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Virtual Sales Assistant: A Chrome Extension for E-commerce Websites

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***Abstract*—The research presents an innovative browser extension that serves as a virtual sales assistant for shoppers across e-commerce platforms. Designed to foster trust and enhance the online shopping experience, this extension enables detailed product inquiries and provides immediate access to compre- hensive specifications, empowering customers to make informed purchasing decisions. By seamlessly integrating with browsing sessions and leveraging natural language processing techniques, the virtual assistant generates accurate and informative responses to product-related queries, positioning e-commerce platforms as authoritative and responsive sources. Beyond functional capa- bilities, the extension aims to transform user engagement by acting as a personalized guide, akin to an in-store represen- tative, thereby heightening satisfaction through tailored service and fostering deeper customer relationships. The research is motivated by factors such as increasing customer engagement, providing round-the-clock support, facilitating product differenti- ation and comparison, harnessing machine learning for enhanced experiences, building trust through expert guidance, ensuring unique integration with e-commerce platforms, iterating through feedback loops for continuous improvement, and supporting small businesses in enhancing customer interactions.**

***Index Terms*—Virtual Sales Assistant, E-commerce, Browser Extension, Customer Engagement, Natural Language Processing, Product Information**

I. Background

In today's era of widespread online shopping, providing real-time assistance to address customer queries about prod- ucts is crucial for building trust and confidence in e-commerce transactions. The lack of immediate support often leads to frustration and uncertainty among shoppers, negatively impacting their trust in the buying process. To address this issue, your project proposes a groundbreaking solution: a browser extension designed to function as a personalized virtual assistant for shoppers on e-commerce platforms. The research aims to enhance trust by facilitating detailed product queries through the extension, empowering shoppers with instant access to comprehensive product specifications, thereby boosting their confidence in making informed purchasing decisions. The virtual assistant seamlessly integrates into the browsing session and leverages advanced natural language processing capabilities to interpret product-related questions and provide accurate, insightful answers. This functionality not only aids shopper in making informed decisions but also positions e-commerce platforms as authoritative and responsive sources of information. The project envisions the extension revolutionizing the online shopping experience by serving as a personalized guide through vast product inventories, replicating the assistance one would receive from an in-store representative. The result is heightened customer satisfaction through tailored service, leading to stronger customer relationships and improved conversion rates for retailers. Ultimately, the project aims to bridge the gap between customers and e-commerce platforms, fostering trust, enhancing satisfaction, and driving growth for retailers in the digital marketplace by providing a seamless and informative shopping experience through the virtual sales assistant.

II. Motivation

The virtual sales assistant Chrome extension endeavors to accelerate customers' confidence and delivers instantaneous product details, while simultaneously aiming to:

A. Increase customer engagement

The Chrome extension enhances the digital shopping journey by fostering active customer engagement. Seamlessly integrating with e-commerce platforms, it facilitates dynamic interactions that transcend passive browsing. A standout feature is the live chat capability, enabling shoppers to communicate in real-time with a virtual assistant.

This chat function empowers users to instantly access assistance, pose inquiries, and receive personalized guidance throughout their shopping experience. Leveraging advanced natural language processing, the virtual assitant comprehends queries and responds with contextually relevant information, replicating the experience of an in-store sales representative.

Moreover, the extension analyzes user data and browsing patterns to tailor product recommendations to each individual's preferences and interests. By presenting relevant suggestions, it actively draws shoppers in, guiding them toward appealing items.This approach streamlines the process while fostering a sense of being understood as a customer.

B. Round the clock support and care

As explained, even in the universe of digital e-commerce has a clear advantage compared to its brick-and-mortar counterparts because it can sell and provide services 24/7 by eliminating time boundaries. But the benefit quickly becomes a liability when users lack real-time help and left to drift in a sea of solitude – especially at the quieter, off-hours times. Dropping in to fill this gap is the virtual sales assistant that comes as a Chrome extension, and stays with you along your online shopping journey–answering queries tirelessly day or night. Unlike its human counterparts, who are constrained by operational hours and shifts — virtual customer reps operate non-stop to enable shoppers with product information, advice or support round-the-clock. With an assurance that all queries will be handled right away if they arise, the availability in turn showcases e-commerce, builds confidence and trust within customers looking to complete a seamless shopping journey. In addition, the 24/7 support of this extension is not only about product details but also directs from browse and compare stages to purchase stage with all purchasing processes and even further regarding inquiries after-purchase as well. This complete approach supports customers at every point in their journey, reducing potential frustrations and uncertainties that often crop up outside of hours when traditional support channels are not operational. it is a reassuring constant for the customer, which helps in taking away his anxiety — it uplifts the online shopping experience and builds the immunity of empowerment & trust with which not all products around time earlier used to be caged into, after decades of limitations that plagued digital realm.

