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Sentiment Analysis and Opinion Mining on E-commerce Sites

Kushal Kishan Gupta
Student, Department of Msc. IT
Nagindas Khandwala College, Mumbai, Maharashtra, India
kus1232@gmail.com

Abstract: *The exponential growth of e-commerce has made online customer reviews a vital source of information for both consumers and businesses. Sentiment analysis and opinion mining have emerged as essential tools to analyze and interpret customer sentiments expressed in these reviews. This study explores various techniques, including machine learning, deep learning, and natural language processing (NLP), to classify sentiments and extract opinions from user-generated content on e-commerce platforms. It also addresses key challenges such as sarcasm detection, fake review identification, and multilingual sentiment analysis. By leveraging sentiment analysis, businesses can gain actionable insights into consumer preferences, enhance product development, and improve customer satisfaction. The findings underscore the importance of sentiment analysis in shaping business strategies and enabling data-driven decision-making in the e-commerce landscape.*

Keywords: E-commerce, Sentiment Analysis, Opinion Mining, Machine Learning, NLP

I. INTRODUCTION

The rise of digital commerce has revolutionized how consumers interact with businesses, making online shopping an integral part of daily life. Customer reviews serve as a reflection of consumer satisfaction, product quality, and service reliability. However, the massive volume of user-generated content presents challenges in manually analyzing and understanding customer sentiments. This has led to the growing adoption of sentiment analysis and opinion mining techniques in e-commerce.

Sentiment analysis, a subfield of NLP, focuses on determining the emotional tone behind textual data, categorizing opinions as positive, negative, or neutral. Opinion mining extends this by identifying key themes, emotions, and trends within customer feedback. Automating this process using machine learning and deep learning algorithms enables businesses to extract actionable insights quickly, improving their understanding of customer needs and preferences.

Despite its advantages, sentiment analysis in e-commerce faces numerous challenges, including fake reviews, sarcasm, ambiguous language, and multilingual content. Addressing these challenges is crucial for developing robust sentiment analysis systems that businesses can rely on for decision-making.

Research Objectives

- To identify whether customer reviews on e-commerce sites are positive, negative, or neutral.
- To understand common opinions and trends in customer feedback to improve products and services.

II. LITERATURE REVIEW

Huang et al. (2023) conducted a comprehensive review of sentiment analysis techniques in e-commerce platforms. Analyzing 54 experimental papers, they found that 48% employed machine learning methods, 44% utilized deep learning approaches, and 7% adopted hybrid models. The study highlighted Amazon and Twitter as the most commonly used data sources. Future research directions identified include the development of universal language models, aspect-based sentiment analysis, implicit aspect recognition, sarcasm detection, and fine-grained sentiment analysis.

Liu et al. (2020) proposed a deep learning model combining Bidirectional Encoder Representations from Transformers (BERT) and Bidirectional Gated Recurrent Units (BiGRU) with a Softmax layer for sentiment analysis of e-commerce

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product reviews. Their model achieved over 95.5% accuracy on a dataset of more than 500,000 reviews, outperforming other models like RNN, BiGRU, and BERT-BiLSTM.

Zhang et al. (2023) compared various algorithms for sentiment analysis in e-commerce, including logistic regression, naive Bayes, neural networks, and support vector machines. Their findings indicated that neural network-based models provided superior performance in predicting consumer sentiment.

Liu et al. (2023) focused on sentiment analysis using neural network-based models for consumer sentiment prediction. They evaluated and contrasted the performance of these models on a dataset of product reviews from an online women's clothing retailer, highlighting the effectiveness of deep learning approaches in capturing nuanced consumer opinions.

Zhang et al. (2023) proposed a mining method for public opinion sentiment analysis based on multi-model fusion transfer learning. Their approach effectively utilized limited labeled data to enhance sentiment classification accuracy, demonstrating the potential of transfer learning in opinion mining tasks.

