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Sentiment Analysis of Customer Reviews on E-commerce Platforms: A Machine Learning Approach

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Abstract
Internet users are a huge segment of the consumer market, and businesses nowadays are trying to enter e-commerce, where customers leave reviews regarding products and services. Sentiment analysis is the process of extracting the customer's real feelings from the reviews of the product or services. This study compares logistic regression, naive Bayes, neural networks, and support vector machine algorithms for sentiment analysis and finds the best-performing classifiers among them. This applied study evaluates the classifiers using accuracy, precision, recall, and F1-score metrics. The dataset was taken from the E-Commence website, on which NLP and other classifiers are employed. The results show that the Naive Bayes model, with 94% accuracy, outperforms the different classifiers, where Logistic Regression and Neural Networks are at a similar level of 93%. In comparison, the SVM gave us an average of about 92%. This study suggests the significance of continuously updating sentiment analysis systems to maintain accuracy and relevance. Real-time sentiment analysis tools are a good technique for any text mining work that can help companies address customer problems based on immediate feedback and improve their products.
Keywords: E-Commerce, Logistic Regression, Naive Bayes, Neural Networks, Sentiment Analysis, SVM

1. Introduction

Information technology is extensively applied in various facets of human life, allowing individuals to tackle multiple issues (Imtiaz et al. 2023; Nasim, Masood, et al. 2023; Nasim, Yousaf, et al. 2023). An illustration of information technology's use in the business realm is evident in online stores. Customers can select from a range of choices and experience the convenience of buying products from home while shopping online. Customer reviews are crucial in online purchases as they influence product decisions and provide valuable information on the quality of sellers' goods and services(Godara et al. 2024). Manufacturers and websites selling goods can significantly increase profit by examining customer evaluations using sentiment analysis techniques to improve their offerings and overall consumer experience.
Machine Learning is a group of methods and programs used to create systems that learn from many different data (Neri et al. 2012). It can conduct forecasting far more rapidly than any human. Machine Learning can enhance human productivity to the maximum extent possible. Numerous machine learning algorithms can be categorized as either supervised or unsupervised, and each algorithm employs a distinct learning methodology (Jet and O 2017).
Sentiment analysis falls within the scope of natural language processing (NLP) and focuses on identifying emotions or opinions conveyed in a text, such as customer reviews (S and S 2013). Individuals can utilize social media platforms and other e-commerce website review sections to offer their opinions and evaluations on different circumstances, products, and services, which might be positive or negative, depending on the customer's encounter. Critical feedback plays a crucial role in the company's development as it enhances the quality of services. In this context, sentiment analysis becomes relevant (Gondhi et al. 2022). Sentiment analysis of sales reviews can help the organization's top management make various decisions. Sentiment analysis is a trendy field of research. Several machine-learning approaches are often used in sentiment analysis. Support Vector Machines, Naive Bayes, Regression Analysis, and Neural Networks have shown robust performance in text classification (Devi, Kumar, and Prasad 2016).
Furthermore, sentiment analysis or opinion mining allows you to ascertain client sentiment regarding many facets of your business without simultaneously perusing a large volume of client feedback. If you receive many submissions, you can only read some comments (Hicks et al. 2022). This swift increase in e-commerce platforms has resulted in a massive rise in customer reviews. Reviews are a significant repository of information, giving feedback on customers' happiness or dissatisfaction with things and services. However, the large quantity of unorganized reviews makes it challenging for businesses to analyze and derive actionable insights manually. Organizations need help going through each review and extracting practical insights manually.
This research article aims to tackle the issue of effectively and precisely analyzing customer evaluations on e-commerce platforms to extract sentiment information.
It is essential to identify the optimal classifier to categorize customers' emotions. Assessing an individual's sentiment should be conducted with utmost caution and sensitivity. The machine learning models must possess a commendably high accuracy score.

2. Literature Review

The analysis of individuals' attitudes towards areas such as businesses, product and service quality, current affairs, occurrences, and subjects, along with the characteristics linked to these areas, is called sentiment analysis (Hovy 2015). The study of sentiment has emerged as a crucial tool for corporate decision-making with the emergence of social media, enabling firms to manage vast volumes of legally stored, biased data. By analyzing user opinions on social media or e-commerce website comments, marketing experts can assess how well a product or service is doing and identify the demographics that prefer or dislike particular features of something (Xu, Chang, and Jayne, 2022). Moreover, sentiment analysis also examines the challenges associated with online purchasing when a customer cannot directly inspect, touch, or try the product (Salehan and Kim 2016). (Jin and Ji Ping 2015) proposed a system that identifies product feature elements and provides detailed customer feedback from online reviews Their suggested co-clustering technique efficiently summarizes customer concerns about different product features. Customers could also give the designers

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concise explanations of their requirements. The method uses conditional random fields to identify specific product attributes and offer comprehensive explanations simultaneously.

