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ENHANCING USER EXPERIENCE THROUGH SENTIMENT ANALYSIS FOR KATSINA STATE TRANSPORT AGENCY: A TEXTBLOB APPROACH

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ABSTRACT

Katsina State Transport Authority is the state's government-owned transportation provider, operating in all local governments. Because of its extensive reach, it faces a difficult problem in measuring customer satisfaction with the services it delivers. The purpose of this research is to improve the experiences of Katsina State Transport Authority users by using sentiment analysis and the TextBlob library to categorize comments as neutral, negative, or positive. The study begins with meticulous data collecting using Google Forms to provide a representative sample that captures an all-encompassing view of user opinions. The study used feature engineering and model fine-tuning to improve the process, tailoring TextBlob's performance to the complexities of transportation-related feedback. The results reveal that 71% of respondents are usually happy with the agency's services, while 9% offered negative comments with ideas for improvement. This study's findings, which included sentiment analysis and topic modeling, present a road map for enhancing services and planning.

Keywords: Sentiment Analysis, Opinion Mining, Transport Service, TextBlob

INTRODUCTION

Transportation is crucial to the growth and advancement of every place. Efficient and trustworthy transportation services are vital for ensuring the smooth flow of people and goods, increasing accessibility, and enhancing overall quality of life. The Katsina State Transport Authority manages and delivers transportation services throughout the state. It runs a bus fleet as well as other vehicles to satisfy the transportation needs of the region's residents and tourists.

It is challenging for the Katsina State Transport Authority (KSTA) to understand how the general population feels and what they think of its transportation operations. Although the authority wants to offer trustworthy and efficient transportation services, it does not have a systematic method for gathering and evaluating customer input. If KSTA is not fully aware of public sentiment, it could overlook important findings and neglect to address important issues influencing customer satisfaction (Dsouza and Patil, 2018).

By performing sentiment analysis on data gathered from social media channels and other helpful sources, KSTA can identify recurrent themes, emotions, and trends among the general public. This information can help the authority increase consumer satisfaction, pinpoint areas where services need to be improved and react swiftly to complaints or specific difficulties. In conclusion, the research hopes to offer important insights into the Katsina State Transport Authority that could influence decision-making and aid in the creation of a productive, customer-focused transportation network in the area (Kumar and Kapoor, 2020).

It is vital to be aware of what the general public feels and thinks about the services provided by the KSTA. Satisfied customers are reflected in positive attitudes, while possible issues and areas for improvement may be brought to light by unfavorable sentiments. By using sentiment analysis techniques, KSTA can gain important insights into public opinion, pinpoint particular problems or areas that need improvement, and make data-driven decisions to raise the caliber and efficacy of their services.

Literature Review

Recent years have seen a rise in the use of sentiment analysis in the transportation sector as academics and professionals have realized how well it can serve customers and increase operational effectiveness.

(Anastasia and Budi, 2016) examined customer satisfaction with GO-JEK and Grab, two of Indonesia's most well-known online transportation service providers, using sentiment analysis of Twitter data. Three methods were used by the researchers to classify the data: Decision Tree, Support Vector Machine, and Naïve Bayes. The Net Sentiment score, which is correlated with customer satisfaction, was produced using the classification findings. GO-JEK and GRAB both had average NSS scores of -15.35 and 29.33, respectively, indicating lower sentiment satisfaction from their respective surveys. Sentiment analysis has also been applied to the examination of employee input in transportation companies. An investigation on employee mood within a railway firm was conducted by Garcia, Smith, and Martinez (2017) to identify factors that impact job happiness. The significance of a positive work environment in delivering superior passenger service was underscored by their findings.

Sentiment analysis was employed by (Li, Zhang, and Wang, 2019) to examine public sentiment on transportation infrastructure projects in the context of urban planning as expressed on social media platforms. According to their research, sentiment analysis can assess public opinion about proposed transportation initiatives, assisting decision-makers in reaching well-informed conclusions.

