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IntelliBargainBot: AI-Driven Price Negotiation System for E-Commerce Platforms

Erukulla Pravalika[1], Dr. V. Uma Rani[2]
[1]*Post Graduate Student, M. Tech (Data Science), Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India*
[2]*Professor, Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India*

Abstract: ***The rapid growth of e-commerce has significantly improved online shopping experiences. However, the traditional bargaining experience is largely absent in most e-commerce platforms due to fixed pricing mechanisms, limiting customer interaction and pricing flexibility.***
This paper presents IntelliBargainBot, an AI-driven price negotiation system that enables personalized bargaining through the integration of machine learning, natural language processing (NLP), and automated negotiation techniques. Customer transaction data is transformed into RFM and behavioral features, which are used by the K-Means clustering algorithm to segment customers based on purchasing patterns.
The identified customer segment guides negotiation strategies, including discount limits, concession behavior, negotiation rounds, and minimum acceptable prices. Product demand and purchase quantity are also considered to personalize negotiation outcomes. A hybrid NLP module combines rule-based keyword matching with transformer-based intent classification to identify customer negotiation intents. Based on the detected intent and customer profile, a polynomial concession model generates adaptive counter-offers, while a template-based response generation module delivers clear and consistent negotiation responses. Experimental results demonstrate that the proposed framework effectively integrates customer segmentation, intelligent intent detection, and adaptive negotiation strategies to improve customer engagement while maintaining seller profitability in e-commerce platforms.
Keywords: E-commerce, Price Negotiation Chatbot, Customer Segmentation, K-Means Clustering, Dynamic Pricing, Natural Language Processing (NLP), Intent Detection, Transformer Models, Automated Negotiation, Machine Learning.

I. INTRODUCTION

The rapid growth of e-commerce has transformed the retail industry by providing customers with convenient access to products, secure digital payments, and personalized shopping experiences. Despite these advancements, most online shopping platforms continue to rely on fixed pricing mechanisms.

Unlike traditional marketplaces, where bargaining enables buyers and sellers to negotiate mutually beneficial prices, online platforms generally do not provide customers with opportunities for personalized price negotiation. This limitation reduces customer engagement and restricts pricing flexibility during online purchases.

To address this challenge, this paper proposes IntelliBargainBot, an AI-driven price negotiation system for e-commerce platforms. The proposed system integrates machine learning, natural language processing, and automated negotiation techniques to facilitate personalized bargaining based on customer purchasing behavior and negotiation intent. By combining customer segmentation with intelligent conversational negotiation, the system aims to improve customer engagement while maintaining business profitability.

A. Problem Statement

Most existing e-commerce platforms use fixed-price selling mechanisms that do not support personalized price negotiation. Current pricing strategies generally ignore customer purchasing behavior, loyalty, negotiation history, and product demand while determining offers. Consequently, customers cannot experience the flexible bargaining process commonly available in traditional marketplaces.

Therefore, there is a need for an intelligent negotiation system capable of analyzing customer behavior, understanding negotiation intent, and generating adaptive counter-offers while ensuring business profitability.

B. Objective

The objectives of the proposed work are:

1) To analyze customer purchasing behavior using RFM and behavioral features.
2) To segment customers using the K-Means clustering algorithm.
3) To identify customer negotiation intent using a hybrid NLP-based intent detection approach.
4) To generate personalized counter-offers based on customer segment, product demand, and purchase quantity.
5) To improve customer engagement while maintaining seller profitability through intelligent automated negotiation.

II. LITERATURE REVIEW

An intelligent conversational agent for automated price negotiation in e-commerce platforms was proposed in **[1]**. The system integrates ensemble machine learning and Natural Language Processing (NLP) techniques to interpret customer requests and generate appropriate negotiation responses.

By supporting interactive bargaining, the chatbot assists users during purchasing decisions and provides discount recommendations through an automated negotiation process.

A chatbot-based negotiation framework for e-commerce platforms was presented in **[2]** to automate bargaining between buyers and sellers. The proposed system employs Natural Language Processing (NLP), intent classification, dialogue management, and negotiation logic to understand customer requests and generate suitable negotiation responses. By enabling conversational price negotiation, the system improves customer engagement and enhances the online shopping experience.

A machine learning-based price negotiation chatbot for e-commerce platforms was introduced in **[3]**. The proposed architecture combines Natural Language Processing, historical price prediction, negotiation algorithms, and session management to support personalized bargaining. In addition, the chatbot supports both text and voice interactions, providing a more interactive shopping experience while enabling dynamic pricing through intelligent negotiation.

The work presented in **[4]** investigates the impact of lexical alignment on price negotiation chatbots. The proposed bargaining chatbot incorporates intent detection, product and price extraction, dialogue management, and response generation to improve conversational quality during negotiations. Experimental results indicate that adapting the chatbot's language to users enhances user engagement, trustworthiness, and the overall bargaining experience.

A Smart Bargain Bot for e-commerce platforms was proposed in **[5]** to support both text- and voice-based price negotiation. The system combines Natural Language Processing, price prediction techniques, and rule-based negotiation strategies to simulate real-world bargaining scenarios. Customers can negotiate prices through conversational interactions, receive adaptive counteroffers, and complete purchases while maintaining seller profitability and improving customer engagement.