Many previous studies on sentiment analysis and customer review classification have been performed using various machine learning models over different e-commerce platforms. Akter et al. (Akter, Begum, and Mustafa 2021)sed the Random Forest, Logistic Regression, Support Vector Machines, k-Nearest Neighbours, and XGBoost models in a comprehensive study at Daraz (Bangali e-commerce store reaching accuracies of 90.84%, 90.33%, 94.35%, 96.25%, and 90.54%; similarly, Oktaviani et al. (Oktaviani et al. 2021) used the Naïve Bayes model to analyze Traveloka Google Play reviews and got an accuracy of 91.20%.

In 2022, Zulfiker et al. (Zulfiker et al. 2022) repeated the customer reviews of e-commerce stores with multiple models: Naïve Bayes 87.75%, Logistic Regression 87.25%, Decision Tree 84.31%, Support Vector Machines 90.44%, Random Forest 83.33% and lastly Stochastic Gradient Descent 89.46%. Alzahrani et al. investigated Amazon customer reviews using LSTM and CNN-LSTM models with 91% and 94% accuracy. Furthermore, Hossain et al. (Hossain et al. 2022) had Daraz, in which they employed Multinomial Naive Bayes 82.67%, Logistic Regression 87.76%, Support Vector Machine 93%, Random Forests 93.34% k-Nearest Neighbours 98% and Decision tree 91%.

Table 1: Performance Metrics of Sentiment Analysis Algorithms of previous studies

Author	Year	Dataset	Algorithm	Accuracy
(Akter, Begum, and Mustafa 2021)	2021	Daraz Bangali E-Commerce Store	Random Forest	90.84%
			Logistic Regression	90.33%
			Support Vector Machines	94.35%
			k-Nearest Neighbors	96.25%
			XGBoost	90.56%
(Oktaviani et al. 2021)	2021	Traveloka Google Play Reviews	Naïve Bayes	91.20%
(Kosasih and Alberto 2021)	2021	Shopee E-commerce	Naive Bayes	80.22%
(Zulfiker et al. 2022)	2022	Customer Review on E-Commerce Store	Naïve Bayes	87.75%
			Logistic Regression	87.25%
			Decision Tree	84.31%
			Support Vector Machines	90.44%
			Random Forrect	83.33%
			Stochastic Gradient Descent	89.46%
(Alzahrani et al. 2022)	2022	Amazon Customer Reviews	LSTM	91%
			CNN-LSTM	94%
(Hossain et al. 2022)	2022	Daraz Bangali E-Commerce Store	Multinomial Naive Bayes	82.67%
			Logistic Regression	87.76%
			Support Vector Machine	93%
			Random Forest	93.34%
			k-Nearest Neighbors	89%
			Decision Tree	91%
(Loukili, Messaoudi, and El Ghazi 2023)	2023	E-Commerce Website Customer Reviews	k-Nearest Neighbors	91.8%
			Logistic Regression	90%
			Random Forest	81.9%
			CatBoost	87.7%
(Bahi et al. n.d.)	2023	E-Commerce Website Customer Reviews	Support Vector Machine	94%
			Logistic Regression	95%
			Naive Bayes	88%
(Sitorus et al. 2024)	2024	Play Store	Naïve Bayes	71.00%
(Tabany and Gueffal 2024)	2024	Amazon Customer Reviews	Support Vector Machine	70%
			Naive Bayes	23%
			Logistic Regression	69%
			Random Forest	66%
(Amin et al. 2024)	2024	Twitter (X)	Gradient Boosting	98%
			Random Forest	96%
			Decision Tree	88%
			Naive Bayes	95%
			Extra Tree	90%

The newer studies conducted by Loukili et al. (Loukili, Messaoudi, and El Ghazi 2023) and Bahi et al. (Bahi et al. n.d.) further investigated the effectiveness of various models with e-commerce website consumer reviews. Loukili et al. utilized k-Nearest Neighbours 91.8%, Logistic Regression 90%, Random Forest 81.9% and CatBoost 87.7%. Bahi et al. (Bahi et al. n.d.) used Support Vector Machine 94%, Logistic Regression 95%, Naive Bayes, and Neural Network. Lastly, Sitorus et al. (Sitorus et al. 2024) Deeply analyzed a set of Play Store reviews using the Naïve Bayes model and attained 71% accuracy.