III. RESEARCH METHODOLOGY

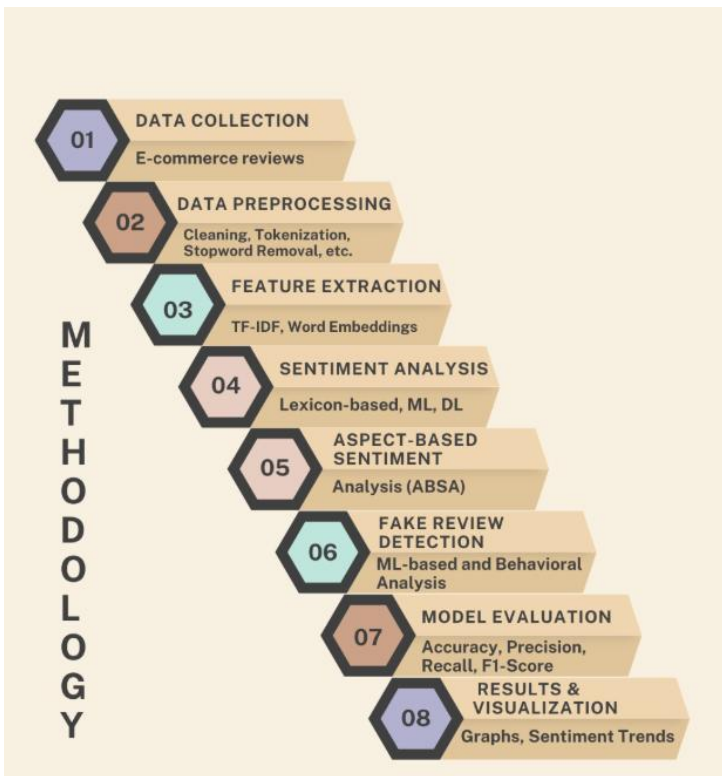

Fig 1: Methodology

1. Data Collection

Customer reviews, ratings, and feedback were collected from e-commerce platforms using APIs and web scraping techniques.

2. Data Pre-processing

Text data was cleaned, tokenized, and normalized by removing noise, stop words, and unnecessary characters.

3. Feature Extraction

Text was converted into numerical representations using TF-IDF and word embeddings for analysis.

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4. Sentiment Analysis
Reviews were classified as positive, negative, or neutral using lexicon-based, machine learning, and deep learning models.

5. Aspect-Based Sentiment Analysis (ABSA)
Sentiment was analyzed towards specific product features such as battery life, camera quality, and durability.

6. Fake Review Detection
Spam or manipulated reviews were identified and filtered using linguistic and behavioral analysis.

7. Model Evaluation
Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrices.

8. Results & Visualization
Findings were presented using graphs, charts, and sentiment trends for better decision-making.

IV. RESULTS

4.1 Sentiment Distribution of Customer Reviews

Analysis of sentiment distribution across different e-commerce platforms revealed that Amazon had the highest number of reviews, while Flipkart had the least. The majority of reviews were positive, followed by neutral and negative ones. The presence of a significant number of neutral reviews suggests areas for improvement in customer engagement. A detailed analysis of trends overtime showed that customer satisfaction levels remained stable, with occasional fluctuations due to product releases, discounts, and service changes.