III. PROPOSED METHODOLOGY

A. System Architecture

The proposed IntelliBargainBot system architecture illustrates the interaction among the frontend, backend, and data layers to enable intelligent price negotiation in an e-commerce environment. The architecture integrates machine learning, hybrid Natural Language Processing (NLP), negotiation policy generation, and adaptive counter-offer mechanisms to provide personalized bargaining experiences. Customers can browse products and add them to the shopping cart through the e-commerce website. For eligible products, the BargainBot chat interface is enabled, allowing customers to initiate the negotiation process. Customer requests are processed by the Flask backend, where customer and product information are retrieved from the database. The backend predicts the customer segment using the trained K-Means model, detects the customer's negotiation intent through the hybrid NLP module, applies rule-based negotiation policies based on customer behavior and product characteristics, and generates adaptive counter-offers using the polynomial concession model. Finally, the template-based response generation module delivers personalized negotiation responses to the customer through the BargainBot interface. The proposed system is implemented using a React.js-based frontend, a Flask backend API, and Python-based machine learning and NLP modules to support real-time customer segmentation and intelligent price negotiation.

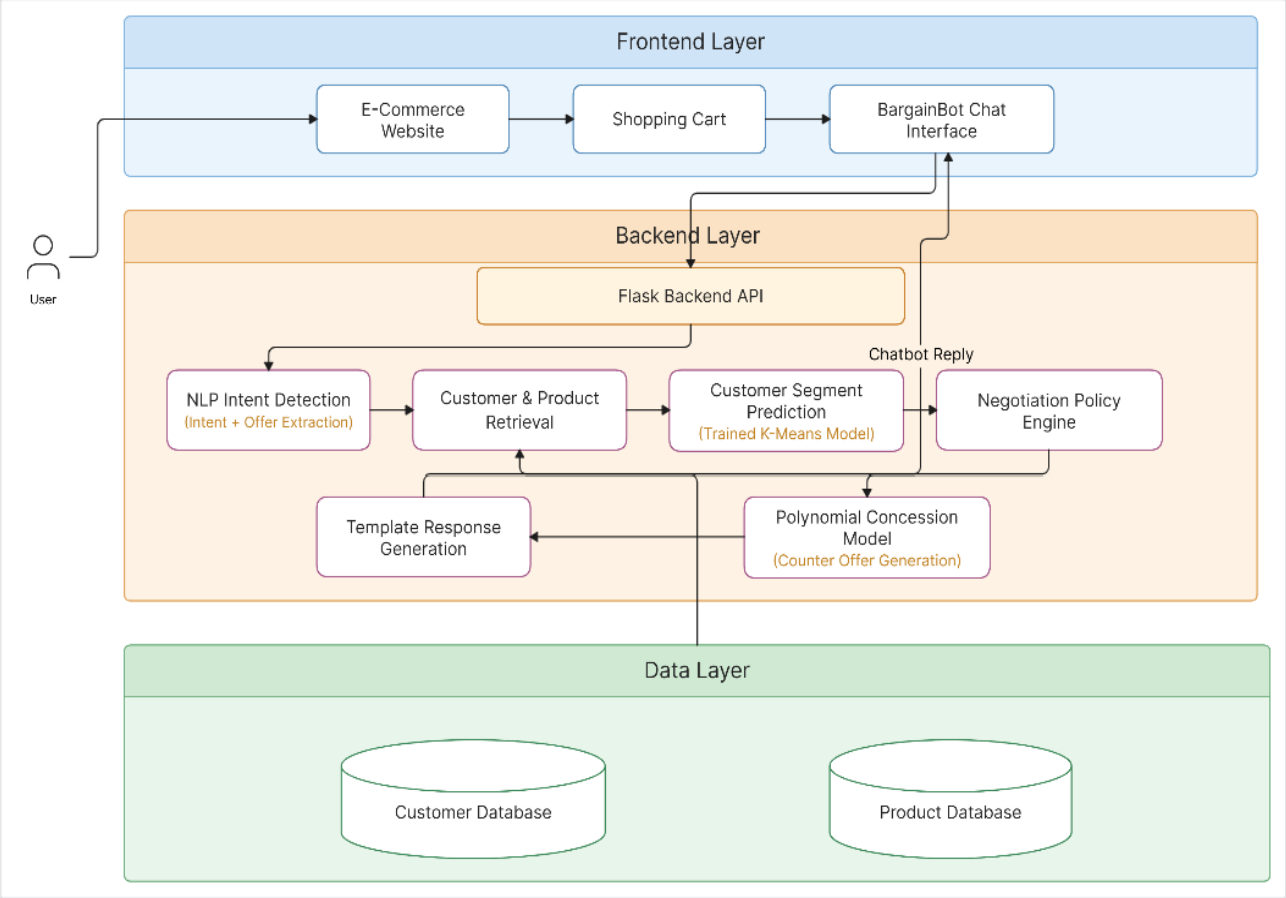

Fig. 1. Architecture of IntelliBargainBot

B. Customer Segmentation

Customer segmentation is performed to categorize customers based on their purchasing behavior using the online retail transaction dataset. The segmentation model is developed through a sequence of data preparation, feature engineering, and K-Means clustering steps, as illustrated in Figure 2.

