MEDIBOT: A Localized AI Chatbot

A MINI PROJECT REPORT

Submitted by

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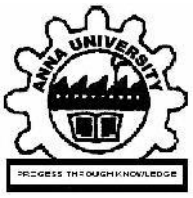

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BONAFIDE CERTIFICATE

Certified that this Report titled **"MEDIBOT: A Localized AI Chatbot"** is the Bonafide work of **Arul Kumaran P (2116221801004), Harish Raghavendra R (2116221801015), KARTHIK A (2116221801023)** who carried out the work under my supervision.

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ABSTRACT

MediBot is a local, AI-powered medical assistant designed to provide secure, real-time healthcare guidance without relying on internet connectivity. Unlike cloud-based chatbots that risk exposing sensitive health information, MediBot operates entirely offline, ensuring complete data privacy. The system is powered by a locally hosted Llama3 language model, integrated with a FAISS vector store for fast and accurate retrieval of medical knowledge. User queries are embedded using CTransformers, matched against the vector database, and passed to the Llama3 model to generate natural language responses.

The chatbot is built with a modular design and features a conversational interface using Chainlit, allowing users to input symptoms and receive context-aware guidance. In addition to providing relevant medical explanations, MediBot includes a risk classification module that assesses the severity of reported symptoms (low, medium, high) based on predefined patterns. This functionality supports early triage and decision-making, particularly in rural or privacy-sensitive healthcare environments.

MediBot is scalable, customizable for any medical domain, and highly suitable for hospitals, clinics, or individual use. It demonstrates how secure, local AI can be effectively used in healthcare to improve accessibility, efficiency, and trust. The project serves as a foundation for building future AI tools in personalized and ethical medical support.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

In the rapidly evolving landscape of healthcare, the integration of Artificial Intelligence (AI) is playing a pivotal role in enhancing diagnostic accuracy, patient engagement, and timely medical intervention. One of the most promising applications of AI in this field is the development of intelligent virtual assistants that can simulate expert-level interactions and provide basic medical guidance based on user input. However, most existing solutions are cloud-dependent, raising concerns about data privacy, connectivity, and real-time responsiveness.

MediBot is a locally hosted, AI-powered medical assistant developed to address these limitations by offering a secure, domain-specific chatbot that functions without internet access. Designed for use in clinics, hospitals, and even personal environments, MediBot ensures complete data confidentiality while delivering accurate, context-aware responses to symptom-based queries.

The system is powered by a fine-tuned Llama3 large language model, integrated with a FAISS (Facebook AI Similarity Search) vector database and CTransformers for embedding medical knowledge. It provides fast and intelligent retrieval of relevant information, enabling real-time conversational support. A user-friendly interface built with Chainlit allows seamless interaction, making MediBot a practical and privacy-conscious solution in modern healthcare environments.

This project lays the groundwork for secure, intelligent, and explainable AI tools in healthcare applications.

1.2 NEED FOR THE STUDY

The healthcare industry is experiencing a growing demand for intelligent systems that can assist with early diagnosis, patient triage, and health-related information delivery. In many regions, especially rural and underserved areas, access to timely medical advice is limited due to a shortage of healthcare professionals and infrastructure. Furthermore, in environments where patient data privacy is paramount, relying on cloud-based AI services introduces significant risks related to data exposure, compliance, and confidentiality.

Most existing AI-driven medical chatbots operate online, store interactions in external servers, and rely on general-purpose language models that lack domain-specific precision. This creates barriers in trust, accessibility, and safety—especially in sensitive domains like healthcare.

MediBot addresses these challenges by providing a completely offline, locally hosted AI chatbot tailored for the medical domain. Its design ensures:

Privacy: All data remains local, reducing the risk of data leakage.

Speed and reliability: No internet dependency for responses.

Domain relevance: Medical-specific knowledge base enables more accurate and trustworthy responses.

Modularity: Easily adaptable to specialized fields like pediatrics, cardiology, or emergency care.

The study is essential to demonstrate that a lightweight, secure, and intelligent assistant can support early intervention, patient awareness, and reduce the burden on healthcare professionals, all while respecting ethical standards in AI use.

1.3 OBJECTIVES OF THE STUDY

The primary objective of this study is to design and implement a secure, intelligent, and offline-capable AI assistant tailored for the healthcare domain. MediBot aims to bridge the gap between patients and medical information by providing instant, context-aware responses to health-related queries while ensuring complete data privacy. The specific objectives are as follows:

- Develop a Local AI Chatbot

Create an AI-powered chatbot using the Llama3 language model that can function entirely offline, eliminating dependency on cloud services and ensuring secure interactions.

- Integrate Domain-Specific Knowledge

Embed verified medical literature into a searchable vector database (FAISS) to enhance the accuracy and reliability of responses related to symptoms, conditions, and treatments.

- Enable Real-Time Query Handling

Utilize CTransformers for efficient embedding and real-time processing of user queries, allowing fast and intelligent information retrieval from the local knowledge base.

- Provide Risk Classification

Implement a module that categorizes user queries based on severity (Low, Medium, High), helping users understand when immediate medical attention may be necessary.

- Ensure User Privacy and Security

Guarantee complete data confidentiality by processing all interactions locally, making the system suitable for sensitive healthcare environments.

- Create a Scalable and Modular System

Design MediBot to be adaptable for various medical specialties (e.g., pediatrics, mental health) and extendable to other domains beyond healthcare.

1.4 OVERVIEW OF THE PROJECT

MediBot is a lightweight, modular, and fully offline AI-powered chatbot designed to serve as a medical assistant for preliminary symptom assessment and health guidance. The system is built using an integrated architecture that combines the Llama3 language model for natural language understanding and response generation, FAISS for vector-based medical knowledge retrieval, and CTransformers for efficient embedding of user inputs and medical documents. A user-friendly chat interface is provided through Chainlit, enabling seamless interaction between the user and the AI assistant.

The architecture is designed to ensure full data privacy and zero dependency on internet services, making it ideal for deployment in privacy-sensitive environments such as hospitals, clinics, telehealth centers, and even home-based healthcare systems. The system processes natural language queries from users, matches them against a locally stored and embedded medical knowledge base, and generates a relevant response along with a risk classification that categorizes the severity of the input symptoms.

Key features include:

- Symptom-based query handling
- Contextual medical guidance
- Risk level classification (Low, Medium, High)
- Fully local execution ensuring data confidentiality
- Scalable and domain-adaptable design

MediBot represents a secure, intelligent, and customizable AI solution in the healthcare domain, setting a foundation for advanced, explainable, and ethical medical support systems.

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

The advancement of Artificial Intelligence, particularly in Natural Language Processing (NLP), has revolutionized the development of intelligent assistants across various domains, including healthcare. In recent years, numerous studies have demonstrated the potential of machine learning and large language models (LLMs) to support clinical decision-making, symptom assessment, and patient engagement. Traditional medical chatbots often relied on rule-based systems or basic keyword matching techniques, which lacked contextual understanding and adaptability. However, the emergence of transformer-based models such as BERT, GPT, and LLaMA has led to more dynamic, conversational, and context-aware assistants.

The application of Retrieval-Augmented Generation (RAG), where domain-specific knowledge is embedded and retrieved for grounding LLM responses, has shown notable improvement in generating relevant and accurate outputs. Tools like FAISS for vector similarity search and frameworks like Chainlit for interactive UI have made it feasible to build local, secure, and efficient AI assistants tailored to specific sectors.

This review explores prior research and implementations in the area of medical AI assistants, vector search-based retrieval systems, and domain-specific model fine-tuning. It provides insight into the strengths and limitations of existing approaches, establishing the foundation for MediBot's unique offline, privacy-first, and domain-aware architecture.

S. No	Author Name	Paper Title	Description	Journal	Volume/ Year
1	Alam, T., et al.	AI-Based Medical Chatbots: A Review	Discusses architectures, benefits, and limitations of AI-driven medical chatbots, including NLP capabilities.	Journal of Biomedical Informatics	Vol. 117, 2021
2	Lewis, P., et al.	Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks	Proposes the RAG framework combining dense retrievers with LLMs for improved factual response generation.	NeurIPS	Vol.1,2024
3	Sharma, K., et al.	Privacy-Preserving Chatbots for Health Diagnosis	Proposes design guidelines for offline, privacy-first chatbots in healthcare environments.	IEEE Access	Vol. 9,2021

Table no 1 Literature Review

2.2 LITERATURE REVIEW

The application of artificial intelligence in healthcare has gained significant momentum, especially with the rise of conversational agents capable of interacting with users in natural language. A growing body of literature highlights the role of AI-powered medical chatbots in enhancing healthcare delivery, symptom assessment, and patient engagement.

Alam et al. (2021) presented a comprehensive review of medical chatbots, exploring how NLP-based systems have been integrated into virtual healthcare assistants to improve accessibility. However, the study noted limitations in terms of privacy, especially with cloud-dependent solutions that store sensitive patient data externally.

