their messaging and outreach strategies.

The aim of this study is to analyze social media sentiments using hike in school fees at Usmanu Danfodiyo University Sokoto and University of Maiduguri as a case study. The objectives of this study are:

1) To investigate the sentiments expressed on social media by students regarding hike in their school fees at Usmanu Danfodiyo University Sokoto and University of Maiduguri.

2) To propose recommendations for the two universities to address sentiments related to school fees increase on social media.

II. LITERATURE REVIEW

The process of sentiment analysis can be undertaken through the application of Deep Learning models or by employing traditional techniques. There has been a notable surge in the adoption of Deep Learning models in recent years, primarily due to their capacity to learn features from data and achieve exceptional performance [7, 8, 9, 10]. This diverse range of deep learning models, including Deep Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Bidirectional Encoder Representations from Transformers, finds applications across a wide variety of domains. [11] analyzed people's opinions on StockTwits about stocks and reported that these models worked well, with CNN worked best at predicting sentiments. The encouraging efficacy of DL is also evident in [12] who used a multi-channel CNN for sentiment analysis and an RNN with LSTMs for aspect extraction from financial headlines. In another study [13], BERT alongside various regression models was used, with the Linear Support Vector Regressor giving best results. [14] demonstrated BERT's potential in education by examining the effects of COVID-19 on teaching in higher education. [15] conducted sentiment analysis on Twitter data using DL and traditional models and noted that Deep Learning models benefitted significantly from augmentation techniques. [15] further stated that while traditional models performed better in training-time and runtime complexities, Deep Learning models outperform in key performance factors and average rankings. Deep Learning models are effective for analyzing sentiments expressed in textual data. However, they rely on large amounts of data [11] for training, which may not be readily available in all scenarios.

Despite the allure of Deep Learning models, Traditional Machine Learning models still hold their own in specific cases. [16] conducted sentiment analysis on three leading companies in the automotive industry, namely Mercedes, Audi, and BMW using Naïve Bayes (NB) algorithm to classify the polarity and emotions. Similar to [16], [17] utilized Naïve Bayes and lexicon dictionaries in their sentiment analysis on two top international apparel brands, Adidas and Nike. Another study by [18] involved the use of different algorithms for analyzing sentiments in an MOOC's forum. Two lexicon (unsupervised) approaches and five machine learning algorithms (supervised) were used. The study reported that Random Forest was the most dependable supervised approach, and the dictionaries method exhibited favorable performance as well. Along the same line, [19] conducted a study to determine customer satisfaction with Traveloka's services by analyzing sentiments expressed in tweets related to Traveloka and noted that Support Vector Machine performed well. In another study conducted [20] on public opinion about two top Indian apparel brands, FabIndia and BIBA, TextBlob was used. Furthermore, [21] reported that Logistic Regression (LR) achieved the highest accuracy in their study. It should be noted, however, that various pre-processing steps like tokenization, filtering, lemmatization, and stemming are often used to clean and prepare data for analysis. Beyond sentiment analysis, machine learning models prove valuable in diverse prediction tasks across various domains [22, 23].

A. Approaches to the Study of Sentiment Analysis

Sentiment analysis involves three approaches [24]:

1) Lexicon-driven Approach: Operating on a predefined word list with sentiment associations, this method works without the need for labeled data. However, crafting a universally adaptable lexical dictionary proves challenging considering the dynamic and context-specific nature of slang [25] cited in [24].

2) Machine Learning Approach: Here, the machine undergoes pretraining using a segment of the actual data to take knowledge from it. Algorithms like Naïve Bayes, Support Vector Machines, Logistic Regressions, Random Forests, etc., fall under the umbrella of machine learning and can be applied to this task [26]. The machine learning approach can handle complex language structures and adapt to diverse datasets.

3) Hybrid Approach: The hybrid approach amalgamates both machine learning and lexicon-based methods. This combined approach holds promise for enhancing sentiment classification performance [24].

B. Levels of Sentiment Analysis

[27] outlines three tiers of sentiment analysis:

1) Document Level: This level examines the entire document, determining its overall polarity [28]. It operates under the assumption that each document conveys opinions about a single event, rendering it unsuitable for documents assessing or comparing multiple entities [27].