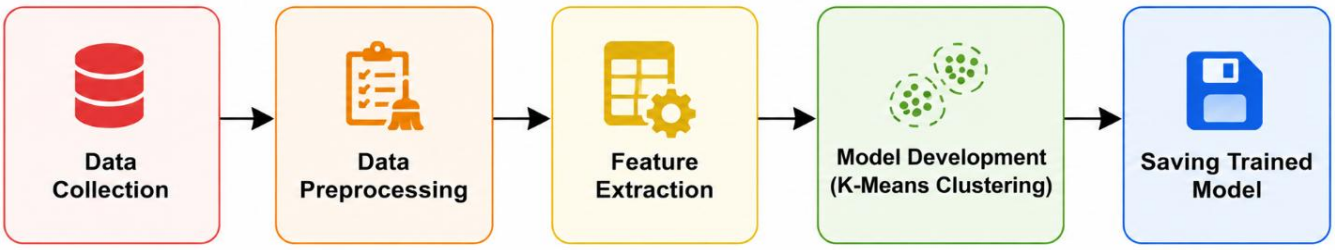

Fig. 2. Customer Segmentation Model Training Workflow

1) *Data Collection:* Customer transaction records were collected from the Online Retail dataset. The dataset contains customer purchase information, including invoice details, product descriptions, quantities, prices, transaction dates, and customer identifiers. These records provide the foundation for analyzing purchasing behavior and developing customer segments.
2) *Data Preprocessing:* During preprocessing, incomplete records, duplicate transactions, and invalid entries were removed to improve data quality. The dataset was then transformed into a structured format suitable for feature extraction and clustering.
3) *Feature Extraction:* Transaction-level data is transformed into customer-level data by computing Recency, Frequency, and Monetary (RFM) metrics along with additional behavioral characteristics. These features effectively represent customer purchasing behavior and serve as inputs to the K-Means clustering model.
4) *Model Development:* The extracted customer features are used to train the K-Means clustering algorithm. The model clusters customers with similar purchasing patterns into meaningful segments, namely New**,** Regular**,** and Loyal customers. These customer segments are subsequently utilized to generate personalized negotiation strategies during the bargaining process.
5) *Customer Segment Prediction:* After training, the K-Means model is saved and integrated into the proposed negotiation system. During online negotiation, customer information is retrieved from the customer database and provided to the saved K-Means model to predict the customer's segment.

C. Hybrid NLP-Based Intent Detection

The Hybrid NLP-Based Intent Detection module is responsible for understanding customer negotiation messages and identifying user intentions during the bargaining process. The proposed approach combines rule-based keyword matching with a transformer-based intent classification model to improve the accuracy and reliability of intent recognition. Initially, customer messages are analyzed using predefined keywords associated with common negotiation actions such as offer submission, acceptance, and rejection. If the intent cannot be confidently determined through keyword matching, the FalconsAI transformer-based intent classification model is utilized to analyze the semantic meaning of the message and identify the most appropriate intent category. In addition to intent detection, regular expression-based pattern matching is employed to extract the customer's offered price from the negotiation message. The detected intent and extracted offer value are then forwarded to the negotiation engine for further processing.

D. Negotiation Policy Engine

The Rule-Based Negotiation Policy Engine determines personalized negotiation strategies using predefined business rules. The negotiation policy is generated based on the predicted customer segment, product demand tier, and purchase quantity. Different negotiation parameters are assigned for New, Regular, and Loyal customers to provide personalized bargaining experiences while maintaining business profitability. The policy defines the maximum discount, minimum acceptable price, concession pace, and maximum number of negotiation rounds. In addition, quantity-based adjustments are incorporated to provide suitable discounts for bulk purchases. The generated negotiation policy serves as the basis for the Polynomial Concession Model to compute adaptive counter-offers.

E. Polynomial Concession Model

The Polynomial Concession Model is employed to generate adaptive counter-offers throughout the negotiation process. The model gradually adjusts the offered price according to the current negotiation round while ensuring that the generated counter-offer does not fall below the predefined minimum acceptable price. The concession behavior is controlled by a concession pace parameter, allowing the system to simulate realistic bargaining strategies. Furthermore, customer-offered prices are incorporated into the concession calculation, enabling the system to generate more personalized and engaging counter-offers while maintaining predefined pricing constraints.

F. Template-Based Response Generation

The Template-Based Response Generation module produces natural and consistent chatbot responses based on the negotiation outcome. Depending on the detected customer intent and the generated counter-offer, the system returns appropriate responses such as counter-offers, offer acceptance, rejection, final offers, clarification requests, or bulk purchase negotiations. Predefined response templates ensure conversational consistency while enabling efficient real-time interaction between the customer and the IntelliBargainBot system.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Evaluation Metrics

1) *Elbow Method (Inertia):* The Elbow Method was employed to determine the optimal number of customer clusters. The inertia value decreases as the number of clusters increases, and the elbow point indicates an appropriate balance between model complexity and cluster compactness.

$$Inertia = \sum_{i=n}^{n} | |x_i - c_i||^2$$

2) *Silhouette Score:* The Silhouette Score evaluates the quality of clustering by comparing a data point's fit within its assigned cluster to that of neighbouring clusters. Higher numbers on the -1 to 1 scale indicate better clustering quality and cluster separation.