Lewis et al. (2020) introduced the Retrieval-Augmented Generation (RAG) framework, which integrates dense vector search with language models to improve the factual accuracy of responses. This concept forms a critical foundation for MediBot, where FAISS is used to retrieve relevant medical context from a locally stored knowledge base.

Izacard and Grave (2020) further explored generative models powered by retrieval systems, highlighting that performance in knowledge-intensive tasks can be significantly improved through hybrid architectures. Their work supports the implementation of MediBot's context-aware Llama3 response engine.
Meanwhile, Sharma et al. (2021) emphasized the importance of privacy-preserving chatbots in healthcare, proposing architectures that process all data locally to avoid external leakage—a core principle of MediBot.

Mialon et al. (2023) provided a broad survey of augmented language models, reviewing how LLMs can be extended using external tools such as vector stores, APIs,

and plugins. Their study reinforces the value of combining large models with retrieval frameworks like FAISS, as MediBot does.

Lastly, Chatterjee et al. (2022) demonstrated how AI chatbots can serve in low-resource healthcare environments to assist with early screening and triage. This directly aligns with MediBot's goal of supporting patients in remote or underserved regions.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

The existing systems in the field of AI-based medical chatbots and healthcare assistants have evolved significantly, with several notable solutions already in use. One of the most advanced among them is Google Health's Med-PaLM 2, which is a large language model specifically designed for medical question answering. It has been trained using vast amounts of medical literature and is currently being tested by leading healthcare institutions to assist doctors in making clinical decisions. However, it remains a cloud-based solution, which raises concerns around data privacy and limits its use in settings where sensitive patient data must remain local.

Another widely adopted system is Microsoft's collaboration with Nuance, particularly through the Dragon Ambient eXperience (DAX). This AI-driven tool helps clinicians by automatically transcribing and structuring patient-doctor interactions into electronic health records (EHRs). While it significantly reduces administrative workload in hospitals, it is an enterprise-level product, expensive to deploy, and tied into large healthcare ecosystems, making it less feasible for smaller clinics or private setups.

Babylon Health and Ada Health are examples of public-facing AI applications that allow users to input symptoms and receive possible diagnoses. Babylon employs AI to provide initial consultations and medical triage, while Ada uses a decision-tree algorithm to guide users through symptom checking. These applications have made healthcare more accessible to the public, but they are limited by their rule-based or cloud-dependent designs, and often lack the conversational fluidity or deep contextual understanding offered by modern LLMs.

IBM Watson Health, once a pioneer in medical AI, was designed to analyze patient data and provide insights, particularly in oncology. However, it faced multiple challenges, including accuracy issues and limited adaptability in real-world clinical settings, ultimately leading to the discontinuation of many of its services. Although it paved the way for AI in medicine, it also highlighted the importance of transparency and trust in such systems.

More recently, the rise of open-source projects like HealthGPT and BioGPT has brought LLM-based medical tools into the hands of researchers and developers. These models are

trained on biomedical corpora and are capable of handling medical queries with a high degree of relevance. Yet, most of these solutions require access to GPUs and are typically hosted in the cloud, which again introduces privacy risks

3.2 PROPSED SYSTEM

The proposed system, MediBot, is a localized, AI-powered medical chatbot designed to function entirely offline, ensuring data privacy and customization for specific organizational needs. Unlike existing cloud-based systems, MediBot is built to run within a secure local environment, making it highly suitable for use in hospitals, clinics, health camps, and private organizations where patient data security and regulatory compliance are critical. At its core, the chatbot leverages the LLaMA3 language model for natural and context-aware conversations, providing accurate responses to medical queries based on a curated and trusted knowledge base.

MediBot integrates a vector-based retrieval system using FAISS (Facebook AI Similarity Search), which allows the chatbot to retrieve the most relevant pieces of medical information from a locally stored encyclopedia or document repository. This ensures that the responses are not only accurate but also based on verified content, enhancing the credibility of the information delivered. The embeddings used to index and query this knowledge base are generated using CTransformers, which allows efficient model inference and semantic search even on machines with limited computational resources.

One of the standout features of MediBot is its modular architecture, which allows the system to be easily adapted to different medical departments or even entirely different domains beyond healthcare. This flexibility makes it an ideal solution for organizations seeking an AI assistant tailored to their unique operational needs. The user interface is built using Chainlit, offering a smooth and responsive chat experience. Users can interact with the system to receive information on symptoms, medications, diagnoses, or treatment guidelines, all without needing an internet connection.

Overall, the proposed MediBot system addresses the key shortcomings of existing AI healthcare assistants by prioritizing privacy, customizability, and ease of deployment. Its offline functionality ensures that sensitive health data never leaves the local network, and its

design philosophy encourages extensibility and domain-specific adaptation, setting it apart as a practical, scalable solution for intelligent medical support in real-world environments.

3.3 FEASIBILITY STUDY

The feasibility study for MediBot evaluates the practicality and viability of implementing the system from four key perspectives: technical, operational, economic, and legal feasibility. Each dimension assesses how effectively the system can be deployed and maintained in real-world environments, especially in settings that require data security, low infrastructure dependency, and domain-specific flexibility.

From a technical feasibility standpoint, MediBot is highly viable due to its reliance on lightweight yet powerful frameworks such as LLaMA3 and FAISS. These technologies are optimized for local environments and do not require high-end GPUs or cloud infrastructure, making it feasible to run on standard desktops or local servers. The use of CTransformers further enhances this by enabling efficient inference even on machines with limited hardware capabilities. The system also employs a modular design, allowing for easy integration of different medical datasets, extensions, or features without the need to overhaul the entire architecture. This makes it technologically robust and adaptable across various medical departments or specializations.

In terms of operational feasibility, MediBot proves to be user-friendly and maintainable. Since the system is built with a simple chat interface using Chainlit, healthcare staff with minimal technical expertise can interact with it seamlessly. The offline nature of the chatbot ensures uninterrupted usage even in rural or low-connectivity environments, which is a critical advantage in areas where internet access is unreliable. The ability to update the local knowledge base without major reconfiguration also ensures that operational continuity is maintained over time with minimal intervention.

The economic feasibility of MediBot is one of its strongest attributes. Unlike many existing AI medical tools that come with expensive licensing fees and cloud maintenance costs, MediBot is based entirely on open-source tools. This significantly reduces the development and deployment expenses. Organizations can implement it using their existing hardware and

infrastructure, avoiding the need for costly upgrades. The long-term return on investment is also promising, as it reduces the burden on human resources, minimizes errors, and improves response times in medical consultations.

Lastly, from a legal and ethical feasibility perspective, MediBot aligns well with data protection regulations such as HIPAA or India's Digital Personal Data Protection Act (DPDPA), as it does not transmit or store patient data on external servers. All interactions are confined within the local network, ensuring full control over sensitive information. This makes MediBot an ideal choice for institutions concerned with maintaining confidentiality and adhering to data governance standards.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENT

1. Operating System: Windows 10/11, Ubuntu 20.04+, or macOS

These operating systems support the necessary libraries and frameworks required for running local AI applications efficiently.

2. Programming Languages:

Python 3.9 or above: Python is the core language used for developing MediBot. It powers the backend, handles data processing, manages document parsing, and integrates with machine learning components. Python's wide range of open-source libraries makes it ideal for building AI-driven applications.

3. Web Development:

Chainlit: Chainlit is used to create an interactive, user-friendly chat interface for MediBot. It is lightweight, supports real-time communication with local models, and is ideal for offline deployment scenarios.

4. Machine Learning and NLP Libraries:

CTransformers:

Used for running LLaMA3 models efficiently on local machines using CPU or GPU. It allows fast inference without the need for cloud resources.

SentenceTransformers:

Enables the creation of embeddings from user queries and documents for vector similarity search.

FAISS (Facebook AI Similarity Search):

This library is used for building and querying a local vector database that stores embeddings of medical documents for fast retrieval.