Pang et al. conducted sentiment classification at the document level using conventional machine learning methods. The researchers employed Naïve Bayes, Maximum Entropy, and SVM methodologies to produce the outcomes for unigrams and bigrams. Through three-fold cross-validation, they achieved an accuracy of 82.9% for unigrams. Additionally, their research is concentrated on gaining a deeper comprehension of the challenges associated with sentiment classification (Pang, Lee, and Vaithyanathan n.d.). On the other hand, the sentiment analysis models require reinforcement and recalibration by frequently debugging them with new data considering changes in language and expressions by the consumers (Hajek, Hikkerova, and Sahut 2023). Thus, the continuous update of the sentiment analysis system's linguistic data and the inclusion of contextual-based algorithms are essential for keeping the systems relevant and accurate, as stated by the scientific findings (Cao et al. 2023)

The fact that the popularity of e-business is growing at the international level, evaluating commentaries in at least two or more languages is a critical issue. This study area has evolved over the years, concentrating more on cross-lingual and multilingual sentiment analysis approaches. For example, studies investigated text translation from one language to another and integrated sentiment analysis of the reviews (Liu 2023). This benefit serves the purpose of studying different consumer groups and assists multinational corporations in the globalization of their strategies (Huang, Asemi, and Mustafa 2023).

Another area is combining sentiment analysis with other data analysis types, including image and video data analysis, to gain more substantial insight into consumers' behavior. Moreover, as machine learning models become more sophisticated, targeting emotion much more effectively is possible by displaying relevant content, offers, and advertisements that change and respond to users' reactions in real-time (Ahmed, Shanto, and Jony 2023).

Table 1 presents various studies for comparison, highlighting the diverse approaches taken in sentiment analysis of e-commerce reviews. However, some of these studies remain contentious, particularly when evaluating their effectiveness and accuracy in different contexts. Notably, based on our review of the existing literature, there appears to be a significant gap in research that combines the use of Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, and Neural Networks within a single framework for sentiment analysis. Our study aims to bridge this gap by integrating machine learning algorithms, offering a more comprehensive and robust approach to analyzing sentiments in e-commerce reviews. This integrated approach enhances accuracy and contributes a novel perspective to the field.

3. Methodology

This section offers a detailed explanation of the sentiment classification method used in the research article. The dataset used originated from an E-Commerce store and underwent further processing.

3.1. Dataset

To obtain precise outcomes, it is necessary to employ a considerable dataset. The dataset used in this research had 11 columns and 19663 rows, each containing unique user reviews.

Table 2: Description of Dataset

Features	Description
Product ID	Numerical categorical variable representing the individual item
Category	Highest-level classification
Subcategory1	This is a more specific classification within the main category. For instance, "Tops" is a type of clothing under the broader "General" category.
SubCategory2	This is an even more detailed classification within Subcategory1. For example, "Fine gauge" and "Knits" specify the types of tops under the "Tops" subcategory.
Location	City from which review was submitted
Channel	The platform through which customers submitted their reviews
Customer Age	Age of Consumer
Review Title	Brief headline provided by customers for their review of the product
Review Text	Written feedback or comments provided by customers about the product.
Rating	Numerical score given by customers to rate the product
Recommend Flag	Product recommended by the customer

