DEVELOPING AN END-TO-END GENERATIVE CHATBOT USING T5 AND FLASK: FROM DATA GENERATION TO DEPLOYMENT

Zainab K. Abbas [1][0000-0001-5203-5676], Zaid Ali Alsarray [2][0009-0001-1726-3670]
[1]Department of Businesses Information Technology, College of Business Informatics, University of Information Technology and Communication, Baghdad-Iraq
[2]Department of Intelligent medical systems, College of Biomedical Informatics, University of Information Technology and Communication, Baghdad-Iraq
Emails: zainabkhudhair@uoitc.edu.iq, zaid.ali-bmic@uoitc.edu.iq

Abstract - Due to the recent widespread use of artificial intelligence (AI) applications in most fields, we believe its use should not be limited to large corporations and institutions alone, but can also be leveraged by small business owners. From this perspective, this research presents an interactive chatbot based on the text-to-text transfer transformer (T5). The chatbot is implemented to cover three possible scenarios. In addition, a question-answer dataset was created and then used to fine-tune the T5. Finally, the trained model is deployed to a Flask web application to give it real-time user interaction. The three scenarios indicated that the proposed system succeeded in handling different user queries.

Keywords: Artificial Intelligence, Chatbot, T5, Flask, Frontend, Backend.

1. Introduction

In recent years, Artificial Intelligence (AI) has become deeply integrated into many aspects of daily life, especially in how people interact with machines. Chatbots are one of the most noticeable examples of this shift, offering automated conversations that increasingly resemble natural human dialogue. Unlike earlier bots, which followed rigid rule-based systems, today's chatbots are capable of understanding context, generating meaningful responses, and adapting to user input. A major reason for this evolution is the development of transformer-based models like the Text-to-Text Transfer Transformer (T5), which treats a variety of language tasks as simple text-to-text problems [1], [2]. This model has played a key role in simplifying the design of natural language applications. By converting the entrance to text and expecting text as an output, developers can use the same architecture for tasks such as answering questions, summarizing materials, or translating languages. The flexibility of such models allows them to work in domains with relatively low-specific training, making them ideal for practical chatbot applications [3]. To make these systems accessible to users, they are often embedded in web interfaces that are built using HTML, CSS, and JavaScript [4]. These will allow for real-time interaction in a browser so that users can input the messages (the question) and get immediate answers.

However, the real treatment occurs in the hill, behind the curtain [5]. The backend processing helps the developers to create scalable and responsive applications. Transformer-based models specifically appeal due to their ability to normalize; models such as pre-trained T5 on a massive dataset can be compatible with new domains with minimal fine-tuning. This is especially useful when creating domain-specific chatbots for businesses that may not have access to large labeled datasets [3]. Instead of building a language model from scratch, developers can customize a pre-trained model with a modest amount of curated data.

In this research, a chatbot is developed and optimized for a cafe domain, which uses a generated data set to train the model. The system is designed to handle customer requests, both normal and specific, and it is distributed using an online interface. The project shows that advanced AI systems can be made available to small businesses and individual developers without the need for resources or infrastructure at the corporate level. This contributes to the broader goal of democratizing AI, which brings powerful tools into the hands of those who need them most. The paper can include a non-

https://doi.org/10.17683/ijomam/issue22.v1.19

limited number of images/figures. Their explanations and legends will be centred under them. Admitted minimum resolution of an image is 300 dpi. All images/figures must be in line with text (wrapping).

2. Related Work

Chatbots are now visible everywhere, from hospitals to stores and schools. They are designed to make things easier, such as ordering appointments, answering questions, helping students, or even analyzing photos. In healthcare, Aparna et al. used Dialogflow and Flask to handle the appointment booking; despite getting an accuracy of up to 92%, the model still had trouble with more open-ended questions [6]. Dalavai et al. proposed a translation chatbot the chatbot worked in multiple languages, although the translations were not always spot-on; the model achieved 87% accuracy [7]. Moreover, a voice bot using BERT was suggested by [8]. The bot works well in quiet rooms; it got an accuracy of 91% but struggled with noise. In rural areas, chatbots based on decision trees hit about 82%, but they were limited by weak internet [9]. Emergency bots were also tested. One of them used GPS and natural language processing (NLP) to help people figure out where to go or what symptoms meant, with 90% accuracy [10]. Another one by Furqan helped with assessing symptoms and suggesting conditions with reasonable accuracy, though it struggles with rare or complex cases [11]. A chatbot for surgery follow-up helped people feel more satisfied after their procedure, though it did not improve outcomes clinically [12].

