International Journal of Sustainable Development Through AI, ML and IoT
Volume 4 | Issue 1 | 2025
ISSN(Online):2584-0827
https://ijsdai.com/index.php/IJSDAI/index

Review Lens: AI-Powered Sentiment Analysis for Brand Comparison

Aditi Bansal[1], Prabhjot Singh[2], Pranay[3], Pooja Thakar[4], Neetu Goel[5]
[1,2,3,4,5]Vivekananda Institute of Professional Studies – Technical Campus, Delhi-110034, India
bansaladiti683@gmail.com, ps844601@gmail.com, prasadpranay2005@gmail.com, pooja.thakar@vips.edu, neetu.goel@vips.edu
Corresponding author: bansaladiti683@gmail.com

ARTICLE INFO
Received: 01st June 2025
Revised: 17th June 2025
Accepted: 20th July 2025

ABSTRACT

Abstract : Review Lens is a sentiment analysis-based system that helps consumers make informed purchasing decisions. By analyzing customer reviews for up to three brands of a given product, it determines the best brand based on positive sentiment distribution. The system utilizes web scraping, NLP (VADER), and data visualization to provide insights through pie charts. This tool is valuable for e-commerce, businesses, and consumers, offering a data-driven approach to brand comparison. This system empowers users to make informed decisions by leveraging sentiment insights, offering a reliable, automated, and user-friendly tool for brand comparison and recommendation

Keywords: Sentiment Analysis, Brand Comparison, NLP, VADER, Web Scraping, Consumer Decision-Making

1.Introduction

The rise of e-commerce and digital marketing has transformed the way consumers make purchasing decisions. Today, before buying a product, customers extensively rely on online reviews available on platforms such as Amazon, Flipkart, Google Reviews, and social media. However, with an overwhelming volume of user-generated content, it becomes increasingly difficult to manually analyze reviews and extract meaningful insights. To address this challenge, we propose an AI-powered sentiment analysis system that automates the process of brand comparison by evaluating customer reviews.

This system enables users to input a product category and select up to three competing brands of their choice for comparison. Using web scraping techniques, the system retrieves real-world customer reviews and applies Natural Language Processing (NLP) techniques to analyze sentiment. The sentiment is classified into three categories: Positive, Negative, and Neutral, based on the VADER (Valence Aware Dictionary and sEntiment Reasoner) model. The results are visualized using pie charts, showcasing the sentiment distribution across brands, and the brand with the highest positive sentiment is recommended as the preferred choice to the consumer. This helps the customer for better decision making and saves their time for chosing right brand as per their requirements.

2. Literature Review

Generally, Sentiment Analysis is applied to find the sentiments of public for a public event / incident such as upcoming elections. Few studies have been done to understand consumer behaviour such as "Sentiment Analysis and Topic Modeling Study: The Comparison of Cosmetics Product Online Reviews" by Meizhen Hannah Zahirah and Tri Widarmanti [1] focused on comparing customer perceptions of three local cosmetics brands in Indonesia by analyzing online reviews. Utilizing sentiment analysis and topic modeling, the researchers extracted and examined customer feedback to determine sentiment distributions across the brands. The findings revealed that the ESQA brand received the highest positive sentiment, followed by Luxcrime, with Make Over ranking last. Positive feedback commonly highlighted long-lasting formulas with good coverage, while negative comments pointed to issues like the need for reapplication and transferability when wearing masks. This research underscores the effectiveness of sentiment analysis and topic modeling in brand comparison within the cosmetics industry.

Another Study by Huwail J. Alantari on "An Empirical Comparison of Machine Learning Methods for Text-Based Sentiment Analysis of Online Consumer Reviews" [2] evaluates various machine learning approaches for automated text-based sentiment analysis of online consumer reviews. Analyzing data from 25,241 products across nine categories and 260,489 reviews from five platforms, the study found that neural network-based methods, particularly pre-trained models, offered the most accurate predictions. Conversely, topic models like Latent Dirichlet Allocation (LDA) provided deeper diagnostic insights but were less effective for predictive purposes. The research highlights the trade-offs between predictive accuracy and diagnostic depth in selecting appropriate sentiment analysis methods for brand comparison.