2) Sentence Level: This tier involves the individual processing and analysis of each sentence, assigning a positive, negative, or neutral opinion to each [29].

3) Entity and Aspect level: This entails a more in-depth investigation [30]. This level enhances the comprehension of sentiment analysis issues, facilitating the identification of sentiments related to entities and/or their aspects, and turning unstructured text into structured data for various qualitative and quantitative analyses [31].

C. Challenges in Sentiment Analysis

Sentiment analysis has some problems associated with it, as highlighted by [32]:

1) Identification of Sarcastic Sentences: An obstacle in sentiment analysis involves discerning sarcastic and ironic sentences, where positive words may convey negative meanings. For instance, a statement like "What a great car, it stopped working on the second day" may lead to erroneous analysis due to its sarcastic nature.

2) Review Spam Detection: Dishonest people may post fake reviews to bolster their products with undeserved positive opinions or malign their competitors through the dissemination of fabricated feedback.

3) Thwarted Expectations: Some sentences start with one context but conclude with a different context. For example, in a review like "The cast was not good, actors performed poorly, but I liked it." Accurately capturing the positive sentiment at the end requires careful consideration.

4) Co-reference Resolution: Sentiment analysis encounters challenges in accurately resolving co-references, which refer to identifying the pronouns or noun phrases' references within the text. For

instance, in the sentence "We watched the movie and went to dinner; it was awful," determining what "it" refers to is essential in analyzing the sentiment correctly.

5) Negation Handling: Effectively handling negation is another issue in sentiment analysis. Negation can reverse the polarity of sentiment, making "the movie was great" and "the movie was not great" convey entirely different meanings.

III. RESEARCH METHODOLOGY

Data from Twitter and Facebook was collected using their respective APIs – Tweepy for Twitter and the Facebook Graph API for Facebook. The data collection occurred in September 2023, encompassing posts and tweets available since January of the same year. The process began by setting up authentication with the APIs and obtaining the necessary credentials. Keyword-based searches (Udus, fees, increase, hike, Unimaid) were performed on both platforms to retrieve relevant posts and tweets. The retrieved data was then pre-processed to remove noise. Subsequent to this, VADER (Valence Aware Dictionary and sEntiment Reasoner) was used to assess the polarity of the texts. The choice of VADER is based on its capacity to handle social media text as it is basically designed for analyzing social media sentiments. [26] reported the effectiveness of VADER. [33] also evaluated VADER and reported that the tool is remarkable for surpassing or at least matching eleven other sentiment analysis tools. [33] further noted that what makes VADER particularly remarkable is its ability to outperform individual human raters, achieving an F1 classification accuracy of 0.96 and 0.84 for classification accuracy and generalization across contexts.

Table 1: Number of Sentiments Collected by University

University	Number of Sentiments
Usmanu Danfodiyo University, Sokoto	152
University of Maiduguri	104

IV. RESULTS AND DISCUSSION

"The process of scrutinizing raw data with the purpose of drawing conclusions about that information is called data analysis. The main aim of data analysis is to convert the available cluttered data into a format which is easy to understand, more legible, conclusive and which supports the mechanism of decision making" [34].

Table 2: Sentiment Distribution

University	Sentiment classification	Frequency	Percentage
Usmanu Danfodiyo University, Sokoto	Positive	7	4.6%
	Negative	12	7.9%
	Neutral	133	87.5%
University of Maiduguri	Positive	0	0%
	Negative	21	19.8%
	Neutral	85	80.2%

Table 1 illustrates the total number of sentiments collected by each university while Table 2 shows the distribution of sentiments within the dataset. The analysis revealed that, for Usmanu Danfodiyo University Sokoto, 4.6% of the data analyzed expressed positive sentiment, 7.9% expressed negative sentiment, and a significant majority (87.5%) were classified as neutral. Similarly, for the University of Maiduguri, 19.8% were negative, 80.2% were neutral, and no positive sentiment was identified. These findings suggest that, overall, many students did not express strong opinions about the fee increase, with a notable prevalence of neutral sentiment. A neutral sentiment in sentiment analysis refers to a state where a piece of text is not strongly positive or negative. The individual may be providing information, stating facts, or discussing a particular topic in a relatively matter-of-fact manner. Figure 1 below provides a visual representation of how sentiments are categorized within the dataset.

