Medical-Chatbot using Retrieval Augmented Generation(RAG)

Prepared by:

- Habiba Ahmed Basuony
- Jana Walid Oraby

Presented to:

- Namasoft Technical

Contents

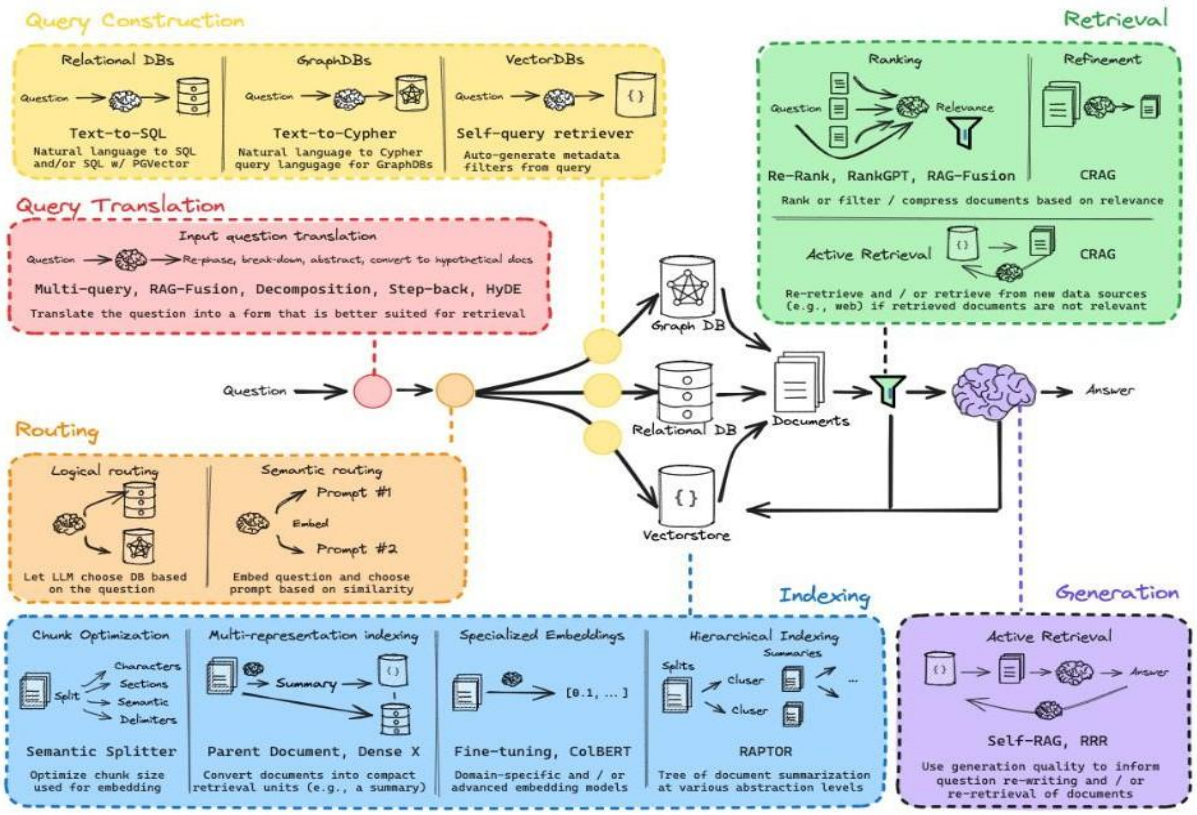
1. Introduction 3
2. Project Overview 3
3. Team Contributions 4
   3.1 Data Collection 4
   3.2 Model Creation 5
   3.3 Deployment 6
4. Code Breakdown 7
   4.1 Environment Setup 7
   4.2 Model Loading 8
5. User Interaction Experience 10
   5.1 User Input 10
   5.2 Document Retrieval 10
   5.3 Response Generation 10
   5.4 Output to User 11
8. Conclusion 11

1. Introduction

This document outlines the development and deployment of a bilingual chatbot designed to assist users with questions about breast cancer. The chatbot uses advanced natural language processing techniques to retrieve relevant information from medical documents and respond to queries in a conversational manner. The project was a collaborative effort, with different team members handling specific components, from data collection to deployment.

