Sentiment Analysis: A Machine Learning perspective

Nadimpalli Madana Kailash Varma
Department of Artificial Intelligence & Machine Learning
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
kailashvarma2k2@gmail.com

Sri Harsh Mattaparty
Department of Artificial Intelligence & Machine Learning
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
yosriharsh98@gmail.com

Shifa Ismail
Department of Artificial Intelligence & Machine Learning
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
shifaismail84@gmail.com

Joel Thaduri
Department of Information Technology
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
joel19thaduri@gmail.com

Dr. Gagan Deep Arora
Department of Artificial Intelligence & Machine Learning
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
Gagandeeparora250379@gmail.com

AnandKumar B
Department of Artificial Intelligent & Machine Learning
Vardhaman College of Engineering
Hyderabad-Telangana, 501286, India
anandbiyani.b@gmail.com

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***Abstract*— An essential part of natural language processing, sentiment analysis makes it possible to automatically extract sentiment from textual input. In this work, we examine how well different machine learning algorithms perform when used to analyze the sentiment of real-time Amazon reviews in the automobile niche. Leveraging a dataset comprising reviews from Amazon users, we employ SVM, KNN, Logistic Regression, and Random Forest algorithms to categorize text sentiment as positive, negative, or neutral. This work evaluates the performance of each algorithm in sentiment analysis tasks using strict evaluation standards and testing. Our findings provide insights into the effectiveness of machine learning approaches for analyzing sentiment in real-time reviews, offering valuable implications for businesses and organizations aiming to leverage customer feedback for decision-making and user experience enhancement.**

Keywords: Random Forest, Logistic Regression, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), NLP, Machine Learning (ML), Sentiment analysis, Reviewer text, Categorization, Predictive tasks.

I. INTRODUCTION

In the rapidly evolving digital landscape, where the volume of textual data generated daily surpasses human capacity for analysis, NLP emerges as a cornerstone technology. NLP enables robots to produce, comprehend, and interpret human language, opening up a vast range of industrial applications. NLP drives innovations that improve communication, automate procedures, and extract insightful information from massive repositories of text data. Examples of these breakthroughs include chatbots and virtual assistants, as well as sentiment analysis and language translation. It serves as faster way to collect customer insight data which is in lower cost than customer insight support [21].

Sentiment analysis, a pivotal area within NLP, focuses on discerning and categorizing the underlying sentiment or emotion expressed in textual content. Leveraging a variety of techniques and algorithms, sentiment analysis algorithms in NLP enable automated extraction of sentiment polarity, ranging from positive and negative to neutral. These algorithms play a crucial role in understanding public opinion, customer feedback analysis, brand monitoring, and market sentiment prediction.

Machine Learning (ML) algorithms, known for their adaptability and ability to discern patterns from data, have emerged as powerful tools in sentiment analysis tasks. SVM KNN, Logistic Regression, and Random Forest algorithms, among [25] others, have found diverse applications in sentiment analysis, each offering unique strengths in categorizing and predicting sentiment from textual data. With labeled datasets as their training set, these ML algorithms may effectively classify text into predefined sentiment categories, facilitating predictive tasks and decision-making processes.

In this study, we present our findings from an investigation into the performance of various ML algorithms for sentiment analysis of real-time Amazon reviews in the automotive category. Leveraging a dataset[31] comprising a diverse range of reviews, we evaluated the efficacy of SVM, KNN, Logistic Regression, and Random Forest algorithms in categorizing reviewer text into positive, negative, or neutral [26] sentiment categories. Our study provides insightful information about the relative performance of different algorithms and clarifies how applicable they are in practical situations.

Research on real-time data holds immense potential for enhancing the capabilities of sentiment analysis algorithms and their practical utility in dynamic environments. Businesses may discover developing patterns, get quick insights on client opinions, and adjust their strategy by monitoring sentiment in real-time reviews. Through our research, Our goals are to further the expanding field of sentiment analysis research and open the door for more efficient application of machine learning algorithms to real-time data analysis.

