The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 8, August 2025
PP 19–30

Vibe Bot: AI-Powered Sentiment Exploration

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Abstract

With the rapid expansion of e-commerce platforms like Amazon and Flipkart, customers rely heavily on product reviews to make informed purchasing decisions. However, the large volume of unstructured reviews, combined with variations in sentiment expression, makes it challenging to extract meaningful insights. VibeBot: AI-Powered Sentiment Exploration addresses this issue by leveraging Natural Language Processing (NLP) and Machine Learning (ML) to analyze customer sentiments, classify feedback into actionable insights, and provide real-time recommendations. The system processes product reviews, detects sentiment polarity (positive, neutral, or negative), and extracts feature-specific feedback to help businesses improve product quality and enhance customer experience. By integrating advanced AI techniques, VibeBot ensures high accuracy in sentiment detection, making it a valuable tool for consumers and e-commerce platforms seeking data-driven decision-making.

Keywords:

Sentiment Analysis, Natural Language Processing (NLP), Machine Learning (ML), Customer Feedback Analysis, Text Classification, AI-Powered Insights, Product Review Analytics, Data-Driven Decision Making.

Introduction

In the digital age, e-commerce platforms like Amazon and Flipkart have revolutionized the shopping experience by providing customers with a vast selection of products and user-generated reviews. Product reviews play a crucial role in influencing purchasing decisions, as they offer firsthand insights into the quality, performance, and reliability of an item. However, the exponential growth of online reviews has created challenges in extracting meaningful information due to the sheer volume of data, variations in language, and diverse sentiment

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expressions. Manually analyzing customer feedback is inefficient and time-consuming, making it difficult for consumers and businesses to identify key trends and actionable insights.

To address this issue, VibeBot: AI-Powered Sentiment Exploration is designed as an intelligent system that leverages Natural Language Processing (NLP) and Machine Learning (ML) to analyze customer sentiment in real time. VibeBot processes and classifies product reviews into positive, neutral, and negative sentiments while extracting key feature-specific feedback. By utilizing advanced AI techniques, the system enhances sentiment analysis accuracy and provides valuable insights that help businesses improve their products and services. Additionally, consumers can make well-informed purchasing decisions based on comprehensive sentiment trends and product evaluations.

This paper explores the development and implementation of VibeBot, highlighting its ability to analyze large-scale review datasets efficiently. The proposed solution aims to bridge the gap between customers and businesses by offering a user-friendly, AI-driven tool for extracting and interpreting product sentiment.

Research Objectives

The primary goal of this research is to develop VibeBot: AI-Powered Sentiment Exploration, an intelligent system for analyzing customer reviews and extracting actionable insights. The specific objectives of this study are:

1. To develop an AI-driven sentiment analysis model that accurately classifies customer reviews into positive, neutral, or negative sentiments using Natural Language Processing (NLP) and Machine Learning (ML) techniques.
2. To extract feature-specific insights from product reviews, enabling businesses to understand customer preferences and areas of improvement.
3. To design a real-time sentiment analysis system that processes large-scale e-commerce reviews efficiently and provides users with instant feedback.
4. To enhance decision-making for consumers and businesses by offering a structured and visual representation of sentiment trends, enabling data-driven purchasing and marketing strategies.
5. To improve the accuracy and efficiency of sentiment classification by leveraging advanced AI algorithms and optimizing model performance for real-world applications.
6. To integrate the sentiment analysis model into a user-friendly application that provides personalized insights and recommendations based on review sentiment.

Literature Survey

The field of sentiment analysis and opinion mining has gained significant attention with the rise of e-commerce platforms and the increasing reliance on customer feedback. Various studies have explored the application of Natural Language Processing (NLP) and Machine Learning (ML) to analyze large volumes of textual data and derive meaningful insights. This section reviews existing research on sentiment analysis techniques, challenges, and applications in the e-commerce domain.