C. Enable product differentiation and comparison

Enter the ever-expanding world of e-commerce, a place where millions of products battle to be no- ticed and one thing becomes extremely important: the in-capacity to stand-out-to-differentiate-properly-guide-the- customer-through-a-purchase. This is where the Virtual Sales Assistant Chrome extension comes in as a possible solution by offering an intelligent way and easy-to-go method for product differentiation and comparison. This extension allows for full access to any product catalog with complete specifications, and supporting details that has been integrated with an e-commerce platform. Leveraging some of the latest and greatest in natural language processing technology, as well as a slew machine learning techniques, this AI boasts the ability to unravel incredibly granular attributes around product information often easily gliding over areas that differentiate products from one another. Upon expressing interest in a particular product or category, the few virtual assistant produces alternatives and provide brief comparisons. These comparisons go beyond just the specifications as it involves peculiarities, advantages, and potential points of difference that allow customers to identify what makes them different. Now, the extension does not just compare products it can customize comparisons like personalized product recommendations. The virtual assistant will personalize recommendations by looking at a customer's navigation traits, as well as past purchases and expressed interests to make sure the comparisons sound like something that would appeal most to them.

D. Leverage machine learning capabilities

The virtual sales assistant Chrome extension is powered by an advanced machine learning algorithm, which uses the richest possible dataset to produce a highly personal and proactive shopping experience. By integrating sophisticated machine learning algorithms, the extension is endowed with a remarkable capacity to crunch enormous amounts of user data ranging from browsing activity and search history all the way up to expressed preferences. This is a data-driven model which allows the Virtual Assistant to develop deep insights into each customer's behavior, interests, and requirements. Then, as users interact with the extension every one of their actions is closely watched and examined in such a way that may evade instant detection by the machine learning models just allowing them to detect additional patterns. In the digital world of e-commerce, where customers are no longer physically in front of friendly and experienced sales associates to provide answers or guidance on fitment/specifications caus- ing confidence-building shopping experiences is critical! The purpose of the virtual sales assistant. Chrome extension is to fill this gap and play a role like an experienced guide who clears doubts, advise on what works best for your skin, and so forth by being authoritative with consumers every step along their shopping journey. Its unique integration with existing e- commerce platforms provides the virtual assistant a window to technical specs, how-to guides, hidden insights, and expert tips across thousands of products. By having such a broad insight into what customers are likely to want, the extension can provide rich answers specific for an individual concerned with location-based guidance.

E. Provides seamless integration with e-commerce platforms

The omnichannel approach is especially effective in eCommerce where you have customers from all corners of the world, meaning it becomes difficult if not next to impossible for a single operator to be able to afford every currency mean or transaction feature at work on his website as different countries prefer their simplicity and ease. What this creates is a disjointed experience—shoppers have to navigate different ecosystems, and adapt to the same-but-different nuances inherent in these digital marketplaces. To tackle this problem head-on, a virtual sales assistant Chrome extension is integrated with the large array of e-commerce platforms making your shopping experience all in one place — an island of normalcy amid madness. This extension through dedicated partnerships and integration frameworks sits within the very heart of leading e-commerce websites – it lays eyes on their product catalogs, prices, users. This synergy of the two ecosystems allows the virtual assistant to deliver personalized help and suggestions that go beyond any specific platform. What this enables is now when consumers head into the ever-expanding digital universe, they are comforted by a dependable companion playing the same songbook at their walk agreeing to give them 'their personalized experience', no matter wherever in e-commerce land they may roam.

F. Establish a feedback and iteration loop

In the majorly dynamic realm of e-commerce, there is an unwavering rule that surpasses all: to be at par with customer wants and desires. Given the importance of this truth, The Virtual Sales Assistant Chrome Extension is always designed to implement a feedback loop that continuously improves — making it an ever-moving and flexible product for all online shoppers.