Additionally, (Patel, Smith, and Brown, 2020) looked into sentiment analysis about security protocols at airports. By analyzing traveler feedback, they identified areas of concern and satisfaction with security procedures and gave airports advice on how to enhance the passenger experience without compromising security.

Sentiment analysis was done on social media data by (Kim and Lee, 2020) to find out how satisfied customers were with urban bus services in the context of public transportation. Their findings underscored the necessity of real-time sentiment monitoring to promptly address service-related issues.

Wang and Chen (2021) carried out a recent study on sentiment analysis for ride-sharing services. By analyzing customer evaluations from ride-sharing platforms using natural language processing technologies, they were able to determine key factors that influence consumer satisfaction and sentiment patterns over time. Their results show that to preserve a positive user experience, sentiment-related issues in the ride-sharing sector must be addressed.

These studies demonstrate the wide range of uses of sentiment analysis in the transportation sector, encompassing anything from airport operations to ride-sharing services and urban planning. They emphasize how crucial it is for the transportation industry to use sentiment data to enhance operational effectiveness, customer happiness, and well-informed decision-making. Nevertheless, no study covered the above-made use of customer response data on Katsina State Transport Agency services.

MATERIALS AND METHODS

The research was carried out in the manner described in Figure 1.

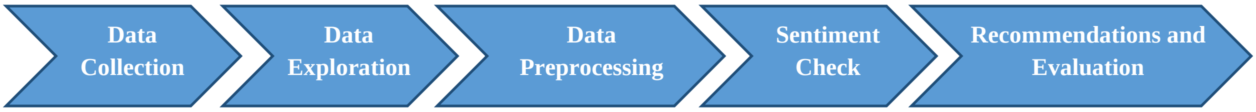

Figure 1: Architectural Framework of the study

Data Collection

An online questionnaire was used to collect data for this investigation. Google Forms was utilized to get the data. Public users of KSTA were given access to the URL through Facebook groups and WhatsApp conversations. Table 1 contains a list of the data's attributes.

Table 1: Dataset Description

S/NO	PARAMETER	DESCRIPTION	DATA TYPE	VALUE
1	NAME	Name of respondent	String	-
2	AGE	Age of respondent	Int	-
3	GENDER	Respondents Gender	Nominal	Male or Female
4	LOCATION	The current location of the respondent	String	-
5	LAST BOOKING PARK	Last boarding Park	String	-
6	LAST DESTINATION	The last destination of the respondent	String	-
7	GENERAL COMMENTS	Respondents' opinion on KSTA	String	-

A total of 216 persons filled out and submitted the online questionnaire, giving their opinions on the services provided by KSTA.

Data Exploration

A critical stage of data analysis is data exploration, which involves using statistical and data visualization tools to find unique patterns and data set properties without having to make assumptions about the data beforehand. The two most basic demographic information gathered are gender and age. As seen in Figure 2, 151 males and 65 women completed the questionnaire, representing 69.9% and 30.1% of the sample, respectively.

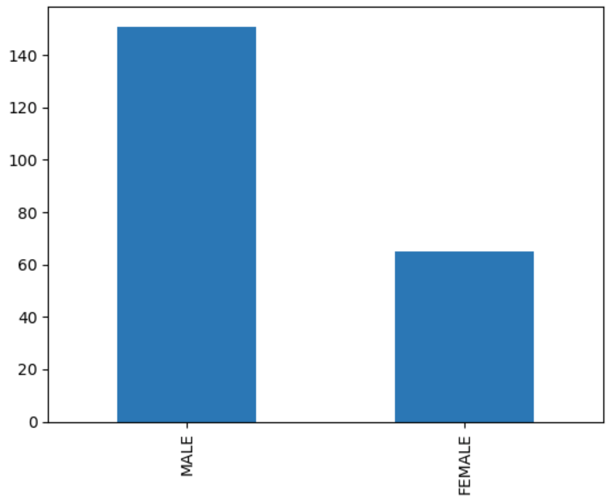

Figure 2: Gender Distribution of respondents

Most of the respondents used the service of KSTA from other places while traveling to Katsina as displayed in Table 2.