Rajkumar S. Jagdale, Vishal S. Shirsat and Sachin N. Deshmukh in their study on Sentiment Analysis of Product Reviews Using Machine Learning Techniques explores various machine learning techniques [3] , including Naïve Bayes and Support Vector Machines, to classify sentiment in product reviews collected from e-commerce platforms. The research emphasizes the importance of data preprocessing and vectorization methods such as TF-IDF in improving model accuracy. The paper concludes that with proper feature selection and training data, machine learning methods can effectively classify sentiment in large-scale review datasets.

Anant Bhardwaj, Pradyumn Pratap Singh, Astha Bharti, Apurva Singh Parihar, and Sandeep Kaur explores in their paper on "Social Media Sentiment Analysis for Brand Monitoring" [4] projects the application of sentiment analysis for brand monitoring by analyzing user-generated content on social media platforms. Employing machine learning algorithms and text mining techniques, the study categorizes emotions in social media posts to provide brands with real-time insights into consumer perceptions. The research discusses successful case studies and addresses challenges related to accuracy, bias, and data privacy, offering suggestions for optimizing sentiment analysis in brand monitoring and decision-making.

Another Study by Jian Jin, Ping Ji, and Ruoxi Gu Named “Identifying Comparative Customer Requirements from Product Online Reviews for Competitor Analysis “ [5] proposes a method to identify comparative customer requirements from online product

reviews to facilitate competitor analysis. By extracting and analyzing comparative opinions, the research provides insights into customer preferences and perceptions of competing products. The methodology aids in understanding the strengths and weaknesses of products from a consumer perspective, contributing to strategic decision-making in brand competition.
All above studies have done analysis very specific on a topic. An open-ended Review process is not available for customers to review their brands on fly. This paper develops the strategy to implement open ended sentiment analysis on end user's choice.

3. Methodology

The Review Lens system follows a structured approach to analyze and compare product reviews using sentiment analysis. The first step involves data collection, where the system gathers user-input data through two main methods. Users can either upload a CSV file containing product reviews from various sources or opt for web scraping via SerpAPI, which fetches online reviews based on the given product and brand name. By integrating these two approaches, the system ensures flexibility, allowing users to analyze both existing datasets and real-time reviews from the web.
Once the data is collected, it undergoes a preprocessing stage to enhance the quality and accuracy of sentiment analysis. The text is cleaned using regular expressions to remove unnecessary elements such as URLs, special characters, and hashtags. Further, the textual data is tokenized and normalized, ensuring uniformity in the dataset. If any missing values are detected, they are appropriately handled by filling in placeholders, preventing any disruption in the analysis. These preprocessing steps refine the data, making it suitable for sentiment classification.
The system utilizes Natural Language Processing (NLP) techniques, specifically VADER (Valence Aware Dictionary and sEntiment Reasoner) from the NLTK library, to perform sentiment analysis on the collected reviews. Each review is assigned a compound sentiment score, which determines whether it is positive, negative, or neutral. A review is classified as positive if the compound score is greater than or equal to 0.05, negative if it is less than or equal to -0.05, and neutral if it falls between -0.05 and 0.05. After classification, the processed dataset is stored in an updated CSV file, ensuring that the results can be used for further evaluation.
The system then moves to the brand comparison phase, where it analyzes sentiment across up to three brands related to the specified product. By scraping and processing reviews for each brand separately, the system determines which brand has the highest proportion of positive sentiment and recommends it as the best choice for the user. To enhance interpretability, the system visualizes the sentiment distribution using interactive pie charts, displaying the percentage of positive, negative, and neutral reviews for each brand. Additionally, another comparison chart is generated to highlight the brand with the most positive reviews, helping users make informed decisions based on real customer opinions.
To provide a seamless user experience, the Flask framework is used for the backend, handling user requests, web scraping, and API calls. The user interface is designed using HTML, CSS, and JavaScript, allowing users to input their queries and view results interactively. The Plotly library is integrated to generate dynamic and visually appealing graphs and charts, ensuring that users can easily interpret the sentiment analysis results. This combination of data science, web technologies, and visualization tools makes Review Lens an effective and accessible platform for brand comparison based on real-world customer sentiment as showcased in flowchart Figure 1. The related code snippet is showcased in

Figure 2.