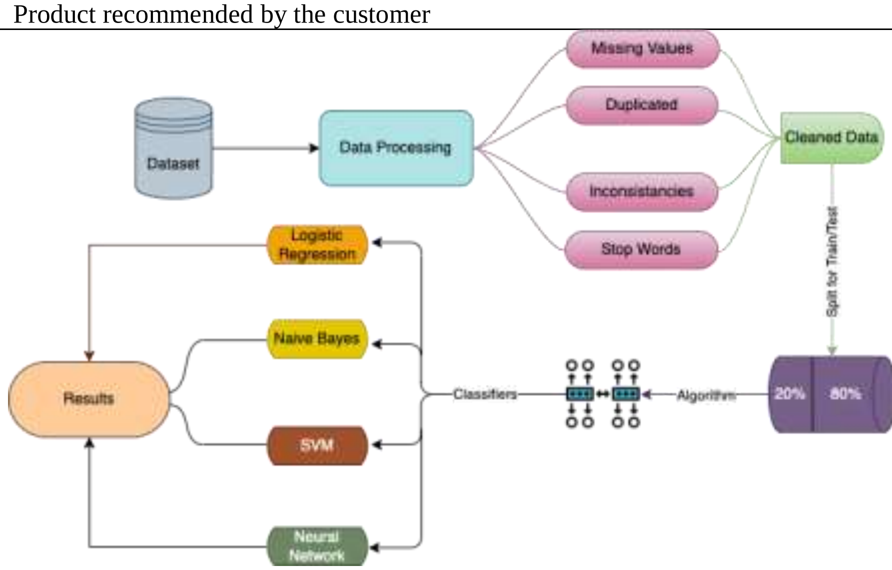

Figure 1: Sentiment Analysis Framework

3.2. Data Preprocessing

This process is crucial to validating data before any analysis; this includes handling the missing values and duplicates and solving inconsistencies in the dataset. For sentiment analysis, text data undergoes preprocessing steps. This procedure relates to data preprocessing that takes care of the waiver of stop words, annotations, and absent values to enhance the text quality before analysis. This step is crucial because it directly affects the results of text mining operations. The tokenization was applied after preprocessing the data. We can break down a sequence of characters in the text by locating word boundaries where one word ends and another begins.

i. Missing Values

Missing values can create problems for algorithms, which typically expect a complete dataset. To obtain a clean dataset, we used the "Pandas" library.

ii. Duplicates

Duplicate records occur when the same entry appears multiple times in the dataset, which can lead to biased results.

iii. Inconsistencies

Inconsistent data refers to entries that should be uniform but are not, often due to errors in data entry.

iv. Stop Words

Stop words are common in a language (like 'the,' 'and' 'is') and often do not add significant meaning to natural language processing (NLP) tasks. Removing them can help reduce the dimensionality of text data.

After processing, the dataset is cleaned, meaning it is free from errors, inconsistencies, and irrelevant information. This Cleaned Data is now suitable for model training.

3.3. Split Data for Train/Test

The cleaned data was divided using the holdout approach for training and testing. The model is trained on 80% of the data and the rest, the remaining 20%, for testing. This study uses machine learning and natural language processing (NLP) methods to analyze customers' sentiments about the e-commerce store. The study aims to determine the relationships between product attributes, customer age, ratings, and consumer opinion by evaluating machine learning methods.

3.4. Machine Learning Algorithms

Various Machine Learning algorithms (classifiers) are applied to the cleaned and split data.

i. Logistic Regression

Logistic Regression is a statistical method used for binary classification tasks. It is highly suitable for fundamental sentiment analysis, aiming to classify text as positive or negative.

ii. Naive Bayes

Naive Bayes is a probabilistic classifier that applies Bayes' theorem with the "naive" assumption that all features (words in the text) are independent.

iii. SVM (Support Vector Machine)

Support Vector Machines are robust classifiers that work by finding the optimal hyperplane that separates different classes (e.g., positive vs. negative sentiment) in the feature space.

iv. Neural Network

Neural networks consist of layers of interconnected nodes (neurons) that can learn complex patterns in data. They are particularly well-suited for tasks like sentiment analysis, where the relationships between words can be complex.

After the classifiers have been trained on the training data, they are tested on the testing data to evaluate their performance. The results of this testing provide insights into how well each model has learned from the data.

Other techniques, such as word clouds, subject modeling, and emotion graphs, were also applied. The data was analyzed and plotted using multiple visualizations, such as bar charts, word clouds, box plots, and ROC curves.

4. Result and Discussion

Exploratory Data Analysis is often performed on investigative data that only occasionally falls in the domain of formal modeling or hypothesis testing. It can also help evaluate whether statistical techniques used to analyze data are appropriate. This study will employ a bar chart, Box Plot, and ROC curve.

