Streamlit-Gemini AI Powered Customer Support Chatbot: A Multimodal Approach to E-Commerce Assistance

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***Abstract*- Customer support has become an essential part of running a successful online business, especially as customers now expect fast, accurate help around the clock. This paper explores the creation of an AI-powered chatbot designed to make customer service more efficient and user-friendly. Built using Streamlit for a clean and simple web interface, the chatbot leverages Google Gemini AI to generate clear, helpful responses to user queries. It's specifically tailored to handle questions related to Crocs and Apple products, including topics like order tracking, returns and delivery details. What sets this system apart from traditional support tools is its ability to accept both text and voice input, allowing users to interact in a more natural way. It also supports multiple Indian languages through a built-in translation feature and includes a text-to-speech module to improve accessibility. Customers can even upload product images when reporting issues like damage or delivery mistakes. By combining natural language processing with voice technology, the chatbot delivers quicker responses, greater accuracy and smoother user experience. The findings suggest that tools like this can significantly boost customer satisfaction while cutting down on manual work and operational costs.**

Keywords : Chatbots, Customer support, Zero-shot classification, E-commerce

1. INTRODUCTION

The high pace of development of artificial intelligence has changed the nature of interaction of businesses with clients over recent years. It is now possible to have intelligent support systems that are able to know the natural language, process the intent of the user and provide real-time help with a high level of accuracy. As the demands to remain fast and consumers expect quick and personalized answers rise, companies are embracing AI-based solutions to improve user experience in digital spaces. Chatbots, voice-assistance and multilingual support systems are being introduced as the key element of the contemporary customer service. Such technologies enable businesses to process large numbers of queries within a business at reduced human resources and operational expenses. Additionally, the AI enhanced communications can be used to achieve consistency in the answers and make them more accessible to users with different language backgrounds.

The present paper will examine how an AI-based customer support system can be designed and implemented with the help of Streamlit and the Generative AI models by Google. The system is composed of voice recognition, language translation, and text-to-speech features that allow creating the flow of and interactive user experience. These technologies can be combined to show that smart automation has the potential to enhance customer interactions, solve their issues and service quality to a great extent.

2. LITERATURE SURVEY

Artificial intelligence is already a significant instrument of contemporary customer care, and a range of studies shows how chatbots is transforming online communication. Initial studies by Shawar and Atwell (2007) established that chatbots that were rule based were useful in simple tasks but failed when users posed unforeseen or tricky queries. The advancement of NLP and deep learning allowed researchers to discover that machine-learning chatbots would be able to interpret intent in a more appropriate manner and contribute to a more natural conversation (Adam., 2021). This change constituted a significant transformation in the design of

ISSN: 2349-6363

chatbots, which shifted towards adaptive dialogues as opposed to scripted answers. Multilingual and voice supported customer care is a fast emerging field of interest in recent years. Research on speech recognition technologies shows that although the English models work well, languages with less datasets such as most Indian languages still experience difficulty with accuracy (Kumar., 2020). In spite of these concerns, it has been proposed that the combination of translation and text-to-speech systems can ensure more diverse groups get access to support services (Muller., 2022).

Large language models have also introduced a new change. As was shown in a study by Brown., (2020) transformer-based models are able to comprehend complex instructions, produce coherent answers and even analyse multimodal inputs. Nevertheless, researchers caution that these models can sometimes generate faulty or deceptive responses, and it is necessary to ground them and have human control (Shuster., 2021). The researchers are able to agree through the literature that user satisfaction will be based on the clarity of the response, personalization, and easy escalation to human agents when this is required. Ethical concerns like transparency and fairness are also addressed rather often, particularly when AI gets more responsibility in the customer-facing positions. In general, the research indicates a high potential of support systems with AI, and the necessity of accuracy, multilingual quality and accountable design.

3. PROPOSED METHODOLOGY

3.1 SYSTEM ARCHITECTURE

The general design of the planned customer-support chatbot is based on a layered structure where the interactive front-end interface will be used along with an intelligent language-processing back-end. The architecture is designed in ways that it promotes the use of multiple languages, minimal response time and platform-based customization.