$$s(i) = \frac{\{b(i) - a(i)\}}{\{max(a(i), b(i))\}}$$

B. Performance Analysis

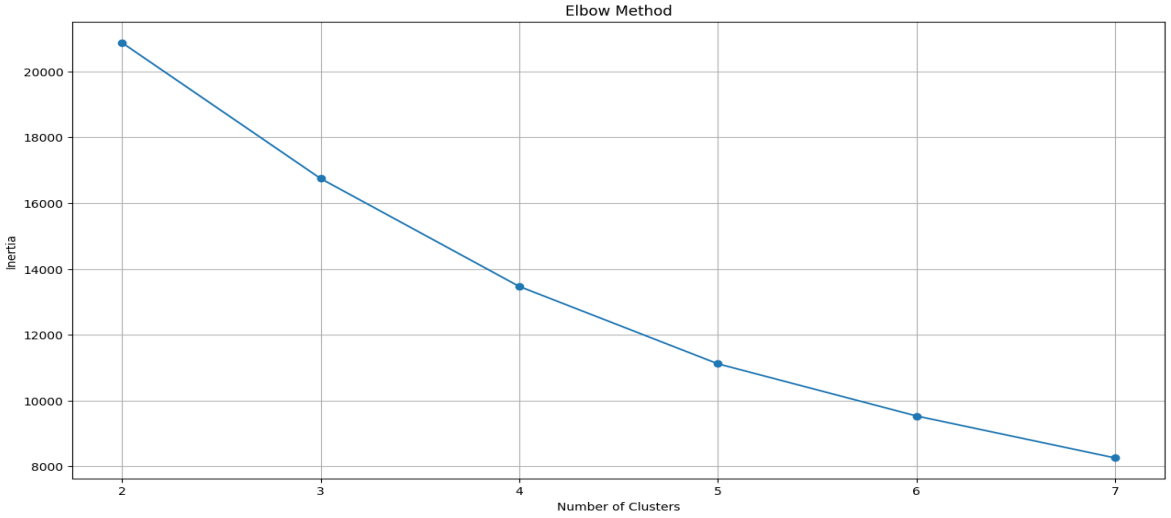

Fig. 3. Elbow Method Analysis for Optimal Cluster Selection

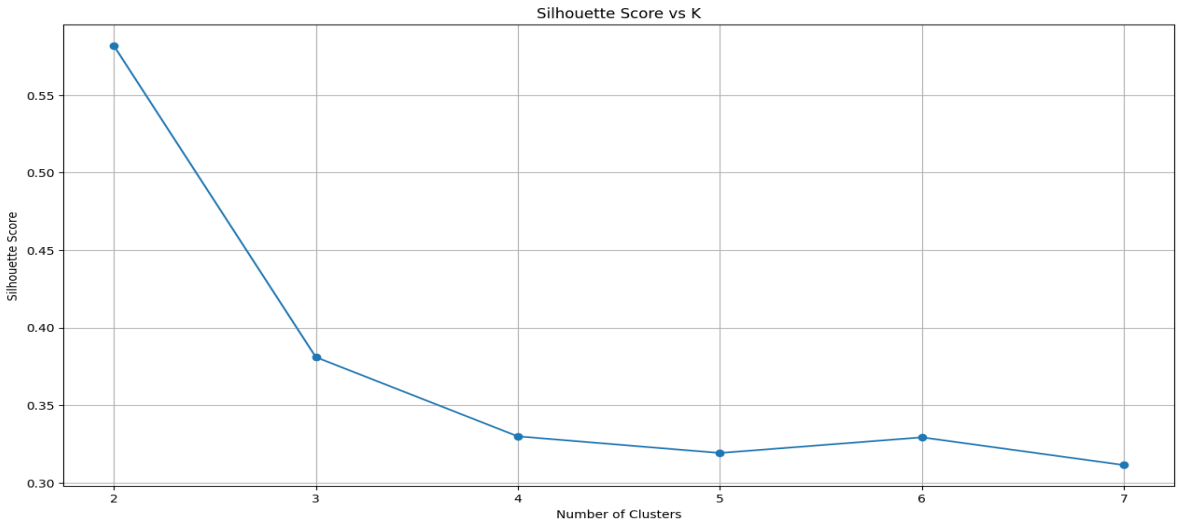

Fig. 4. Silhouette Score Evaluation Across Different Cluster Sizes

K	INERTIA	SILHOUETTE SCORE
2	20877.26	0.5819
3	16749.45	0.3809
4	13471.16	0.3298
5	11121.22	0.3191
6	9536.10	0.3292
7	8261.15	0.3113

Table 1: K-Means Clustering Evaluation Results

The inertia values decrease as the number of clusters increases, while the Elbow Method indicates that the reduction begins to stabilize after K=3, suggesting an appropriate balance between cluster compactness and model complexity. Although the highest Silhouette Score was observed at K=2, K=3 was selected because it provides three meaningful customer segments (New, Regular, and Loyal) that better support personalized negotiation strategies.

C. Customer Segmentation Visualization

1) Feature Correlation Analysis: The correlations between the customer behavioural characteristics utilised in segmentation are depicted in the correlation heatmap. While other indicators show varied degrees of positive and negative associations, there are strong positive correlations between total orders and total spending.