In business, chatbots are used mostly in customer service. Banking bots that followed rules worked well with direct questions—around 90% accuracy, but they did not handle more natural conversation [13]. Yadav and Thrimoorthy, on the other hand, built a bot using MySQL and machine learning; the bot got between 84% and 93% right, but they did not do great with weird or unclear inputs [14], [15]. Rodriguez et al. applied Partial Least Squares Structural Equation Modeling (PLS-SEM) on survey data from 361 users that showed strong positive effects on satisfaction, while empathy was statistically insignificant, highlighting limitations in emotional connection [16]. A bot that judged tone (sentiment analysis) proposed by [17] using the LSTM model, the proposed bot got an accuracy of 88%. Huang et al. suggest a ticket bot; they used a large models with QR codes for tickets, but the model becomes slow when too many people use it [18]. Christian et al. used a string search method (Knuth-Morris-Pratt), which worked at 82%. The limitation in this work was that it was English-only support and weak handling of untrained or informal phrases [4].

In education, chatbots are used to help students. Samad suggests a bot that could answer college questions; the bot got an accuracy of 99% of the time, but the bot only deals with English [19]. Another bot was suggested by Priyanka and Mahant, using NLP; the bot handled 92–94% of student queries well [20], [21]. Moreover, Kondreddy used neural networks and Natural Language Toolkit (NLTK); the model got 99% for basic structured questions, but it was not easy to adjust to new topics [22]. Also, college recommendation bots like Padmavathi's did about 86%, and FAQ bots like Patil's worked well with 79% but needed manual updates [23], [24]. Besides that, career advice bots by Abinaya's worked fine with 90% but their limitation lies in the lack of machine learning and language flexibility [25]. Visual chatbots are also gaining attention. Augustine built one that took both pictures and text and answered based on both with 88% accuracy. Although it provides balanced and accurate responses, performance may degrade with poor image quality or under high server load [26]. Another one called PicQuest used MobileNet and NLP to help students with diagrams or objects. It got 86%, but image quality made a big difference [5]. Another chatbot was implemented using Python, NLTK, and MongoDB for data storage, with 85% accuracy in handling predefined customer queries, but struggled with slang and required manual data updates [27]. According to Kagan et al., users are reluctant to use chatbots in general and experience an algorithm aversion, which led to their success rates of 34% to 42% versus 79% to 87% when communicating with an agent [28]. Whereas Venkatchalam et al. presented a fully functional ticketing system powered by Dialogflow, which utilizes NLP and received 88% user satisfaction and reduced resolution time by 35%. However, purposeful ambiguity existed in conversations between agents and chatbots [29]. As for Kalmath, specialized in chatbot architectures (including integrations - Dialogflow & Watson), while Puspitasari et al. constructed a business acquisition web-based chatbot using Python and neural networks, while citing pre-trained data and limited accuracy of being adaptive [30], [31].

Finally, Shekgola et al. referenced chatbot public service examples in their paper on smart governance under Society, adding that chatbots would provide 24/7 support; however, they also noted sector issues such as digital literacy and infrastructure gaps [32].

So overall, chatbots are doing well. Most of them get over 80–90% accuracy in what they're built for, but they are still not great at free, complex conversations. They often miss the “human” side of things. And even the best bots need regular updates and tuning. Still, they are useful and growing fast.

3. Methodology

The system that was suggested is a chatbot powered by AI, developed to efficiently handle the requests of the customers and provide information about a specific domain. The conversation bot can respond in English and manage text-based exchanges. The work's fundamental tenet is to approach every text processing issue as a "text-to-text" problem, meaning that each input text is converted into an output text. Figure 1 shows the system architecture. The system is made up of multiple essential parts that cooperate to guarantee the chatbot's operation. These elements consist of:

1-The Q&A dataset. 2- User interface (UI). 3- Flask. 4 The AI model.

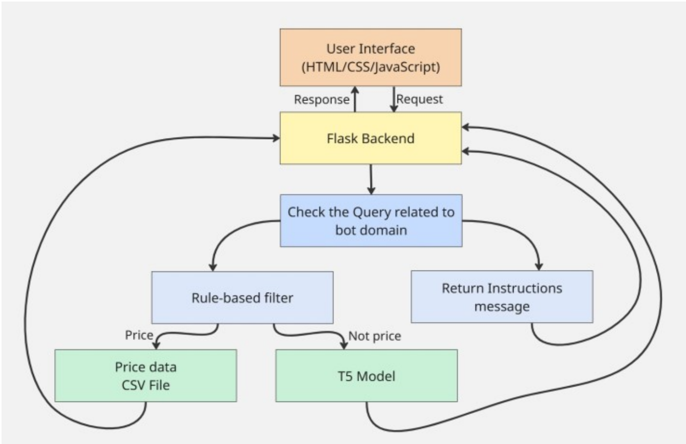

Figure 1: System architecture

3.1. The Q&A Dataset

In this section, the creation of the question and answer (Q&A) dataset for a specific domain will be discussed.