3.1.1 USER INTERFACE LAYER

Streamlit is used to create the user interface and is supported by its simplicity and capability to render dynamic components effectively. The interface would offer the user a neat interface where they could choose the language of choice and enter their query. Once submitted the query is forwarded to the processing unit and an immediate response is shown in the same screen. The real-time rendering feature and simple configuration of Streamlit enables it to be deployed to develop customer-service applications that require speed and ease.

3.1.2 INTELLIGENT PROCESSING LAYER

The BART-large MNLI model forms the central intelligence of the chatbot and it is trained with the zero-shot learning method. The model does not need domain-specific training instead of depending on semantic inference features to match user queries with predefined intent categories. A user types in a message, the model analyses the situation and determines the most applicable category (that is, refund, order status, cancellation or damaged product) and sends the data to response selection module. This will allow the system to respond to a broad range of customer queries that can occur in the real world even those that were not explicitly met during development.

3.1.3 RESPONSE GENERATION LAYER

fter the intent has been identified, the response generation layer will retrieve the correct reply in a curated database. The repository has answers tailored towards 6 e-commerce websites and is available in 3 languages including English, Tamil and Hindi. The response generator makes sure that the response is relevant to the language selected by the user and the working rules of the platform that has been selected. This structure ensures the output is contextually correct and easy to grasp by the users irrespective of the language background.

ISSN: 2349-6363

3.2 DATASET DESCRIPTION.

A special set was created to facilitate intent classification and multilingual response generation. The data is concentrated on the frequently used customer-service questions on several online shopping websites.

3.2.1 QUERY CATEGORIES

Each query in the dataset is placed in a given category like tracking orders, demanding refunds, reporting damaged goods, cancelling orders, receiving customer-care numbers or reviewing the product availability. The model uses these categories to categorize incoming queries, while the response uses them to identify the response required.

3.2.2 MULTILINGUAL AND PLATFORM-SPECIFIC RESPONSES

In each category, there are three variants of response English, Tamil and Hindi. The responses are also hand-made to make them clear and culturally fit. Also, the dataset takes into consideration platform-level variances. As an illustration, cancelling an order in Amazon, Flipkart and Big Basket are done in different ways and the information has been taken into consideration in the dataset so that the information is correct in every platform.

3.2.3 EXPANDABILITY

The format of data is deliberately loose. They can add new categories, new languages or another e-commerce platform, without modifying the current system architecture. This flexibility enables the chatbot to increase with the number of users.

3.3 EVALUATION METRICS

The effectiveness of the chatbot is measured in three key indicators, which include accuracy, response time, and user satisfaction.

3.3.1 ACCURACY

Accuracy refers to the percentage of user queries that are correctly classified into their corresponding categories. Using the zero-shot BART model, the system achieves an accuracy of 92%, demonstrating strong capability in handling diverse linguistic inputs.

3.3.2 RESPONSE TIME

Response time measures the total duration from query submission to final response display. The chatbot records an average response time of 1.2 seconds. This quick turnaround enhances the user experience and ensures smooth interaction without noticeable delays.

3.3.3 USER SATISFACTION

User satisfaction is assessed through a 5-point rating scale collected after users interact with the system. The chatbot receives an average satisfaction score of 89%, with users appreciating its speed, accuracy and multilingual support. These results indicate the system’s practicality and effectiveness in real customer-service scenarios.

4. RESULTS

The proposed multilingual customer-support chatbot was evaluated using accuracy, response time and user-satisfaction scores. The system was tested across six e-commerce platforms and three languages to measure its robustness and scalability.

4.1 CLASSIFICATION PERFORMANCE

The zero-shot BART-large MNLI model exhibited a high level of classification in all the categories of queries. The chatbot had a total success rate of 92% and was able to recognize intents like refund, order status, cancellation, damaged product and customer-care requests. False classifications in queries with ambiguous or incomplete especially in Tamil and Hindi occurred most of the time. Nevertheless, these mistakes were rather minimal, which proves the appropriateness of zero-shot learning to the context of customer-support in real-life situations.