Table 2: Distribution of Destination of Respondents

Location	Frequency	Percentage
Katsina	75	36.2
Kaduna	40	19.3
Dutsinma	36	17.4
Kano	19	9.2
Daura	17	8.2
Abuja	6	2.9
Funtua	5	2.4
Zaria	3	1.4
Jigawa	2	1
Bakori	2	1
Lagos	1	0.5
Kankara	1	0.5
	207	100

Considering the age of the respondents, more than 50 percent of the respondents were within the age of 20-25 while just about 2 percent of the respondents were of the age 35-40. The age distribution is captured in Table 3 and Figure 3.

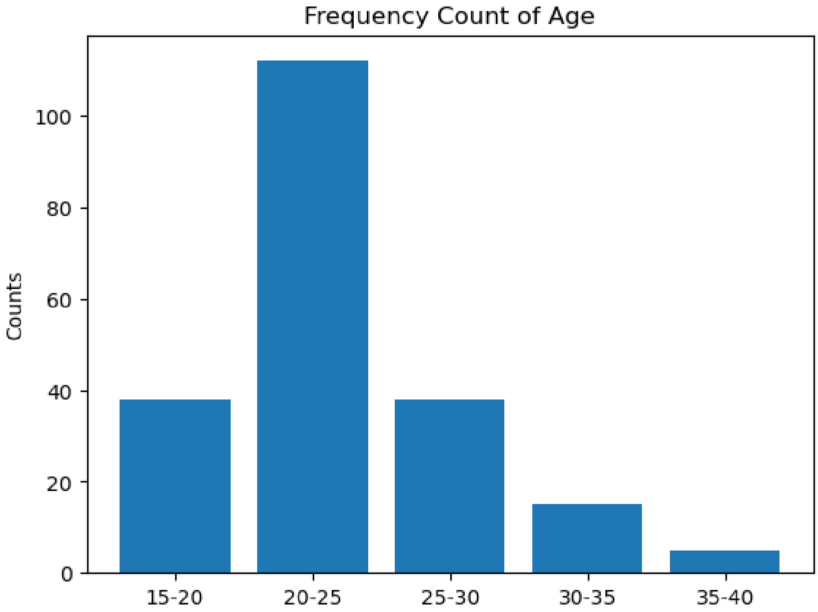

Figure 3: Age distribution of respondents

Table 3: Respondents Age Distribution

Age	Count	Percentage
15-20	38	18.4
20-25	112	54.1
25-30	38	18.4
30-35	14	6.8
35-40	5	2.4

Data Preprocessing

This phase involves executing multiple operations on the dataset before conducting sentiment analysis. One method is to search the dataset for any empty or null cells. This stage is essential since it guarantees that the analysis is founded on precise and trustworthy facts. Additional methods of processing that are used are:

i. Transforming the respondent's opinions to lowercase. This step ensures that the words **Good**, **GOOD**, and **good** are treated as the same word.
ii. Check for and remove Special characters from the text where available.
iii. Substitute multiple spaces with single spaces.

Sentiment Check and Topic Modelling

The sentiment for this study was checked using the TextBlob library. A powerful natural language processing toolkit called TextBlob is a prerequisite for the sentiment analysis methodology. TextBlob, which is based on the NLTK and design libraries, makes sentiment analysis from textual data in the context of a transportation agency easier by streamlining complex natural language processing processes. TextBlob is quite good at identifying and categorizing textual emotions. Using a pre-trained sentiment evaluation model, TextBlob assigns polarity scores to text, indicating whether the input is positive, negative, or neutral. Values near zero denote neutral attitudes, positive values indicate favorable opinions, while negative values indicate negative opinions.