II. LITERATURE REVIEW

In Sentiment analysis has become increasingly vital in NLP with numerous studies shedding light on its methodologies, applications, and challenges.

In order to address the issue of accurate sentiment classification at both the sentence and review levels, Fang and Zhan (2017) presented a comprehensive method for classifying sentiment polarity using online product reviews from Amazon.com [1]. Their comprehensive study underscores the significance of NLP techniques in extracting valuable insights from consumer feedback, crucial for understanding market sentiments and improving product offerings. It is easy to act on the customer suggestions, making the strength and weakness of organization [21].

Sindhura (2020) discussed the collaboration between NLP and Machine Learning (ML) in sentiment analysis, particularly in digital platforms where customer feedback influences brand perception and consumer decisions [2]. By elucidating the sentiment analysis process and its relevance in digital contexts, the paper highlights the role of advanced technologies in understanding and interpreting human language, essential for businesses to adapt and thrive in competitive markets. Linking linguistic content with the alliance rating [22].

An examination of sentiment analysis techniques, applications, and difficulties was carried out by Wankhade et al. in 2019, addressing the growing need for accurate sentiment interpretation in internet-based platforms and social media [3]. Their thorough examination offers insightful information about the benefits and drawbacks of the state-of-the-art sentiment analysis methods., guiding future research directions towards more effective sentiment analysis solutions. In view of the results of semantic technique based on neural networks with 2710 results [23].

Khan and Islam (2021) compared sentiment analysis techniques using NLP and various ML algorithms on US airline Twitter data, highlighting the effectiveness of advanced techniques in handling large, imbalanced datasets [4]. By demonstrating the importance of employing sophisticated methods to extract actionable insights from social media data [24], their study contributes to optimizing sentiment analysis processes in real-world applications.

Shetha et al. (2018) conducted a comparative study of classification machine learning methods, reaffirming the importance of selecting the appropriate algorithm based on dataset characteristics [5]. Their study provides valuable guidance for researchers and practitioners in choosing classification models tailored to specific application requirements, ensuring optimal performance in sentiment analysis tasks.

Das et al. investigated hate speech detection on Twitter using various ML models, achieving high accuracy rates with SVM, Decision Tree, and Random Forest models [6]. By focusing on the pressing issue of hate speech detection, their research contributes to enhancing online safety and promoting positive interactions on social media platforms.

Classification algorithms like KNN, Naive Bayes, and Logistic Regression play crucial roles in data science and decision-making processes, as emphasized by Wohlwend [7]. Their research emphasizes how important these algorithms are for effectively categorizing data [25], which results in more precise decision-making across a range of industries.

When Hassan et al. (YEAR) examined machine learning methods for text categorization, they found that KNN performed better on the SPAM dataset whereas Logistic Regression and SVM performed better on the IMDB dataset [8]. By evaluating different algorithms on diverse datasets, their study offers insightful information on how well different machine learning methods perform in text classification tasks.

Sentiment analysis, a significant aspect of NLP, involves extracting sentiments from text data. Singh et al. explored sentiment analysis optimization using ML classifiers, achieving high accuracy rates with Naive Bayes and OneR [9]. Their study demonstrates the effectiveness of these classifiers in accurately predicting sentiment polarity, essential for applications such as customer feedback analysis and opinion mining.

When Kawade and Oza examined user reaction on Twitter over the Uri incident, they found a considerable amount of distaste among users [10]. Their work, which makes use of text mining tools, sheds light on public opinions on social media platforms and shows how sentiment analysis may be used to comprehend and resolve societal problems.

Jemai et al. developed a classifier for comment polarity prediction, achieving greater precision compared to previous works [11]. Their research contributes to improving sentiment analysis accuracy, essential for applications such as comment moderation and social media monitoring.

Grana investigated sentiment analysis as part of NLP, focusing on automatic classification approaches with supervised ML algorithms [12]. Their work sheds light on the efficacy of machine learning (ML) algorithms in sentiment analysis [24] tasks by examining various categorization strategies. This information can help researchers choose the best models for certain applications.