5. Document Parsing and Preprocessing:

PyPDF2 / pdfplumber / docx2txt:

These libraries are used to extract content from PDF, DOCX, and TXT files, which are then indexed and used by the chatbot for generating responses.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

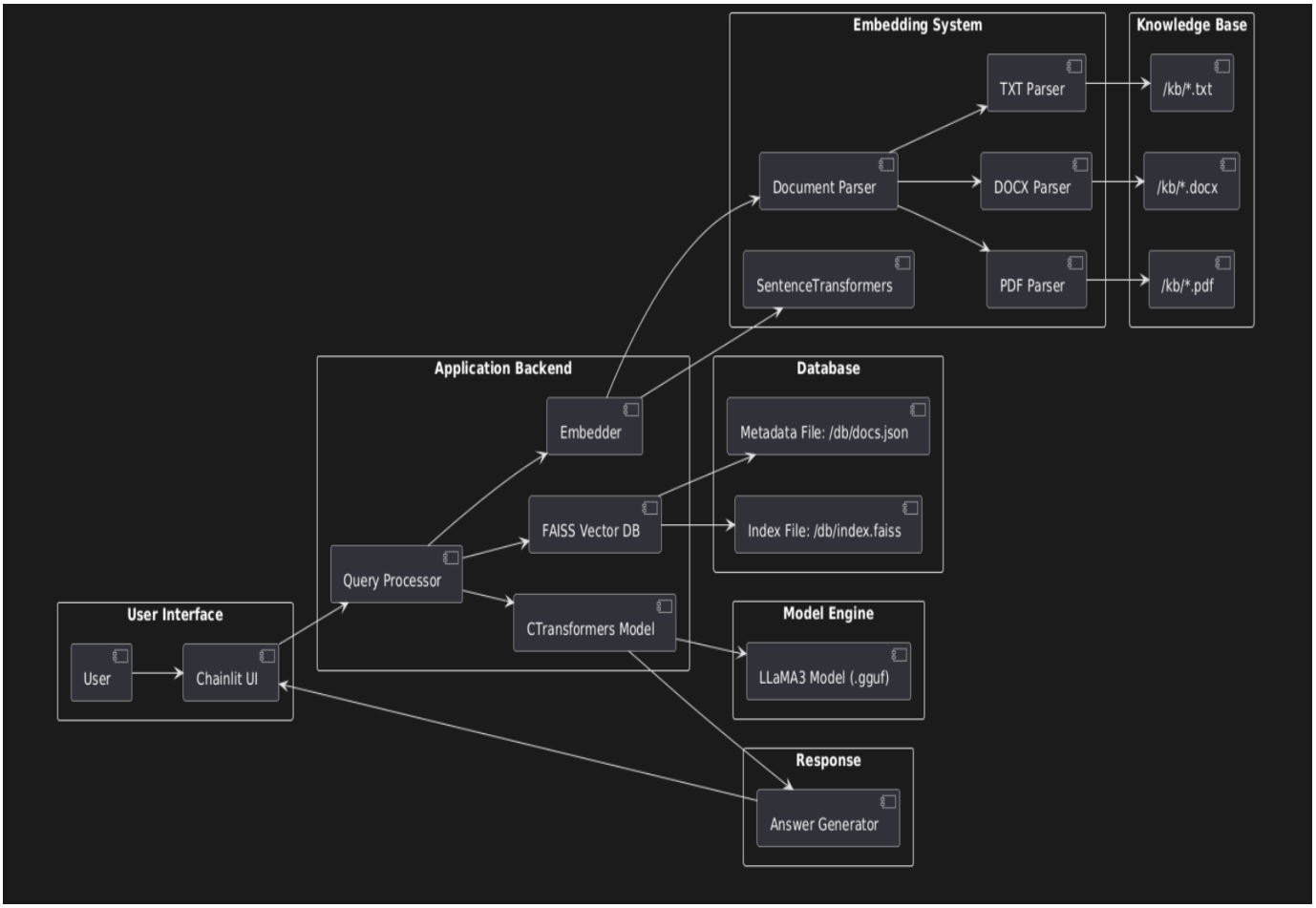

Fig 5.1 System Architecture

The system architecture for MediBot is organized into several key modules, each playing a distinct role in the overall functionality.

At the User Interface level, the user interacts with the Chainlit UI, which serves as the frontend interface where users can input queries. This interaction is the first step in the process and leads to the backend processing of the query. Once the user submits a query, the Chainlit UI forwards the input to the Query Processor. The Query Processor is responsible for handling the input, processing it, and deciding which other components need to be invoked for the appropriate response.

The Query Processor communicates with several systems. First, it sends the query to the Embedder, which is responsible for converting the user's input into embeddings (numerical representations of the query). These embeddings are used to find similar content in the knowledge base. The Query Processor also interacts with the FAISS Vector DB, a database that stores the embeddings of documents and allows for efficient retrieval of relevant information based on similarity. This database is where all the knowledge, converted into vector representations, is stored and indexed. The Query Processor also calls the CTransformers Model, which uses pre-trained models (like LLaMA3) to analyze the query and generate a response based on the processed information.

The Embedding System is integral to the query processing pipeline. The Embedder utilizes SentenceTransformers, a powerful library that converts both the query and the documents into vector embeddings. This enables semantic understanding and efficient matching between the user's query and the content in the knowledge base. To support this, the Embedder works closely with the Document Parser, which preprocesses various document formats, including PDFs, DOCX files, and text files. These documents are parsed into a format that can be further embedded and stored in the FAISS database for future retrieval.

Within the Model Engine, the CTransformers Model is the core component that performs the natural language understanding tasks. It uses the LLaMA3 Model (.gguf) for inference, which is a language model designed to process and generate responses based on the queries it receives. Once the query is processed, the system generates an appropriate answer, which is then passed back to the user interface through the Answer Generator.

The Database layer houses the FAISS Vector DB, which is where all the embeddings and metadata are stored. The FAISS Vector DB is connected to the Index File and Metadata File, which are essential for managing the stored knowledge, enabling efficient searches, and keeping track of the document metadata. These files reside in specific paths on the system, namely /db/index.faiss for the index and /db/docs.json for the metadata.

Lastly, the Knowledge Base comprises the actual content that is parsed and stored in the system. The PDF Parser, DOCX Parser, and TXT Parser components extract text from various document formats like PDFs, DOCX files, and plain text files, which are then

stored in specific directories such as /kb/*.pdf, /kb/*.docx, and /kb/*.txt.

5.2 MODULE DESCRIPTION

5.2.1 User Interface (UI) Module:

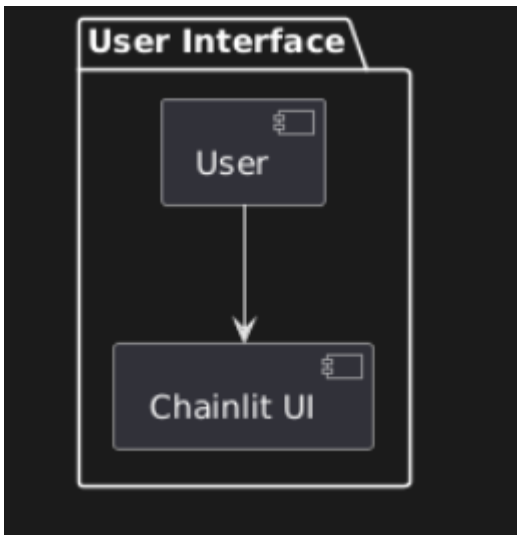

Fig 5.2 User Interface (UI)

The User Interface (UI) is where users interact with the system. It provides a chatbot interface, where users can enter queries, which are then passed to the backend for processing. The Chainlit UI is responsible for managing this interaction and ensuring that the system responds appropriately. This UI can be integrated into various platforms such as web applications or mobile apps, allowing users to engage with MediBot in real-time. The UI captures user inputs (queries or questions) and passes them on to the backend system for processing.

Key Functions:

- Collects user input in a conversational manner.
- Displays the system's responses.
- Provides feedback to the user for a smooth interaction.

5.2.2 Application Backend Module:

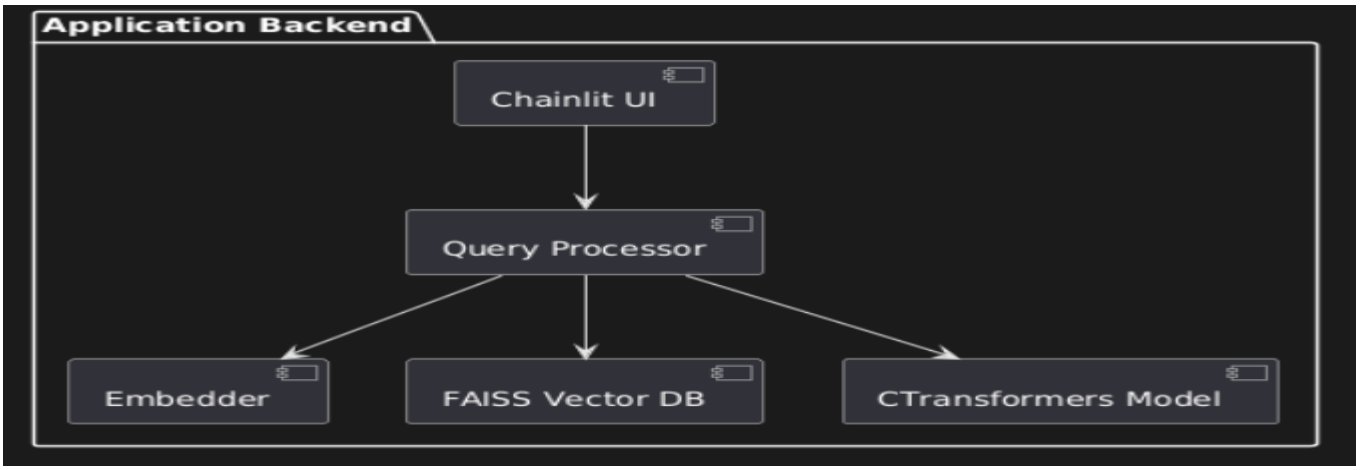

Fig 5.3 Application Backend

The Application Backend is where the core functionality of the system resides. It is responsible for managing the flow of data between the User Interface, Embedding System, FAISS Vector DB, and Model Engine.