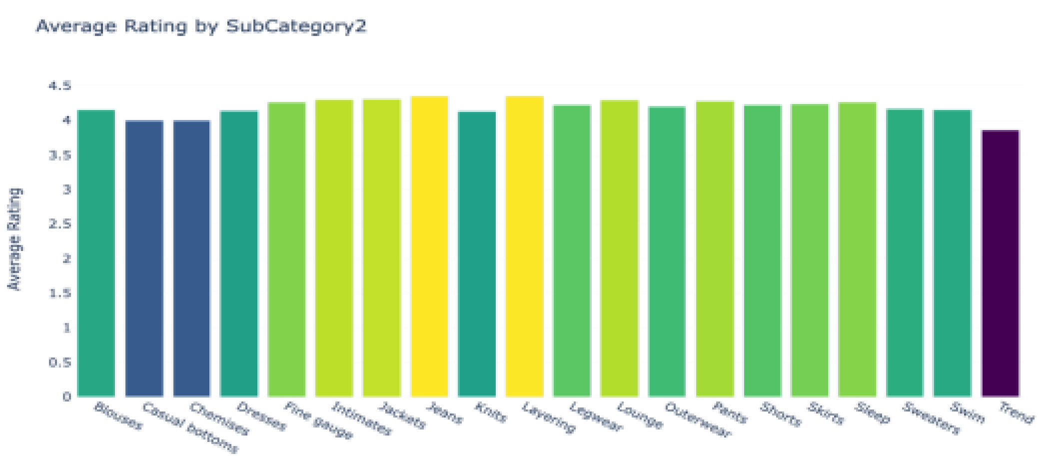

Figure 2: Average Product Ratings by Subcategory

Figure 2 represents the average ratings of various clothing subcategories labeled “SubCategory2," with their corresponding average rating values on the y-axis. The ratings are on a scale from 0 to 5.
It illustrates that most clothing subcategories have high average ratings, indicating overall customer satisfaction. However, the "Swim" and "Trend" subcategories are areas that might need improvement based on their lower average ratings.

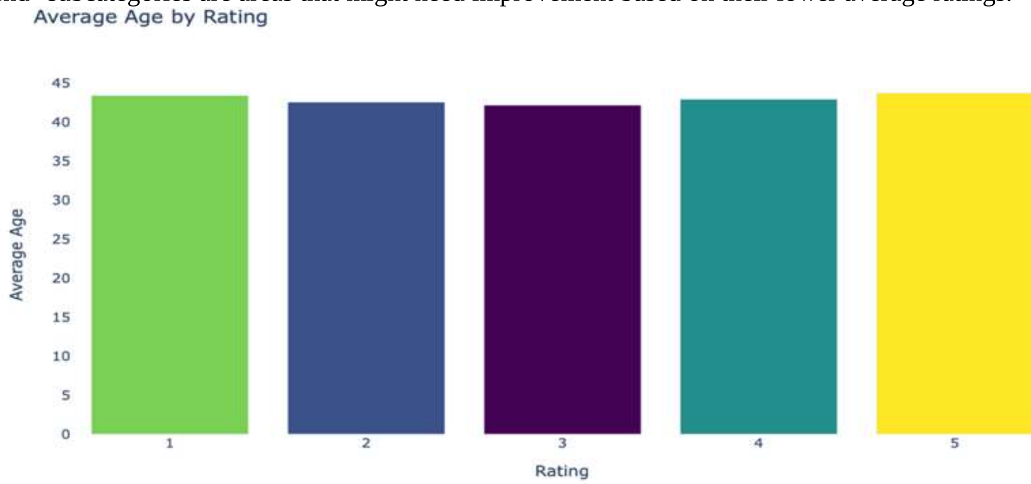

Figure 3: Average Product Ratings by Subcategory

In Figure 3, the average age of customers hovers around 41 to 42 for all ratings levels. The distribution is almost identical for people from different age groups, so this shows that it does not matter what you are when submitting a review.

4.1. Word Cloud

Word clouds illustrate the distribution of sentiments and descriptive words drawn from text responses. They are a visual representation of text data, and their surface area shows the size or importance of words.

Figure 4: **Word cloud**

Figure 4 Word cloud representing a set of emotional or descriptive words - the size of the word signifies its frequency.
Sound words like great, love, happy, unique, and marvelous are frequently used, which indicates a strong positive sentiment in the text.
Negatively charged words like "disappointed," "bad," sad," or terrible also make an appearance. Still, they are usually much smaller, hinting at a lower frequency and intensity when contrasted to positively loaded terms.

