Sentiment Analysis-Driven Recommendations for Optimal Products and Brands Based on User Feedback

P. Pirapuraj and M.A.C.M. Niflan

Abstract In recent years, sentiment analysis has emerged as a powerful tool for identifying popular products. This study explores the application of sentiment analysis to determine the most favored product models or brands based on customer feedback. The research involves collecting consumer reviews from diverse sources and analyzing the sentiments expressed in these comments. Using SentiWordNet, a lexical resource that assigns sentiment scores to words through semantic relationships, the study evaluates the overall sentiment of the reviews. The results demonstrate that sentiment analysis is an effective method for identifying customer preferences, enabling the recognition of highly regarded product models or brands. The findings have significant implications for product development and marketing strategies, as they can guide efforts to enhance customer satisfaction and drive sales. However, the study also highlights the critical role of data quality and quantity in achieving accurate sentiment analysis. Inadequate or insufficient data can negatively impact the reliability of results. Additionally, the research underscores the importance of considering the context in which feedback is provided and the necessity of thorough data preprocessing before analysis. Proper preparation ensures that sentiment analysis accurately reflects consumer opinions. This study offers valuable insights for businesses aiming to leverage sentiment analysis to understand market trends, improve product offerings, and optimize promotional strategies. By integrating sentiment analysis into decision-making processes, companies can better align their products with consumer expectations, fostering stronger customer engagement and competitive advantage.

***Index Terms*— — Sentiment Analysis, Customer Feedback, Product Recommendations, SentiWordNet, Marketing Strategies**

I. Introduction

OVER the past two decades, the rise of online shopping has significantly transformed consumer purchasing habits. Online product reviews, reflecting the experiences of actual users, have become a crucial resource for decision-making, allowing consumers to rely less on advice from friends or relatives. These reviews help build trust, attract potential buyers, and increase website traffic and engagement. Customers can access evaluations and comments on products and services, enabling them to rank offerings based on personal experiences.

However, existing systems face significant challenges in processing the vast amount of customer feedback, particularly when it involves unstructured formats like text, emojis, and mixed sentiments. For example, conventional sentiment analysis tools often struggle to handle feedback that expresses contradictory sentiments within a single review (e.g., "I used to love this product, but the recent changes have taken away the quality I loved"). Additionally, many tools are limited to processing feedback in a single language, restricting their applicability in multilingual markets[1]. While online shopping offers convenience and cost savings, it remains less advantageous for consumers seeking experiential items due to the difficulty of gathering sufficient information. In contrast, search products are more commonly purchased online, as they are easier to evaluate before purchase.

The internet has created a global platform where individual opinions can influence countless others, spreading beyond personal circles to a vast audience. Through forums, blogs, and social media platforms, consumers share their thoughts, provide reviews, and discuss various products, brands, and services. These evaluations not only guide purchasing decisions but also contribute to improving product quality. Text-based reviews, along with emojis and star ratings, allow consumers to express feedback in diverse formats, ranging from single words to detailed narratives. While the feedback format is unstandardized, reviews can offer positive, negative, or neutral sentiments [2]. Figure 1 shows some types of feedback. Such customer insights transform experiential goods into searchable items by highlighting essential features, enabling informed purchasing decisions across diverse sources [3].

Sentiment analysis, also known as opinion mining, involves extracting and classifying subjective information from textual data, such as reviews, tweets, or articles. It leverages natural language processing, machine learning, and computational linguistics to determine whether the sentiment expressed is positive, negative, or neutral. With applications spanning social media monitoring,

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market research, and customer feedback analysis, sentiment analysis has become a critical tool for understanding consumer preferences.