Dang et al. explored hybrid deep learning models for sentiment analysis, achieving increased accuracy compared to single models, especially when combined with SVMs [14]. Their study demonstrates the potential of hybrid models in improving sentiment analysis performance, offering a promising direction for future research in the field.

Talaat proposed deep learning models combining BERT with BiLSTM and BiGRU algorithms, demonstrating superior performance in sentiment analysis tasks [15]. By leveraging advanced deep learning techniques, their research contributes to enhancing sentiment analysis accuracy, crucial for applications such as opinion mining and social media sentiment analysis.

Jemai et al. presented a novel hybrid approach, RoBERTa-GRU, which combines RoBERTa Transformer model with GRU architecture, achieving high accuracies on benchmark sentiment analysis datasets [16]. Their research showcases the effectiveness of hybrid models in addressing challenges associated with sentiment analysis, offering a promising solution for real-world applications.

Kanojia et al. explored practical applications and challenges of sentiment analysis across various domains, equipping NLP researchers with insights into real-world SA applications [17]. By examining the practical implications of sentiment analysis, their study provides valuable guidance for researchers and practitioners in deploying sentiment analysis solutions in diverse contexts.

Jain et al. advanced sentiment analysis technology across several modalities by creating a real-time sentiment analysis system for multimedia inputs [18]. By integrating sentiment analysis with multimedia data processing, their research contributes to enhancing real-time sentiment analysis capabilities, essential for applications such as social media monitoring and content analysis [30].

Rajput et al. proposed a methodological framework integrating semantic analysis with machine learning for sentiment classification of tweets, achieving promising results in real-time sentiment analysis [19]. Their work highlights the potential of semantic analysis techniques to improve sentiment analysis accuracy and offers a comprehensive framework for sentiment analysis in the dynamic context of social media interactions. The system's linguistic and semantic approach makes it possible to classify a variety of materials. Because it is founded on the syntactical tree of the phrase under analysis as well as the positive or negative polarities [27].

Jain and Kashyap conducted a systematic review of sentiment analysis research trends related to COVID-19 [29], offering insights into sentiment analysis methodologies and applications in the context of public health emergencies [20]. Through the examination of sentiment analysis patterns in relation to the COVID-19 epidemic, their review provides valuable guidance for researchers and policymakers in comprehending how the general public views health problems and reacts to them.

In conclusion, the literature review highlights the evolving landscape of sentiment analysis in NLP, showcasing the diverse methodologies, applications, and challenges in this field. From the exploration of advanced ML algorithms to the development of hybrid deep learning models, Effective feature extraction requires aspects and review-related characteristics that are distinguished by hybrid vectors [28], researchers are continually striving to enhance sentiment analysis accuracy and applicability across various domains. Sentiment analysis is crucial for understanding other people's thoughts, feelings, and behaviors, as demonstrated by its integration with real-time multimedia inputs and its examination of sentiments around social events like as the COVID-19 epidemic. As long as sentiment analysis is used extensively in decision-making and social media monitoring, further research efforts are warranted to address emerging challenges and optimize sentiment analysis techniques for real-world applications.

III. Research Methodology

In this study, we employed a systematic approach to conduct a comparison of algorithms for machine learning (ML) for Sentiment Analysis on real-time customer reviews from the automotive category on Amazon [31]. The methodology encompassed several key steps, including data preprocessing, model training, evaluation, and analysis, aiming to assess the efficacy of SVM, KNN, Random Forest algorithms and Logistic Regression in categorizing sentiment.

Initially, the dataset comprising customer reviews was acquired and loaded into a pandas DataFrame. The data underwent exploratory data analysis (EDA) to identify any missing values and gain insights into the dataset's structure and distribution. Subsequently, relevant columns such as 'reviewerID', 'reviewerName', 'reviewText', 'summary', and 'overall' were selected for further analysis to ensure comprehensive coverage of the dataset[31].