3.1.1. Generating and preprocessing the dataset

Due to a lack of dataset in general, in this work, the Q&A dataset for the chosen domain (cafe) was generated, using Python code that contained the keywords used in the cafe in general, such as the names of the items, availability times, location of the cafe, other services provided by the cafe, etc. After generating the Q&A dataset randomly, it was passed to the data cleaning phase, in which the redundancy in the question and answer at the same time was removed from the dataset; the redundancy in the question only or in the answer only was kept because it does not affect the training process. Because the data was generated using code, this may have caused the generation of some stop words. Therefore, the data was reviewed, and the stop words were removed from the data. Finally, approximately 1,307 questions and answers were generated for the most common questions without repetition and saved in a CSV file.

In addition, the price item dataset was generated and saved in a separate CSV file. Figure 2 illustrates the process of generating the dataset. A sample of the dataset can be seen in Figure 3.

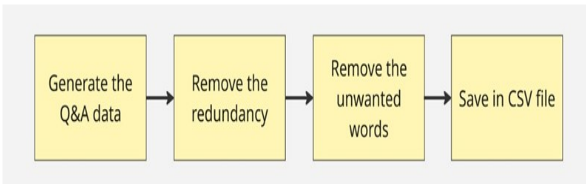

Figure 2: The dataset generation process.

What type of coffee do you have?	We offer various coffee items like Macchiato, Latte, Flat White.
What type of pastry do you have?	We offer various pastry items like Brownie, Cinnamon Roll, Scone.
What type of coffee do you have?	We offer various coffee items like Latte, Cappuccino, Mocha.
What type of coffee do you have?	We offer various coffee items like Mocha, Espresso, Latte.
What type of coffee do you have?	We offer various coffee items like Americano, Mocha, Flat White.
Is Chai Latte vegan?	Chai Latte is vegan-friendly.
What type of food do you have?	We offer various food items like Avocado Toast, Salad, Panini.
What type of coffee do you have?	We offer various coffee items like Americano, Flat White, Mocha.
Is Cinnamon Roll gluten-free?	Cinnamon Roll is gluten-free.
What type of tea do you have?	We offer various tea items like Matcha Tea, Black Tea, Green Tea.
What type of food do you have?	We offer various food items like Soup, Panini, Salad.
What type of drink do you have?	We offer various drink items like Sparkling Water, Milkshake, Cold Brew.
What type of food do you have?	We offer various food items like Avocado Toast, Soup, Panini.
What type of coffee do you have?	We offer various coffee items like Cappuccino, Mocha, Affogato.
What type of tea do you have?	We offer various tea items like Mint Tea, Black Tea, Green Tea.
What type of food do you have?	We offer various food items like Quiche, Salad, Wrap.
Do you have Soup on the menu?	Yes, Soup is on the menu.

Figure 3: Sample of the dataset

3.1.2. The Dataset Transformation

When the dataset was completed, it was important to put the data into a form suitable for the model for training. The technique of tokenization divides the text into separate parts known as tokens, whereas the process of embedding transforms the words or tokens into numerical value vectors [1]. In this work, the inputs were converted into tokens using a particular transformer tokenizer, and the tokens were then transformed into the format that the transformer T5 model accepted by applying an embedding process to convert them into matching numerical IDs in the pre-trained vocabulary.

3.2. User Interface (UI) – Frontend

The frontend is what the user sees [4]. The user interface (UI) is a web-based application that allows users to enter text messages to communicate with the chatbot. In this work, HTML, CSS, and JavaScript were used to design the UI. Figure 4 displays the chatbot interface.

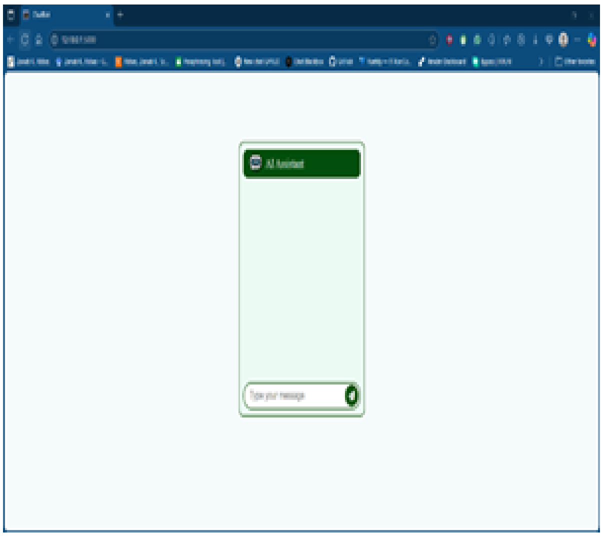

Figure 4: Chatbot interface

3.3. Flask Server - Backend

The backend is everything behind the scenes, like logic, dataset, model, etc [4]. In this work, the T5 mode, the check of the CSV file for price, and the rules applied to decide if the question is about the chatbot domain or not, all of them involve a backend.