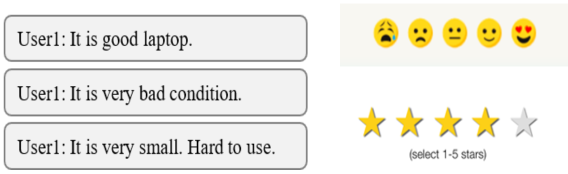

Fig. 1: The different types of feedbacks

Despite advancements in sentiment analysis techniques, significant gaps remain in prior studies. Many existing methods rely heavily on prebuilt sentiment lexicons like SentiWordNet, which natively supports only English, limiting their effectiveness for multilingual feedback. As online shopping continues to grow, customer reviews have become increasingly essential for both businesses and consumers [4]. However, the unstructured nature and sheer volume of reviews present significant challenges for manual analysis. Automated sentiment analysis provides a solution by processing these reviews to extract actionable insights, enabling businesses to better understand customer sentiments and improve their offerings [5].

Recent advancements in sentiment analysis have empowered marketers to derive more nuanced insights from unstructured online reviews. Beyond simply determining whether a product feature is liked or disliked, sentiment analysis now examines specific aspects of customer experiences [6][7]. Techniques such as document-level, sentence-level, and aspect-level analysis enable deeper exploration of customer feedback. Lexicon creation, a foundational step in sentiment analysis, involves categorizing words based on sentiment through scored reviews or general-purpose sentiment dictionaries. This approach enhances accuracy in identifying product-specific sentiments. By combining feedback from diverse sources like social media, e-commerce platforms, and blogs, sentiment analysis helps businesses tailor their strategies, improve customer satisfaction, and empower consumers to make informed decisions. Despite challenges like conflicting opinions and complex review formats, sentiment analysis continues to evolve as a vital tool in modern decision-making [8][9][10].

II. Literature Review

A. Feedbacks or Reviews

Over the past two decades, online shopping has revolutionized consumer purchasing behavior, with an increasing reliance on online product reviews to make informed decisions. Unlike in the past, where advice from friends and family played a pivotal role, today's consumers leverage the perspectives of actual users shared across web forums, blogs, and social media platforms [11][12]. These reviews not only enhance user trust but also attract visitors and boost website engagement, making them a critical resource for businesses and customers alike. Customer feedback, presented in various forms such as text, star ratings, or emojis, significantly shapes product reputation. Sentiment analysis plays a vital role by systematically analyzing this feedback, enabling consumers to evaluate products or brands effectively [13].

Several studies have advanced our understanding of customer feedback and its applications. For instance, Mukku [14] proposed a semi-supervised method to categorize customer input into actionable insights like defect reports and improvement suggestions. This approach demonstrated comparable accuracy to fully supervised models without requiring manual annotation, thereby aiding businesses in enhancing customer satisfaction. Similarly, Costas Assimakopoulos et al. [15] developed a framework for identifying critical customer relationship management (CRM) components in the hospitality sector, emphasizing the role of CRM systems in supporting reputation management and incorporating guest feedback. Lasse X. Jensen and colleagues explored how researchers perceive feedback's role in teaching and learning, advocating for intentional conceptualization to advance the study of online feedback practices. Bahri et al. [16] examined customer feedback in retail, highlighting its dual role in addressing issues and driving product and service improvements for market-oriented businesses.

B. Sentiment Analysis

Sentiment analysis is a machine learning technique used to determine the positive or negative sentiment expressed in text. It is particularly useful for analyzing customer experiences shared through comments on social media platforms. This analysis helps businesses better understand customer perceptions of their shopping experiences, providing valuable insights for improvement. As a subdomain of artificial intelligence, sentiment analysis enables computer systems to interpret human language, processing text from various sources such as social media, surveys, and e-commerce reviews [17]. By extracting meaningful insights from unstructured textual data across diverse online platforms, sentiment analysis empowers businesses to gauge customer opinions effectively.

Harsheta Pandita and Dr. Naveen Kumar Gondhi [18] presented a comprehensive approach to sentiment analysis, discussing its procedures, essential tasks, and techniques. Their work also explored various challenges associated with sentiment classification processes. Similarly, Kumar and Bhatia (2016) addressed the challenge of feature extraction in document classification, particularly given the unstructured nature of text data. They utilized SentiWordNet[19][20], an ontology that assigns numeric scores to indicate the positive or negative sentiment of words, to extract sentiment features from 185 song lyrics. Their study assessed the effectiveness of sentiment features in categorizing lyrics into four groups using three classification algorithms and six measures for attribute relevance analysis. These approaches illustrate the ongoing advancements in leveraging sentiment analysis to extract actionable insights from textual data.