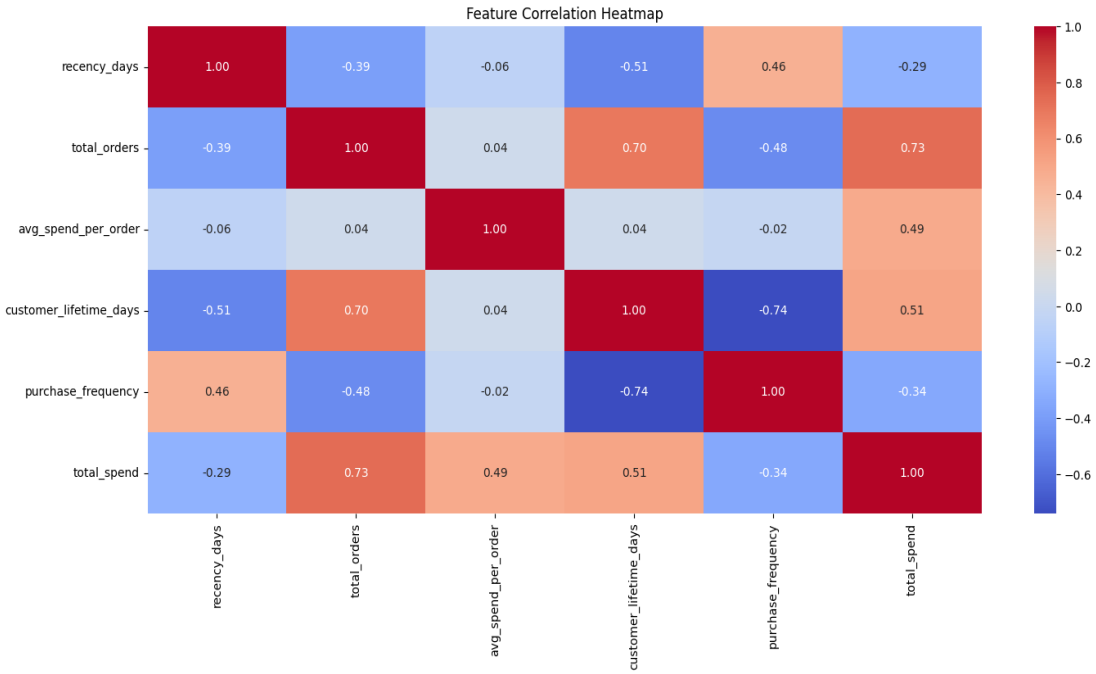

Fig. 5. Feature Correlation Heatmap

2) PCA-Based Cluster Visualization: PCA was used to project the multi-dimensional customer feature space into two dimensions for visualisation purposes. The scatter plot offers a visual depiction of the clustering result and shows how the K-Means clustering technique separates consumer categories.

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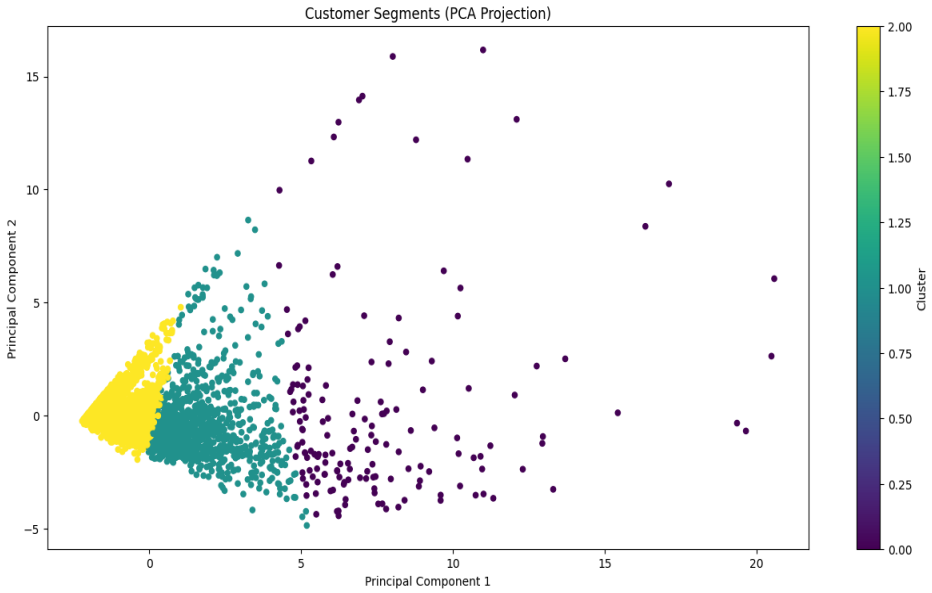