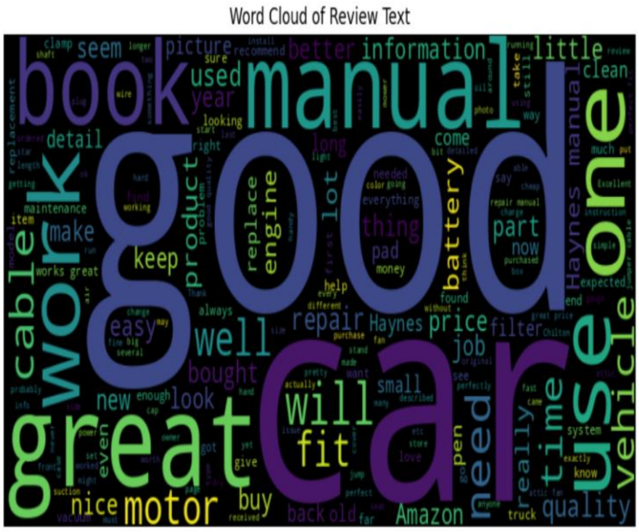

Fig. 1. Most commonly used words in “ReviewText” feature from dataset.

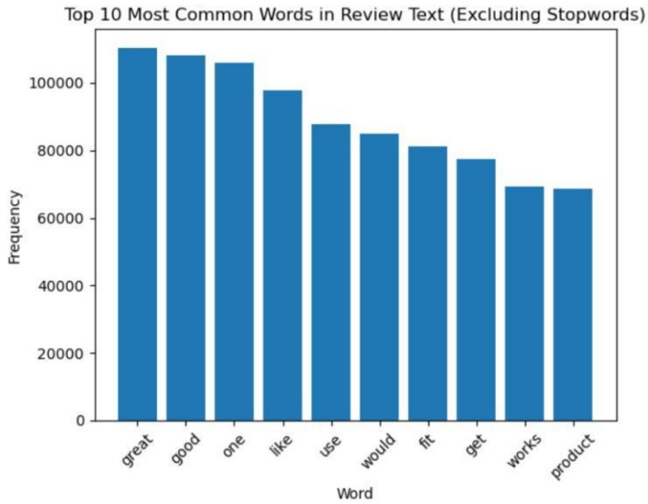

Fig. 2. Frequency of most commonly used words in “ReviewText” feature from dataset.

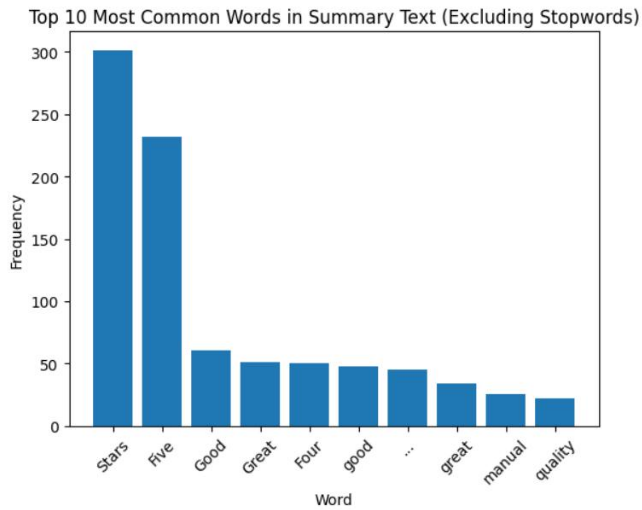

Fig. 3. Frequency of most commonly used words in “Summary” feature from dataset.