III.Design and Methodology

The shift towards online shopping has significantly influenced consumer purchasing behavior, with online reviews becoming a key factor in decision-making. However, extracting enough useful

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information about products, particularly experience-based products, remains a challenge for many consumers. As a result, shoppers often favor search products over experience products. To address this issue, we propose a framework that automatically collects product reviews from e-commerce websites and classifies them as positive, negative, or neutral. This allows consumers to easily compare products based on real-time feedback, facilitating informed purchasing decisions.

This section outlines the methodology for gathering and analyzing real-time customer reviews from e-commerce platforms. The process begins with web scraping, a technique used to extract data from web pages. By leveraging web scraping, we are able to collect product reviews in real-time, which can then be analyzed for sentiment. This approach allows businesses to gain insights into customer opinions and preferences, ultimately informing product development and marketing strategies. Fig. 2 explains the overview of the proposed approach.

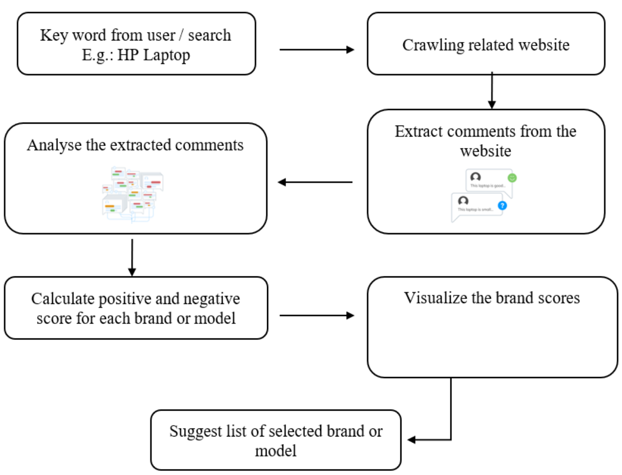

Fig. 2: Overview of proposed approach

A. Data Collection

The first step is to collect customer reviews from e-commerce websites. To achieve this, we employ a web crawling and scraping process. Web crawlers explore the internet to gather general information about websites, while web scrapers extract specific data from web pages. For this research, we focus on scraping customer reviews related to specific products. By automating this process, we can efficiently gather a large volume of data that is crucial for the next stages of analysis.

For our study, we used the Scrapy Python library, a popular tool for web scraping, to collect customer feedback on a variety of technological products, such as laptops and cameras, from e-commerce platforms. Once the reviews were collected, they were saved in text files for subsequent processing.

B. Preprocessing

The next step in our methodology is the pre-processing of the scraped data. Natural Language Processing (NLP) techniques are employed to clean and prepare the text for sentiment analysis. We utilize the Natural Language Toolkit (NLTK) for this purpose, which provides a wide array of text processing tools such as tokenization, stemming, and part-of-speech tagging.

The data preprocessing steps include:

- Tokenization: Splitting the text into individual words or sentences to create manageable units for analysis.
- Stop Word Removal: Filtering out common words (e.g., "is," "the," "and") that do not contribute to the sentiment analysis.
- Stemming: Reducing words to their root form to focus on their core meaning. For instance, "helpful" and "helper" are reduced to the root "help."
- POS Tagging: Assigning grammatical labels (e.g., noun, verb) to words to help in extracting meaningful patterns.
- Negation Phrase Identification: Detecting negations such as "not good" or "nothing impressive" to adjust sentiment scores accordingly.

By applying these NLP techniques, we convert the unstructured textual data into structured forms that can be effectively analyzed.

C. Algorithm for Negation Phrase Identification

To enhance the accuracy of sentiment classification, our methodology includes an algorithm to identify negation phrases in customer feedback. Negation phrases can significantly alter the sentiment conveyed in a review, such as turning a positive sentiment into a negative one. The algorithm, designed to identify these negation patterns, first tags the parts of speech in the text. It then searches for negative prefixes (e.g., "not," "never") and identifies the adjectives or verbs that these prefixes modify.