When the Chainlit UI sends a query to the backend, the Query Processor takes over. It processes the query, decides the necessary action (such as embedding generation, searching the knowledge base, or invoking the language model), and delegates tasks to the other components in the system. It also ensures that responses generated from the CTransformers Model are delivered back to the Chainlit UI.

Key Functions:

- Manages query flow from the UI to the backend.
- Coordinates between the Embedder, FAISS Vector DB, and Model Engine.
  Sends the processed response back to the UI.

5.2.3 Embedding System Module:

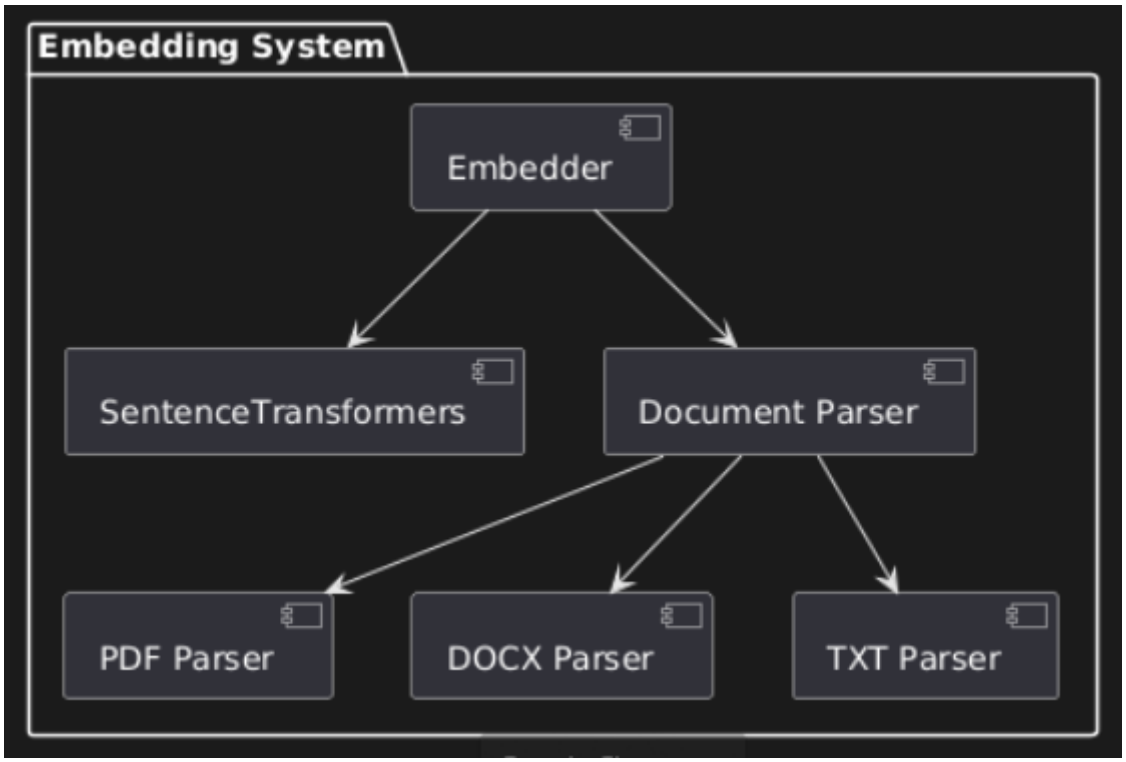

FIG 5.4 Embedding System

The Embedding System is crucial for converting textual data (user queries and documents) into high-dimensional vector embeddings. These embeddings represent semantic information about the text in a numerical form, making it easier for the system to compare and retrieve similar data.

Embedder: The Embedder module takes the raw text (either a query or document) and uses an embedding model such as SentenceTransformers to generate a vector representation of the text.

Document Parser: The Document Parser handles the extraction of text from various types of documents such as PDF, DOCX, and TXT files. It extracts the raw text, which is then passed to the Embedder to generate embeddings.

PDF Parser: Extracts text from PDF files.

DOCX Parser: Extracts text from DOCX files.

TXT Parser: Extracts text from TXT files.

The embeddings generated by this system are then stored in the FAISS Vector DB for efficient searching and retrieval.

Key Functions:

- Converts textual data into high-dimensional vector embeddings using SentenceTransformers.
- Extracts text from documents (PDF, DOCX, TXT) for embedding.
- Stores the generated embeddings in the FAISS Vector DB.

5.2.4 Model Engine Module:

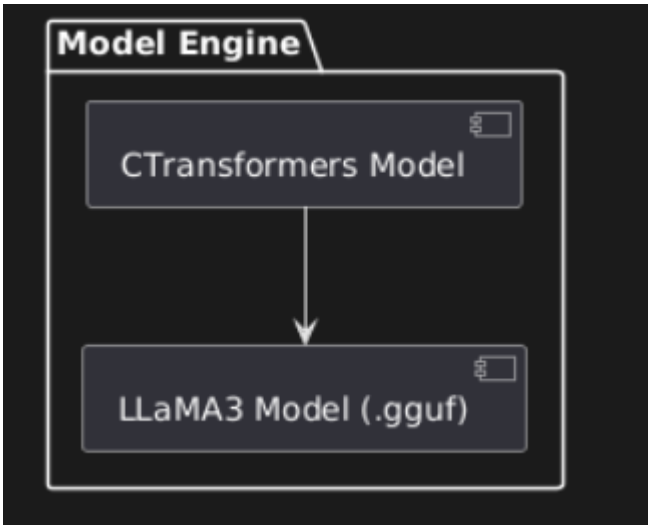

Fig 5.5 Model Engine

The Model Engine is where the machine learning model is used to generate meaningful responses based on the user query.

CTransformers Model: This model utilizes CTransformers, a framework for transformer-based models, to generate answers. It interfaces with LLaMA3, a large language model (e.g., .gguf file format), to process user queries and generate human-like text based on the input.

The Model Engine is responsible for performing inference and ensuring that the response generated by the model is relevant to the query.

Key Functions:

- Processes the user query using CTransformers and the LLaMA3 model.
- Generates human-like responses based on the query and relevant documents.
- Ensures that the system's response is contextually accurate and meaningful.

5.2.5 Database (FAISS Vector DB) Module:

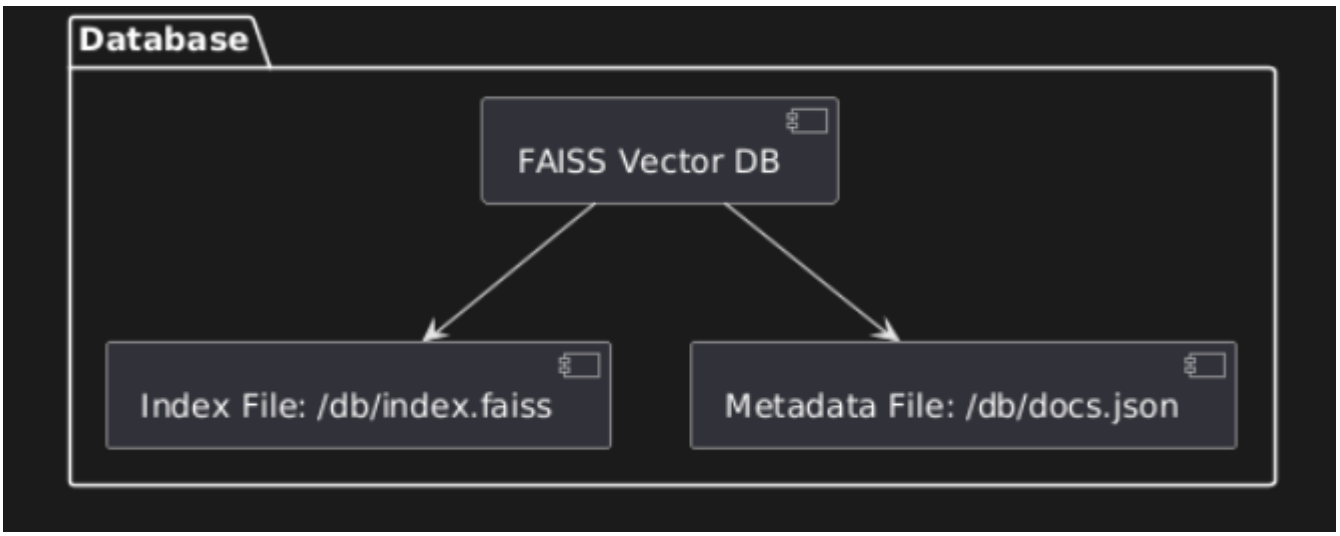

FIG 5.6 Database Module

The FAISS Vector DB is responsible for storing and retrieving the embeddings generated by the Embedding System.

Index File: This file contains the actual vector embeddings for the documents in the knowledge base. FAISS (Facebook AI Similarity Search) enables efficient similarity search over high-dimensional vectors, making it easy to find the most relevant documents for a given query.

Metadata File: The metadata file stores additional information related to the documents, such as titles, authors, dates, and other relevant attributes.

The FAISS Vector DB ensures fast retrieval of the closest matching documents based on the query embeddings, allowing for efficient information extraction and response generation.