The server is a part of the backend, listens to the user inquiries, and forwards the input to the backend. Flask server, which is used to handle the user inquiries, communicates with the model and provides the response to the user [5]. To make the chatbot interactive on the website, a Flask app was used; without Flask, the model would only work in the command line. In this work, Flask does the following:

1-User interface: Serves the web page of the chatbot.
2-Routing: Handles the incoming requests.
3-Backend Logic: Call the Python function to get the response.
4-Integration: Connect the system with the web interface.
5-Deployment: Make the chatbot accessible from the local server (http://localhost:5000).

3.4. The AI Model

After the data preprocessing and transformation were complete, it was split into 90% for training the model and 10% for validating the model. The text-to-text transfer transformer (T5) model, which was designed and trained by [2], was used in this research. The T5 training strategy is bidirectional; the model has an embedding size equal to 512, 8 attention heads, 6 blocks, and 60M parameters [3].

Hugging was used to fine-tune the T5-small in this work, and the model was trained on Visual Studio Code (VSC). The AdamW optimizer was used due to its efficiency with T5. Many hyperparameters were changed to find the optimal value for the model, like number of epochs, batch size, and learning rate; the optimal variable values are listed in Table 1.

Table 1: The hyperparameter values

Parameter name	Value range testing	Optimal value
Number of epochs	1e-1 – 1e-5	1e-3
Batch Size	4-16	8
Learning rate	1-16	15

The system was implemented on the GPU, Python 3.8.19, and a PC with specifications listed in Table 2.

Table 2: The PC specification

Name	Value
Graphics processing unit	NVIDIA GeForce MX450
Microsoft Windows	11
Operating system	64-bit
Processor	Intel Core i7
RAM	16 GB
SSD hard drive	1 TB

Figure 5 illustrates the loss curve of the training and validation. The graphic displays the T5 model's training and validation loss over 15 epochs. Effective learning is indicated by the training loss (blue), which reduces substantially at first and then continually stabilizes after a few epochs. There is no noticeable growth in the validation loss (orange), which indicates that the model is not overfitting.
The close convergence of both curves indicates that the model seems to have trained successfully overall.

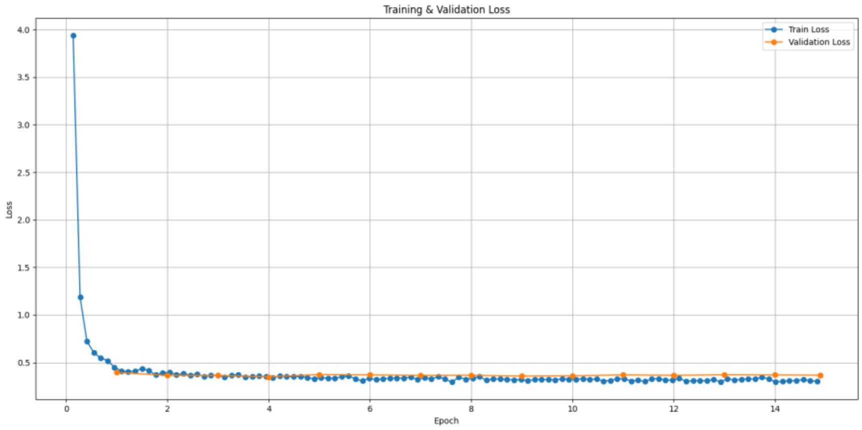

Figure 5: The T5 model train and validation loss curve

4. The System Workflow

To ensure a flawless user experience and effective processing of information, the chatbot and website communicate according to a set of rules.

The workflow describes the sequence of actions performed by users and backend operations required to provide accurate replies and obtain necessary information. Figure 6 illustrates how the system handles the user inquiry.