Sentiment Analysis in E-Commerce

Sentiment analysis, also known as opinion mining, is the process of extracting subjective information from textual data to determine the sentiment polarity (positive, neutral, or negative). According to Liu (2012), sentiment analysis plays a crucial role in understanding customer satisfaction and improving business strategies. Several studies have focused on applying sentiment analysis to e-commerce reviews to assist both consumers and businesses in decision-making. For example, Pang et al. (2002) introduced machine learning-based sentiment classification methods using Naïve Bayes, Maximum Entropy, and Support Vector Machines (SVM) for movie reviews, which later influenced research in e-commerce review analysis.

Machine Learning and Deep Learning Approaches

Traditional machine learning algorithms such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees have been widely used for sentiment classification. However, recent advancements in deep learning techniques have significantly improved the accuracy of sentiment analysis models. Studies by Socher et al. (2013) demonstrated the effectiveness of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models in capturing complex sentiment patterns in textual data. Similarly, the introduction of transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) by Devlin et al. (2019) has revolutionized sentiment analysis by achieving state-of-the-art performance in natural language understanding tasks.

Feature-Specific Sentiment Analysis

While traditional sentiment analysis focuses on overall sentiment classification, feature-based sentiment analysis aims to identify sentiments related to specific product attributes (e.g., battery life, camera quality, or durability). Hu and Liu (2004) proposed a feature-based sentiment extraction model to identify and categorize product-specific sentiments from customer reviews. Recent research has leveraged Aspect-Based Sentiment Analysis (ABSA) techniques, which use dependency parsing and deep learning models to extract fine-grained sentiments associated with different product features.

Challenges in Sentiment Analysis
Despite advancements in sentiment analysis, several challenges persist, including:

- Ambiguity and Contextual Understanding: Sarcasm, irony, and figurative language often lead to incorrect sentiment classification (Ghosh et al., 2017).
- Domain-Specific Sentiment Shifts: Sentiment words may have different meanings in different domains, requiring domain adaptation techniques (Blitzer et al., 2007).
- Handling Imbalanced Data: Many real-world datasets contain a disproportionate number of positive or negative reviews, leading to biased model predictions.
- Multilingual Sentiment Analysis: Customer reviews on global e-commerce platforms appear in multiple languages, requiring multilingual NLP techniques (Pérez-Rosas et al., 2012).

AI-Powered Sentiment Bots for E-Commerce
Recent studies have explored the integration of AI-driven chatbot systems for sentiment analysis. AI-powered sentiment bots provide real-time customer assistance, personalized recommendations, and automated review analysis. Vinyals and Le (2015) introduced Seq2Seq models for conversational AI, laying the foundation for modern chatbot-based sentiment analysis. The use of reinforcement learning for chatbot optimization has further improved customer interaction and engagement in e-commerce applications.

Methodology

The VibeBot: AI-Powered Sentiment Exploration system employs a structured methodology integrating Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL) to extract meaningful insights from vast amounts of unstructured e-commerce review data. This methodology ensures high accuracy in sentiment classification while enabling interactive and personalized user engagement. The process consists of the following key phases:

1. Data Collection
The first phase involves gathering customer reviews from e-commerce platforms like Amazon and Flipkart through web scraping and API-based retrieval methods. The collected data includes review text, user ratings, timestamps, and product details. The dataset is structured to facilitate efficient preprocessing and analysis.

2. Data Preprocessing

Preprocessing is crucial to refining textual data before analysis. This involves:

Text Cleaning: Removal of duplicates, special characters, and unnecessary symbols.

Tokenization & Lemmatization: Breaking text into meaningful components and reducing words to their base forms.

Stopword Removal: Eliminating common words (e.g., "the", "and", "is") to enhance efficiency.

Negation Handling: Detecting phrases like "not good" to ensure accurate sentiment classification.

3. Feature Extraction and Representation

To enhance the accuracy of sentiment analysis, feature extraction techniques are employed:

TF-IDF (Term Frequency-Inverse Document Frequency): Captures the importance of words in the review corpus.

