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An Analysis of Customer Satisfaction from Airline Tweets Using Machine Learning Approach

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Abstract

This paper explores the application of machine learning (ML) techniques to analyze customer satisfaction from airline-related tweets. Social media platforms like Twitter offer a wealth of real-time customer feedback that can be valuable for airlines to monitor and improve service quality. This research focuses on implementing various machine learning models, including sentiment analysis, emotion detection, and topic modeling, to understand the key factors that influence customer satisfaction in the airline industry. The study also discusses the challenges involved in analyzing unstructured data from tweets and evaluates the effectiveness of different ML approaches for actionable insights.

Keywords: ***Airline Customer Satisfaction, Machine Learning, Sentiment Analysis, Twitter Data, Topic Modeling, Natural Language Processing (NLP), Social Media Feedback.***

1. Introduction

In the highly competitive airline industry, customer satisfaction plays a pivotal role in determining an airline's reputation and long-term success. Traditionally, airlines have relied on surveys and feedback forms to gauge customer satisfaction, but these methods are often limited in scope and frequency. With the rise of social media platforms, particularly Twitter, passengers are increasingly sharing their experiences in real time, providing airlines with an unprecedented opportunity to understand customer sentiment through a wealth of unstructured data.

Twitter, as one of the most popular social media platforms, has become a key channel for customers to express their opinions, both positive and negative, about various aspects of their flight experiences. From complaints about delays and cancellations to praise for in-flight service or helpful staff, airline-related tweets offer a rich source of real-time feedback. Analyzing this feedback, however, presents significant challenges due to the vast volume of data, the unstructured nature of tweets, and the use of informal language, abbreviations, and emojis.

Machine learning (ML) offers powerful tools to address these challenges by automating the analysis of large-scale social media data. Techniques such as sentiment analysis, emotion detection, and topic modeling can extract meaningful patterns and insights from raw text, allowing airlines to monitor customer satisfaction, identify areas for improvement, and respond promptly to customer concerns. By applying natural language processing (NLP) and deep learning models, airlines can analyze tweets more effectively and gain a deeper understanding of customer needs and expectations.

This research focuses on leveraging machine learning techniques to analyze customer satisfaction from airline-related tweets. Specifically, the study aims to investigate how different ML models can be applied to classify sentiments, detect emotions, and uncover key topics in customer feedback. Through this analysis, the research will provide insights into the main factors affecting customer satisfaction in the airline industry and explore how real-time feedback can be harnessed to enhance service delivery.

2. Literature Review

Hasan et al. (2024) Since internet technologies have advanced, one of the primary factors for company development is customer happiness. Online platforms have become prominent places for sharing reviews. Twitter is one of these platforms where customers frequently post their thoughts. Reviews of flights on these platforms have become a concern for the airline business. A positive review can help the company grow, while a negative one can quickly ruin its revenue and reputation. So it’s vital for airline businesses to examine the feedback and experiences of their customers and enhance their services to remain competitive. But studying thousands of tweets and analyzing them to find the satisfaction of the customer is quite a difficult task. This tedious process can be made easier by using a machine-learning approach to analyze tweets to determine client satisfaction levels.

Some work has already been done on this strategy to automate the procedure using machine learning and deep learning techniques. However, they are all purely concerned with assessing the text's sentiment. In addition to the text, the tweet also includes the time, location, username, airline name, and so on. This additional information can be crucial for improving the model's outcome. To provide a machine learning-based solution, this work has broadened its perspective to include these qualities. And it has come as no surprise that the additional features beyond text sentiment analysis produce better outcomes in machine-learning-based models.[1]

Akshada et al. (2023) Sentiment Analysis is one of the key research areas under the machine learning. In this research, the sentiment analysis is applied on the tweets which are based on airlines services. Sentiment analysis is done to classify the sentiments into either positive or negative. Various supervised and unsupervised machine learning algorithms are applied and their accuracy scores are estimated. Based on the accuracy score estimation the best machine learning algorithm for sentiment analysis is identified. The Experiment is carried out with the help of 14640 Airlines related tweets. Support Vector Machine algorithm shows the highest performance accuracy results of 90% and the lowest accuracy result of 79% is given by Decision tree machine learning algorithm. The result shows Support Vector machine algorithm performs better for the sentiment analysis of airlines tweets.[2]