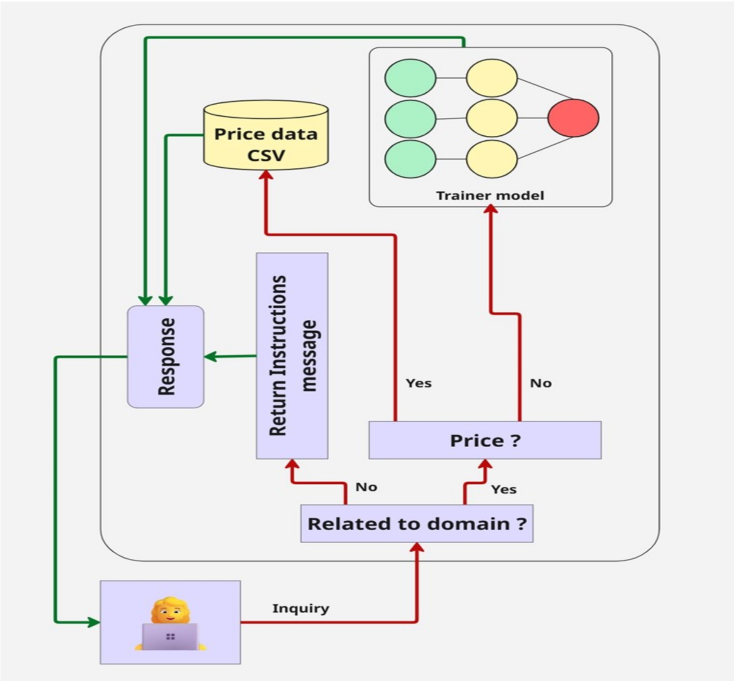

Figure 6: The user's inquiry is handled by the system

When the user enters an inquiry, the system first checks whether the inquiry is related to the domain (Cafe) or not. After it is confirmed that it is related to the domain, it is transferred to the second stage, in which the inquiry will be checked to see if it is about the price of the items or if it is a general question about the domain field. In the case of the inquiry about the price, it will be sent to the CSV file dataset, which contains all item prices, and return the response to the user. However, if the inquiry is about the cafe, it is transferred to the T5 model to find the appropriate answer, and then the answer is returned to the user.

If the question is not about the domain, a unified answer will appear to the user, such as asking the user to visit the website page for more information.

The process of entering the inquiry by the user and displaying the answer is done on the frontend side, while the process of processing the inquiry, determining whether it is related to the field of the domain, determining if it is related to the price, and generating an answer from the model is done on the backend side, i.e., on the server, which is a Flask in this work. Figure 7 displays the chatbot response in the VSC environment.

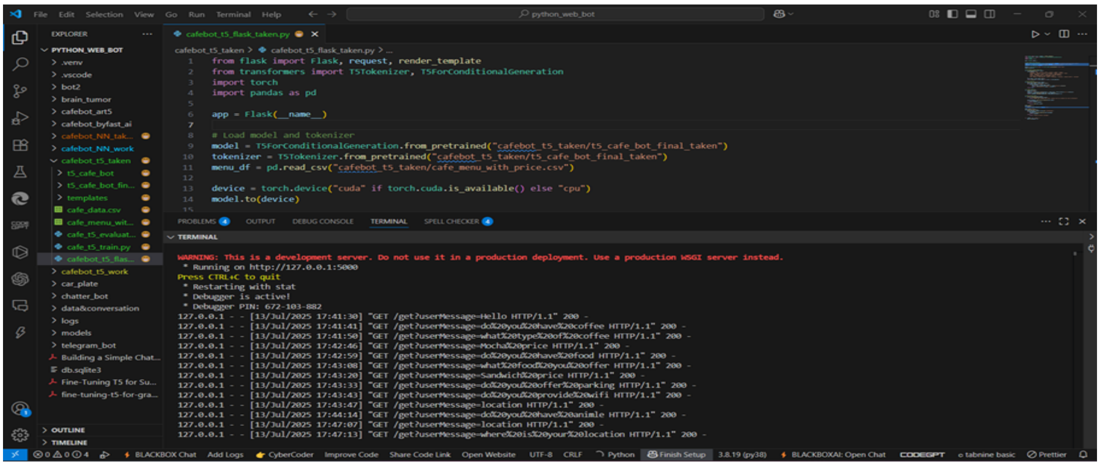

Figure 7: The chatbot response in the VSC environment

5. Evaluation and Result

The response of the chatbot can be divided into three scenarios in general. In the first scenario, a normal conversation was conducted with the chatbot. The user started by greeting the chatbot and then sent a sequence of questions related to the bot's domain. The questions were about the price and another question about the chatbot domain. The chatbot succeeds in replying with a suitable answer for each question. Figure 8 displays the chatbot response for the first scenario.