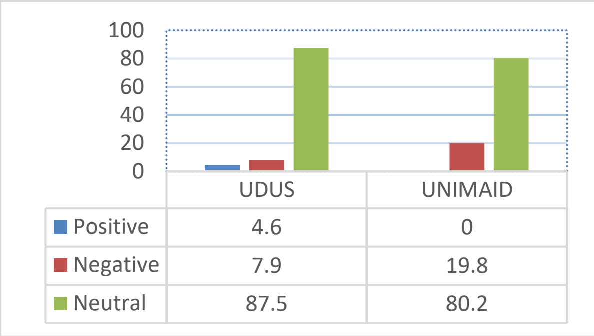
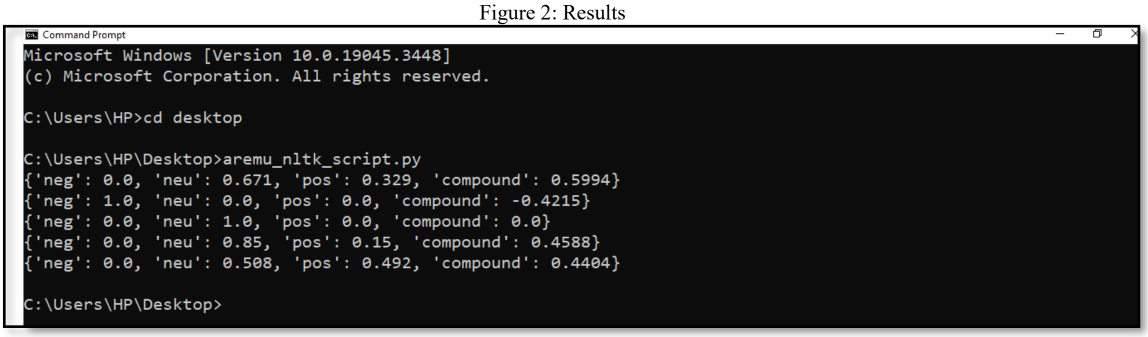


Figure 1: Sentiment Classification Chart

A. Limitations of VADER in the Study

Although [26] and [33] reported VADER as effective for analyzing social media data, [32] stated that sentiment analysis tools find it hard identifying sarcastic or ironic sentences. VADER erroneously analyzed the sentiments: "Congratulations on a 50% increase. So funny 😅" and "Congratulations for what?" as positive. However, the sentiment "Congratulations on a 50% increase. So funny 😅" is likely sarcastic or ironic. The writer found the idea of congratulating someone on a 50% increase amusing in a sarcastic manner. They might be mocking the notion of celebrating something that is generally considered undesirable. "Congratulations for what?" could imply criticism or questioning the appropriateness of congratulating students on a fee hike. Also, "UDUS is one of the cheapest federal universities. God bless you all" was classified as neutral as it can be seen in Figure 2 where its classification, along with four others, was generated from the script in Figure 3. This can be considered as a limitation especially when common sense would suggest that the sentiment is positive.