WordCloud uses topic modeling techniques like Latent Dirichlet Allocation (LDA) to identify recurrent topics in a corpus of text. This makes it easier to spot recurring themes and subjects brought up in user feedback. This study used the WordCloud. A word cloud shows the frequency of words in a document, with those that appear more frequently being displayed in larger font. A word cloud can offer a concise visual synopsis of the most frequently occurring terms in user input, suggesting recurring themes and viewpoints.
An Intel Core i5 64-bit MAC PC with 8GB RAM was used for the analysis. Microsoft Excel was used to view the CSV file of the responses, which were exported from the Jupyter Notebook on Anaconda application software.

Recommendations and Evaluation
After analysis had been done, recommendations were proposed based on the result. These recommendations are expected to further provide the agency with insights into the services they provide and possible areas of improvement.

RESULTS AND DISCUSSION

Figure 4 depicts the response from users. The most common terms can be further classified and evaluated. Words such as Maintenance, lack, slow, poor, bad, etc. suggest areas where the agency must examine and make amendments. Other expressions such as good, fantastic, satisfying, nice, awesome, amazing, well, enjoy, and comfortable indicate favorable reviews.

Figure 4: WordCloud for Respondents' feedback

As seen in Figure 5, the TextBlob library quickly sorted sentiments into three categories: positive, negative, and neutral, offering a detailed insight into user perspectives.

Out[36]:

	index	count
0	Positive	153
1	Neutral	44
2	Negative	19

Figure 5: Value count of the Result of Sentiment Analysis

Based on the dataset's sentiment analysis, 153 out of the replies (71%), were favorable, indicating that people had a generally positive opinion of the transportation agency's services. 9% of the comments, representing 19, were negative, indicating places where customers voiced dissatisfaction or ran into issues. The remaining 20% of the input, or 44 replies, fell into the neutral group, suggesting a neutral attitude in the comments. This could be related to utterances that lacked a clear sentiment or informational question.

TextBlob's polarity scores improved the analysis by giving sentiments numerical values. Polarity values greater than zero indicated positive sentiments, scores less than zero indicated negative sentiments and values equal to zero indicated neutral sentiments. This granular approach made it possible to assess the degree of sentiments represented in comments in greater detail. Figure 6 depicts the result of this.