Praphula Kumar JainandRajendraPamula (2020) presented systematic reviews of literature to compare, analyze, evaluate, and understand the efforts and the proper management and research spaces to show the future scope of this pairing. This work contributes to the existing literature in two ways; first, the purpose of first reading and analyzing the application of machine learning processes for consumer emotional analysis in online updates in the hospitality and tourism domain. Second, in this work, we introduced a systematic way of identifying, collecting observational evidence, results from analysis, and conducting all-quality research-related assistance to address specific research questions specific to the defined research area.[3]

Prayag Tiwari et al. (2019) proposed a machine-readable method of distinguishing passenger tweets in relation to aviation services to understand the emotional pattern. We welcome Random Forest (RF) and Logistic Regression (LR) to divide each tweet into positive, negative and neutral impressions. Analysis of the actual data collected shows that these two methods are able to achieve ≈80% accuracy. [4]

James A. Danowski et al. (2020) experimenting with a feature-based network analysis model that combines sensitivity with respect from shortcuts between sensory names and target words across the acorpus. Two real-world databases in which human annotations judge whether tweets are acceptable or not are a force that tests the internal and external functionality of a default network, testing how the goals of this method match the annotations. We found that tweets described as has has an automated negativity score that is almost twice as much as positivity, while well-defined tweets have six times the potential for confidence rather than negligence. To assess the veracity of the method, we have analyzed the sentiments associated with the detection of coronavirus in television news from January 1 to March 25, 2020. Support found four hypotheses tested, indicating the use of the method. H1: broadcast news reveals fewer feelings about coronavirus, panic, and social madness than non-broadcast areas. H2: there is a negative bias in the news at all channels. H3: an increase in mood is associated with an unrelenting volume of news stories. H4: emotions are associated with uncertainty in matters affecting the coronavirus over time. We also found that as the type of channel shifted from broadcast network news to 24-h business, mainstream and foreign news increased with coronavirus, panic, and social isolation. [5]

Abdullatif Ghallab et al. (2020) recently increased attention from various research mining communities, there is a flexible body of work on Arabic Sentiment Analysis (ASA). (The paper introduces a systematic review of existing ASA-related literature. (The purpose of the review email is to support research, to suggest other future study areas in the ASA, and to block further research for other researchers of related subjects. In addition, the limitations of existing approaches are highlighted in the process of progression, exposure, and sensitivity mechanisms. Other potential future research methods with the ASA are suggested in both practical and theoretical aspects. [6].

3. Methodology

In this section, we present the proposed architecture and how it works in the classification of sentiments of customers

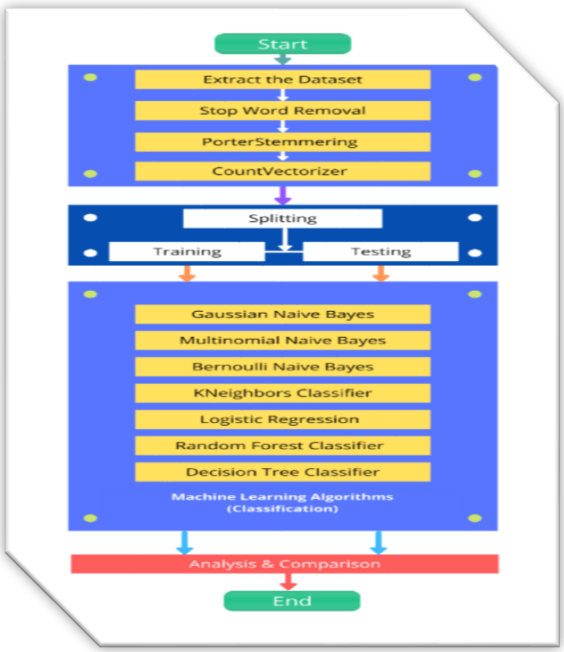

Fig. 1 Proposed Architecture

The Architecture is divided into following steps

1. Web searching of Dataset

The very first step of any kind of machine learning problem is to look for a raw dataset to work on. Sentimental Analysis is a technique that needs two segments of any data one is the text and the other is the opinion or the required opinion. For the proposed system we need a lot of tweets in the dataset whose polarity may vary in Negative/Neutral/Positive. The dataset which we will go to use to implement the solution must be authentic or collected by any official institute. We looked the web for database and Kaggle the official store of databases had a database similar to our requirements so we picked that dataset up and now we have our raw dataset to work on. Now the next step will be extraction or pre-processing of the dataset.
Output of the step:

- ➔ We have "Tweets.csv" as our raw dataset.