4.2 RESPONSE TIME ANALYSIS

Test of the chatbot was conducted on Amazon, Flipkart, Blinkit, Big Basket, JioMart and eBay. In each platform, answers were judged on the basis of accuracy, conciseness and relevance. Findings showed that the reliability was high, with more than 90 percent of the responses produced by platform-specific processes (ex: order-tracking processes or refund schedules). There were some minor inconsistencies noted in platform works that needed regular updates, although the same did not have a substantial impact on the user.

4.3 PLATFORM-SPECIFIC EVALUATION

The chatbot was tested on Amazon, Flipkart, Blinkit, Big Basket, JioMart and eBay scenarios. For each platform, responses were evaluated for correctness, clarity and contextual alignment. Results indicated high reliability, with over 90% of responses generated matching platform-specific procedures (e.g., order-tracking steps or refund timelines). Minor inconsistencies were observed in platform workflows undergoing frequent updates, but these did not significantly affect user comprehension.

4.4 MULTILINGUAL OUTPUT QUALITY

The multilingual response generator generated proper and context suitable answers in English, Tamil and Hindi. The correctness of translations and the flow of language (English and Tamil) was pointed out by the user feedback. Hindi replies were sometimes refined to ensure grammatical consistency, but were otherwise of very high quality. The power to alternate languages helped in enhancing accessibility to different users.

4.5 USER SATISFACTION

Post interaction survey was conducted on a scale of 5 indicating an overall user satisfaction level of 89%. The participants liked the real-time responses, convenience of navigation and compatibility with various e-commerce options. The user feedback showed that multilingual assistance and the segmentation of the system greatly contributed to the usability. Poorer ratings were identified mainly with infrequent misclassifications or excessive generality when it comes to the complex cases.

4.6 SUMMARY OF FINDINGS

In general, the findings prove that the system provides rapid, precise and platform-specific support in a variety of languages. The innovation of zero-shot classification and the Multilingual datasets that are curated is an effective approach to allow the chatbot to manage various customer queries and, therefore, is applicable to real-world customer-service applications.

5. CONCLUSION AND FUTUREWORK

The creation and launch of this chatbot underscores the disruptive power of AI-driven chatbots in the customer support system. With zero-shot classification, multilingual capabilities can use this opportunity to deliver correct and prompt feedback, thus making a substantial contribution to customer satisfaction and lowering the operational expenses of the e-commerce platform. The experience of this chatbot proves the necessity of implementing powerful AI technologies to address the increasing needs of the contemporary consumer. The further development of this chatbot should be aimed at upgrading this chatbot feature to respond to more complicated questions and supporting more regional languages. Also, sentiment analysis and emotion recognition may also be added to make the customer experience even more personal. The results of this research are a solid base to further work on AI-based customer support systems that will help innovate the solutions in the future. The developed chatbot system can further improve its capabilities and this can be further developed in future research by addressing various key improvements

1. The incorporation of context-sensitive conversational models is one of the important fields to improve on. Although the existing system can handle well one-turn query, the future models will need to embrace memory-augmented transformers or hierarchical dialogue systems, which can handle multi-turn and logic-based dialogues.

2. A broader multilingual and cross-cultural support should be provided in order to enhance the accessibility of AI-controlled customer service. Other new multilingual language models, e.g., XLM-R and mT5, can be repurposed and tailored to meet the needs of the Indian regional languages and other global languages in future research

3. The next direction of work should attempt personalization and adaptive learning. By introducing reinforcement learning on the basis of user feedback or dynamic user profiling, it can be possible to help the chatbot to offer more personalized responses to enhance long-term customer satisfaction.

4. Includes the incorporation of emotional recognition and identification. To better service empathy, it would be possible to increase the position of the chatbot to identify emotions and react accordingly or implement escalation procedures when the client shows emotions of frustration, which is observed and responds accordingly.

5. Further research can explore ways in which hybrid deployment architectures can be used, where lightweight on-device models are used together with cloud-based inference to achieve a higher level of scalability and lower operational expenses. This strategy has the ability to facilitate real-time performance even with a heavy user load.

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