Fig. 6. PCA-Based Visualization of Customer Segments

D. System Demonstration

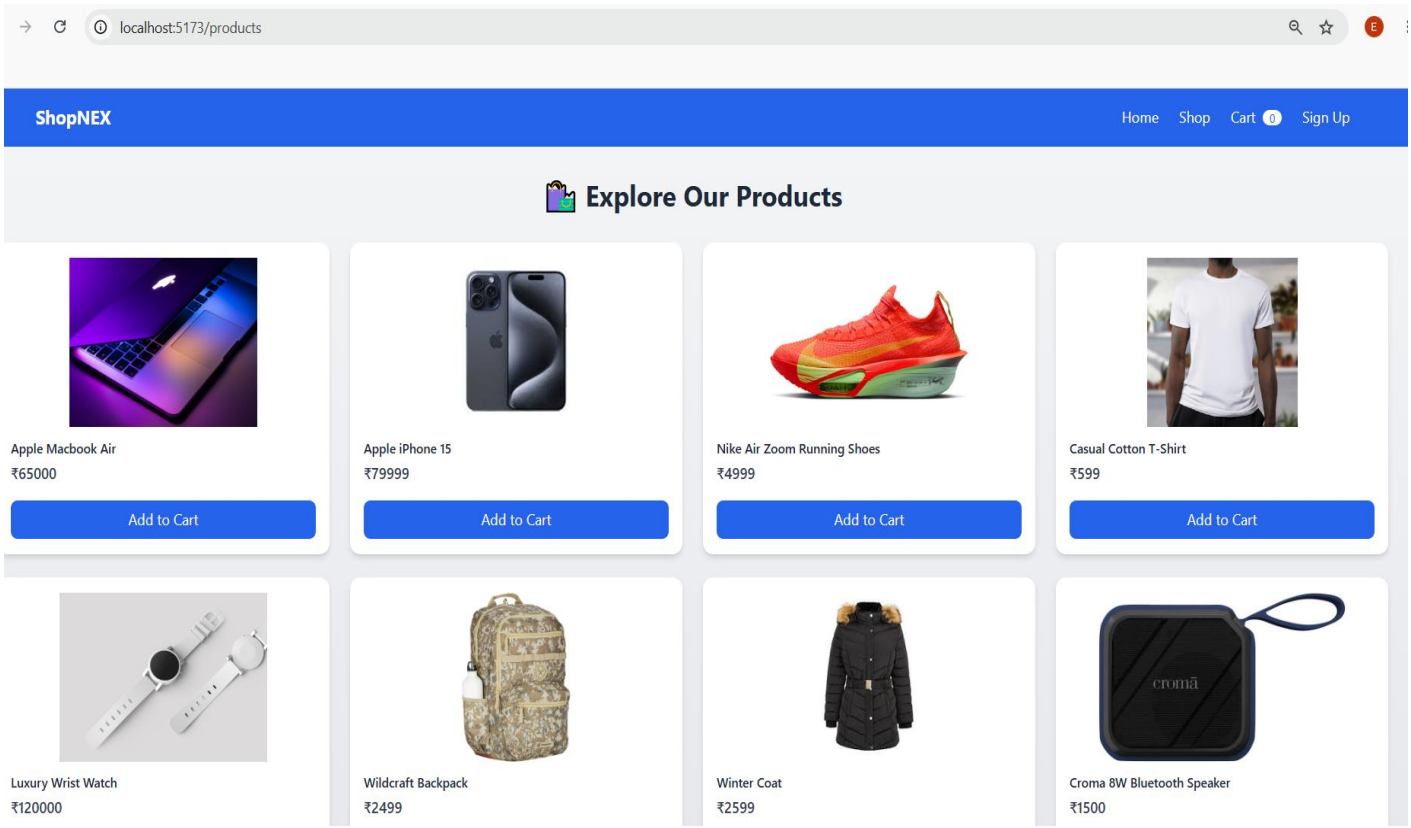

Fig. 7. Products Browsing Page

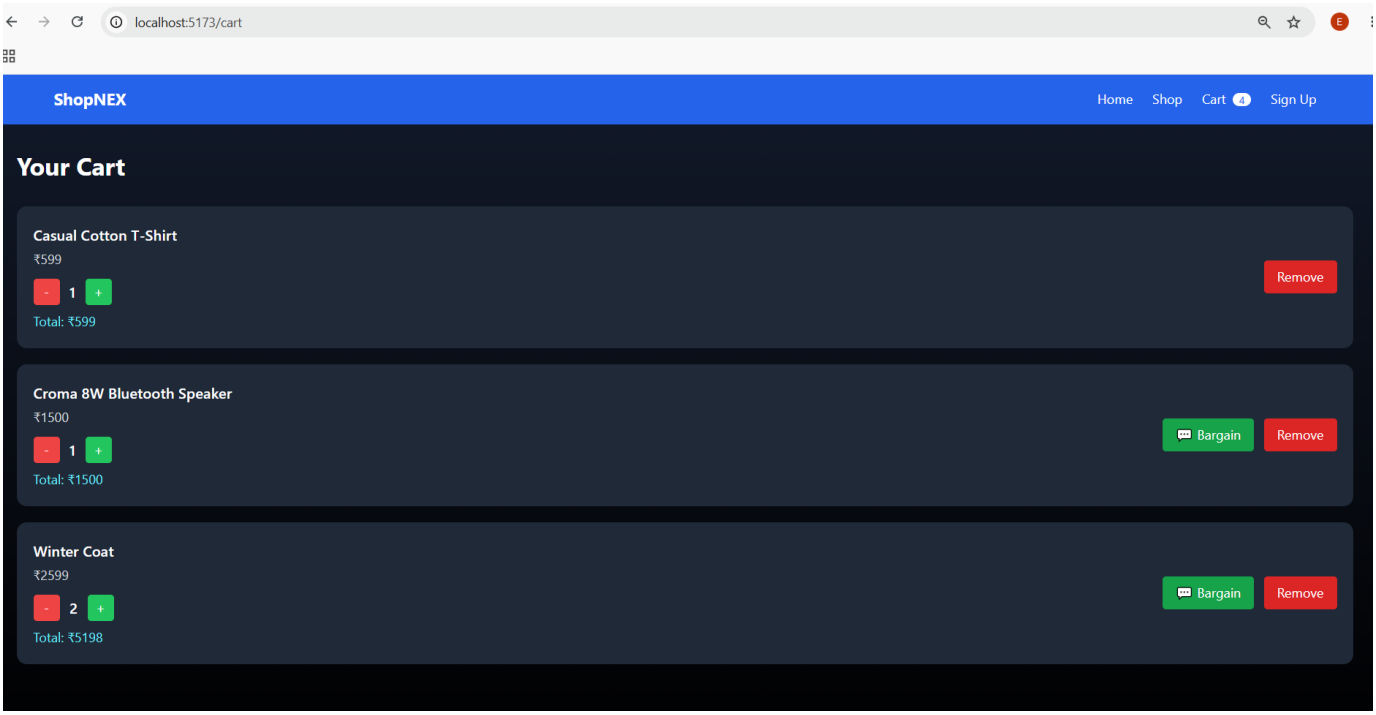

Fig. 8. Shopping Cart

The BargainBot interface becomes available for eligible products after they are added to the shopping cart, allowing customers to initiate the negotiation process.