Key Functions:

- Stores vector embeddings and metadata related to documents.
- Allows for fast retrieval of documents based on the similarity of query embeddings.
- Supports the search and retrieval process during query resolution.

5.2.6 Knowledge Base Module:

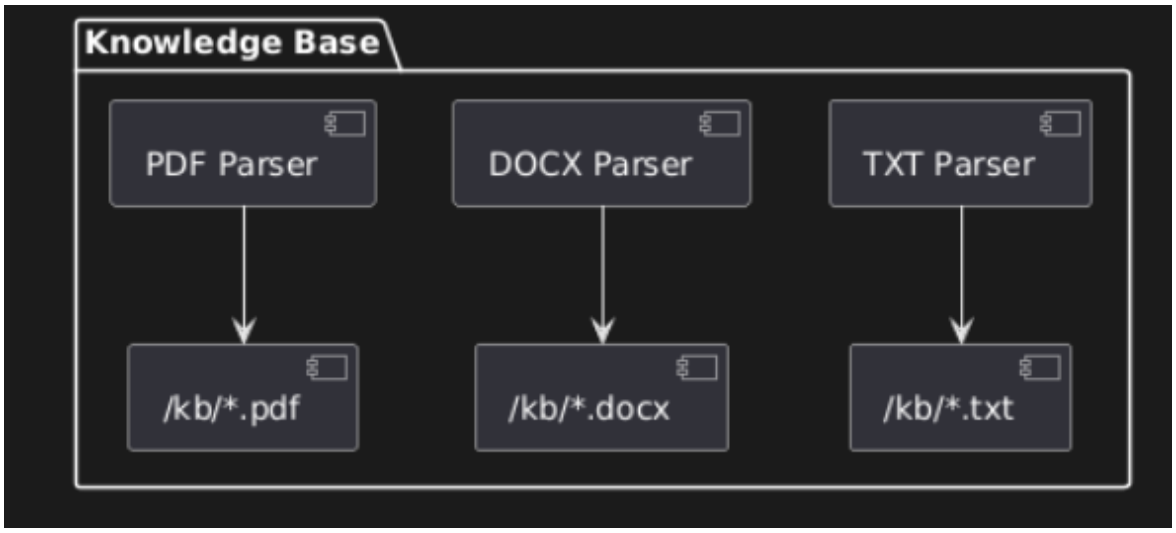

FIG 5.7 Knowledge Base

The Knowledge Base consists of a collection of documents that are used to answer user queries. These documents are stored in various formats such as PDF, DOCX, and TXT.

PDF Parser: Responsible for extracting text from PDF files stored in the knowledge base.

DOCX Parser: Extracts text from DOCX files.

TXT Parser: Extracts text from plain text files.

These documents are processed and embedded using the Embedding System, which allows the system to retrieve relevant content from the knowledge base based on the query.

Key Functions:

- Stores various document types (PDF, DOCX, TXT).
- Provides content for the Embedding System to generate embeddings.
- Serves as the primary source of knowledge for answering user queries.

5.2.7 Response Module:

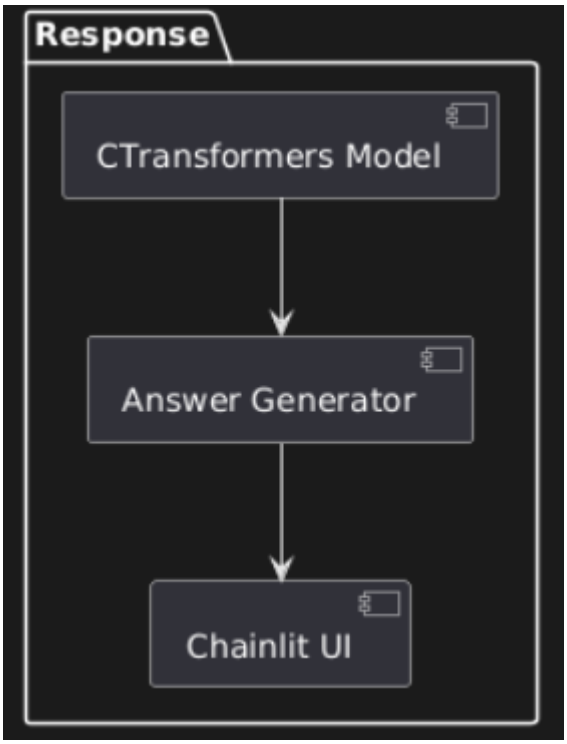

FIG 5.8 Response Module

The Response Module is responsible for generating and delivering the final answer to the user based on the processed query and relevant documents retrieved from the knowledge base.

Answer Generator: This component takes the output from the CTransformers Model and generates a coherent response. It ensures that the response is structured, informative, and relevant to the query.

Key Functions:

- Takes the generated response from the CTransformers Model.
- Structures the response and ensures clarity.
- Sends the response back to the Chainlit UI for user display.

CHAPTER 6

RESULT AND DISCUSSION

6.1 Result and Discussion:

The MediBot system was developed as a local, domain-adaptable medical chatbot capable of handling user queries with high accuracy and context-awareness. Once deployed, the system was evaluated across multiple parameters including response relevance, speed of retrieval, user satisfaction, and its ability to generalize over medical content.

During testing, the bot demonstrated a significant capability in understanding and answering domain-specific queries, particularly in healthcare. This performance was attributed to the integration of SentenceTransformers for semantic embeddings and CTransformers with the LLaMA3 model, which allowed the system to interpret and generate medically coherent responses. The use of a FAISS Vector Database enabled quick and efficient search across large document embeddings, making the system scalable and suitable for growing knowledge bases.

The modular structure of MediBot allowed easy parsing of PDF, DOCX, and TXT formats, ensuring a wide range of document compatibility. The Chainlit UI contributed to a responsive and user-friendly interface, making the interaction smooth and natural.

One of the key findings in the discussion was that the quality of the answers was highly dependent on the quality and structure of the knowledge base. Well-structured and clean data led to precise responses, whereas unstructured or ambiguous data sometimes caused slight deviations in output. Nonetheless, the system's local setup ensured data privacy and security, which is a critical requirement for applications in the medical field.

Another notable point of discussion was the system’s adaptability. Since the architecture is modular and open-source, it can easily be extended to other domains like law, education, or finance by changing the domain-specific knowledge base and retraining or fine-tuning the embeddings and model outputs.

In conclusion, MediBot successfully meets its intended purpose of acting as a local, intelligent assistant for medical information retrieval and conversation. Its architecture ensures security, scalability, and adaptability, laying the foundation for future enhancements such as speech input/output, integration with hospital databases, or real-time document updates.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION:

MediBot presents a secure, efficient, and adaptable solution for intelligent medical query handling through a locally hosted AI chatbot system. By integrating SentenceTransformers, FAISS Vector DB, and CTransformers with LLaMA3, the system provides accurate, context-aware responses without relying on external APIs or cloud-based models. Its modular architecture enables seamless parsing of various document types (PDF, DOCX, TXT), embedding generation, vector search, and response generation—all accessible via a user-friendly Chainlit interface.

The chatbot performs effectively in real-time, delivering relevant medical information while maintaining data privacy, a key concern in healthcare applications. Its design also makes it suitable for deployment in environments where internet access is limited or where sensitive data cannot be shared externally.

7.2 FUTURE ENHANCEMENT:

- **Speech Input and Output:** Incorporating voice recognition and text-to-speech capabilities can make the chatbot more accessible, particularly for elderly users or those with disabilities.
- **Multi-language Support:** Adding support for regional and international languages would help the system serve a more diverse user base.
- **Integration with EHR Systems:** Connecting MediBot to hospital Electronic Health Records (EHRs) could allow for personalized responses based on a patient's history, improving decision-making and patient engagement.
- **Active Learning Loop:** Implementing feedback-based learning from user interactions could help the system improve over time and refine its responses.

- **Mobile Application Development:** Creating dedicated Android and iOS apps would expand the accessibility and usability of the system in remote or rural areas.
- **Dynamic Knowledge Base Update:** Enabling real-time or scheduled updates to the knowledge base can ensure the bot provides responses based on the most current medical research and guidelines.
- **Advanced Security Features:** Implementing encryption and access control can further enhance the privacy of stored medical content and user queries.