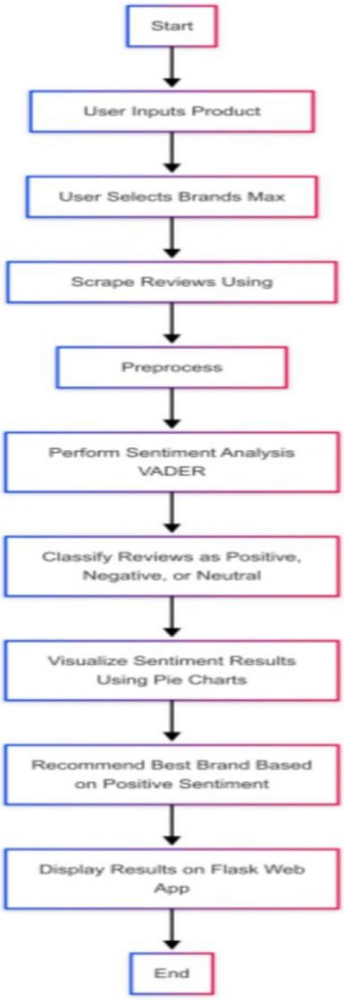

Figure 1: Flowchart of the Review Lens

4. Findings and Discussion

The Review Lens system was tested with multiple product categories and brands, analyzing real-world customer reviews to determine the best brand based on sentiment analysis. The key findings include:

1. Accurate Sentiment Classification:
   - The VADER Sentiment Analyzer effectively categorized reviews into Positive, Neutral, and Negative sentiments.
   - The sentiment distribution was visually represented using pie charts, making it easy to interpret.
2. Brand Comparison:
   - The system compared multiple brands based on customer feedback.
   - The brand with the highest percentage of positive reviews was identified as the best choice for consumers.

3. Efficiency in Data Extraction:
   - Using the SerpAPI for web scraping allowed automated extraction of up-to-date reviews.
   - The system successfully retrieved and analyzed 200+ reviews per brand within seconds.

4. Graphical Insights:
   - The generated pie charts provided an intuitive understanding of sentiment distribution across brands.
   - Users could visually compare how each brand performed in terms of customer satisfaction.

5. User-Friendly Implementation:
   - The Flask web interface allowed users to input product names and select brands easily.
   - CSV export functionality enabled further analysis and data storage.

The Result Snippets in Figure 2 showcases the results generated by Review Lens.