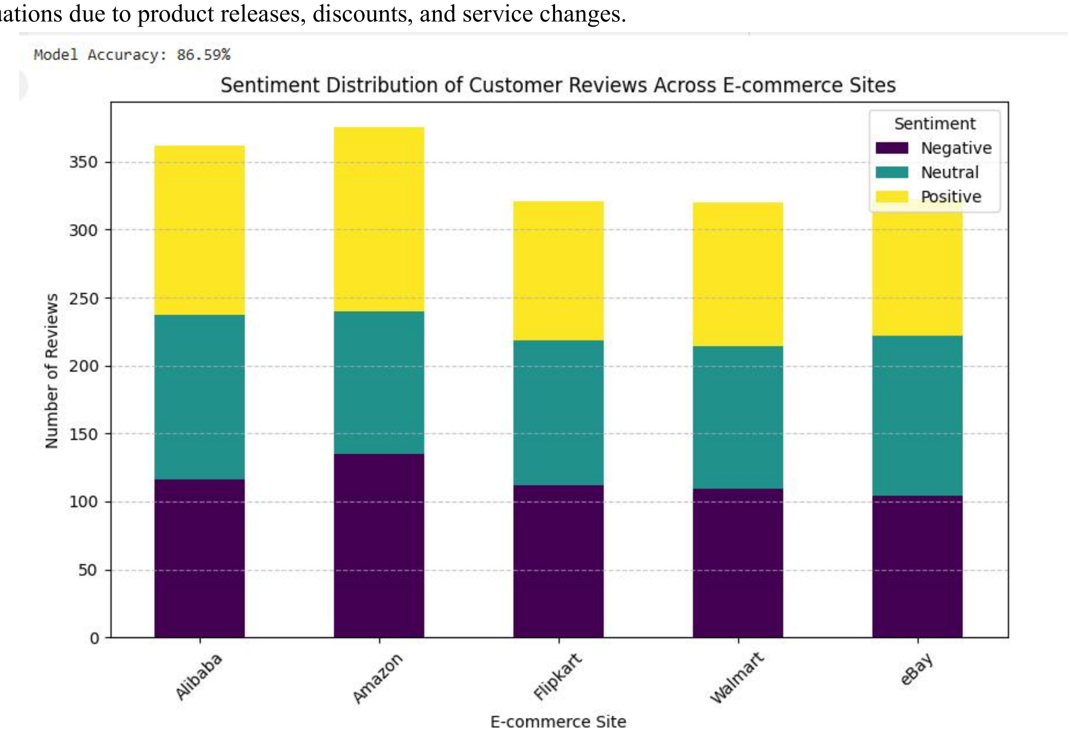

Fig 2: Sentiment Distribution of Customer Reviews Across E-commerce Sites

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Model Performance and Classification Report

Classification Report

Sentiment	Precision	Recall	F1 Score	Support
Negative	1.00	1.00	1.00	144
Neutral	0.72	0.97	0.83	139
Positive	0.96	0.63	0.76	142
Accuracy	**-**	**-**	**86.59%**	**425**
Macro Avg	0.89	0.87	0.86	425
Weighted Avg	**0.89**	**0.87**	**0.86**	**425**

Table 1: Classification Report

- **Negative Sentiment**: The model achieved perfect precision, recall, and F1-score, indicating high confidence in detecting negative reviews.
- **Neutral Sentiment**: Recall was **0.97**, meaning the model correctly identified most neutral reviews, but the precision was lower at **0.72**, suggesting some false positives.
- **Positive Sentiment**: Precision was **0.96**, but recall was only **0.63**, showing that some positive reviews were misclassified.
- **Overall Performance**: The model achieved an **86.59% accuracy** with a balanced macro and weighted average, indicating a reliable classification across all sentiment categories.