2. Project Overview

The chatbot is powered by a combination of state-of-the-art machine learning models, including a transformer-based model for generating responses, and FAISS for efficient document retrieval. This architecture allows the chatbot to quickly search through medical documents and provide accurate answers based on the retrieved context.



3. Team Contributions

Our team consists of two members who collaborated closely throughout the project. We shared responsibilities to ensure the successful development and deployment of the chatbot.

3.1 Data Collection

Together, we gathered and prepared the medical documents used in this chatbot, focusing on ensuring that the data is comprehensive and medically accurate regarding breast cancer. Our tasks included sourcing reliable medical papers, cleaning the data by removing irrelevant or duplicate information, and organizing the content into PDFs for efficient processing.

Contributions:

- Data Sourcing: gathered a wide array of medical documents, research papers, and reports related to breast cancer from reputable medical sources.
- Data Cleaning: They worked on cleaning the data, removing irrelevant or redundant information, to ensure that the content fed into the model was reliable and meaningful.

- PDF Preparation: The data included in this project was organized and structured in PDF format for efficient processing.

Click here to view the data related to breast cancer diagnosis and analysis.

3.2 Model Creation

We jointly developed the core chatbot model. We selected the LLaMA 3.1-8B Instruct model for its strong language generation capabilities and fine-tuned it to handle medical queries in both English and Arabic. We also generated embeddings using Sentence-Transformers to help the system retrieve relevant information efficiently. To enable fast document retrieval, we integrated FAISS into our pipeline.

Key Contributions:

- **Model Selection:**chose the LLaMA 3.1-8B Instruct model for this project, a powerful transformer-based model known for its language generation capabilities. The model was fine-tuned to respond to medical queries in both English and Arabic.
- **Embedding Generation:** They used Sentence-Transformers, a highly effective tool for generating embeddings, which are numerical representations of text that enable the system to understand and retrieve relevant information based on user queries.
- **FAISS Integration:** To enable fast and scalable document retrieval, the team integrated FAISS (Facebook AI Similarity Search), a library that performs efficient similarity searches across documents. This allows the chatbot to sift through thousands of pages of medical literature within milliseconds and retrieve the most relevant content.

```
from transformers import AutoTokenizer, AutoModelForCausalLM, BitsAndBytesConfig
```

```
    model_id = 'meta-llama/Llama-3.1-8B-Instruct'
    tokenizer = AutoTokenizer.from_pretrained(model_id)
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_use_double_quant=True,
        bnb_4bit_quant_type='nf4',
        bnb_4bit_compute_dtype=torch.bfloat16
    )
    model = AutoModelForCausalLM.from_pretrained(
        model_id,
        quantization_config=bnb_config,
        low_cpu_mem_usage=True
    )
    return tokenizer, model
```

```
embedder = SentenceTransformer('distiluse-base-multilingual-cased-v2')
pdf_embeddings = embedder.encode([doc.page_content for doc in documents])
```

3.3 Deployment

4. We worked together to deploy the chatbot using Streamlit for the web interface, making it user-friendly and accessible. We used localtunnel to expose the app to the web and integrated Hugging Face for secure model access and token management.

Key Contributions:

- **Deployment Environment:** e utilized Streamlit to build an intuitive and interactive user interface, making it easy for users to interact with the chatbot.

- **Localtunnel Integration:** They used localtunnel to expose the app to the web, allowing external access through a unique URL.
- **Hugging Face Integration:** The team also worked on integrating the model into the Hugging Face Hub, ensuring secure and fast access to the pretrained models. They managed tokenized access seamlessly using the Hugging Face API.

```
!streamlit run /kaggle/working/app.py  & npx localtunnel --port 8501
```

```
Collecting usage statistics. To deactivate, set browser.gatherUsageStats to false.


  You can now view your Streamlit app in your browser.

  Local URL: http://localhost:8501
  Network URL: http://172.19.2.2:8501
  External URL: http://35.237.2.123:8501

your url is: https://petite-squids-drive.loca.lt
```