4.2. Sentiment Analysis

The process of sentiment analysis involves analyzing text data to determine the sentiment expressed in it.
The sentiment analysis tool analyzer—polarity-scores function—was used in this research article. This function assigns scores from -1 to 1.

i. Positive Sentiment

Positive if the sentiment score is more significant than 0.05.

ii. Neutral Sentiment

Neutral if the score falls between -0.05 and 0.05, inclusive.

iii. Negative Sentiment

It is harmful if the sentiment score is less than -0.05.
Figure 5 displays the distribution of sentiments in a dataset of customer reviews. Positive ratings make up 18,295 (93.0% of total reviews). This category has a green bar, indicating that most customer evaluations are promising. Most clients were satisfied.
The Gray bar is neutral, with 214 reviews, which is 1.1% of all. A few indifferent reviews indicate that customers were pleased with the product.
That last red bar represents 1,154 reviews or 5.9% of the negative feedback collected in this data set. Very few negative ratings mean unhappy customers.
Overall, most reviews are good, as shown in the chart. Numerical counts and percentages help clarify the dataset's sentiment distribution.

Table 3: Customer Reviews and Sentiment Score

	Customer Age	SubCategory2	Review Text	Rating	Word Counts	sentiment_score	sentiment
0	34	Fine gauge	- this really is lovely. the overall design fr...	4	{'and': 1, 'arms': 1, 'back': 1, 'design': 1, ...	0.7832	positive
1	34	Knits	-i normally don't go for these tops because wi...	4	{'an': 1, 'and': 4, 'because': 1, 'bottom': 1,...	0.8928	positive
2	34	Jackets	-like others, i agree that this is a staple th...	5	{'agree': 1, 'and': 1, 'as': 1, 'at': 1, 'can'...	0.8906	positive
3	34	Knits	-this was actually at my local retailer store....	5	{'______________': 1, 'actually': 1, 'and': 1, ...	0.9062	positive
4	33	Dresses	... between looking fat and looking like you h...	4	{'also': 1, 'and': 2, 'another': 1, 'appear': ...	0.7113	positive
...	...	...	...	...	...	...	...
19658	66	Knits	You won't break the bank with this cute tee. I...	4	{'adds': 1, 'and': 2, 'bank': 1, 'because': 1,...	0.9325	positive
19659	54	Sweaters	You would expect anything woolen to be slightl...	4	{'ag': 1, 'and': 2, 'anything': 1, 'are': 1, '...	-0.0258	neutral
19660	34	Skirts	You've probably read through the other reviews...	5	{'___________': 1, 'and': 5, 'are': 1, 'be': 1,...	0.9302	positive
19661	60	Dresses	Yummy, soft material, but very faded looking. ...	3	{'am': 1, 'back': 1, 'but': 1, 'faded': 2, 'fo...	0.6652	positive
19662	30	Dresses		5	{}	0.0000	neutral

19663 rows × 7 columns

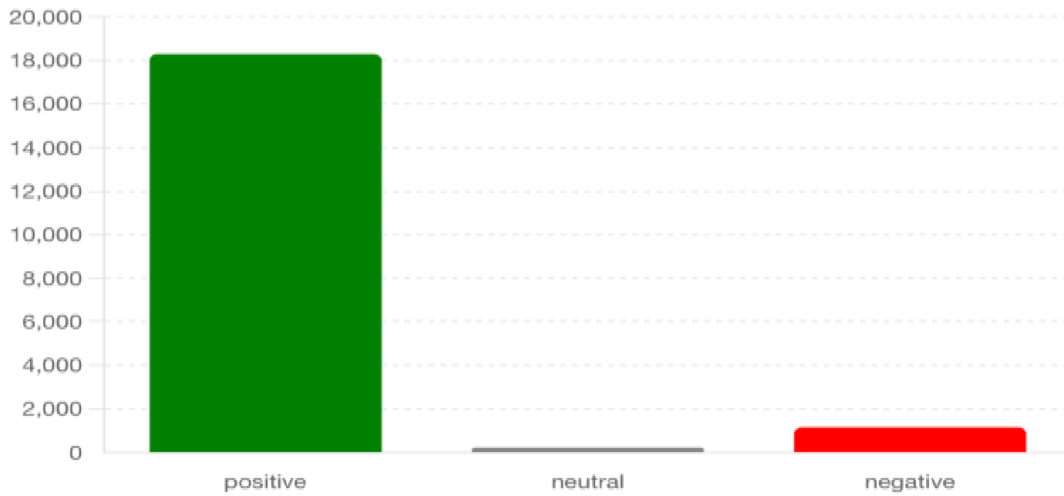

Figure 5: Distribution of Sentiment in Customer Reviews

4.3. Sentiments vs. Ratings

The results are plotted in a box displaying the ratings for comments with positive, neutral, and negative sentiments. This visualization shows each sentiment group's ratings, with average and variability.

