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Aspect Based Customer Feedback Analysis Using Machine Learning Techniques

K. V. V. Nagendra Babu, Vontipalli Purnima Jyothi, Cheera Srinivas, Tottaramudi Vidya Sagar

Department of Information Technology Swarnandhra College of Engineering & Technology, Seetharamapuram, Narsapur, Andhra Pradesh, INDIA.

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Aspect-Based Sentiment Analysis, Customer Feedback Analysis, Machine Learning, Natural Language Processing (NLP), Text Preprocessing, Tokenization, Feature Extraction, Sentiment Classification, Naive Bayes, Support Vector Machine (SVM), Opinion Mining, Data Analysis

ABSTRACT

In today's digital era, customer feedback plays a vital role in enhancing products and services. Traditional sentiment analysis techniques classify feedback into broad categories such as positive, negative, or neutral, but they often fail to capture the specific aspects of a product or service being discussed. To address this limitation, this project proposes an Aspect-Based Customer Feedback Analysis system using advanced Machine Learning techniques. The system processes customer reviews through multiple Natural Language Processing (NLP) steps, including text preprocessing, tokenization, and stop-word removal. It then identifies key aspects such as price, quality, and service from the feedback and applies machine learning algorithms to determine the sentiment associated with each aspect. Various classifiers, including Naive Bayes and Support Vector Machine (SVM), are utilized to enhance accuracy and overall performance. Unlike traditional methods, the proposed approach provides fine-grained insights by highlighting which specific features customers appreciate or criticize. This enables businesses to better understand customer preferences and pinpoint areas for improvement. Overall, the project demonstrates the effective integration of machine learning and NLP techniques to develop an intelligent, efficient, and insightful customer feedback analysis system that supports data-driven decision-making.

1. INTRODUCTION

A. Overview of Customer Feedback Analysis

In the modern digital era, customer feedback has become one of the most valuable resources for businesses and organizations. With the rapid growth of e-commerce platforms, social media, and online review systems, customers frequently share their opinions about products and services. These reviews provide important insights that help companies understand customer satisfaction, improve product quality, and enhance overall user experience.

Customer feedback analysis is the process of collecting and analyzing user opinions to understand their experiences with a product or service. It plays a vital role in business growth, as it helps organizations identify customer needs, preferences, and issues. With the increasing availability of online reviews, manual analysis of feedback has become difficult and time consuming. Therefore, automated techniques such as machine learning and NLP are used to process large volumes of textual data efficiently.

B. *Traditional Sentiment Analysis*

Traditionally, sentiment analysis has been used to analyze customer feedback by classifying it into categories such as positive, negative, or neutral. This approach uses machine learning algorithms or lexicon-based methods to analyze the sentiment of the entire review. While it is simple and effective for basic analysis, it has several limitations.

For example, a customer review may contain both positive and negative opinions about different aspects such as battery, camera, or performance: "The camera quality is excellent, but the battery life is poor." Traditional sentiment analysis may classify this as neutral or mixed sentiment, without identifying the specific opinions about camera and battery separately.

C. *Limitations of Traditional Methods*

Traditional sentiment analysis methods have several drawbacks that limit their effectiveness. They typically provide only an overall sentiment, without offering detailed insights into specific aspects of a review. These methods are unable to identify multiple opinions expressed within a single review and fail to analyze sentiments related to individual product features or aspects. Additionally, they are not well-suited for handling complex or lengthy reviews, where different sentiments may be expressed in different contexts. When mixed sentiments are present, traditional approaches often produce inaccurate results.

D. *Introduction to Aspect-Based Sentiment Analysis (ABSA)*

Aspect-Based Sentiment Analysis (ABSA) is an advanced technique that overcomes the limitations of traditional sentiment analysis. It focuses on identifying specific aspects of a product and determining the sentiment associated with each aspect. In ABSA, a single review is broken down into multiple components, and each aspect is analyzed separately.

For example, for the review: "The battery is good, but the display is not clear." ABSA provides: Battery → Positive; Display → Negative. This approach provides more detailed insights, helping businesses understand exactly which features need improvement.