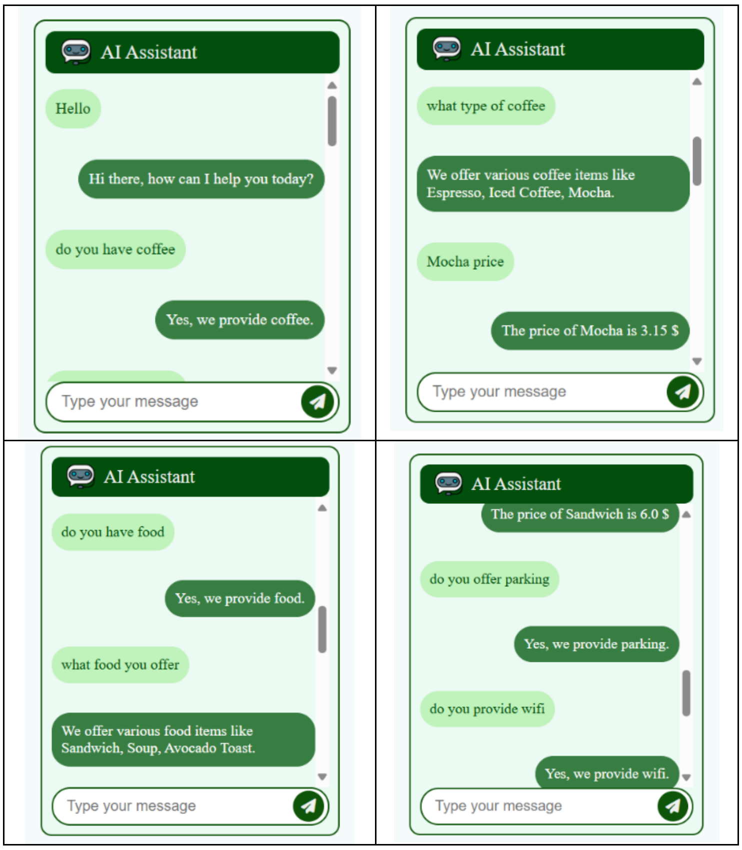

Figure 8: The chatbot response for the first scenario

In the second scenario, while the user conducted a conversation and sent a question not related to the chatbot domain, the response was a message asking the user to visit the website for more information. Figure 9 displays the chatbot response for the second scenario.

In the third scenario, the user asked the same question to the chatbot but in a different format. This scenario is considered the most difficult scenario ever, but the proposed model proved its efficiency as it was able to answer the question correctly despite the difference in format. Figure 10 displays the chatbot response for the third scenario.

The three scenarios indicated that the proposed system succeeded in handling different user queries. The model learned the task, and it is giving valid responses in English, which is the main objective of this work.

The chatbot's limited capability for English is one of the research's weaknesses. Future research needs to be improved to support Arabic. In addition, only the information contained in the training data is known to the chatbot. As an example, unless retrained, the bot won't be willing to recognize a new item added to the menu.

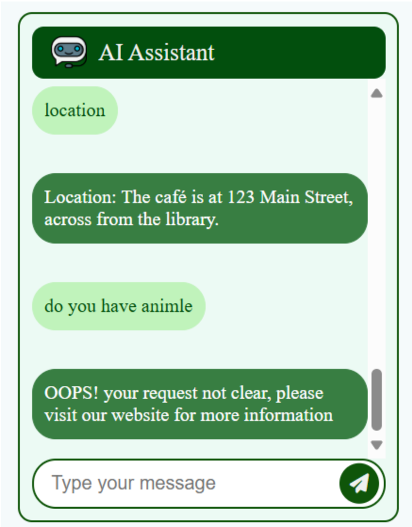

Figure 9: The chatbot response for the second scenario

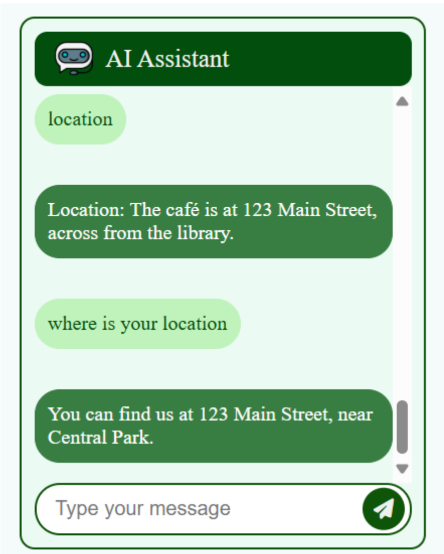

Figure 10: The chatbot response for the third scenario

6. Conclusions and Future Work

In this work, an interactive chatbot was designed using the T5 model; the suggested chatbot was evaluated in three scenarios. In the first scenario, a normal conversation was conducted with the chatbot, while in the second scenario, the user conducted a conversation and sent a question not related to the chatbot's domain, and in the last scenario, the user asked the same question to the chatbot but in a different format. These scenarios are considered the most difficult scenarios ever, but the proposed model proved its efficiency as it was able to answer the question correctly despite the difference in format. In the future, more datasets will need to be included, which will make the proposed chatbot more thorough and adaptable, giving you the impression that you are speaking with a real person. In addition, chatbot optimization to support Arabic.