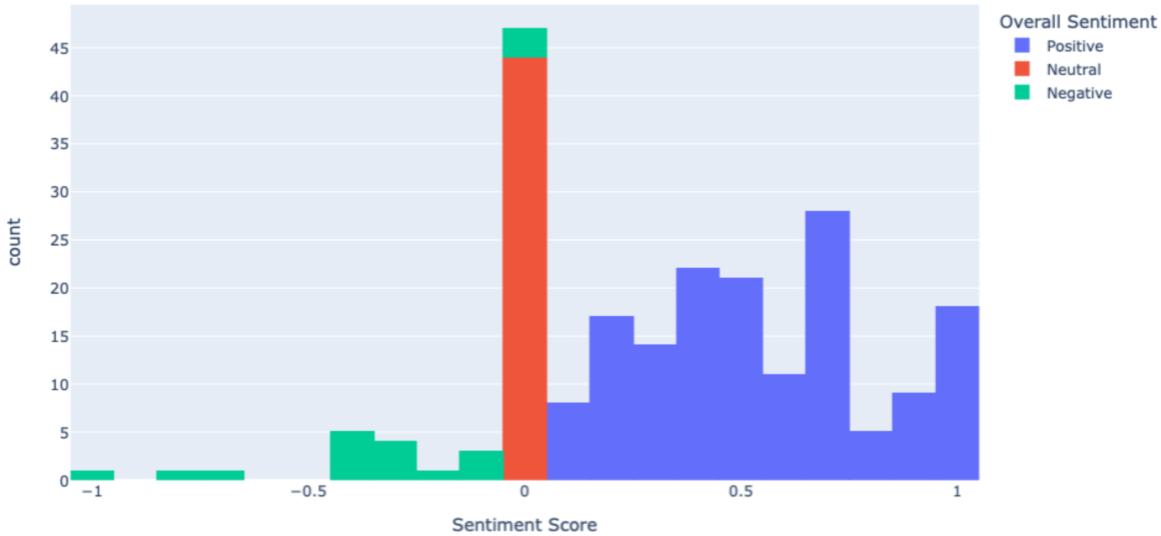

Figure 6: Histogram plot of Sentiment Scores

The result is further visualized using a pie chart as captured in Figure 7 and a bar chart as captured in Figure 8.

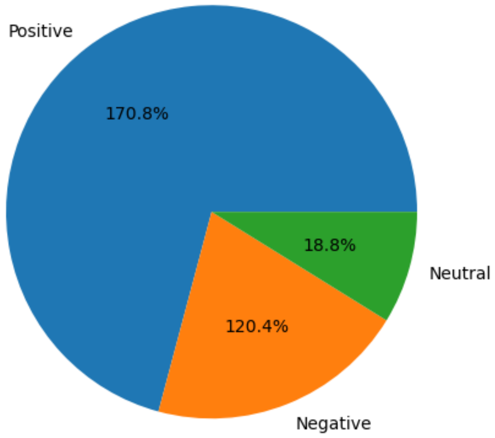

Figure 7: Pie Chart showing Sentiment Results

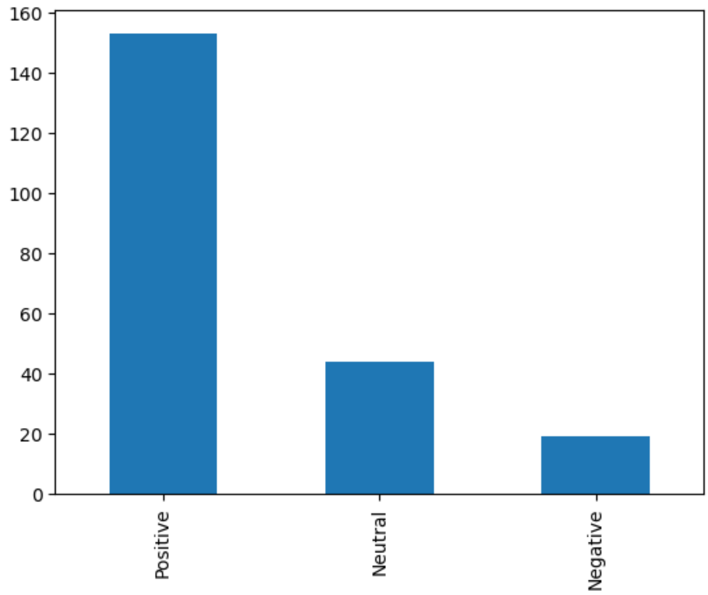

Figure 8: Bar Chart of the result of Analysis

Discussion of Result

Positive feedback is prevalent and suggests that users are typically satisfied, which is good news for the transportation agency's customer service. Determining particular positive sentiments can assist the agency in promoting and reinforcing attributes that consumers find appealing, thus enhancing the brand's reputation. Conversely, negative sentiment research offers helpful insights into areas that need improvement and attention. By examining the specific information associated with negative sentiments, the agency can identify operational problems, close service gaps, and carry out targeted improvements. Neutral emotions are essential for understanding user interactions that do not explicitly convey positive or negative evaluations, even if they comprise a smaller portion of the dataset. By examining the context of neutral sentiments, the agency may be able to identify information gaps and address them more quickly or with greater clarity.