1) The Heartbeat:- A Strong Feedback Loop: And within this feedback loop is a rich system of capturing and analyzing input (user data), as well as interactions. By using strategically located surveys, intuitive rating systems and open-ended feed-back fields the extension prompts customers to express what they felt about their interaction with the virtual assistant. Their direct input serves as a rich vein of information, exposing where we are strong and vulnerable while pointing the way toward improvements.

2) Journey to Perfection: But, this feedback loop isn't limited to just collecting data. It is a constantly evolving exercise in user feedback, laser-focused data analysis, and then an iterative coding process that integrates those insights into the foundational building blocks of the extension. In this iterative cycle, the virtual assistant matures while responding to new customer behaviors and patterns and refining its modus operandi at every engagement.

G. Support small businesses

Many of the big companies in the e-commerce world have quite enough resources to upgrade their online shopping experiences. Yet, achieving the same personalized service and customer experience can prove to be a bit of an uphill challenge for small businesses. Therefore, the virtual sales assistant Chrome extension attempts to close this gap by being a fuller and more accessible way out. This tool is designed to help small businesses provide that all-important customer interaction and grow their sales pipeline, effectively leveling the playing field.

III. Literature Review

A. Analysis of Literature Review

[1]A research initiative of the paper "ProductQnA: Answering User Questions on E-Commerce Product Pages" undertaken by Kulkarni et al. from Amazon Machine Learning India has put forth an innovative framework tailored for question-answering systems on e-commerce product pages. The method proposed employs the elements like query category classifier, question-answer matching models, and answer generation module. Leveraging the capabilities of deep learning and semantic matching solutions which can integrate structured knowledge graphs, this framework is used to efficiently solve some representative user queries about product features, compatibility conditions, or review summar-ies in an e-shopping context. By combining distributional semantics, deep learned from words in context with structured domain-specific ontology-based semantics the model scores surprisingly well on Precision at locating user questions that it can process and improve customer journey. Of particular note, the suggested approach also improved precision by 66% relative to a baseline model making it an interesting direction for increasing accessibility and understanding of product data on e-commerce platforms..

[2] In the research paper "Answer Generation for Questions With Multiple Information Sources in E-Commerce, Flipkart India", A research endeavor undertaken by Rajasekar and Garera of Flipkart India has introduced an innovative pipeline, dubbed MSQAP (Multiple Source Question Answering Pipeline), tailored for automatic question- answering within the e-commerce domain. The given pipeline effectively taps into various sources of information like reviews, specifications, and duplicate question-answer pairs to obtain correct responses for user's queries relevantly. Three key stages of the MSQAP pipeline include relevancy prediction, ambiguity filtering, and answer generation. This prediction model built on the BERT-QA architecture directly selects some candidates considered most promising from different information sources. The ambiguity filtering part is responsible for eliminating answers that might not be accurate or consistent, delivering the required reliability and coherence. Then, the Seq2Seq and fine-tuned T5 models are used to generate the final response via the answer generation component.

[3] The research paper "SuperAgent: A Customer Service Chatbot for E-commerce Websites" by Pranav Rajpurkar, introduces SuperAgent, a conversational agent meticulously crafted to cater to customer service needs within the realm of e-commerce websites. SuperAgent adeptly harnesses the wealth of large-scale and publicly accessible data sources pertaining to e-commerce, encompassing in- depth product descriptions, customer inquiries, and their corresponding responses, as well as customer-generated reviews. The architectural underpinnings of this chatbot ingeniously deconstruct the chat engine into three distinct sub-engines: a dedicated fact question-answering engine for product information, an FAQ search engine tailored to customer questions and answers, and an opinion mining and text question-answering engine specifically geared towards customer reviews. Leveraging cutting-edge natural language processing (NLP) and machine learning techniques, SuperAgent deftly selects the most appropriate response from the existing data sources within the product page, drawing upon product information, customer questions and answers, and customer reviews. This innovative approach is poised to offer pragmatic and cost-effective solutions for addressing the recurring customer inquiries that pervade e-commerce websites.