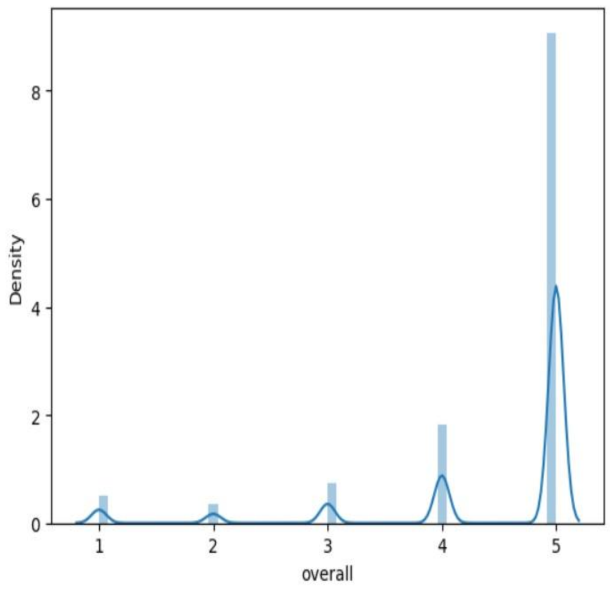

Fig. 4. Density plot for "overall" feature in dataset[31].

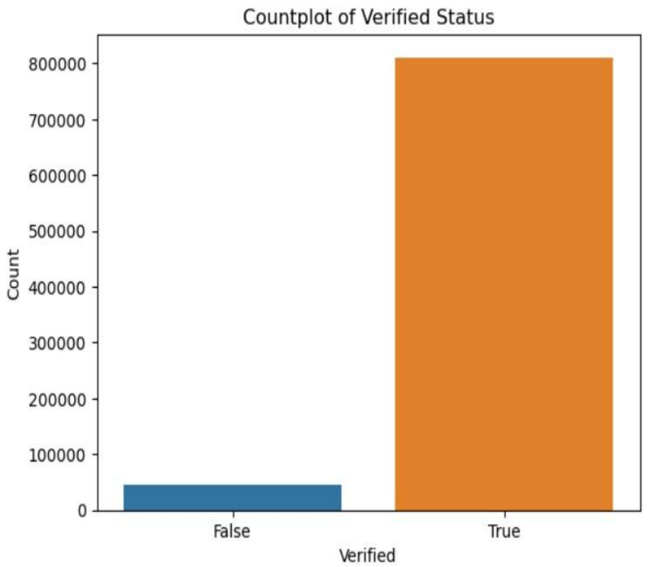

Fig. 5. Bar plot that indicates "Verified" samples from dataset[31].

To facilitate sentiment analysis, the 'overall' feature shows the ratings provided by users which are mapped to sentiment categories ('Positive', 'Negative', 'Neutral') using predefined thresholds. This process involved the implementation of a custom function to categorize ratings based on sentiment polarity.

Next, using the train-test split function from sci kit-learn, the dataset was divided into training and testing sets, with 25% of the data put aside for testing to guarantee a robust model evaluation. Textual data in the 'summary' feature has been vectorized using the Term Frequency-Inverse Document Frequency (TF-IDF) technique, allowing for the conversion of text data into numerical feature vectors suitable for ML algorithms.

Subsequently, four ML algorithms—Random Forest, Logistic Regression, SVM, and Naive Bayes—were trained on the TF-IDF transformed training data to predict sentiment labels. Model predictions were generated for the test data, and accuracy scores were calculated using the accuracy_score function to evaluate each algorithm's performance.

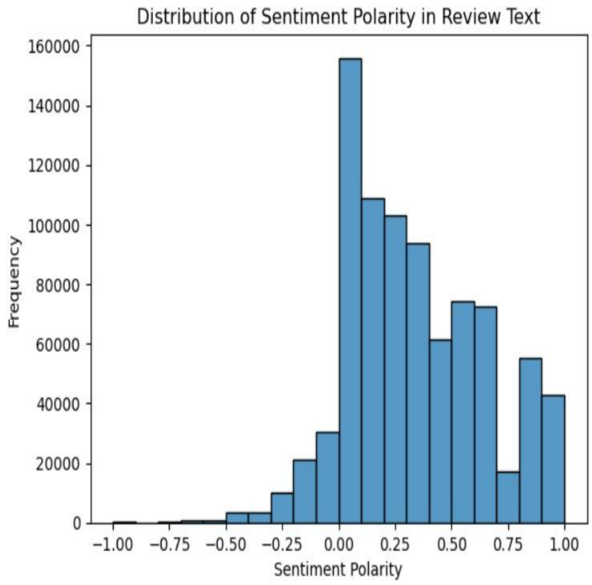

Fig. 6. Sentiment Polarity for "Review Text" feature using NLP library (Textblob).