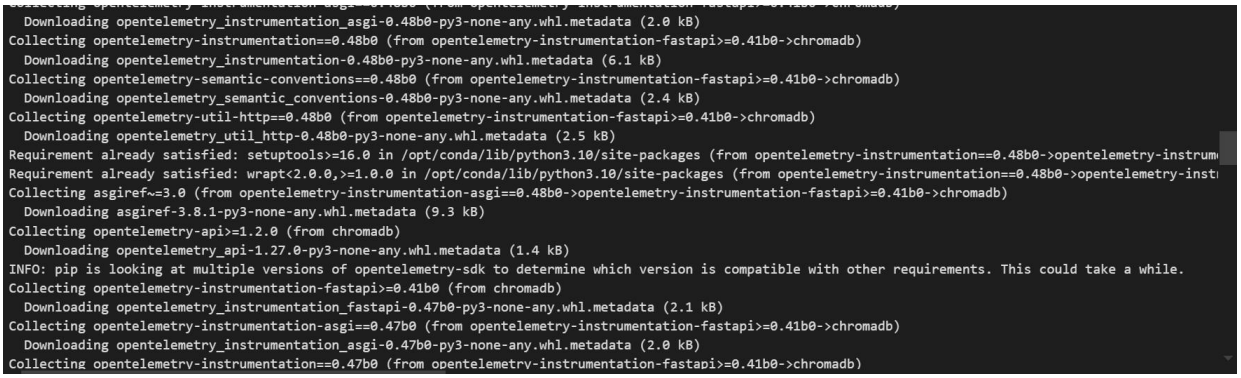
5. Code Breakdown

5.1 Environment Setup

The first step in the project implementation was setting up the required environment by installing the necessary libraries. The following libraries were installed:

- Streamlit: A framework used to create the user interface for the chatbot.
- Langchain C langchain-community: These libraries helped in document processing, splitting the content into manageable chunks for embedding generation.
- Sentence-Transformers: This library was used to generate embeddings from the text, converting large documents into vector representations that the model could search through.

- FAISS: A similarity search library used to quickly retrieve relevant sections of the documents based on the user's query.
- Transformers: This library was used to load the pretrained language model, LLaMA, from Hugging Face for natural language generation.
- Hugging Face Hub: To access the LLaMA model and manage tokens securely for model authentication.
- PyPDF: For reading and extracting text from the PDFs that contain the medical information.
- BitsAndBytes: For optimizing the transformer model to work in reduced precision (4-bit quantization), enabling it to run efficiently with lower memory usage.



5.2 Model Loading

The LLaMA model was loaded and prepared using Hugging Face Transformers. This step involved tokenizing the input text and configuring the model for optimal performance in a real-time setting. The following steps were followed:

- Quantization: The model was loaded using BitsAndBytesConfig in 4-bit precision, significantly reducing memory consumption while maintaining accuracy.
- Model Loading: The LLaMA 3.1-8B model was loaded from Hugging Face using secure tokenized access. This model is known for handling both conversational and context-based question answering tasks efficiently.

- Generation Arguments: Specific generation parameters were set, such as a maximum token limit of 256, no repeated n-grams, and a repetition penalty, to ensure the chatbot generated coherent, concise answers.

6. User Interaction Experience

The user interaction experience is crafted to facilitate easy access to information for individuals seeking answers about breast cancer. The chatbot initiates the conversation and guides users through their queries. Here's a step-by-step breakdown of the interaction:

6.1 User Input

Users can input their questions in either English or Arabic. The chatbot employs natural language processing to understand the intent and context of the queries. This process includes:

- Text Preprocessing: The user's input is cleaned and tokenized to prepare it for processing.
- Language Detection: The system detects the language of the input to route the query to the appropriate language model.

6.2 Document Retrieval

Once the input is processed, the chatbot utilizes FAISS to search for relevant documents. This step includes:

- Embedding Generation: The user query is transformed into an embedding using the Sentence-Transformers library.
- Similarity Search: FAISS performs a similarity search to identify the most relevant documents based on the user's query embedding.

6.3 Response Generation

With the relevant documents retrieved, the chatbot generates a response by:

- Context Extraction: The system extracts context from the selected documents to formulate a coherent answer.
- Response Generation: Using the LLaMA model, the chatbot generates a natural language response that is both informative and relevant.

6.4 Output to User

Finally, the generated response is sent back to the user in a conversational format, ensuring clarity and understanding.

8. Conclusion

The deployment of the bilingual chatbot marks a significant achievement in providing accessible information about breast cancer. Through collaboration and advanced technologies, the project team has created a valuable resource that aids individuals in navigating their questions and concerns related to breast cancer. As a standalone project, it exemplifies the potential of integrating AI into healthcare communication.