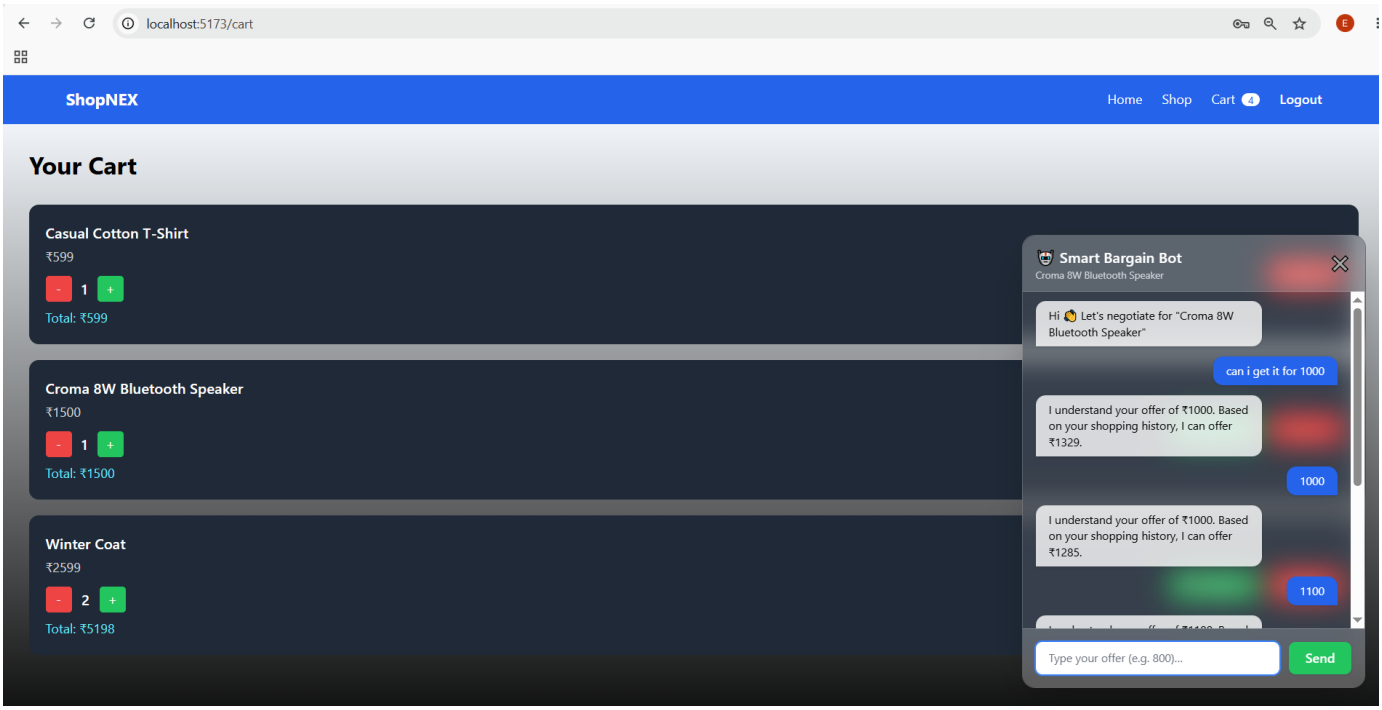

Fig. 9. BargainBot Negotiation Interface

The BargainBot analyzes the customer's negotiation request, predicts the customer segment, and generates personalized counter-offers based on the negotiation policy.