Word Embeddings (Word2Vec, GloVe, BERT): Converts words into vector representations to preserve contextual meaning.

Aspect-Based Sentiment Analysis (ABSA): Extracts sentiment related to specific product features, e.g., "battery life" or "camera quality."

4. Sentiment Classification

The extracted features are then processed using ML and DL models for sentiment classification:

Baseline Models: Naïve Bayes, Support Vector Machines (SVM), and Decision Trees for initial classification.

Advanced Deep Learning Models: Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Transformer-based models (BERT, Roberta) for improved sentiment accuracy.

Model Training: Using an 80-20 train-test split, models are optimized through hyperparameter tuning and evaluated with performance metrics such as accuracy, precision, recall, and F1-score.

5. Real-Time Sentiment Analysis and Visualization

Upon classification, sentiment trends are visualized for better interpretability:

Sentiment Labeling: Each review is categorized as positive, negative, or neutral.

Dashboard Representation: Using Matplotlib, Seaborn, and Plotly, sentiment trends, word clouds, and distribution graphs are displayed.

6. Interactive Chatbot Integration

A core component of the system is VibeBot, an AI-driven chatbot that interacts with users in real-time:

User Engagement: Provides summarized sentiment reports, feature-specific insights, and personalized recommendations.

Reinforcement Learning (RL): The chatbot learns from user interactions to refine its responses over time.

Multilingual Support: Leveraging mBERT and XLM-R models, enabling analysis of reviews in multiple languages.

Deployment: Implemented using FastAPI or Flask, ensuring smooth integration with web and mobile platforms.

7. System Evaluation and Performance Testing

The system undergoes rigorous evaluation to validate its effectiveness:

Benchmark Datasets: Testing with IMDB reviews, Amazon product reviews, and real-world datasets.

Performance Metrics: Accuracy, precision, recall, and F1-score are analyzed to assess model efficiency.

User Validation: Conducting A/B testing with users to measure chatbot usability and effectiveness.

Implementation

Sentiment Analysis Implementation

The first stage of sentiment analysis implementation involves collecting customer reviews from various e-commerce platforms such as Amazon and Flipkart. This data is gathered through web scraping techniques or API integration, ensuring a comprehensive collection of product reviews. The dataset includes essential details such as product name, category, subcategory, price, discounts, user ratings, and customer comments. The collected data is then stored in a structured format like CSV, JSON, or a relational database to facilitate efficient processing.

Once the data is collected, it undergoes preprocessing to remove unnecessary elements and enhance the quality of the analysis. The text is tokenized to break it into individual words or sentences. Stopwords, which are common words that do not contribute to sentiment analysis, are eliminated. Lemmatization is applied to convert words into their root forms, ensuring consistency across textual data. Furthermore, special characters, emojis, and redundant symbols

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are removed to create a cleaner dataset. Negation handling is incorporated to accurately interpret phrases where negations, such as "not good," impact the overall sentiment.

After preprocessing, feature extraction techniques are applied to convert text into numerical representations that machine learning models can understand. Term Frequency-Inverse Document Frequency (TF-IDF) is employed to highlight significant words in the review corpus. Additionally, word embedding methods such as Word2Vec, BERT, or GloVe are used to capture semantic relationships between words. Aspect-based sentiment Analysis (ABSA) is also incorporated to determine sentiments specific to product attributes, such as battery performance or display quality.

Sentiment classification is then performed using machine learning and deep learning models. Traditional machine learning approaches such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees provide baseline classification. More advanced deep learning architectures, including Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), and Transformer-based models like BERT and RoBERTa, are implemented for superior accuracy. Hyperparameter tuning is carried out to optimize model performance, ensuring precise sentiment predictions.

To provide meaningful insights, sentiment analysis results are visualized through graphical representations. Tools such as Matplotlib, Seaborn, and Plotly are used to generate sentiment distribution graphs, word clouds, and product-specific sentiment trends. These visual insights help users understand the overall sentiment associated with a product, enabling informed decision-making.