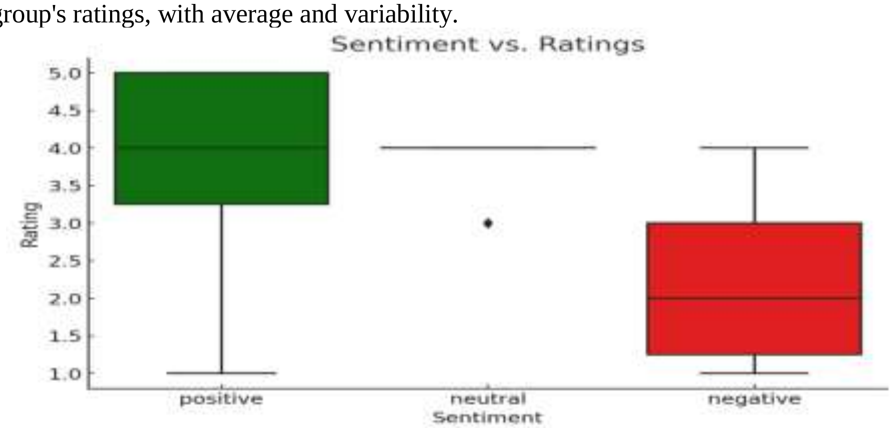

Figure 6: Comparison of Ratings Across Different Sentiment Categories

Figure 6 shows how ratings differ by sentiment. The high rating counts are for positive sentiments, the low ones for negative sentiments, and the middle ones for sentiment-neutral opinions; there are a few data points of middle-scale ratings. This plot helps see the relationship between customer sentiment and how they rated their product.

The SVM, Logistic Regression, Naive Bayes, and Neural Network classifier models were evaluated using accuracy, precision, recall, and F1-score. We examined feature selection and engineering procedures, such as using stop words, stemming, or lemmatization, for each model. We performed a test to explore how different parameter combinations affect the model's performance. It is possible to evaluate the performance of each model and examine the methods employed for feature selection.

The study includes applying various machine learning models and natural language processing (NLP) approaches to analyze the sentiment of reviews of women's clothing on online retailers. The main objective was to find the connections between product features and customer opinion. Word clouds, topic modeling, sentiment analysis graphs, and other NLP techniques were used with the evaluated models Naive Bayes, SVM, and a Neural Network.

The performance of the SVM, Logistic Regression, Naive Bayes, and Neural Network models employed for sentiment analysis of the E-Commerce store ratings was assessed using the following metrics:

Accuracy refers to the proportion of ratings accurately classified out of the total number of ratings (Hicks et al. 2022)

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Precision refers to the actual positive rate, calculated by dividing the number of correctly anticipated positive ratings by the total number of expected positive reviews.(Hicks et al. 2022)

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

Recall is the proportion of accurately predicted positive outcomes compared to the total number of positive outcomes (Hicks et al. 2022)

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-score is a statistical metric that quantifies the harmonic mean of precision and recall (Hicks et al. 2022)

$$F1 - Score = \frac{2*(Percision*Recall\ )}{(Percision+Recall\ )} \quad (4)$$

Table 4: Performance Metrics of Classification Algorithms

Algorithm	Accuracy	Precision	Recall	Fi-Score
Logistic Regression	0.93	0.93	0.93	0.93
Naïve Bays	0.94	0.94	0.94	0.93
SVM	0.92	0.92	0.92	0.91
Neural Network	0.93	0.93	0.93	0.93

Table 4 presents a concise overview of the performance measures for four distinct machine learning models: Logistic Regression, Naive Bayes, SVM, and Neural Network. The metrics consist of Accuracy, Precision, Recall, and F1 Score, all computed as weighted averages.