References

[1] H. Usama and F. Rustam, "Research Paper Summarization Using Text- To-Text Transfer Transformer (T5) Model," School of Computing National College of Ireland, 2023.

[2] C. Raffel *et al.*, "Exploring the limits of transfer learning with a unified text-to-text transformer," *J. Mach. Learn. Res.*, vol. 21, pp. 1–67, 2020.

[3] M. Ballout, U. Krumnack, G. Heidemann, and K. U. Kühnberger, "Investigating Pre-trained Language Models on Cross-Domain Datasets, a Step Closer to General AI," *Procedia Comput. Sci.*, vol. 222, pp. 114–126, 2023, doi: 10.1016/j.procs.2023.08.147.

[4] Y. Christian and M. Erline, "Web-Based Chatbot With Natural Language Processing and Knuth-Morris-Pratt (Case Study: Universitas Internasional Batam)," *JST (Jurnal Sains dan Teknol.*, vol. 11, no. 1, pp. 132–141, 2022, doi: 10.23887/jstundiksha.v11i1.43258.

[5] P. A. Khachane, T. Patil, S. Pansare, and S. Ukarde, "PicQuest - Image Recognition Chatbot," *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 4, pp. 2456–2165, 2025, doi: https://doi.org/10.38124/ijisrt/25apr848.

[6] and A. S. R. Dr.G. Aparna, A. Nivas Reddy, V. Sai Rishik Reddy, S. Shirly, "AI Chatbot for Hospital Management System," *Int. Res. J. Adv. Eng. Hub*, vol. 3, no. 5, pp. 1553–2558, 2025, doi: https://doi.org/10.47392/IRJAEH.2025.0380.

[7] L. Dalavai, D. B. Sree, Katam V. Krishna, C. Venkatarao, and K. M. Brahmendra, "AI-Driven Healthcare Chatbot with Multilingual Support," *Int. J. Mod. Trends Sci. Technol.*, vol. 11, no. 03, pp. 350–359, 2025, doi: 10.5281/zenodo.15171446.

[8] M. E. K, "BERT Enabled AI Chatbot for Enhanced Voice Interaction," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 13, no. 5, pp. 4436–4445, 2025, doi: 10.22214/ijraset.2025.71007.

[9] O. Shaikh, R. Varia, and G. Kulkarni, "AI Healthcare Chatbot for Rural Area," *Interantional J. Sci. Res. Eng. Manag.*, vol. 09, no. 04, pp. 1–9, 2025, doi: 10.55041/ijsrem44104.

[10] C. A. I. Ventura and E. E. Denton, "Artificial Intelligence Chatbots and Emergency Medical Services: Perspectives on the Implications of Generative AI in Prehospital Care," *Open Access*

Emerg. Med., vol. 15, no. September, pp. 289–292, 2023, doi: 10.2147/OAEM.S420764.

[11] S. Furqan, "Saving Lives with AI: A Chatbot Solution for Accessible Medical Assistance," *IOSR J. Comput. Eng.*, vol. 27, no. 3, pp. 39–45, 2025, doi: 10.9790/0661-2703033945.

[12] J. P. Rainey *et al.*, "Clinical Outcomes and Overall Satisfaction of Patents Enrolled in an Artificial Intelligence–Powered Chatbot Following Periacetabular Osteotomy," *Arthroplast. Today*, vol. 34, p. 101752, 2025, doi: 10.1016/j.artd.2025.101752.

[13] S. M, "AI Chatbot in Banking Support," *Int. Sci. J. Eng. Manag.*, vol. 04, no. 06, pp. 1–9, 2025, doi: 10.55041/isjem04533.

[14] S. l Yadav1, "AI-Integrated Chatbot for Business Automation," *Interantional J. Sci. Res. Eng. Manag.*, vol. 09, no. 03, pp. 1–9, 2025, doi: 10.55041/ijsrem42608.

[15] D.. N Thrimoorthy, "Customer Service Chatbot With ML," *Interantional J. Sci. Res. Eng. Manag.*, vol. 09, no. 01, pp. 1–9, 2025, doi: 10.55041/ijsrem40893.