Website Implementation

The website front end is designed using a combination of HTML, CSS, and JavaScript to ensure an interactive and user-friendly interface. Frameworks such as Bootstrap or Tailwind CSS are utilized for responsive design, enabling seamless access across different devices. The website features dynamic dropdown menus for category and subcategory selection. It also includes an intuitive product selection interface, allowing users to explore products based on personalized preferences. Additionally, filter options enable users to refine their searches by setting a preferred price range and minimum rating requirements.

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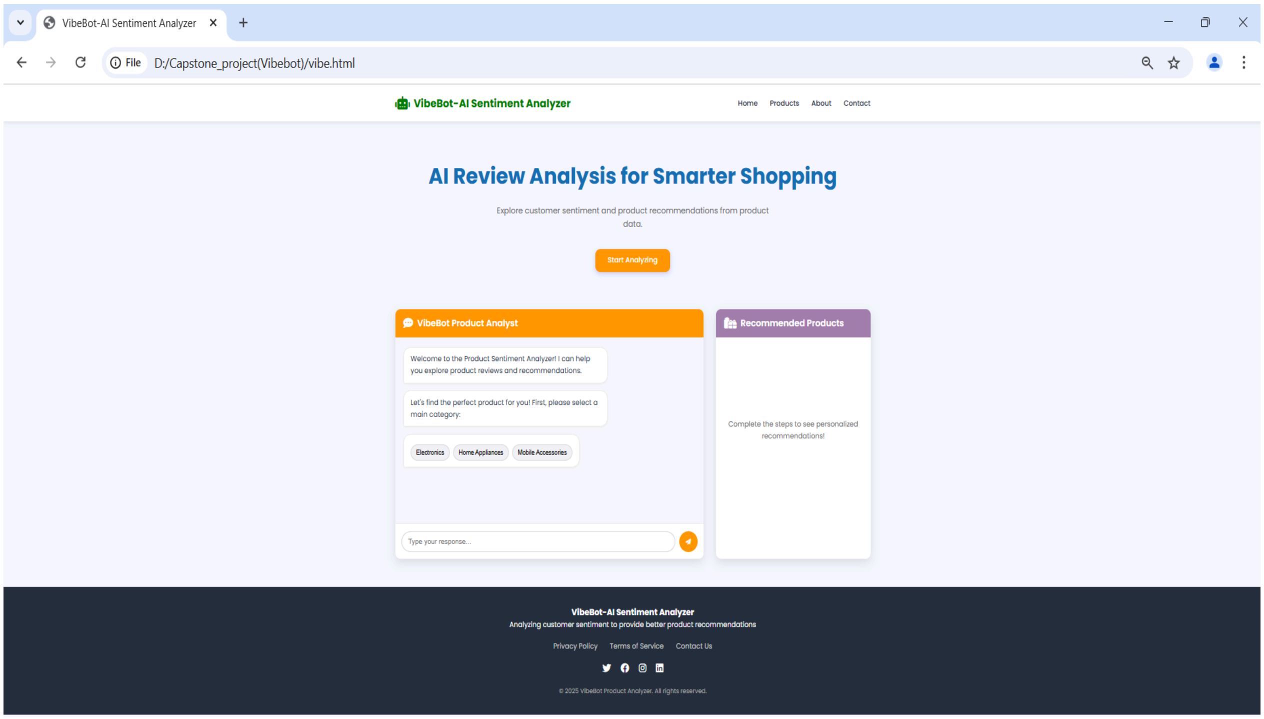

Fig-1

The backend of the website is developed using Python-based web frameworks such as Flask or FastAPI. API endpoints are established to handle data retrieval and filtering. These endpoints manage functions such as fetching product categories and subcategories, retrieving relevant product listings, and filtering the products based on user-defined criteria, including price and rating. Once a user specifies their preferences, the system processes the available data and displays recommended products that align with the user's requirements. Each recommendation includes key details such as product price, discounts available, and a direct purchase link.