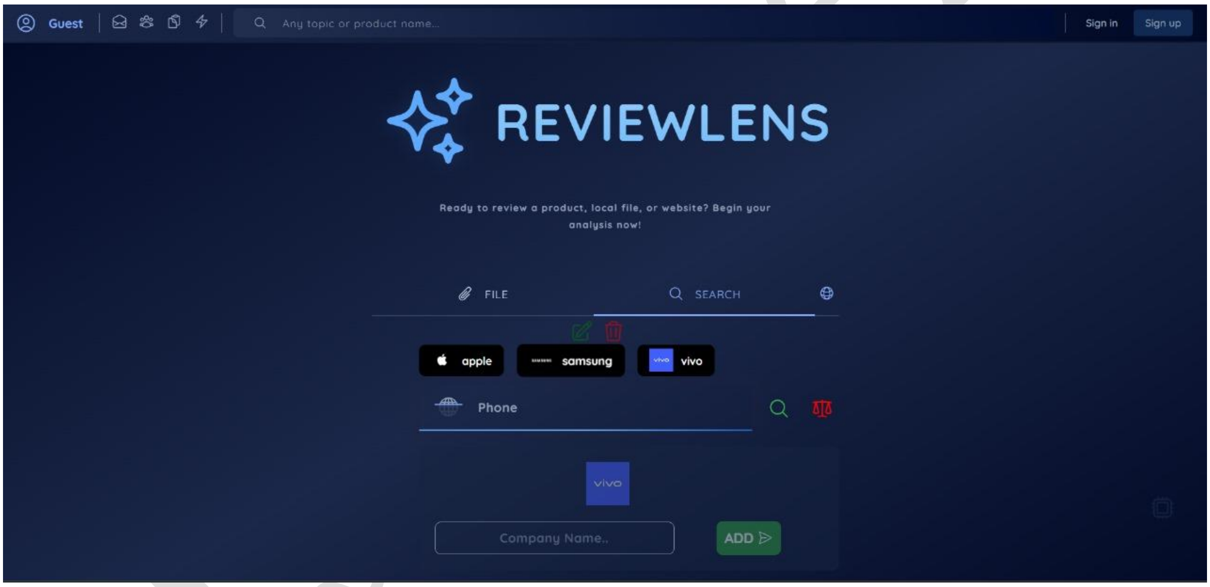

Figure 2: Result Snippets

6. Conclusion and Future Scope

The Review Lens system successfully implements sentiment analysis to assist consumers in making informed purchasing decisions. By analyzing customer reviews from various sources, it identifies the best brand for a given product based on positive sentiment distribution.

Key takeaways from this research include:

- Automated Review Analysis: The system efficiently scrapes and processes large volumes of customer feedback.
- Brand Comparison: Users can compare up to three brands, with the best-performing brand highlighted based on sentiment scores.
- Visual Insights: The sentiment distribution is presented through pie charts, making it easy to interpret brand performance.
- Real-World Application: The project can benefit e-commerce platforms, businesses, and consumers by simplifying decision-making.

Future enhancements could include multilingual support, advanced NLP models (e.g., BERT, GPT-based sentiment analysis), and integration with real-time data sources to further improve accuracy and usability.

The success of Review Lens demonstrates the potential of sentiment analysis in consumer behavior studies and e-commerce analytics, making it a valuable tool in the modern digital shopping landscape.

References

[1] Meizhen Hannah Zahirah, & Tri Widarmanti. (2022). Sentiment Analysis and Topic Modeling Study: The Comparison of Cosmetics Product Online Reviews. International Journal of Sciences: Basic and Applied Research (IJSBAR), 64(1), 50–65. Retrieved from https://www.gssrr.org/index.php/JournalOfBasicAndApplied/article/view/14579

[2] Huwail J. Alantari, Imran S. Currim, Yiting Deng, Sameer Singh, An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews, International Journal of Research in Marketing, Volume 39, Issue 1, 2022, Pages 1-19, ISSN 0167-8116, https://doi.org/10.1016/j.ijresmar.2021.10.011.

[3] Jagdale, R. S., Shirsat, V. S., & Deshmukh, S. N. (2019). Sentiment analysis on product reviews using machine learning techniques. In Cognitive Informatics and Soft Computing: Proceeding of CISC 2017 (pp. 639-647). Springer Singapore.

[4] Anant Bhardwaj, Pradyumn Pratap Singh, Astha Bharti, Apurva Singh Parihar, Sandeep Kaur, 2024, Social Media Sentiment Analysis for Brand Monitoring, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 13, Issue 10 (October 2024),

[5] Jian Jin, Ping Ji, Rui Gu, Identifying comparative customer requirements from product online reviews for competitor analysis, Engineering Applications of Artificial Intelligence, Volume 49, 2016, Pages 61-73, ISSN 0952-1976, https://doi.org/10.1016/j.engappai.2015.12.005.