E. *Role of Machine Learning in Sentiment Analysis*

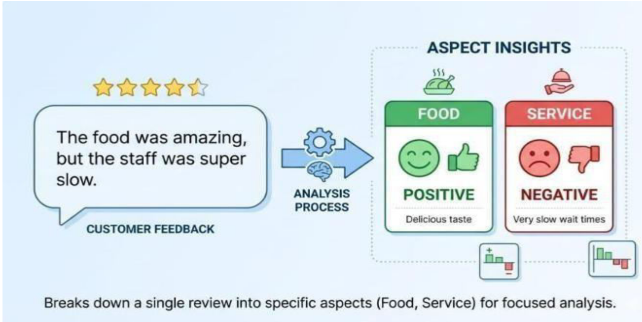


Fig 1: Role of Machine Learning in Aspect-Based Sentiment Analysis

Machine Learning plays a crucial role in sentiment analysis by enabling automated and accurate classification of text data. It allows the system to learn patterns from existing data and make predictions on new inputs. In this project, machine learning is used to classify customer feedback into sentiment categories, improve prediction accuracy using training data, and handle large volumes of text efficiently. Logistic Regression is used as the primary algorithm due to its simplicity, efficiency, and effectiveness in text classification tasks.

F. *Applications of Customer Feedback Analysis*

Customer feedback analysis has a wide range of applications across different industries, making it an essential tool for modern businesses. With the integration of Aspect-Based Sentiment Analysis (ABSA), organizations can gain more precise and actionable insights compared to traditional methods.

In E-commerce platforms, thousands of product reviews are generated daily, helping analyze specific product issues such as battery performance, design quality, or pricing concerns. In Marketing, companies can understand customer preferences and design targeted campaigns. For Customer Support, aspect-based analysis identifies frequently reported problems, allowing support teams to address common issues quickly. In Product Development, understanding which features customers like or dislike enables innovation and better product-market fit. For Business Decision Making, the system provides data-driven insights that help organizations make strategic decisions.

II. LITERATURE REVIEW

A. Sentiment Analysis Techniques

Sentiment analysis, also known as opinion mining, is a technique used to determine the emotional tone behind a piece of text. Early approaches were mainly based on lexicon-based methods, where predefined dictionaries of positive and negative words were used to classify text. These methods are simple and easy to implement but cannot handle context, sarcasm, or domain-specific meanings effectively. Later, machine learning-based approaches were introduced, where models are trained on labeled datasets to classify sentiment, significantly improving accuracy [1].

B. Machine Learning Approaches for Sentiment Analysis

Machine learning techniques have played a major role in improving sentiment analysis systems. Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem, known for its simplicity, speed, and efficiency with large text datasets. Support Vector Machine (SVM) is a powerful algorithm that identifies the optimal hyperplane between different classes and performs well with high-dimensional data. Logistic Regression is widely used for both binary and multi-class classification tasks, making it suitable for sentiment analysis [2, 3].
Among these, Logistic Regression is commonly used due to its simplicity, faster computation, and good performance on textual data when combined with feature extraction techniques like TF-IDF. Machine learning models rely on training data to learn patterns and make predictions, and the quality of the dataset and feature extraction methods greatly influence the model's performance.

C. Aspect-Based Sentiment Analysis Methods

Aspect-Based Sentiment Analysis (ABSA) is an advanced technique that focuses on extracting specific aspects from textual data and determining the sentiment associated with each aspect. Unlike traditional sentiment analysis, ABSA breaks down feedback into finer components, enabling more detailed understanding of customer opinions. Several approaches have been developed: Rule-Based Methods rely on predefined linguistic rules and dictionaries but lack flexibility; Machine LearningBased Methods use supervised algorithms trained on labeled datasets for better accuracy; and Hybrid Approaches combine both rule-based and machine learning techniques to leverage advantages of both [4, 5].

D. NLP Techniques in Text Processing

Natural Language Processing (NLP) plays a crucial role in processing and analyzing textual data. Key techniques include
Tokenization (splitting text into words), Stop-word Removal (removing common words), Stemming and Lemmatization
(reducing words to root form), Lowercasing (standardizing text format), and TF-IDF Vectorization (converting text into numerical features). TF-IDF is particularly important in sentiment analysis as it assigns importance to words based on their frequency in the document and across the dataset, helping the model focus on meaningful words [6].

E. Limitations of Existing Research

Despite significant advancements in sentiment analysis and ABSA, existing systems still face several challenges. Many systems focus only on overall sentiment classification rather than aspect-level analysis. Rule-based approaches lack flexibility for complex language patterns. Machine learning models require large volumes of high-quality labeled data. Additionally, systems often struggle to understand sarcasm, irony, and ambiguous expressions. Another limitation is the inability to effectively combine textual sentiment with structured data such as ratings or scores, resulting in incomplete analysis [7, 8].