[4]The research paper ”Research Paper on Question Answering System using BERT, Industrial Engineering Journal” explores the implementation of the BERT (Bidirectional Encoder Representations from Transformers) algorithm in a Question Answering System. It addresses the challenges associated with processing large textual data and proposes a system that leverages natural language processing (NLP) techniques and the BERT model for text summarization and question-answering tasks. The paper highlights the benefits of the BERT architecture, such as its ability to achieve contextual understanding and perform bidirectional learning. It emphasizes the potential of BERT in improving the accuracy and efficiency of question-answering systems by leveraging these capabilities. While the specific evaluation metrics used in the paper are not explicitly mentioned, the research focuses on demonstrating how the BERT model can enhance text summarization and question- answering capabilities in a question-answering system.

[5] The researchers behind the paper” SQuAD: 100,000+ Questions for Machine The Stanford Question Answering Dataset (SQuAD)” are Pranav Rajpurkar They introduced the Stanford Question Answering Dataset (), a challenging and large-scale reading comprehension dataset to stimulate research in the field. The dataset is impressively large with over 100,000 questions sourced meticulously by human contributors from a wide range of Wikipedia articles. The chance to create a single language model trained on all of SQuAD was particularly appealing as the answers are verbatim spans from each reading passage; no external knowledge, ontology structure or elaborate reasoning is required.To reach a better understanding of the complex reasoning mechanisms necessary to answer questions in SQuAD, they performed an extensive analysis using features from dependency and constituency tree structures. This careful examination helped to address the dataset linguistic complexities and challenges, adding more value as new knowledge about the domain is uncovered. To evaluate the performance of models on SQuAD, they first proposed a strong logistic regression model as a benchmark with an impressive F1 score 51.0%. Nonetheless, human performance on the dataset was much better with an F1 score of 86.8 %. This point illustrates the difficulty of SQuAD, as well as its capacity to inspire future research in areas such as machine reading comprehension and question-answering.

[6] A groundbreaking methodology was proposed for cop- ing with the long-standing problems of Question Answer- ing Systems (QAS) in a research paper entitled ”Auto- matic question-answer pairs generation and question simi- larity mechanism in question answering system” by Shivani G. Aithal et al., which focused on how QAS inherently performs sooner than anticipated due to the complexity of natural language questions, analysis at various levels is needed including that leading up to reductionist conversion processes. In this new method, a Question Similarity technology for pre-processing is to be introduced. The crux of the matter lies in identifying and filtering non-answerable/noisy questions so that they never make it to the QAS for processing. In this inheritance mechanism, a point-wise comparison of the ques-tions asked to those that could have been possibly dynamically generated from any given passage is performed carefully and then finally by calculating what it called a Question Similarity Score quantitatively. The proposed mechanism achieves the dual benefit of not only boosting the performance, by letting QAS concentrate on answering queries answerable to some extent but also mimics human-like reasoning paradigm fixing an important loophole in traditional methods. This method is very effective as it skips the training which saves a lot of resources.

The synthesized contribution emerges from the research article that introduces an implementational executable, which generates question-answer pairs directly from a text passage and has potential to serve as useful resource for training or fine-tuning QAS models hence creating benchmarks at up-to-date level in this area.

[7] The research paper ”Building Task-Oriented Dialogue Systems for Online Shopping” has put forth a novel solution for developing chat-based online business systems, with the primary objective of simplifying conversational interactions to assist customers in completing multiple purchases seam-lessly. The authors demonstrate a pragmatic approach that leverages existing language processing techniques, data pro-cessing methods, and crowdsourcing strategies to create these conversational systems tailored for e-commerce businesses. Notably, the proposed system has been successfully integrated into mobile business applications and is actively utilized by millions of real customers, providing valuable insights derived from the analysis of human-machine interaction engines. The research paper addresses various current challenges and offers future directions for further research and development in this domain. The researchers employed algorithms such as Con-volutional Neural Networks (CNN) and Naive Bayes for the proposed solution, achieving promising results with a precision of 89.8%, a recall of 67.7%, and an F1 score of 77.2%, demonstrating the efficacy of their approach. Furthermore, the paper sheds light on future research scopes, including enhanced personalization capabilities, multimodal dialogue systems, and real-time adaptation and learning mechanisms, with the overarching aim of improving the overall user experi-ence and system performance in these conversational systems.