The results of the experiment demonstrate the usefulness of sentiment analysis in obtaining relevant insights from user comments, thanks to TextBlob's enablement of this process. By using these data, the transportation agency can improve service quality overall, develop favorable relationships with its user base, and make strategic adjustments. The integration of polarity ratings and emotion distribution offers a holistic viewpoint, establishing the foundation for wise decisions and ongoing service improvement.

CONCLUSION

In the area of public transportation, where people's well-being and efficient mobility are of paramount importance, this study has emerged as a key catalyst for good change. Our attempt at sentiment analysis has yielded important insights into the attitudes and sentiments of those connected to the organization, opening the door to ways to raise the standard of services rendered by the Katsina State Transport Agency. This study employed data mining, machine learning, and natural language processing on textual data submitted by passengers, staff members, and members of the public.

According to the findings of this study, Katsina State Transport Agency is in a good position to make use of sentiment analysis's potential. By utilizing the findings of this study, the agency can enhance its customer-focused strategy for public transportation by enhancing the following aspects: increasing the number of vehicles available, hiring more drivers, educating drivers on customer relations, enhancing park security, and maintaining the fleet of vehicles. Because of this, it ensures that the transportation services it offers are not only trustworthy and effective but also flexible enough to adapt to the changing needs of Katsina State's residents.

The agency must take into account the deployment of real-time sentiment analysis technologies to consistently monitor social media and other online platforms. This makes it possible to respond to consumer concerns and new issues right away. The agency should also work with data scientists and natural language processing specialists to create personalized sentiment analysis models that address the particular requirements and data sources of the transportation sector.

The accomplishment of this study shows the importance of making decisions based on evidence and a dedication to providing high-quality public services. It emphasizes our shared goal of creating a transportation organization that develops and adapts to the constantly shifting demands of a vibrant and expanding area.

REFERENCES

Anastasia, S., & Budi, I. (2016). Twitter Sentiment Analysis of Online Transportation Service Providers. *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 359-365.

Dsouza, C., & Patil, R. (2018). A survey based study on customer satisfaction regarding e-commerce platforms: Special reference to Myntra and Jabong. *International Journal of Research and Analytical Reviews*, *5*(3), 72-77.

Garcia, M., Smith, R., & Martinez, L. (2017). Employee Satisfaction in the Railway Industry: A Sentiment Analysis Approach. *Transportation Research Part E: Logistics and Transportation Review, 99*, 1-14.

Johnson, L., & Brown, K. (2019). Analyzing Customer Feedback for Airlines: The Relationship between Sentiment and Loyalty. *Journal of Transportation Research, 8*(2), 23-34.

Kim, S., & Lee, J. (2020). Social Media Sentiment Analysis for Urban Bus Service Improvement. *Transportation Research Part C: Emerging Technologies*, 116, 102685.

Kumar, A., & Kapoor, N. (2020). A study on customer satisfaction and retention: A marketing perspective. *International Journal of Science and Engineering Research, 11*(3), 1481-1491.

Li, X., Zhang, M., & Wang, D. (2019). Analyzing Public Opinion on Transportation Infrastructure Projects: A Social Media Sentiment Analysis Approach. *Transportation Research Part A: Policy and Practice, 119*, 124-139.

Patel, K., Smith, T., & Brown, A. (2020). Enhancing Airport Security Procedures through Sentiment Analysis of Passenger Feedback. *Journal of Air Transportation Management*, 85,101812.

Smith, A., Johnson, B., & Davis, C. (2018). Enhancing Customer Experiences in Airlines: A Sentiment Analysis Approach. *Transportation Research Part A: Policy and Practice, 112*, 66-78.

Wang, Q., & Chen, Y. (2021). Analyzing User Sentiment for Ride-Sharing Services: A Natural Language Processing Approach. . *Transportation Research Part C: Emerging Technologies*, 123, 102953.

Windasari, I. P., Uzzi, F. N., & Satoto, K. I. (2017). Sentiment analysis on Twitter posts: An analysis of positive or negative opinion on GoJek. *4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*, 266-269.