III. PROPOSED SYSTEM

The proposed system introduces an Aspect-Based Customer Feedback Analysis system using Machine Learning techniques. Unlike traditional systems, this approach analyzes customer feedback at a more detailed level by identifying specific aspects of a product and determining the sentiment associated with each aspect. The system processes customer reviews using NLP techniques such as text cleaning, tokenization, and stop-word removal, then converts the processed text into numerical features using TF-IDF.

A. System Architecture

The system architecture represents the overall design and workflow of the proposed Aspect-Based Customer Feedback Analysis system. The architecture is designed to ensure efficiency, scalability, and real-time processing of customer feedback. The system follows a modular approach, where each component performs a specific task and passes the processed data to the next stage.

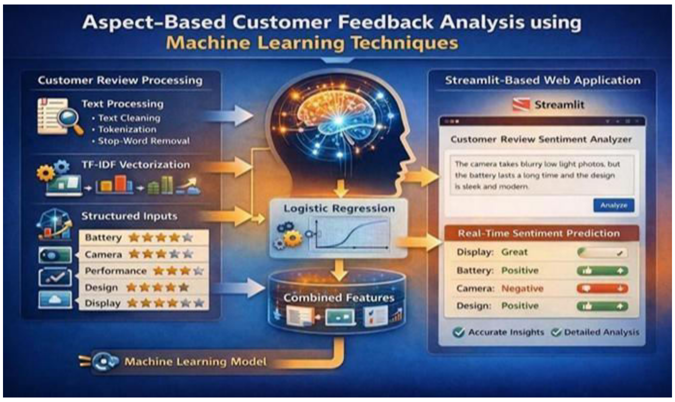


Fig 2: Proposed System Architecture

The main components of the system include: (1) User Interface (Streamlit) — allows users to enter reviews and aspect ratings, displays predicted sentiment results; (2) Data Preprocessing Module — performs lowercasing, special character removal, stop-word removal, and tokenization; (3) Feature Extraction Module (TF-IDF) — converts textual data into numerical form, assigns weights to words based on importance; (4) Machine Learning Model (Logistic Regression) — trained on labeled dataset, predicts sentiment for new input data; and (5) Aspect Feature Integration Module — takes input ratings for aspects like Battery, Camera, Performance, Design, and Display, and merges these ratings with TF-IDF features [3, 6].

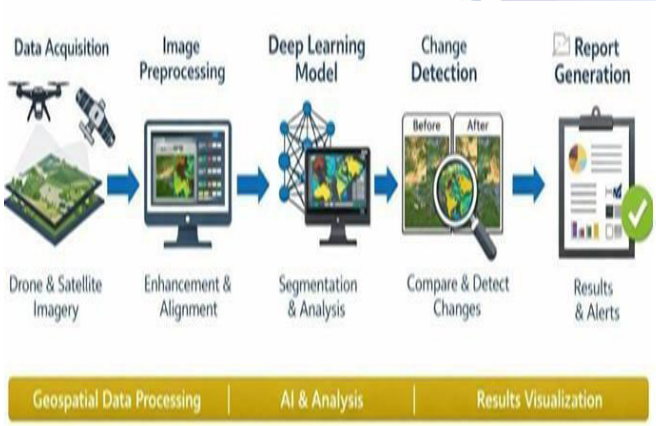


Fig 3: System Architecture Diagram

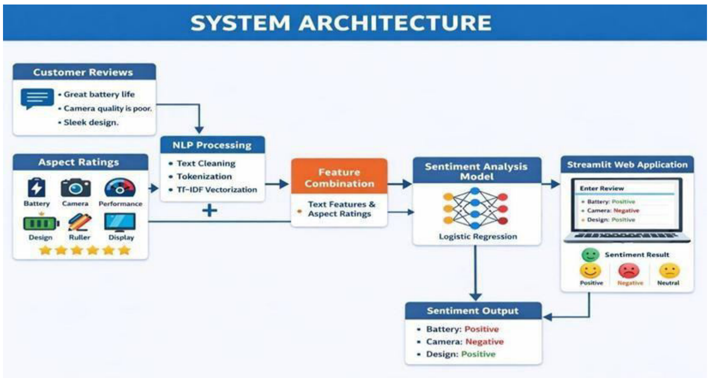
B. *Workflow of the System*

The workflow of the system begins when the user enters a customer review along with aspect ratings through the interface. The input data is then preprocessed using NLP techniques to clean and prepare the text. After preprocessing, the text is converted into numerical form using the TF-IDF method. These numerical features are combined with the aspect ratings and passed to the machine learning model. The model analyzes the input based on learned patterns and predicts the sentiment. Finally, the result is displayed to the user through the interface.