B. Research Gap

Several Sensitive Hurdles of using the Proposed Question-answering Solution on E-commerce Platforms Data integrity and regulatory enforcement are a significant concern as the system relies heavily on legacy product descriptions that may have expired or no longer be accurate. Comprehending intri-cate and context-specific user requests can be quite difficult particularly if the natural language processing capability of a system is constrained. In a similar vein, the effectiveness of product listings with very brief or no descriptions on the web as there isn't enough data to train it. Many types of questions are very difficult, especially those that require a subjective answer or comparison between products. Automated systems can trigger significant decrease in user engagement and trust because customers start to doubt the information they have access from such system. Also, structural and design changes in e-commerce websites frequently may end up into difficulty to extract the data or system down. Lastly, data scraping practices provoke security and privacy concerns as they involve entering an e-commerce platform to pull out information.

IV. Methodology

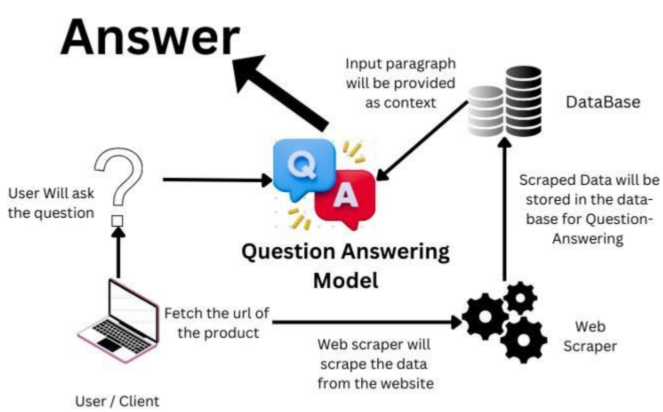

Fig. 1. System Architecture

A. User/Client

The user initiates the interaction and serves as the starting point of the process. The user represents himself as an individual or an entity that poses a question to the system.

B. User Will Ask the Question

The user completes this step by formulating and then submitting their query to the system. The query could pertain to a particular product, service, or any other relevant information.

C. Web Scraper

A component designed to fetch and extract data from various websites on the internet. Triggered upon receiving the user's question, it navigates through relevant web pages and gathers pertinent information.

D. Web

This is related to the World Wide Web, a huge web of interlinked websites accessible via the internet. This network is used by the web scraper component to search and extract data that can be matched with a user request.

E. Scraped Data Will Be Stored in the Database for Question Answering

Web Scraper saves the extracted data with question into specific database. This database is a store of the scrapped data which will be used in further use actions. This helps in the simplicity of data retrieval and analyzing it as well.

F. Question Answering Model

This is a more specific model that we trained with the you scraped data stored in our database It uses numerous sophisticated algorithms and methods to analyze, model the data. When a user inputs a question and then the model fetches relevant information from its database, it generates an appropriate response.

G. Response Generation

The user query is processed alongside that from scrapy data which gets stored in the Database. This will trigger question answering model to generate the expected response. The generated response is expected to be appropriate and in the context of the user's inquiry.

H. User Receives the Response

If a response is formulated, the system will give it back to you or whatever is asked. Then, the user request comes in and it just obeys the cycle by giving the requested information or solution.

Working of BERT

Bidirectional Encoder Representations from Transformers, also known as BERT, is a transformer-based language model developed by Google. As the architecture and training methodology can efficiently capture contextual information, it outperforms other models on many natural language programming-related tasks.

1) Text Tokenization: The input text first has to be tokenized before it is submitted as input in the model (tokenization involves breaking down a given text into smaller units that are called tokens). The purpose of tokenization is to change the text into something meaningful for a machine while maintaining its meaning.

2) Token Embedding: Word embedding is when the token is mapped to a vector representation. These embeddings summarize the semantic and syntactic information about the words within the context of the sentence.

3) Positional Encoding: To better understand the order of the words in a sentence, the BERT model includes positional encoding as the input text is sequential.

4) Transformer Encoder Layer: The BERT Model is composed of multiple transformer encoder layers. Each of these layers performs two functions on the input tokens that is the self-attention mechanisms and feed-forward neural networks.