Analysis of the results revealed varying degrees of accuracy across the ML algorithms, with Random Forest exhibiting the highest accuracy among the models evaluated. Visualizations, including bar plots and confusion matrices, were utilized to depict the comparative performance of the algorithms and visualize the classification results.

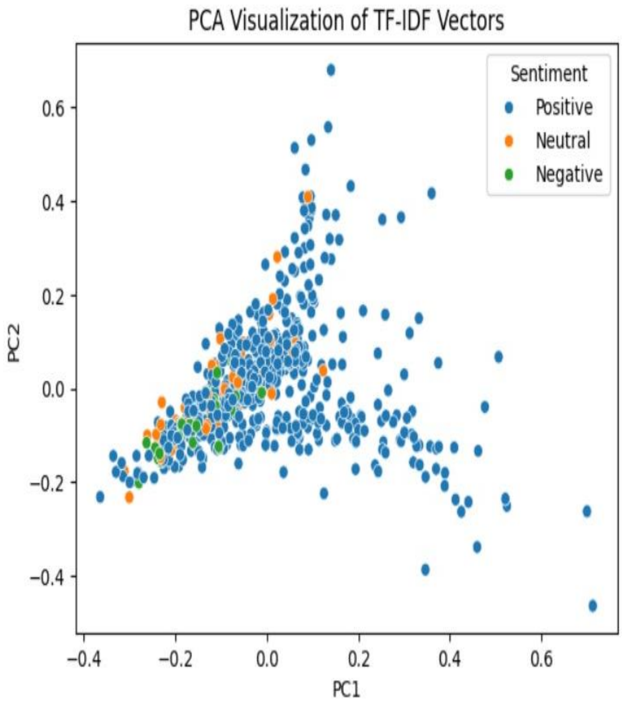

Fig. 7. Distribution of data in vector space using Principle Component Analysis(PCA).

By using this technique, we want to further research in NLP and ML-based text categorization tasks by offering insights into the efficiency and applicability of ML algorithms for sentiment analysis on real-time customer evaluations.

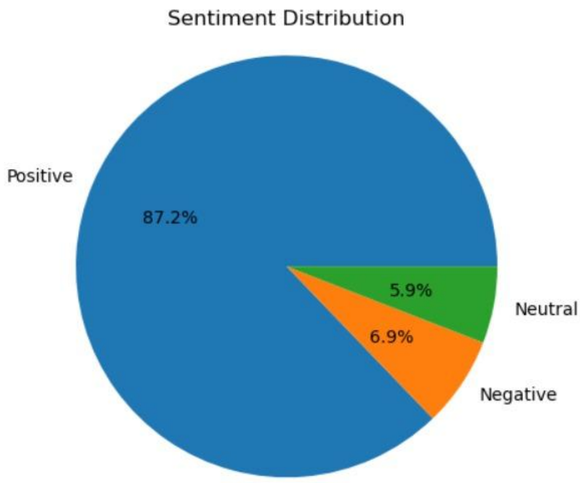

Fig. 8. Sentiment distribution from "Review Text" feature in dataset[31].

IV. Results

The performance metrics of the Random Forest, Naive Bayes, SVM, and Logistic Regression algorithms for sentiment analysis on real-time customer reviews from Amazon's automotive category are shown in the results section.

With an accuracy rate of 92.17%, the SVM method proved to be the most successful at classifying sentiment from textual data. This demonstration demonstrates how well SVM can reliably categorize reviews as neutral, negative, or positive depending on their content.