2. Extracting of Dataset

As the raw dataset has 15 columns, the dataset is detailed as the institute which designed the dataset. The Proposed model has its own set of requirements, so the dataset needs to be filtered out as per the requirements. Sentimental analysis usually needs two different segments of the dataset one is the feature or the text which needs to be analysed another one is the label or the opinion, these two segments will be used to train the machine learning model. The raw dataset has two columns that have the text of the tweets so we will pick those two columns as the features. The column which has the opinion will be picked as the label. So we need only those three columns from the raw dataset.

3. Stop Word Removal

Stop word removal is the process of removing the words which don't have any role in opinion mining or which don't have any opinion. Like the, i, an, in, etc. Such words are known as stop words which don't have any kind of opinion. So we simply remove all the stop words from all the sentences from the whole database.
The list of stop word in English is like:
'ourselves', 'hers', 'between', 'yourself', 'but', 'again', 'there', 'about', 'once', 'during', 'out', 'very', 'having', 'with', 'they', 'own', 'an', 'be', 'some', 'for', 'do', 'its', 'yours', 'such', 'into', 'of', 'most', 'itself', 'other', 'off', 'is', 's', 'am', 'or', 'who', 'as', 'from', 'him', 'each', 'the', 'themselves', 'until', 'below', 'are', 'we', 'these', 'your', 'his', 'through', 'don', 'nor', 'me', 'were', 'her', 'more', 'himself', 'this', 'down', 'should', 'our', 'their', 'while', 'above', 'both', 'up', 'to', 'ours', 'had', 'she', 'all', 'no', 'when', 'at', 'any', 'before', 'them', 'same', 'and', 'been', 'have', 'in', 'will', 'on', 'does', 'yourselves', 'then', 'that', 'because', 'what', 'over', 'why', 'so', 'can', 'did', 'not', 'now', 'under', 'he', 'you', 'herself', 'has', 'just', 'where', 'too', 'only', 'myself', 'which', 'those', 'i', 'after', 'few', 'whom', 't', 'being', 'if', 'theirs', 'my', 'against', 'a', 'by', 'doing', 'it', 'how', 'further', 'was', 'here', 'than'.
Input:

- ➔ I am a Powerful Man.
- ➔ Power is good.

Output:

- ➔ Powerful Man.
- ➔ Power good.

4. Porter Stemming

It a process of checking the base words for all kinds of words. All the words in a sentence must not be in higher variants of words if it is so the word needs to be replaced by the root word of the same. As in sentimental analysis words like "Like" and "Likes" have the same opinion so the words used must be root words only.
Input:

- ➔ Powerful Man.

Output:

- ➔ Power Man.

5. Count Vectorizer

Now we have the final text data don't we need to transform it into some other data form to make it a suitable input for a classifier? We need to encode the text data into integer data which process is known as vectorization or it is also known as feature extraction. This process is carried out to transform the text data into data that can give a good score in machine learning problems. It works like the counter of the word, you can see in the example below.

Input Sentence:

- ➔ Man Power.
- ➔ Power Good.

4. Result Analysis

In this section of the work, we perform the result analysis on different measuring parameters like score, and accuracy, is done between the proposed methodology (logistic regression), Gaussian NB, Multinomial NB, Bernoulli NB, Kneighbors Classifier, Random Forest Classifier and Decision Tree Classifier.

4.1 Score Analysis

The score parameter is used to prove the qualification on various machine learning techniques and the comparative analysis of this parameter is done among different machine learning such as random forest, Gaussian NB, Multinomial NB, Bernoulli NB, Kneighbors Classifier, and Decision Tree Classifier and our proposed method (logistic regression). The simulation results of our proposed method and existing method is shown in table 1 and it is 94% which is much more about the other exiting approach. The analysis is done using the comparison graph shown in figure 2 and it is found that our proposed method has higher value than the others. It means that the proposed method is more success in the prediction of movie success or hit.