The algorithm is capable of detecting two types of negation phrases: Negation-of-Adjective (NOA) and Negation-of-Verb (NOV). These negation phrases are critical for ensuring that the sentiment analysis correctly interprets feedback that may initially appear positive or neutral but is altered by negation. The algorithm helps in refining sentiment analysis by ensuring that negated sentiments are accurately captured, especially in cases where phrases like "not good" or "never recommended" are used, which would otherwise skew the sentiment results.

The following pseudocode outlines the procedure used to identify negation phrases in the text:

Algorithm: Negation Phrase Identification

Input: Tagged Sentences, Negative Prefixes
Output: NOA Phrases, NOV Phrases

```
for each Tagged Sentence in the text:
   for each word/tag pair (i, i+1):
      if i+1 is a Negative Prefix:
         if there is an adjective tag or verb tag in the pair:
            add (i, i+2) to NOV Phrases
         else if there is an adjective tag or verb tag:
               add (i, i+2, i+4) to NOV Phrases
return NOA Phrases, NOV Phrases
```


ISSN: 2961-5992

D. Sentiment Analysis

Once the data is pre-processed, we proceed with sentiment classification to determine whether a review is positive, negative, or neutral. To accomplish this, we use SentiWordNet, a lexical resource that assigns sentiment scores to words based on their part of speech and semantic orientation. Each word in a review is given three sentiment scores: positivity, negativity, and objectivity. The overall sentiment of the review is determined by aggregating these individual word scores.

For instance, the sentence "I love this product" would receive a high positive score for the word "love" and a neutral score for "product," resulting in an overall positive sentiment classification. On the other hand, a sentence like "The product is not as good as expected" would likely be classified as negative due to the presence of negative sentiment words and negation.

Handling Mixed Sentiments in Feedback Analysis: The algorithm leverages advanced sentiment analysis techniques, including context-aware processing, to handle mixed sentiments in feedback. For example, the feedback *"I used to love this product, the recent changes have taken away the quality I loved"* contains both positive sentiment ("used to love") and negative sentiment ("recent changes have taken away the quality").

In such cases, our algorithm performs:

- *Token-Level Sentiment Scoring*: Words and phrases such as "love" are assigned positive scores, while negative phrases like "taken away the quality" are assigned negative scores.
- *Compute the score*: The algorithm evaluates the overall tone by considering both positive and negative and by considering contextual phrases like "used to" and "recent changes."
- *Final Classification*: The feedback is classified based on the aggregated sentiment score. In this example, the negative sentiment outweighs the positive, and the feedback would be categorized as negative.

This approach ensures nuanced feedback is accurately interpreted, reflecting customer dissatisfaction despite the presence of positive words.

To calculate the positive and negative percentages, the number of positive and negative feedback comments can be counted, and the total number of feedback comments can be determined. The positive percentage is calculated as the number of positive feedback comments divided by the total number of feedback comments, multiplied by 100. Similarly, the negative percentage is calculated as the number of negative feedback comments divided by the total number of feedback comments, multiplied by 100. The equation (1) indicates the positive percentage calculation.

$$Positive\ Percentage = \frac{\sum(Positive\ Feedbacks\ for\ brand)}{\sum(Positive\ feedbacks\ for\ brand) + \sum(Negative\ feedbacks\ for\ brand)} \quad (1)$$

E. Categorization and Visualization

After the sentiment scores are computed for each review, we categorize the feedback by product model or brand. This enables a comparison of sentiment across different products. To visualize the sentiment distribution, we generate graphs that show the percentage of positive and negative feedback for each product. This visualization helps to identify trends and patterns in customer opinions.

We further enhance the visualization by calculating the weighted score for each product, which takes into account the total number of feedback comments and their respective sentiment scores. The formula for calculating the weighted score is in equation (2).

$$Weighted\ score = \frac{Positive\ Percentage\ for\ brand * \sum(total\ feedbacks\ for\ brand)}{\sum(Positive\ feedbacks) + \sum(Negative\ feedbacks)} \quad (2)$$

By ranking the products based on their weighted scores, we can recommend the best-performing models to consumers based on their sentiments.