5) Self-Attention: Within each transformer encoder layer, self-attention mechanisms allow the model to weigh the importance of each token concerning every other token in the input sequence. This capability enables the model to capture contextual information effectively.

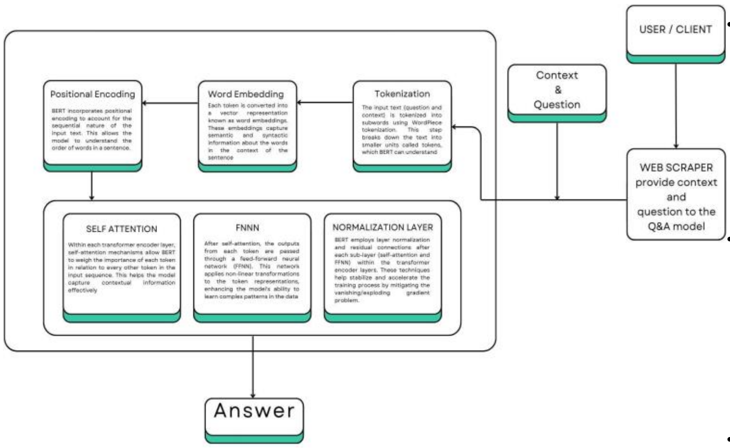

Fig. 2. Working of Bert Model

6) Feed-Forward Neural Network: The network receives the output of the tokens after self-attention mechanisms. This network applies non-linear transformations to the token representation which will enhance the model's ability to learn complex patterns of data.

7) Normalization and Residual Connections: In BERT, layer normalization, and residual connections are utilized after each sub-layer (self-attention and FFNN) within the transformer encoder layers. These techniques assist in stabilizing and accelerating the training process by addressing the vanishing/exploding gradient problem.

8) Multiple Layers: BERT is composed of several transformer encode layers stacked together. This design enables the model to capture a range of representations of the input text, starting from basic word embeddings up to sophisticated contextualized representations at different levels of abstraction.

9) Output: The final hidden states from the top transformer encoder layer are utilized for downstream tasks, such as question answering. These representations contain rich contextual information about the input text and can be fine-tuned for specific tasks.

V. Equations

- Contextual Embeddings: BERT converts input text into contextual embeddings. Let E be the embedding matrix for the input tokens. Each token is represented as e_i in the embedding space.

$$-E = [e_1, e_2, ..., e_n]$$

- Self-Attention Mechanism: BERT uses self-attention to capture token relationships. Q, K, and V represent query, key, and value matrices.

$$Attention(Q, K, V) = softmax((QK^T)/sqrt(d_k))V \quad (2)$$

- Contextualized Representations: BERT computes contextualized representations using multi-head attention layers and feed-forward networks.
  MultiHead(E) = Concat($head_1$, ..., $head_h$) W_O

$$head_i = \text{Attention}(E \cdot W_{Qi}, E \cdot W_{Ki}, E \cdot W_{V\,i}) \quad (3)$$

- Start and End Token Predictions: BERT predicts the start and end positions of the answer span.

$$P_{\text{start}} = \text{softmax}(E \cdot W_{\text{start}}) \quad (4)$$

$$P_{\text{end}} = \text{softmax}(E \cdot W_{\text{end}}) \quad (5)$$

- Loss Function BERT's loss function combines predictions of start and end positions.

$$\text{Loss} = -\log(P_{\text{start}}[s]) - \log(P_{\text{end}}[e]) \quad (6)$$

where s and e are the true start and end positions.

VI. Result And Discussion

A. Test case 1

Comparing the results of the model with the actual data present on the website (Redmi Note 12 5G)

*1) **Actual**:*

- What is the name of this mobile phone?
  Ans. Redmi Note 12 5G Frosted Green.
- What is the color of the mobile phone?
  Ans. Frosted Green.
- Which type of display is used?
  Ans. Super AMOLED (1080x2400) Display with 120Hz Refresh rate; 1200nits peak brightness; 240Hz Touch sampling rate.
- What is the battery capacity of the mobile phone?
  Ans. 5000 mAh.
- Which processor is used in the phone?
  Ans. Snapdragon 4 Gen1 6nm Octa-core 5G processor for high performance and efficiency with Adreno 619 GPU; Up to 2.0GHz.
- What is included in the box?
  Ans. Handset, Charger, Manual.
- What is the storage capacity of the phone?
  Ans. 128GB ROM.
- What is the battery capacity of the mobile phone?
  Ans. 5000 mAh.