[16] P. A. Rodriguez and J. P. M. Chan, "Power Up with Chatbot Platform: Analysis on the Impact of E-Commerce Chatbots on Customer Satisfaction Power Up with Chatbot Platform: Analysis on the Impact of E-Commerce Chatbots on Customer Satisfaction," *Rev. Integr. Bus. Econ. Res.*, vol. 14, no. 4, pp. 106–121, 2025.

[17] S. Lakkangoudra, "The Impact of Chatbots on Customer Satisfaction in Online Shopping," *J. Informatics Educ. Res.*, vol. 5, no. 2, pp. 3218–3226, 2025, [Online]. Available: http://jier.org.

[18] W. Huang, J. Jiang, R. B. King, and L. K. Fryer, "Chatbots and student motivation: a scoping review," *Int. J. Educ. Technol. High. Educ.*, vol. 22, no. 1, pp. 1–27, 2025, doi: 10.1186/s41239-025-00524-2.

[19] S. Samad, "AI Chatbot for College Queries," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 13, no. 5, pp. 1690–1697, 2025, doi: 10.22214/ijraset.2025.68413.

[20] G. Chitra Priyanka, "Chatbots in Education System," *Int. J. Sci. Res. Eng. Manag.*, vol. 09, no. 04, pp. 1–9, 2025, doi: 10.55041/ijsrem45861.

[21] G. Mahant, "CollegeConnect AI: An Intelligent Chatbot for Student Support," *Int. J. Sci. Res. Eng. Manag.*, vol. 09, no. 05, pp. 1–9, 2025, doi: 10.55041/ijsrem47592.

[22] I. Kondreddy, "Advanced NLP Models for Technical University Information Chatbots," *Int. J. Sci. Res. Eng. Manag.*, vol. 09, no. 05, pp. 1–9, 2025, doi: 10.55041/ijsrem47406.

[23] K. S. Padmavathi, M. Prasanna, K. V. J. Rana Prathap, and T. Madhu, "Chatbot Deployment for College Recommendation," *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 5, pp. 3381–3386, 2025, doi: 10.38124/ijisrt/25may2088.

[24] R. Patil and K. L. Dhiman, "College Information Portal Ai Chatbot," *Int. Sci. J. Eng. Manag.*, vol. 04, no. 03, pp. 1–7, 2025, doi: 10.55041/isjem02508.

[25] S. Abinaya, S. Anugraha, and V. U. Ashika, "TECH PATH – CAREER GUIDANCE CHATBOT," *Int. Sci. J. Eng. Manag.*, vol. 4, no. 5, pp. 1–2, 2025, doi: 10.55041/ISJEM03682.

[26] P. J. Augustine, T. A. Kishan, K. S. A. I. Karthik, and B. A. Kumar, "Conversational Image Recognition Chatbot," *Int. J. Sci. Res. Eng. Manag.*, vol. 9, no. 5, pp. 1–6, 2025, doi: 10.55041/IJSREM47015.

[27] M. Adharsh, B. N. Chandan, K. V. Vardhan, and B. S. Jathin, "Customer Support Chatbot with MI for Restaurant," *Int. J. Sci. Res. Eng. Manag.*, vol. 9, no. 5, pp. 1–14, 2025, doi: 10.55041/IJSREM47912.

[28] E. Kagan, B. Hathaway, and M. Dada, "Deploying Chatbots in Customer Service: Adoption Hurdles and Simple Remedies," pp. 1–39, 2025.

[29] A. P. Venkatchalam, S. K. Hussain, S. H. Basha, U. A. Hussain, and S. Ameersha, "Online Chatbot Based on Ticketing System," *Int. J. Sci. Res. Eng. Manag.*, vol. 09, no. 05, pp. 1–9, 2025, doi: 10.55041/ijsrem47373.

[30] M. N. Kalmath, "Development of Chatbots Development of Chatbots," *Int. J. Innov. Res. Technol.*, vol. 10, no. 10, pp. 506–511, 2024.

[31] A. Puspitasari, A. N. Paradhita, Y. W. Tineka, and V. Sulistyowati, "Natural Language Processing (NLP) Technology for Chatbot Website," vol. 10, pp. 319–324, 2024, doi: 10.29303/jppipa.v10iSpecialIssue.8241.

[32] M. Shekgola and M. Modiba, "Utilising an AI chatbot to support smart digital government for Society 5.0 in South Africa," *South African J. Inf. Manag.*, vol. 27, no. 1, pp. 0–10, 2025, doi: 10.4102/sajim.v27i1.1983.