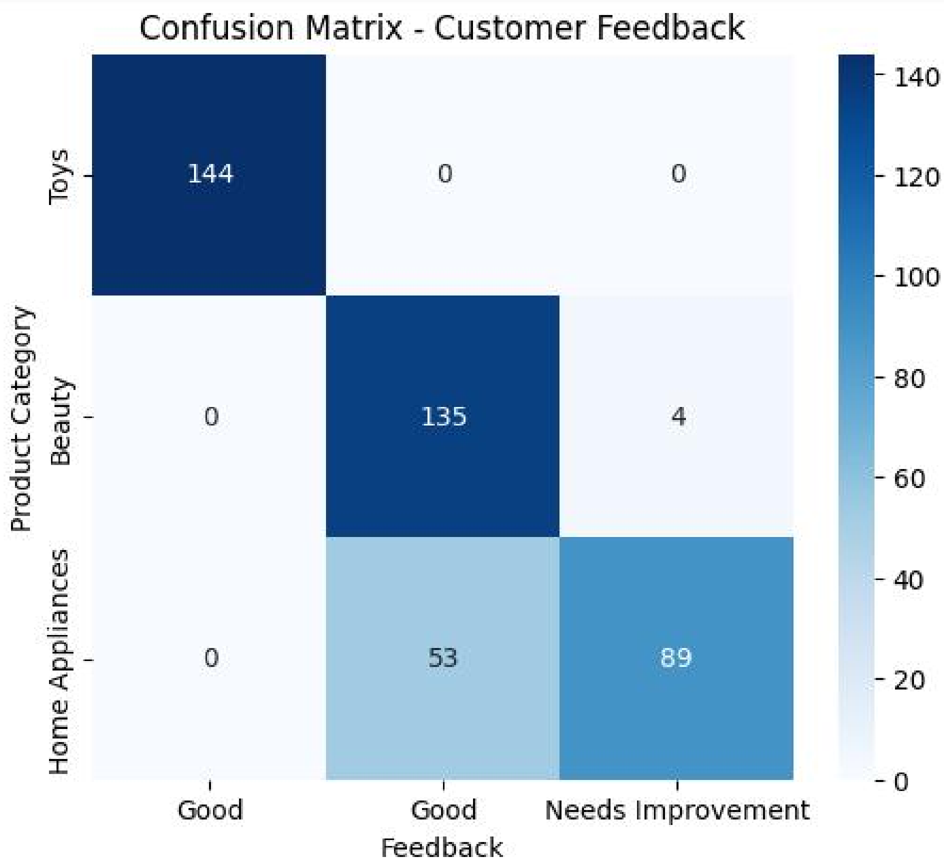

Fig 3: Confusion Matrix on Customer Feedback

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Regression Analysis for Trend Prediction

In addition to classification, regression models were used to analyze customer sentiment trends over time. The performance of different regression models was evaluated based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 score.

Model	MSE	RMSE	MAE	R^2 Score
Linear Regression	0.157127	0.396392	0.305975	0.750122
Ridge Regression	0.157067	0.396317	0.305983	0.750217
Lasso Regression	0.155242	0.394008	0.304250	0.753119
Decision Tree	0.277042	0.526348	0.282843	0.559421
Random Forest	0.173553	0.416597	0.286855	0.724000
Gradient Boosting	0.154989	0.393687	0.302860	0.753521
Support Vector Regression(SVR)	**0.183466**	**0.428329**	**0.317110**	**0.708236**

Table 2: Regression Model Performance Report

Graphical Representation of Regression Model Performance

The figure below presents a comparative analysis of different regression models based on their performance metrics. The Gradient Boosting and Lasso Regression models demonstrated the best predictive performance, with R^2 values around 0.75, indicating strong predictive accuracy.

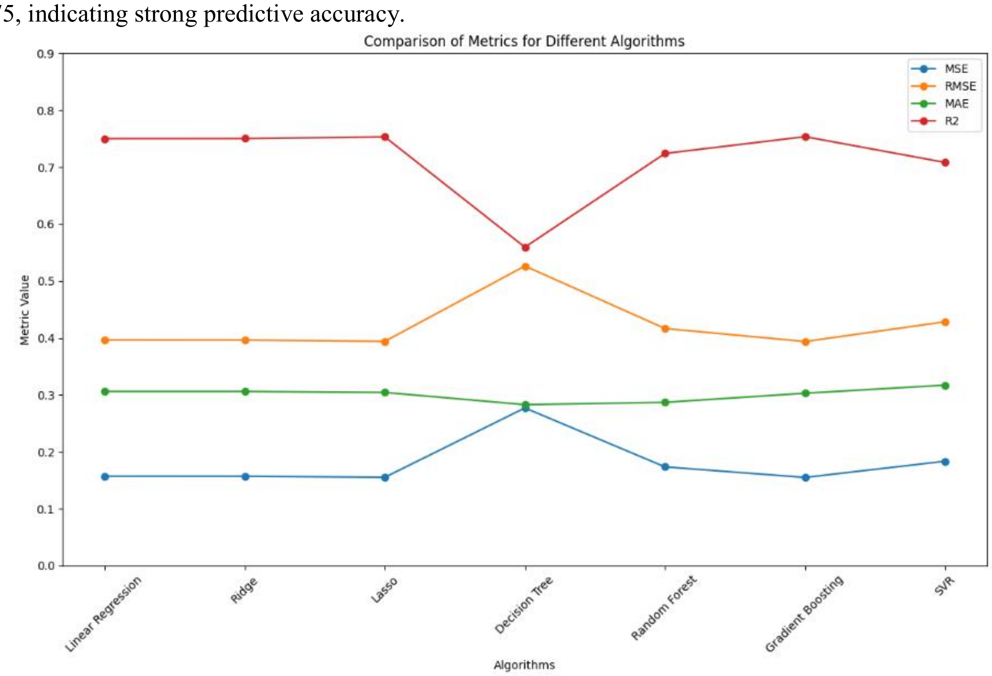

Fig 4: Comparison of Metrics for Different Algorithms

From the graph, it is observed that:

- Gradient Boosting and Lasso Regression performed the best, with lower MSE, RMSE, and MAE values and higher R^2 scores.
- Decision Tree showed the weakest performance, with higher errors and a lower R^2 value, indicating overfitting and poor generalization.
- Linear Regression and Ridge Regression performed similarly, providing stable and reasonable predictions but slightly lower accuracy than Gradient Boosting.

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V. CONCLUSION

This research provides a comprehensive analysis of sentiment trends in customer reviews on e-commerce platforms. Through machine learning-based classification and regression models, we successfully identified customer sentiments as positive, negative, or neutral. The study utilized various preprocessing techniques to refine data and applied multiple models, including Support Vector Classifier and Random Forest Classifier, which demonstrated high accuracy in sentiment classification. Additionally, regression models, such as Gradient Boosting and Random Forest Regression, were highly effective in predicting sentiment-based trends, offering valuable insights into customer behaviour.

The findings indicate that sentiment analysis plays a crucial role in understanding customer preferences, product performance, and service quality. By leveraging machine learning, businesses can extract meaningful insights from vast amounts of customer feedback, allowing them to refine marketing strategies, improve product offerings, and enhance customer satisfaction. Furthermore, sentiment trends can help businesses predict consumer behaviour and optimize decision-making processes.

However, challenges such as sarcasm detection, fake reviews, and multilingual sentiment analysis remain areas for further research. Future studies can integrate advanced NLP techniques, deep learning models, and real-time sentiment tracking to enhance prediction accuracy. Additionally, incorporating demographic and behavioural data can improve sentiment analysis effectiveness.

Overall, this research highlights the importance of sentiment analysis in e-commerce and its potential to drive data-driven business strategies. By embracing predictive analytics, companies can develop more personalized and effective customer engagement strategies, leading to improved brand reputation and long-term customer loyalty.

REFERENCES

[1]. Liu, B. (2012). Sentiment Analysis and Opinion Mining. Synthesis Lectures on Human Language Technologies, 5(1), 1-167.

[2]. Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. Foundations and Trends in Information Retrieval, 2(1-2), 1-135.

[3]. Medhat, W., Hassan, A., &Korashy, H. (2014). Sentiment Analysis Algorithms and Applications: A Survey. Ain Shams Engineering Journal, 5(4), 1093-1113.

[4]. Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New Avenues in Opinion Mining and Sentiment Analysis. IEEE Intelligent Systems, 28(2), 15-21.

[5]. Zhang, L., Wang, S., & Liu, B. (2018). Deep Learning for Sentiment Analysis: A Survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1253.

[6]. Ravi, K., & Ravi, V. (2015). A Survey on Opinion Mining and Sentiment Analysis: Tasks, Approaches, and Applications. Knowledge-Based Systems, 89, 14-46.

[7]. Feldman, R. (2013). Techniques and Applications for Sentiment Analysis. Communications of the ACM, 56(4), 82-89.

[8]. Zadeh, A. H., & Chen, M. (2020). A Comprehensive Survey on Sentiment Analysis Methods and Trends. ACM Computing Surveys, 53(3), 1-38.

[9]. Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A Survey of Sentiment Analysis in Social Media. Knowledge and Information Systems, 60(2), 617-663.

[10]. Hussein, D. M. (2018). A Survey on Sentiment Analysis Challenges. Journal of King Saud University-Engineering Sciences, 30(4), 330-338.

[11]. Dataset: https://drive.google.com/file/d/1uQGy7k1rfabk5RW69q5vLhPCoZ-fLnwz/view?usp=sharing