To manage data efficiently, the system integrates a database solution that stores product information, user preferences, and sentiment analysis outcomes. A relational database, such as MySQL or PostgreSQL, or a NoSQL alternative, such as MongoDB, is employed based on the scalability requirements. Additionally, real-time API integration fetches updated product details from e-commerce platforms. A dedicated sentiment analysis API processes customer reviews and generates insights to enhance the recommendation system.

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The website incorporates a chatbot, VibeBot, to enhance user interaction. Built using chatbot frameworks like Dialogflow, Rasa, or OpenAI's GPT, VibeBot assists users in finding suitable products based on their inquiries. The chatbot provides summarized sentiment reports, feature-specific insights, and tailored recommendations. By integrating reinforcement learning, the chatbot continuously improves its responses through user interactions. Furthermore, multilingual capabilities are supported through models such as mBERT and XLM-R, allowing analysis of reviews in multiple languages.

Deployment and User Journey

The complete system is deployed on cloud platforms such as AWS, Heroku, or Firebase, ensuring scalability and high availability. Continuous Integration and Continuous Deployment (CI/CD) pipelines are implemented to facilitate seamless updates and maintenance. The platform is optimized for both desktop and mobile access, ensuring an engaging user experience across various devices.

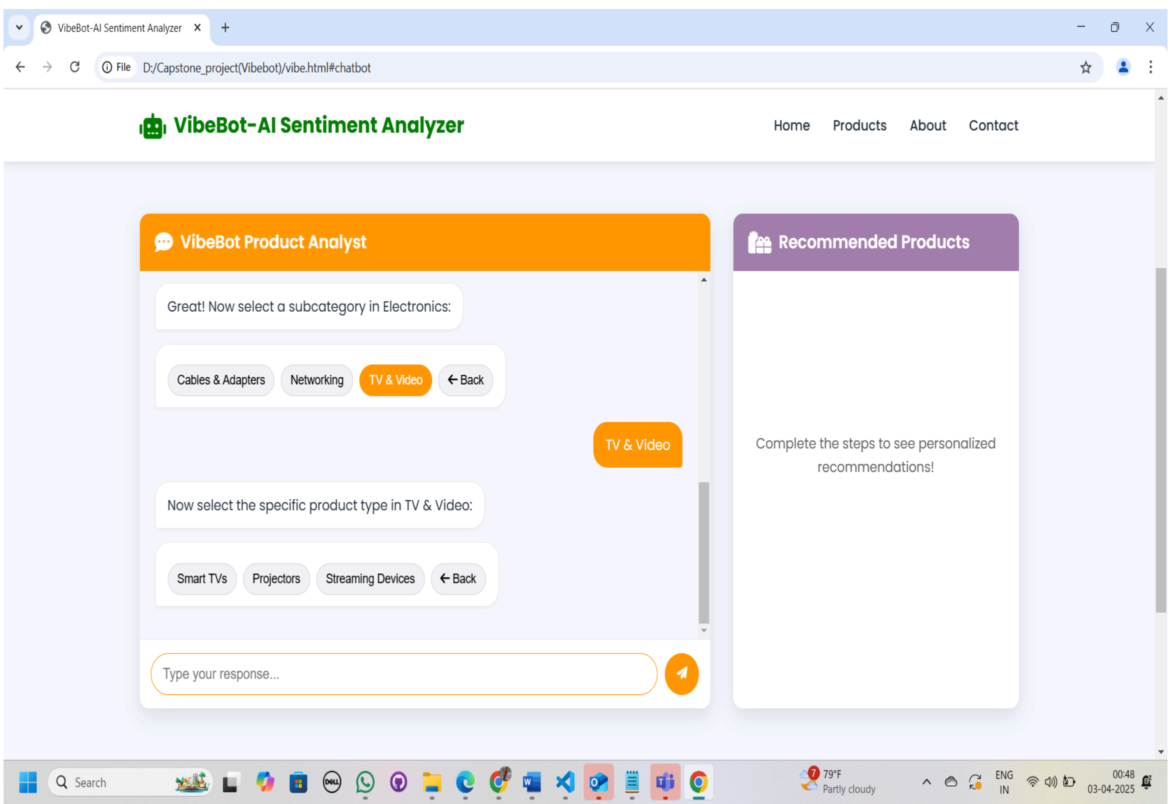

Fig-2

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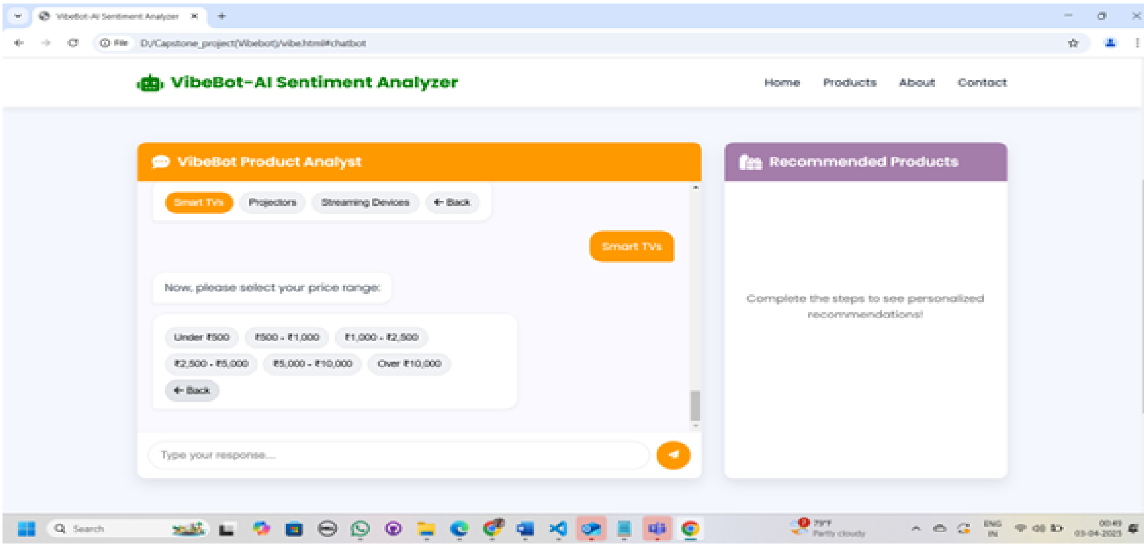

Fig-3

Users interact with the VibeBot AI Sentiment Analyzer through a structured journey. Upon visiting the website, they begin by selecting a product category, such as electronics or fashion. They then choose a subcategory, such as mobile phones or laptops, leading to a list of relevant products. The user selects a product for detailed sentiment analysis and specifies a price range along with a preferred rating. Based on these inputs, the system filters the available products and presents the best recommendations.