Figure 2: Results



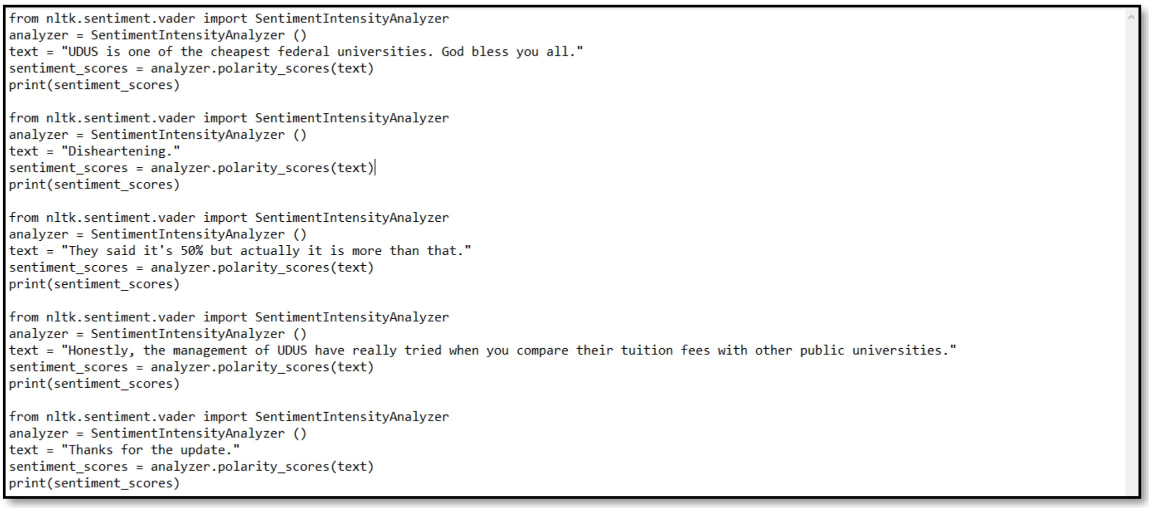
```
Command Prompt
Microsoft Windows [Version 10.0.19045.3448]
(c) Microsoft Corporation. All rights reserved.

C:\Users\HP>cd desktop

C:\Users\HP\Desktop>aremu_nltk_script.py
{'neg': 0.0, 'neu': 0.671, 'pos': 0.329, 'compound': 0.5994}
{'neg': 1.0, 'neu': 0.0, 'pos': 0.0, 'compound': -0.4215}
{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
{'neg': 0.0, 'neu': 0.85, 'pos': 0.15, 'compound': 0.4588}
{'neg': 0.0, 'neu': 0.508, 'pos': 0.492, 'compound': 0.4404}

C:\Users\HP\Desktop>
```

Figure 3: Script



```
from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer ()
text = "UDUS is one of the cheapest federal universities. God bless you all."
sentiment_scores = analyzer.polarity_scores(text)
print(sentiment_scores)

from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer ()
text = "Disheartening."
sentiment_scores = analyzer.polarity_scores(text)
print(sentiment_scores)

from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer ()
text = "They said it's 50% but actually it is more than that."
sentiment_scores = analyzer.polarity_scores(text)
print(sentiment_scores)

from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer ()
text = "Honestly, the management of UDUS have really tried when you compare their tuition fees with other public universities."
sentiment_scores = analyzer.polarity_scores(text)
print(sentiment_scores)

from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer ()
text = "Thanks for the update."
sentiment_scores = analyzer.polarity_scores(text)
print(sentiment_scores)
```

B. RECOMMENDATIONS

Given the widespread use of social media and the impact it can have on Usmanu Danfodiyo University Sokoto and the University of Maiduguri's reputation, this study recommends that the two universities should seek feedback from students through surveys or student leaders to understand the opinions of their students regarding fee hikes. The universities should offer scholarships to assist indigent students, as this will demonstrate their sensitivity to students' challenges in paying their school fees.

V. CONCLUSION

This study found that the sentiments expressed on Facebook and Twitter by the students of Usmanu Danfodiyo University Sokoto and University of Maiduguri regarding hike in their school fees were largely neutral. Only 4.6% positive and 7.9% negative sentiments were found for Usmanu Danfodiyo University Sokoto, while 0% positive and 19.8% negative sentiments were found for University of Maiduguri. Usmanu Danfodiyo University Sokoto had 87.5% neutral sentiment whereas University of Maiduguri had 80.2% neutral sentiment. The findings allow us to understand students' position on their school fees hike and it can assist the two universities in future decision making. This study suggests that future research should, if possible, gather a larger data and use a Deep Learning model for a more comprehensive and accurate result.

ACKNOWLEDGEMENT

No funding was received from any party for this research and its publication.

AUTHOR CONTRIBUTIONS

Abdulahi Olarewaju Aremu: Data Curation, Formal Analysis, Methodology, Original Draft Preparation, Writing – Review and Editing
Isah Muhammad: Conceptualization, Visualization, Formal Analysis

CONFLICT OF INTERESTS

We have no conflict of interests to disclose.

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