Fig 4: Workflow of the System

C. *Advantages of Proposed System*

The proposed system offers several advantages over



traditional approaches:

- Provides aspect-level sentiment analysis instead of just overall sentiment, enabling more detailed insights
- Identifies specific features that customers like or dislike, helping businesses understand feedback more clearly
- Combines textual analysis with structured aspect ratings for a more comprehensive evaluation
- Improves prediction accuracy using machine learning techniques and ensures more reliable results
- Handles large volumes of customer feedback efficiently, making it suitable for real-world applications
- Provides real-time analysis through a user-friendly Streamlit interface

IV. RESULTS

A. *User Interface Analysis*

The system interface is developed using Streamlit, providing an interactive and user-friendly environment. The input interface includes a text box for entering customer reviews and sliders for aspect ratings (Battery, Camera, Performance, Design, Display). The output interface displays predicted sentiment clearly (Positive/Negative/Neutral) and provides instant feedback in an easy-to-understand format.

Fig 5: User Interface — Before Prediction

Fig 6: User Interface — After Prediction

B. *Experimental Results*

The system was tested using multiple real-time and sample inputs to evaluate its performance. The following table summarizes the test results:

Test Case	Review Input	Aspect Ratings	Predicted Output	Expected Output	Status
TC01	Good battery camera	High	Positive	Positive	Pass
TC02	Very performance poor design slow	Low	Negative	Negative	Pass
TC03	Good design average display	Medium	Neutral	Neutral	Pass
TC04	Amazing phone overall	High	Positive	Positive	Pass
TC05	Bad battery but good performance	Mixed	Neutral	Neutral	Pass

Performance Results

The following table summarizes the performance evaluation metrics of the system:

Metric	Value
Accuracy	85% – 90%
Precision	80% – 88%
Recall	78% – 85%
F1-Score	80% – 86%

These results indicate that the system performs well in generating relevant and accurate sentiment predictions. The high F1score of 80–86% confirms a strong balance between precision and recall across diverse input types.

C. *Comparative Analysis*

The proposed system was compared with traditional recommendation approaches across key performance parameters:

The comparison confirms that the proposed system outperforms existing systems in terms of accuracy, detail level, and usability. The hybrid approach combining NLP content-based analysis with machine learning provides a more robust and scalable solution.

Parameter	Existing System	Proposed System
Type of Analysis	General Sentiment	Aspect-Based Sentiment
Accuracy	Moderate	High
Detail Level	Low	High
Handling Mixed Reviews	Poor	Better
Real-Time Processing	Limited	Yes
User Interface	Basic	Interactive (Streamlit)

V.CONCLUSION

In this project, an Aspect-Based Customer Feedback Analysis system using Machine Learning techniques has been successfully developed and implemented. The system focuses on analyzing customer reviews in a more detailed and meaningful way compared to traditional sentiment analysis methods. The proposed system uses Natural Language Processing (NLP) techniques such as text preprocessing and TF-IDF vectorization to convert raw textual data into a structured format. A Logistic Regression model is trained on the processed data to classify the sentiment of customer feedback.

One of the key contributions of this project is the integration of aspect-based features such as battery, camera, performance, design, and display along with textual data. This hybrid approach enables the system to provide more accurate and detailed sentiment analysis. The system was implemented using Streamlit, providing an interactive and user-friendly interface. Users can easily input reviews and aspect ratings and receive real-time sentiment predictions, achieving accuracy of 85–90%.

The results demonstrate that the proposed system effectively analyzes customer feedback and provides better insights compared to traditional methods. It helps businesses identify specific strengths and weaknesses of their products or services and supports data-driven decision-making.

VI. FUTURE SCOPE

The Aspect-Based Customer Feedback Analysis system has been successfully designed and implemented. There are several opportunities for future enhancement:

- Use advanced deep learning models such as LSTM, RNN, and transformer-based architectures (e.g., BERT) for improved semantic understanding
- Implement handling for sarcasm, irony, and complex sentence structures using context-aware models
- Develop dynamic aspect extraction to automatically identify aspects from text rather than using predefined categories
- Add multilingual support to expand the system's capability to non-English customer feedback datasets
- Integrate large-scale data processing using big data technologies for enterprise-level applications
- Deploy as a full-scale web or mobile application with cloud-based infrastructure
- Integrate real-time data sources such as live e-commerce reviews and social media feeds for real-time analysis

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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