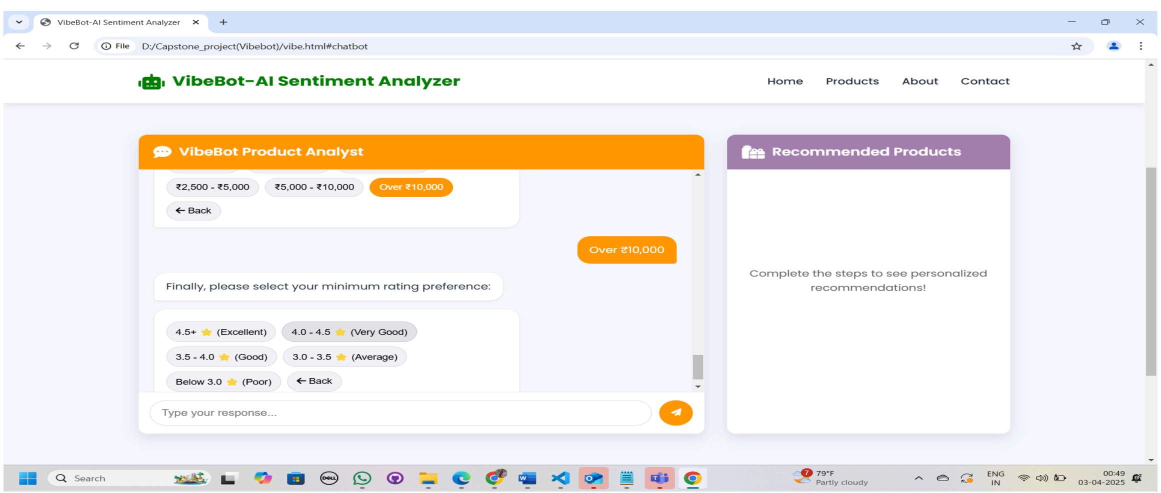

Fig-4

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The displayed information includes product price, discount details, sentiment analysis results, and a direct link to the e-commerce platform for purchasing. Users also have the option to interact with the chatbot for additional recommendations and insights. Finally, after reviewing the suggested products, the user makes a purchase decision through an external link provided by the system. This structured approach to sentiment analysis and website implementation ensures a seamless and personalized shopping experience, empowering users to make data-driven purchasing decisions.

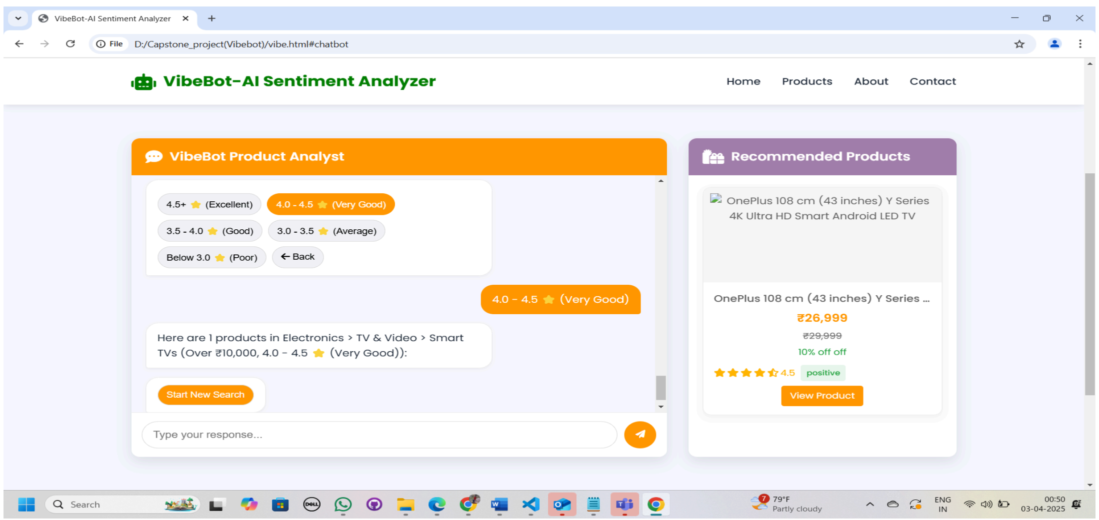

Fig-5

Conclusion

The VibeBot – AI Sentiment Analyzer effectively combines sentiment analysis with product recommendations using machine learning and deep learning techniques. It accurately interprets customer reviews to provide insightful suggestions. The website ensures seamless navigation, real-time filtering, and chatbot-assisted recommendations. A Python-based backend enables efficient data retrieval and processing.Through rigorous testing, VibeBot proves its efficiency in sentiment classification and recommendation generation. Its ability to extract meaningful insights supports informed purchasing decisions. Future improvements could include multilingual analysis, advanced models, and expanded datasets for greater accuracy.

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