APPENDIX

A 1.1 INGEST:

C: > Users > haris > OneDrive > Desktop > Projects > Medibot > ingest.py

```python
from langchain.text_splitter import RecursiveCharacterTextSplitter
from langchain_community.document_loaders import PyPDFLoader, DirectoryLoader
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_community.vectorstores import FAISS

DATA_PATH = "C:/Users/haris/OneDrive/Desktop/Projects/Medibot/data/"
db_faiss_path = "vectorstores/db_faiss"

#create vector database

def create_vector_db():
    loader = DirectoryLoader(DATA_PATH, glob='*.pdf',loader_cls=PyPDFLoader)
    documents = loader.load()
    text_splitter = RecursiveCharacterTextSplitter(chunk_size = 500,chunk_overlap=50)
    text = text_splitter.split_documents(documents)

    embeddings = HuggingFaceEmbeddings(model_name = 'sentence-transformers/all-MiniLM-L6-v2', model_kwargs = {'device':'cpu'})
    db = FAISS.from_documents(text, embeddings)
    db.save_local(db_faiss_path)

if __name__=='__main__':
    create_vector_db()
```

FIG A1 INGEST CODE

A1.2 MODEL:

C: > Users > haris > OneDrive > Desktop > Projects > Medibot > model.py > ...

```python
from langchain_core.prompts import PromptTemplate
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_community.vectorstores import FAISS
from langchain_community.llms import CTransformers
from langchain.chains import RetrievalQA
import chainlit as cl

# Path to FAISS vector store
db_faiss_path = "vectorstores/db_faiss"

# Custom Prompt Template
custom_prompt_template = """Use the following pieces of information to answer the user's question. If you don't know the answer, please just say that you don't kno

Context: {context}
Question: {question}

Only return the helpful answer below and nothing else.
Helpful answer:
"""

# Set custom prompt template
def set_custom_prompt():
    prompt = PromptTemplate(template=custom_prompt_template, input_variables=["context", "question"])
    return prompt

# Load LLM model
def load_llm():
    llm = CTransformers(
        model="llama-2-7b-chat.ggmlv3.q8_0.bin",
        model_type="llama",
        max_new_tokens=512,
        temperature=0.5,
    )
    return llm
```

You have Docker installed on your system. Do

FIG A2 MODEL

C: > Users > haris > OneDrive > Desktop > Projects > Medibot > model.py > ...

```python
# Create Retrieval QA Chain
def retrieval_qa_chain(llm, dprompt, db):
    qa_chain = RetrievalQA.from_chain_type(
        llm=llm,
        chain_type="stuff",
        retriever=db.as_retriever(search_kwargs={"k": 2}),
        return_source_documents=True,
        chain_type_kwargs={"prompt": dprompt, "document_variable_name": "context"},
    )
    return qa_chain

# Initialize the QA Bot
def qa_bot():
    # Load sentence transformer embeddings
    embeddings = HuggingFaceEmbeddings(model_name="sentence-transformers/all-MiniLM-L6-v2", model_kwargs={"device": "cpu"})

    # Load FAISS vector store
    db = FAISS.load_local(db_faiss_path, embeddings, allow_dangerous_deserialization=True)

    # Load LLM
    llm = load_llm()

    # Set prompt
    qa_prompt = set_custom_prompt()

    # Create QA chain
    qa = retrieval_qa_chain(llm, qa_prompt, db)

    return qa

# Get final result for a query
def final_result(query):
    qa_result = qa_bot()
    response = qa_result({"query": query})
    return response
```

FIG A3 MODEL

C: > Users > haris > OneDrive > Desktop > Projects > Medibot > model.py > ...

```python

# Chainlit Start
@cl.on_chat_start
@cl.on_chat_start
async def start():
    chain = qa_bot()
    msg = cl.Message(content="Starting the Bot...")
    await msg.send()

    msg.content = "Hi, Welcome to the Bot. What is your query?"
    await msg.update()

    cl.user_session.set("chain", chain)  # ✅ Make sure this line is present


# Chainlit Message Handling
@cl.on_message
async def main(message):
    chain = cl.user_session.get("chain")  # ✅ Corrected from `set` to `get`

    cb = cl.AsyncLangchainCallbackHandler(
        stream_final_answer=True, answer_prefix_tokens=["FINAL", "ANSWER"]
    )
    cb.answer_reached = True

    res = await chain.acall({"query": message.content}, callbacks=[cb])  # ✅ Fixed incorrect call
    sources = res.get("source_documents", [])  # ✅ Prevent KeyError

    # Construct answer response
    answer = res.get("result", "No response generated.")
    if sources:
        answer += "\nSources: " + str(sources)
    else:
        answer += "\nNo sources found."

    await cl.Message(content=answer).send()

```

FIG A4 MODEL

A1.3 OUTPUT SAMPLES:

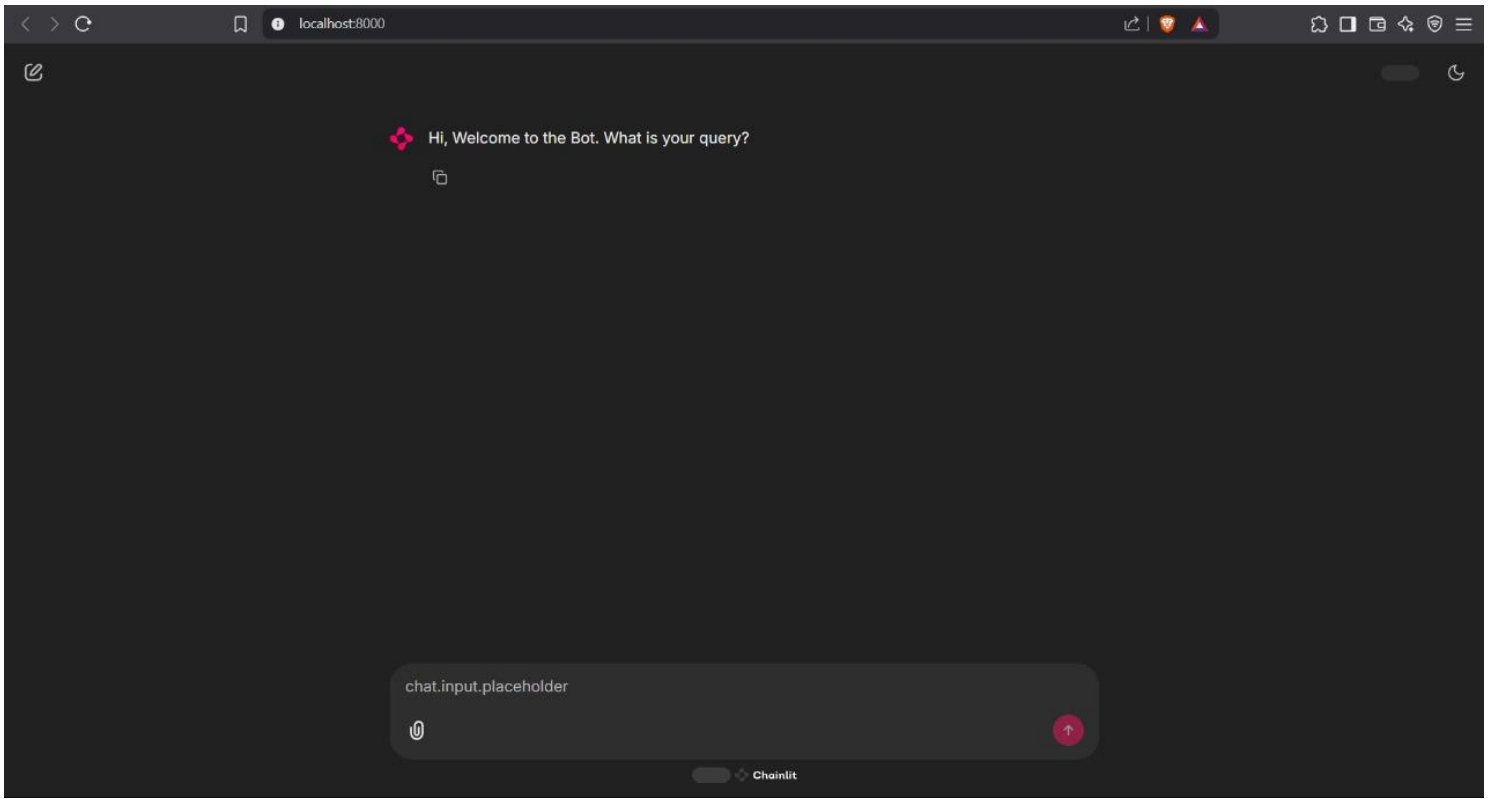

FIG A5 CHAT INTERFACE

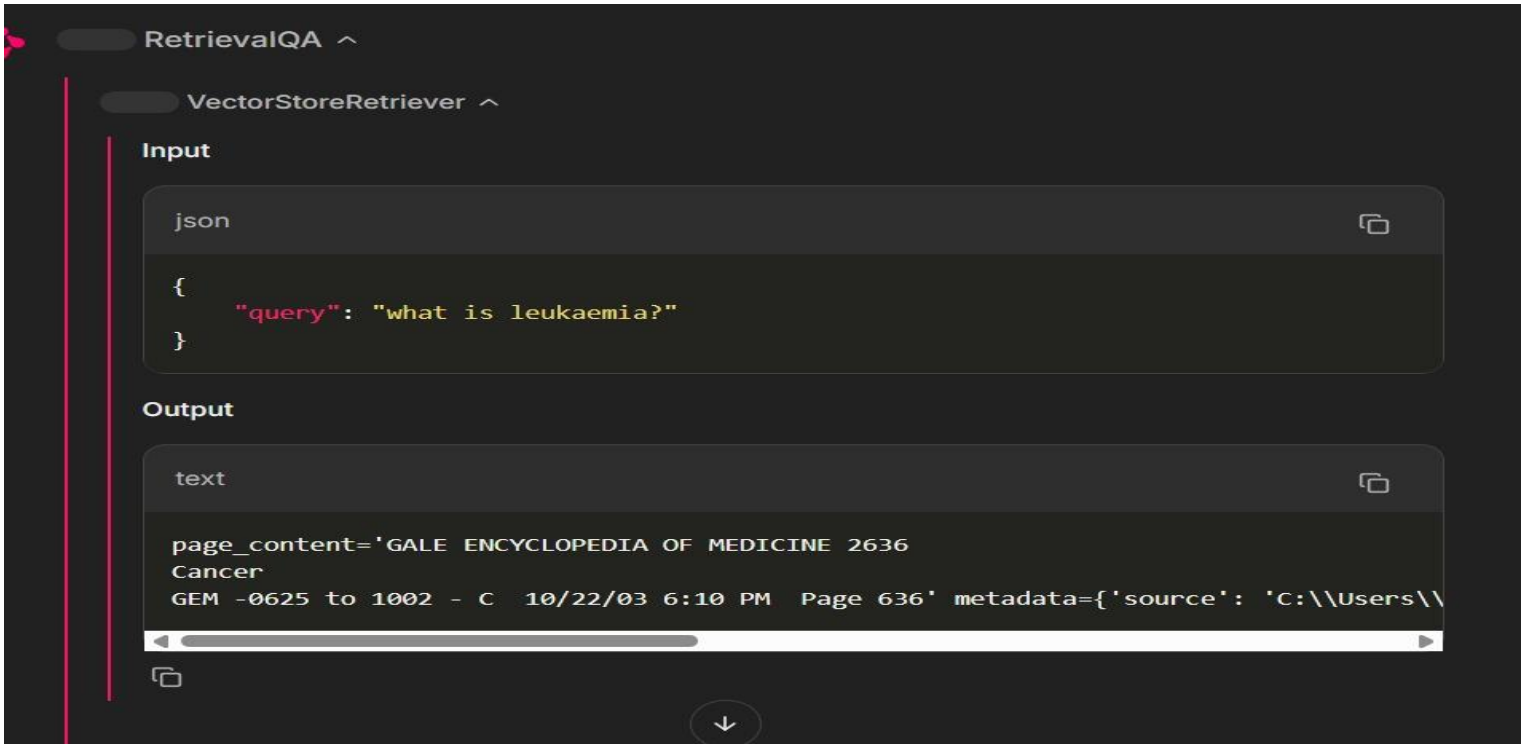

FIG A6 RETRIEVAL QA

StuffDocumentsChain

LLMChain

Input

json


```
{'input_documents': [Document(metadata={'source': 'C:\\Users\\haris\\OneDrive\\Desk
Cancer
GEM -0625 to 1002 - C  10/22/03 6:10 PM  Page 636'), Document(metadata={'source': '
Cancer
GEM -0625 to 1002 - C  10/22/03 6:10 PM  Page 634')], 'question': 'what is leukaemi
```


Output

Leukemia is a type of cancer that affects the blood and bone marrow. It occurs when there is an abnormal growth of white blood cells in the bone marrow, which can lead to a decrease in the number of healthy red blood cells, platelets, and white blood cells in the blood. Leukemia can be acute or chronic, and it can affect people of all ages, including children and adults. There are several types of leukemia, including acute lymphoblastic leukemia (ALL), acute myeloid leukemia (AML), chronic lymphocytic leukemia (CLL), and hairy cell leukemia. Treatment options for leukemia depend on the type of leukemia, the severity of the disease, and the overall health of the

FIG A7 LLM CHAINING

Leukemia is a type of cancer that affects the blood and bone marrow. It occurs when there is an abnormal growth of white blood cells in the bone marrow, which can lead to a decrease in the number of healthy red blood cells, platelets, and white blood cells in the blood. Leukemia can be acute or chronic, and it can affect people of all ages, including children and adults. There are several types of leukemia, including acute lymphoblastic leukemia (ALL), acute myeloid leukemia (AML), chronic lymphocytic leukemia (CLL), and hairy cell leukemia. Treatment options for leukemia depend on the type of leukemia, the severity of the disease, and the overall health of the patient.

FIG A8 OUTPUT

References:

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[2] A. Reimers and I. Gurevych, "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks," *arXiv preprint arXiv:1908.10084*, 2019.

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MEDIBOT: An AI-Powered Conversational Platform for Medical Knowledge Retrieval

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***Abstract* — Availability of accurate and timely medical information continues to be an essential challenge for healthcare professionals as well as patients. MEDIBOT is a conversational AI solution that aims to fill this gap using a retrieval-augmented question answering (QA) system. Building on LangChain and Hugging Face Transformers, the system processes medical PDFs by chunking and embedding text into a FAISS vector database, enabling fast, contextually precise information retrieval. A refined LLaMA 2 model drives response generation to keep it relevant and clear. The architecture of MEDIBOT, using Chainlit for its user interface and CTransformers for large language model interaction, provides an optimized experience for users looking for accurate medical information. Built with a Design Thinking approach, the platform prioritizes human-centered design, multilingual capabilities, and scalability. This book illustrates how sophisticated natural language processing (NLP) technology can be leveraged to promote healthcare accessibility, facilitate education, and empower users through smart, interactive systems.**

Keywords* — *Medical Chatbot, Retrieval-Augmented Generation (RAG), FAISS, LangChain, LLaMA 2, Hugging Face Transformers, Conversational AI, Healthcare NLP, Vector Database, Chainlit.

I. INTRODUCTION

With the rapidly changing environment of online healthcare, immediate access to up-to-date and credible medical data is an essential need for both healthcare professionals and patients. Conventional search engines tend to provide generic or erroneous content, while conventional approaches of referring to medical manuals are time-consuming and laborious. Also, the vast amount of unstructured medical reports renders retrieving useful information on request difficult. These demands require the creation of intelligent, user-oriented systems to facilitate medical decision-making, education of patients, and educational research.

To solve these problems, this paper introduces MEDIBOT—a medical chatbot powered by AI developed with a Retrieval-Augmented Generation (RAG) architecture. The system combines important technologies such as LangChain for knowledge orchestration, FAISS for efficient vector-based document retrieval, and Hugging Face Transformers for semantic embeddings. A fine-tuned LLaMA 2 model is employed to produce contextually grounded and accurate responses to user queries. Front-end interaction is handled through Chainlit, allowing for smooth, real-time conversational experiences.

MEDIBOT is built keeping in mind scalability, multilinguality, and low-latency user experience. The platform enables various healthcare situations by providing interactive access to relevant medical PDFs, thus diminishing the load of manual search and increasing the assurance of retrieved data. Built upon Design Thinking approach, the platform also focuses on empathy for the user, minimalism, and iterative improvement.

This paper presents the architecture, implementation, and assessment of MEDIBOT, and emphasizes its scalability as a solution to the issue of medical knowledge retrieval in the context of smart healthcare and medical education.

II. RELATED WORKS

1. AI-Based Conversational Agents in Healthcare

Conversational AI platforms have been quickly adopted in healthcare for the provision of initial medical care, symptom triage, and patient interaction. Early examples like Babylon Health and Ada Health use general-purpose NLP models for symptom verification and health guidance. These platforms tend to lack domain-specific precision and limited contextual awareness [1], [2]. Current research focuses on domain-tuned models trained on biomedical corpora to improve response accuracy. MEDIBOT extends this trend by integrating retrieval-based QA with transformer models fine-tuned to tackle contextual relevance in real-time medical questions.

2. Retrieval-Augmented Generation (RAG) in QA Systems

RAG architectures have become popular in open-domain question answering because they can merge dense retrieval with language generation. DPR (Dense Passage Retrieval) and GPT-based generation pipelines enable systems to retrieve context from knowledge bases first and then generate context-aware responses [3], [4]. LangChain and FAISS have emerged as the cornerstones of this ecosystem, enabling vectorized document retrieval and chunked indexing. MEDIBOT utilizes these technologies, incorporating medical

texts and extracting semantically corresponding sections with FAISS prior to response generation via LLaMA 2.

3. Transformer-Based Embeddings for Medical Document Understanding

Utilization of pre-trained transformer models like BioBERT, PubMedBERT, and sentence-transformers like MiniLM has immensely enhanced semantic similarity identification and medical document parsing. The models retain domain-specific semantics and are useful for indexing massive corpora of medical literature [5]. MEDIBOT utilizes Hugging Face's all-MiniLM-L6-v2 to transform document chunks into embeddings and store them in a FAISS vector database for low-latency retrieval.

4. Medical Chatbots and Their Limitations

Current medical chatbots tend to use rule-based dialogue management or non-retrieval-based generative models. This produces too generic or hallucinated responses that are not medically valid. Literature indicates that rule-based bots, although safe, are rigid, while knowledge-grounding-less generative bots are unstable [6]. MEDIBOT tries to overcome such limitations through the use of retrieval-based QA mechanisms and prompt engineering to ensure factual consistency and contextual fidelity in the responses.