F. Additional Preprocessing Steps

To ensure the accuracy of our results, we perform several additional checks during the data pre-processing stage. These include:

- Removing Duplicates: Identifying and eliminating any duplicate reviews to prevent skewing the analysis.
- Correcting Misspellings: Identifying common spelling errors and correcting them to ensure consistent analysis.
- Removing Irrelevant Feedback: Filtering out reviews that do not contribute meaningful insights, such as non-product-related comments.

We also consider specific product features mentioned in reviews, such as durability or design, and incorporate these aspects into our analysis. This helps provide a more comprehensive understanding of customer sentiments and preferences.

IV. RESULTS AND EVALUATION

In this section, we present the results of our research study, which aimed to recommend the best product or brand based on customer feedback using sentiment analysis. We conducted two stages of analysis to evaluate the performance of our sentiment analysis tool, assess the system's ability to recommend the best brand, and explore the effectiveness of sentiment analysis across various languages.

A. Assessing the Level of Agreement or Similarity Between Extracted Feedback and Available Resources for the Same Product or Brand

One of the key objectives of our study was to assess how well our system performs in extracting and analyzing feedback from e-commerce platforms, particularly in relation to the feedback available for the same product or brand on those platforms. In this evaluation, we compared feedback data extracted by our system using web scrapers to the actual feedback available on e-commerce

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websites such as Amazon and eBay.

We extracted 4,995 feedback entries from Amazon, which represented approximately 88.17% accuracy in comparison to the actual 5,565 feedback entries available on the site. For eBay, the system correctly extracted all 178 feedback entries. These results highlight that while the system was largely successful in gathering relevant feedback, network issues or overloading may have impacted its efficiency in some cases.

TABLE I
COMPARISON OF EXTRACTED FEEDBACK WITH AVAILABLE RESOURCES

Website	Total Feedback Extracted	Total Feedback Available	Accuracy (%)
Amazon	4,995	5,565	88.17
eBay	178	178	100.00

B. Evaluation of Sentiment Analysis Tool Performance for the Extracted Feedback

To evaluate the sentiment analysis tool's effectiveness in classifying customer feedback as positive, negative, or neutral, we used SentiWordNet, a lexical tool that assigns polarity scores to words. These scores were used to determine the overall sentiment of each feedback. The algorithm initially classifies feedback based on sentiment scores derived from token-level sentiment scoring and contextual weighting. This automated process ensures scalability when handling large datasets. To ensure the accuracy of the algorithm and validate edge cases (such as mixed sentiments or ambiguous feedback), a subset of feedback is manually reviewed by domain experts. Feedback from the manual review is used to improve the algorithm by fine-tuning parameters or updating sentiment lexicons.

We selected feedback from eBay to evaluate the tool's performance. The comparison showed that the sentiment analysis system correctly identified the sentiment of most feedback entries, with an 80% match rate compared to manual analysis. However, two cases showed discrepancies between the system's output and manual classification.

TABLE II
FEEDBACK SENTIMENT CLASSIFICATION RESULTS

No.	Feedback	System Sentiment	Manual Sentiment
1	"These won't fit everyone perfectly..."	Positive	Negative
2	"The sound and clarity are better..."	Negative	Negative
3	"These AirPods are insane..."	Positive	Positive
4	"I bought the 'good' refurbished item..."	Positive	Positive
5	"These work appropriately 50' from..."	Negative	Positive
6	"I was amazed how easy to work with..."	Positive	Positive
7	"Was nervous about buying airpods..."	Positive	Positive
8	"I bought these for my daughter..."	Negative	Negative
9	"Absolutely amazing sound quality..."	Positive	Positive
10	"I switched from gen 2 to gen 3..."	Positive	Positive

In the TABLE II, we can see that the sentiment analysis tool's results mostly align with manual classification, confirming its overall reliability. The accuracy of sentiment classification in this case was 80%.

C. Evaluation of System Performance

Next, we assessed the overall performance of our system in recommending the best brand or model of a product. We extracted feedback from five eBay listings, grouped them by model or brand, and compared the system's output to manual calculations.