*2) **Predicted**:* Fig 3

B. Test Case 2

(1) Comparing the results of the model with the actual data present on the website (Apple iPhone 14 Pro)

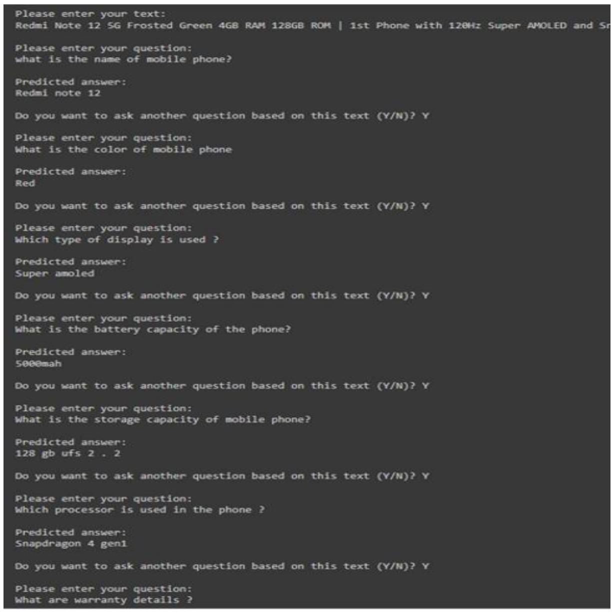

Fig. 3. Test Case 1 Predicted Output

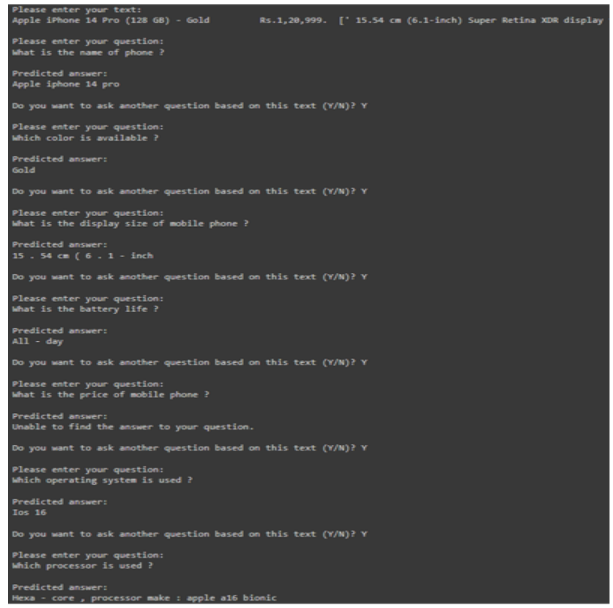

Fig. 4. Test Case 2 Predicted Output

1) ***Predicted***: Fig 4

2) ***Actual***:

- What is the name of the phone?
  Ans. Apple iPhone 14 Pro (128 GB) – Gold.
- Which color is available?
  Ans. Gold.
- What is the display size of the mobile phone?
  Ans. 15.54 cm (6.1-inch) Super Retina XDR display featuring Always-On and ProMotion.
- What is the battery life?
  Ans. All-day battery life and up to 23 hours of video playback.
- What is the price of the mobile phone?
  Ans. Rs. 1,20,999.
- Which operating system is used?
  Ans. iOS 16.
- Which processor is used?
  Ans. A16 Bionic, the ultimate smartphone chip.

VII. CONCLUSION

In summary, we have created a unique chatbot seamlessly integrated into a Chrome extension, specifically designed to aid users in the mobile phone category. Utilizing the vast knowledge from the CoQA dataset, our chatbot has been meticulously trained to deliver insightful and valuable responses to user inquiries concerning mobile phones. With this innovative chatbot embedded directly into the browser extension, users can now access real-time assistance while exploring mobile phone products online, streamlining their shopping experience. This solution not only enhances user satisfaction but also fosters trust between consumers and e-commerce platforms, ultimately boosting confidence in purchase decisions.

VIII. RE

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