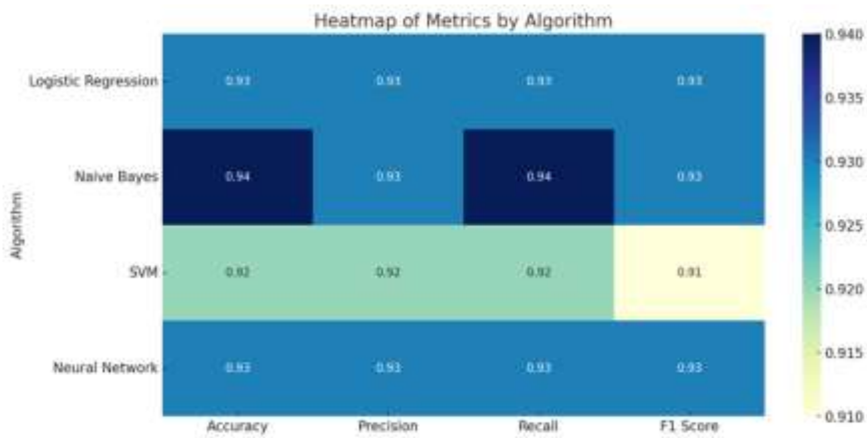

Figure 7: Heatmap of Metrics by Algorithm

Logistic Regression and Neural Network attained an accuracy of 93%, indicating a correct classification rate of 93%. Their accuracy, recall, and F1 scores frequently achieve a high value of 93%, indicating a favorable equilibrium between precision and memory. Consequently, these models exhibit efficacy in accurately detecting both true positives and negatives, rendering them dependable for the assigned classification task.

The Naive Bayes model achieved a significantly higher accuracy of 94%, surpassing the other three. The precision and F1 score exhibits a consistent value of 94%; however, the recall demonstrates a slightly higher value of 94%, suggesting a superior capability to recognize positive situations accurately.

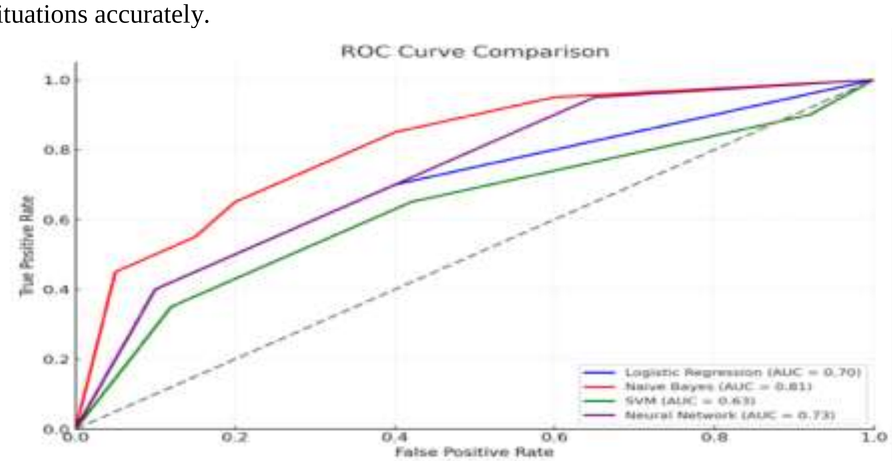

Figure 8: ROC Curve Comparison of Classification Algorithms

The accuracy of the Support Vector Machine (SVM) model was marginally lower, measuring 92%. Although the precision and recall values are both good, with a score of 92%, the F1 score is somewhat lower at 91%. The marginal decrease in the F1 score indicates that SVM, although still efficient, can exhibit a slightly elevated incidence of false positives or false negatives compared to the other models.

5. Conclusion

The research utilized machine learning and natural language processing techniques to identify patterns in online shopping reviews on e-commerce platforms. The Naïve Bays model showed the highest accuracy score and another performance measurement for predicting customer sentiment. Businesses can gain significant knowledge from the word cloud, topic modeling, and sentiment analysis insights to better understand customer opinions and enhance their product offerings.

The extent and breadth of the dataset cannot comprehensively reflect subtle variations in the market or its mood, thus limiting our research. An imbalance of emotion classes within a dataset can also affect the performance and accuracy of the classifiers, resulting in bias. Textual data cannot represent all the demographics, purchase behavior, or product attributes, including sentiment and antecedents.

Future work needs to incorporate more advanced NLP techniques and deep learning models to increase the accuracy of sentiment analysis. In addition, integrating approaches written in different languages and the breadth of metrics can lead to more comprehensive insights into consumers globally. Including audio and visual reviews in the analysis could broaden its scope and yield more insightful data on client feedback. In addition, they might build sentiment analysis applications that generate immediate feedback about customer behavior as well as occasional nudges for changes in a company's products or services. This will allow customer service systems to incorporate these models, be more active in satisfying customers, and identify and resolve user complaints and responses. Therefore, sentiment analysis using machine learning has profound opportunities and threats in e-commerce domains. Over time, enhancing the techniques will achieve extra accuracy in sentiment analysis, optimizing the implementation of e-commerce strategies.

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