The system's recommendations were compared to manually calculated results based on positive and negative feedback percentages. The system demonstrated a high degree of accuracy, with a similarity rate of 97.5% between the system's and manual results. While minor differences were noted in some cases, the system proved effective in identifying the best model or brand. The Fig. 3 showing the list of suggested models from the system's recommendations.

Brand Name	Total Feedback	Positive Feedback %	Total Score %
Apple	249	87.15%	21.30%
L09	160	87.50%	13.74%
ELESNOW	129	82.95%	10.50%
WirelessWhite	115	86.09%	9.72%
LUZIDY	110	86.36%	9.32%

Fig 2: List of Suggested Models

D. Assessing the Performance of the Sentiment Analysis Tool in Handling Various Languages

To evaluate the performance of our sentiment analysis tool across different languages, we tested it with customer feedback in English, Spanish, and French. Since SentiWordNet is natively designed for English and does not directly support Spanish or French, additional steps were incorporated to enable cross-linguistic compatibility. Feedback in Spanish and French was translated into English using Google Translate process. This step ensured that the sentiment analysis tool could process feedback in a language supported by SentiWordNet. For Spanish and French, we supplemented SentiWordNet with publicly available sentiment lexicons specific to these languages. These lexicons were used to enhance the accuracy of token-level sentiment scoring during preprocessing.

Results showed that the sentiment analysis tool performed well in English, with an accuracy of 85%. However, the tool's accuracy was lower when analyzing Spanish (67%) and French (72%) feedback. These results suggest that while cross-linguistic compatibility can be achieved through translation and lexicon adaptation, further optimization is required to address language-

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specific nuances effectively.

TABLE III
SENTIMENT ANALYSIS ACCURACY ACROSS DIFFERENT LANGUAGES

Language	Accuracy (%)
English	85
Spanish	67
French	72

These results suggest that while the sentiment analysis tool is effective for English text, additional work is required to improve its performance for other languages. One potential factor contributing to the discrepancy in accuracy is the availability of high-quality data in different languages. In future work, we plan to explore strategies to enhance the tool's accuracy by improving data quality and quantity for languages other than English.

V. DISCUSSION

The development of this sentiment analysis-based system highlights its significance in today's e-commerce landscape, where the sheer volume of products and brands can overwhelm consumers. This system simplifies the decision-making process by providing a list of top-performing models or brands based on real-time customer feedback. This approach not only aids consumers in making more informed purchasing decisions but also enhances their confidence, potentially leading to higher satisfaction and brand loyalty.

For brands, the benefits are equally substantial. Access to customer sentiment data offers valuable insights into consumer perceptions, enabling them to refine their products and marketing strategies effectively. By analyzing trends and feedback, businesses can pinpoint areas for improvement, adapt to customer preferences, and foster a stronger connection with their audience.

The framework's use of advanced lexicon and rule-based and natural language processing techniques ensures a robust and dynamic analysis process. The visualization of feedback in graph form provides an intuitive understanding of the sentiment distribution, allowing businesses to identify high-performing products quickly.

While the system addresses critical pain points for both consumers and businesses, it is essential to acknowledge its current limitations, such as restricted data sources and the potential exclusion of feedback from platforms other than e-commerce websites. Despite these challenges, the system demonstrates significant potential to transform the online shopping experience, making it more seamless and efficient for all stakeholders involved.

VI. CONCLUSION

In conclusion, this research demonstrates the potential of sentiment analysis-based systems to streamline the product selection process for consumers and provide actionable insights for businesses. By utilizing real-time feedback from e-commerce websites, the framework addresses the challenges of information overload and enhances decision-making for consumers. For businesses, it offers a tool to gauge customer sentiment, improve products, and align marketing strategies with consumer preferences.

Although the system has limitations, such as dependency on web scraping and exclusion of non-e-commerce feedback, these constraints do not diminish its value as a practical and impactful solution. With future advancements in data collection methods and machine learning algorithms, the system can evolve further, offering even greater accuracy and insight. Ultimately, the framework represents a significant advancement in leveraging technology to enhance both customer experience and business performance in the dynamic world of e-commerce.

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