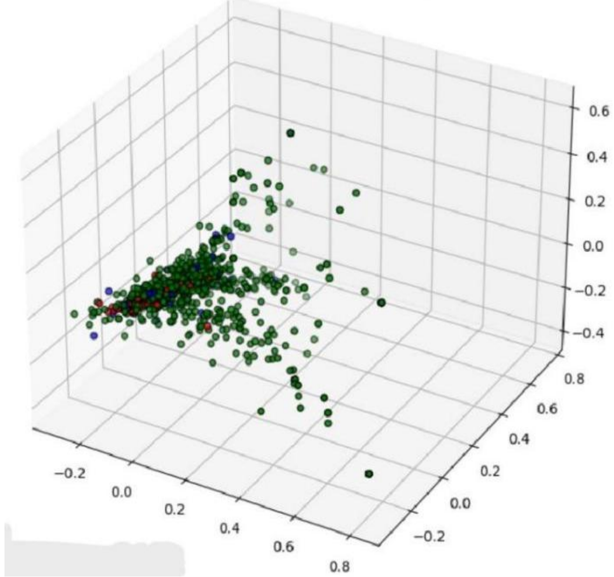

Fig. 9. Distribution of data samples in 3-dimentional space(SVM).

Following closely, the Random Forest algorithm attained an accuracy rate of 90.37%, indicating its robustness in sentiment analysis tasks. The ensemble-based approach of Random Forest enables it to effectively handle complex relationships within the data, resulting in accurate sentiment classification.

Logistic Regression, a linear model widely used in classification tasks, exhibited a commendable accuracy rate of 90.27%. Despite its simplicity, Logistic Regression demonstrated competitive performance in sentiment analysis, demonstrating its usefulness in applications for text categorization.

A probabilistic classifier founded on Bayes' theory, Naive Bayes, similarly attained an accuracy rate of 87.79%. Naive Bayes performed remarkably well in classifying sentiment from customer reviews, even though it is simple and assumes feature independence.

These results underscore the importance of selecting appropriate ML algorithms and highlight the potential of SVM, Logistic Regression, Naive Bayes and Random Forest are used in a variety of fields, including as customer service and e-commerce, for sentiment analysis applications.

TABLE I. Accuracy Score of Algorithms

S.no.	Evaluation Table		
	Machine learning algorithms	***Sample data Accuracy***	***Complete data Accuracy***
1.	SVM	87.40%	92.17%
2.	Random Forest	86.42%	90.37%
3.	Logistic Regression	86.41%	90.27%
4.	Naive Bayes	86.40%	87.79%

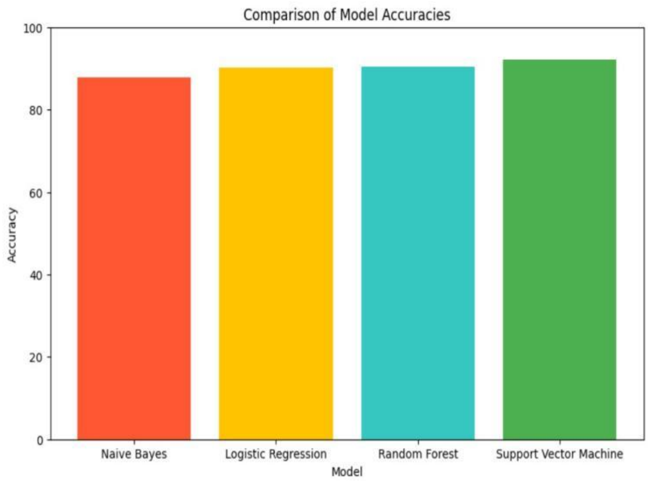

Fig. 10. Actual accuracies obtained by training with complete data.

V. Conclusion

In conclusion, this study shows how machine learning algorithms, such as Naive Bayes, Random Forest, SVM, and Logistic Regression, can effectively classify sentiment from real-time customer reviews on Amazon in the automobile sector.. With high accuracy rates achieved, these algorithms offer practical solutions for automating sentiment analysis tasks, allowing companies to obtain insightful knowledge on the attitudes and preferences of their customers. By leveraging machine learning techniques, this project contributes to the advancement of sentiment analysis research and underscores the potential of automated solutions in enhancing decision-making processes and driving customer-centric strategies across various industries.

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