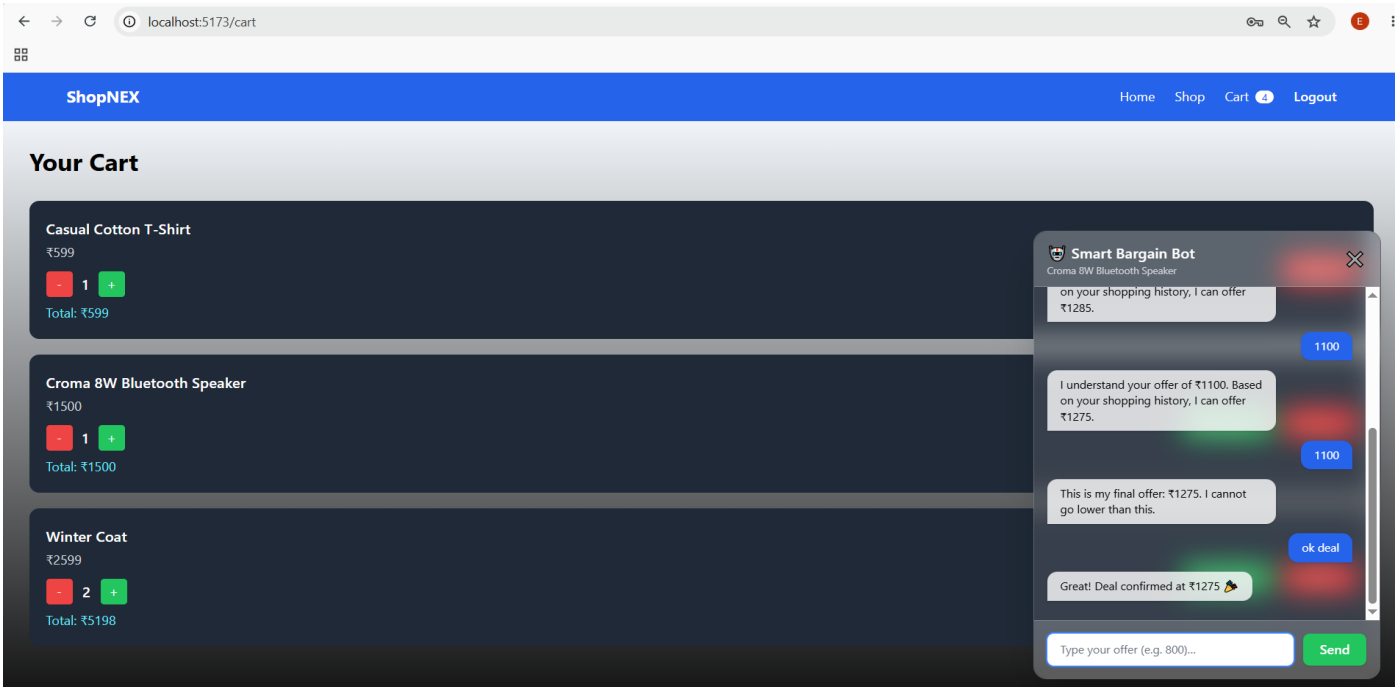

Fig. 10. Final Negotiation Outcome

The final negotiated price is displayed after the bargaining process, demonstrating successful completion of the personalized negotiation.

V. CONCLUSION

This paper presented IntelliBargainBot, an intelligent price negotiation system that enables personalized bargaining in e-commerce platforms. Experimental results demonstrated that the proposed framework effectively supports customer-specific negotiation strategies, resulting in flexible and personalized pricing while maintaining predefined business constraints. The integration of customer segmentation and intelligent negotiation mechanisms improves customer engagement, enhances the online shopping experience, and supports fair pricing decisions. Overall, the proposed system provides an effective solution for incorporating automated price negotiation into modern e-commerce platforms while balancing customer satisfaction and business profitability.

VI. ACKNOWLEDGEMENT

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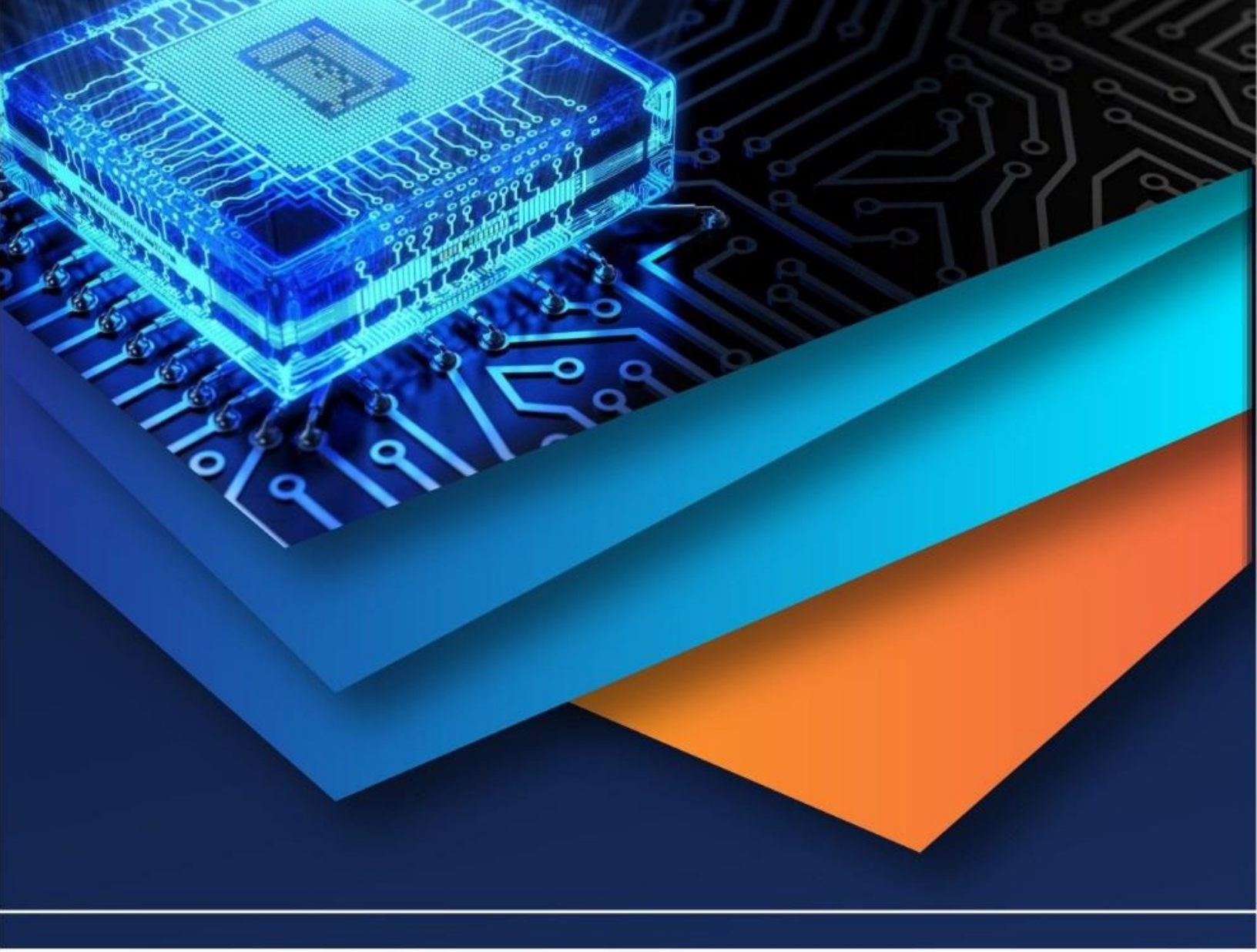

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