Table 1: Comparative analysis of score parameter

S. No.	Model Name	Score
1	Gaussian NB	0.84
2	Multinomial NB	0.86
3	Bernoulli NB	0.93
4	Kneighbors Classifier	0.87
5	Logistic Regression	0.94
6	Random Forest Classifier	0.92
7	Decision Tree Classifier	0.91

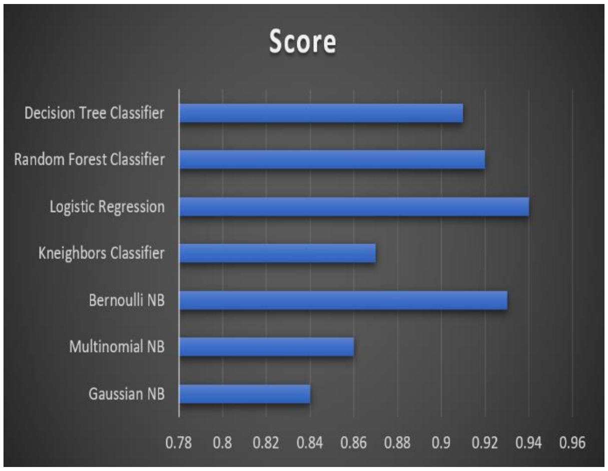

Fig. 2 : Analysis of Score parameters

4.2 Accuracy Analysis

This section presents the comparison of accuracy parameter to show the accuracy of customer satisfaction for airline tweets using sentiment analysis of this parameter is done among different machine learning such as random forest, Gaussian NB, Multinomial NB, Bernoulli NB, Kneighbors Classifier, and Decision Tree Classifier and our proposed method (Logistic Regression). The simulation results of our proposed method and existing method is shown in table 2 and it is 94% which is much more about the other exiting approach. The analysis is done using the comparison graph shown in figure 3 and it is found that our proposed method has higher accuracy value than the others. In this the value of accuracy is equivalent to score parameter. If score of the customer satisfaction will high accuracy of the movie prediction will high. And it is analyzed that the proposed method is more success in the accuracy analysis of customer satisfaction.

Table 2: Comparative analysis of accuracy parameter

S. No.	Model Name	Accuracy
1	Gaussian NB	0.84
2	Multinomial NB	0.86
3	Bernoulli NB	0.93
4	Kneighbors Classifier	0.87
5	Logistic Regression	0.94
6	Random Forest Classifier	0.92
7	Decision Tree Classifier	0.91

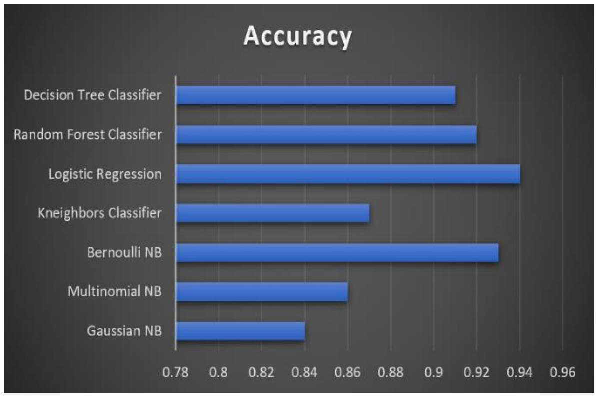

Fig. 3 : Analysis of accuracy parameters

5. Conclusion

We employ machine learning techniques, such as Guassian NB, Multinomial NB, Bernoulli NB, KNeighbors Classifier, Decision Tree, Logistic Regression, and Random Forest, for our experiments in this dissertation. These techniques offer strong classification capabilities. A comparative study between the suggested approach and the current method is conducted through the use of performance measuring factors such as accuracy, and score. Python is used for the simulation of the suggested approach and the current method since it is simple to use and requires less processing time than other languages. After simulation, the suggested method produced a result for the accuracy and score parameter of 94%, which is significantly higher than the result for the current method. Comparably, the precision and recall parameters are used to analyze the proposed and current methods. The suggested methods' value is 94%, which is higher than the existing method. Afterwards, the F1 score is used to analyze the proposed and current methods; the result is 94%, or roughly 2-10% more than the current approach. The suggested model can analyze the sentiment of tweets or feedback with more than 90% accuracy based on these characteristics. In future, the study recommends the ensemble classifier for analysis on tweets data to gain insight into tweets to help relevant airlines improve their customer experience.

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