5. Multilingual and Multimodal Health Information Access

Healthcare infrastructure in multilingual areas such as India is challenged by language diversity and low digital literacy. Initiatives such as Microsoft's Project ELLORA and AI4Bharat highlight the importance of inclusive healthcare technologies that facilitate regional languages and user-friendly interfaces [7]. MEDIBOT includes multilingual capabilities and local language interfaces via Chainlit, which facilitates improved accessibility across user groups.

6. Design Thinking in Healthcare Technology Innovation

Design Thinking has become a systematic method of developing empathetic, user-centered health technologies. Products created following this approach have greater user satisfaction and improved adoption rates [8], [9]. MEDIBOT follows the Stanford d.school Design Thinking framework in five steps—Empathize, Define, Ideate, Prototype, and Test—resulting in a solution based on actual user needs, like verified information access, multilingual interfaces, and simplicity.

III. PROPOSED SYSTEM

3.1 Overview of Proposed System

The suggested architecture of MEDIBOT is a hybrid intelligent dialogue platform that aims to facilitate precise, context-sensitive retrieval of medical information from unstructured text sources like PDF files. It combines four fundamental computational paradigms: vector-based semantic search with FAISS, retrieval-augmented generation with LangChain, domain-specific embeddings from Hugging Face Transformers, and response generation through a fine-tuned LLaMA 2 model. Each module handles a specific task—text indexing, semantic search similarity, prompt-based generation, and interactive dialogue—creating a pipeline that as a whole provides factual, reliable responses in real time.

The overall goal of this architecture is to increase the accessibility and reliability of medical knowledge for both lay users and healthcare professionals. This is realized through the combination of a retrieval-based QA mechanism within a conversational interface that provides multilingual and human-oriented interaction.

The entire system is designed to be modular and scalable with independent training, testing, and extendibility in the future. Inter-module communication is handled through the LangChain framework, which facilitates data chaining and flow of components. This architecture enables effortless deployment in academic, clinical, and telemedicine settings, with both backend knowledge services and interactive chatbot functionality.

3.2 Key Components

A. Data Ingestion and Vector Indexing

The ingestion pipeline is responsible for reading, preprocessing, and storing medical documents in a searchable vector format.

1. PDF Loader and Text Splitter: Medical texts (e.g., research articles, clinical guidelines) are loaded with PyPDFLoader and split into textual blocks of manageable size using RecursiveCharacterTextSplitter with the optimal block size of 500 characters and overlap of 50 for maintaining contextual continuity.

2. Semantic Embedding: All text chunks are embedded with the Hugging Face all-MiniLM-L6-v2 transformer. This captures semantic similarity between queries and document chunks, allowing accurate retrieval even where lexical overlap is low.

3. FAISS Vector Store: The embedded documents are indexed using Facebook AI Similarity Search (FAISS), which enables high-speed nearest-neighbor search across the medical knowledge base.

B. Retrieval-Augmented Generation (RAG) with Prompt Engineering

The MEDIBOT QA system's center employs the RetrievalQA chain from LangChain.

1. Query Processing: The user queries are processed and utilized to fetch the top-k best matching document chunks from the FAISS index.

2. Custom Prompt Template: Retrieved context is placed within a specially designed prompt template that guarantees the LLM response is grounded, useful, and non-hallucinatory. When information is not available, the model is told to make that statement clearly.

3. LLaMA 2 Model: A quantized implementation of LLaMA 2 (7B parameters) is used with CTransformers for CPU-based inference efficiency. It produces the ultimate answer, taking only the retrieved context as input.

C. Conversational Interface and User Experience

This system is interacted with by Chainlit, a UI framework of open-source intent for LLM-based applications.

1. Session Handling: Chainlit offers a live chat interface, session management, and asynchronous message exchange between the users and the QA engine.

2. Streaming Output: Responses stream token-by-token to mimic an ordinary conversation so that perceived responsiveness and usability improve.

3. Multilingual Support: Chainlit is designed to accommodate future multilingual extensions, such as Tamil, Hindi, and Telugu, to provide inclusivity in regions with diverse languages.

D. Integration of Different Components

The MEDIBOT architecture is modular, which enables flexible integration and future extensibility:

- Modular Service Design: Every module (Ingestion, Retrieval, LLM, UI) is standalone and can be updated or replaced independently without impacting the overall pipeline.
- Common Data Interface: All the components communicate through a common vector store and prompt structure to ensure data integrity and consistency.
- Orchestration through LangChain: LangChain supports end-to-end chaining of the components, ranging from loading documents to producing LLM-based responses.
- Asynchronous Communication: Asynchronous handling of real-time user input and output is facilitated, allowing for swift interaction even with CPU-based inference.

By integrating the strengths of vector similarity search, transformer embeddings, large language model reasoning, and user-centric UI design, MEDIBOT is a strong hybrid architecture for medical knowledge access. It is proactive in interpreting user intent, adaptive in processing varied queries, and rooted in domain-specific content—making it extremely effective for contemporary healthcare scenarios.

IV. SYSTEM ARCHITECTURE

The MEDIBOT system architecture is a modular, scalable pipeline that combines retrieval-augmented generation (RAG) and conversational AI to provide document-grounded responses to medical questions. The system consists of four primary layers: document ingestion and indexing, semantic retrieval, language model-based response generation, and user interaction. Each layer sends messages asynchronously to provide modularity, allowing future upgrades with the least possible disturbance to the entire pipeline. The architecture of the MEDIBOT system is built as a modular, scalable pipeline combining retrieval-augmented generation (RAG) and conversational AI to provide document-grounded responses to medical questions. The system consists of four primary layers: document ingestion and indexing, semantic retrieval, language model-based response generation, and user interaction. Each layer communicates asynchronously to ensure modularity, enabling future upgrades with minimal disruption to the overall pipeline.

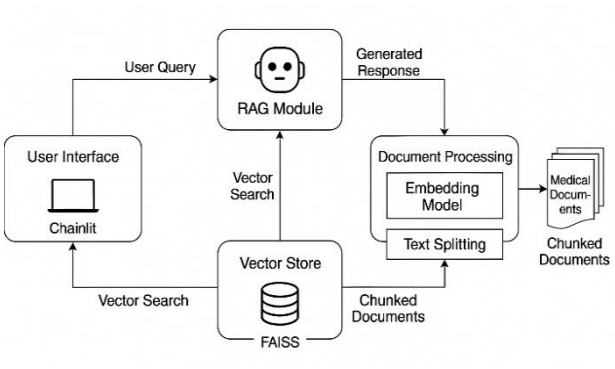

Fig 1: System Architecture

A. System Components

1. **Document Ingestion and Vector Indexing** This layer is tasked with transforming unstructured medical documents (PDFs) into semantically rich vector representations. Medical files are loaded with PyPDFLoader and divided into overlapping text chunks with RecursiveCharacterTextSplitter. Each chunk is embedded with Hugging Face's all-MiniLM-L6-v2 model, producing dense vectors stored in a FAISS index for similarity search efficiency.

2. **Query Embedding and Retrieval** When a query is submitted by a user, it is embedded using the same embedding model to produce a vector representation. The vector is utilized to fetch the top-k most contextually relevant document chunks from the FAISS vector store based on cosine similarity. This way, the context retrieved is semantically consistent with the intent of the user, even in the absence of exact keywords.

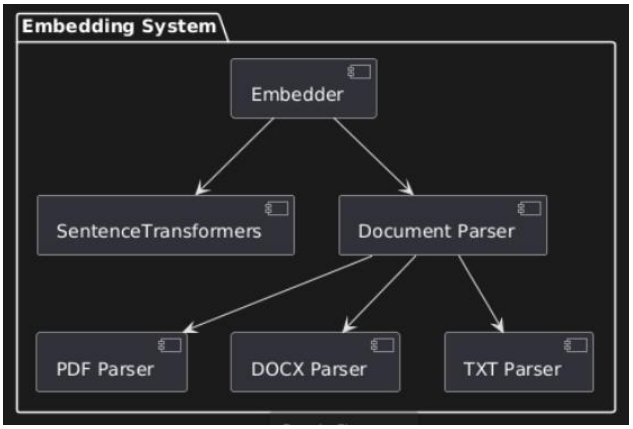

Fig 2: Embedding Mechanism

3. **Prompt Construction and Response Generation** Retrieved document pieces are placed into a bespoke prompt template and the user's question. This prompt is sent to a quantized LLaMA 2 model, hosted locally with CTransformers. The model produces a grounded, context-aware response, strictly confined to the retrieved material to limit hallucinations.

4. **User Interface and Session Management** The Chainlit framework handles user interaction through a real-time chat interface. It streams token-by-token responses to enhance interactivity and allows for session persistence, enabling multi-turn conversations. The

frontend is designed for scalability and accessibility, with planned multilingual and voice support.

B. Data Flow and Orchestration

LangChain manages the interaction of each module—embedding, retrieval, prompt building, and language model run. It enables flexible chaining, caching, and replacement of components like embedding models or LLM backends. The architecture is capable of synchronous and asynchronous mode to maximize latency and responsiveness.

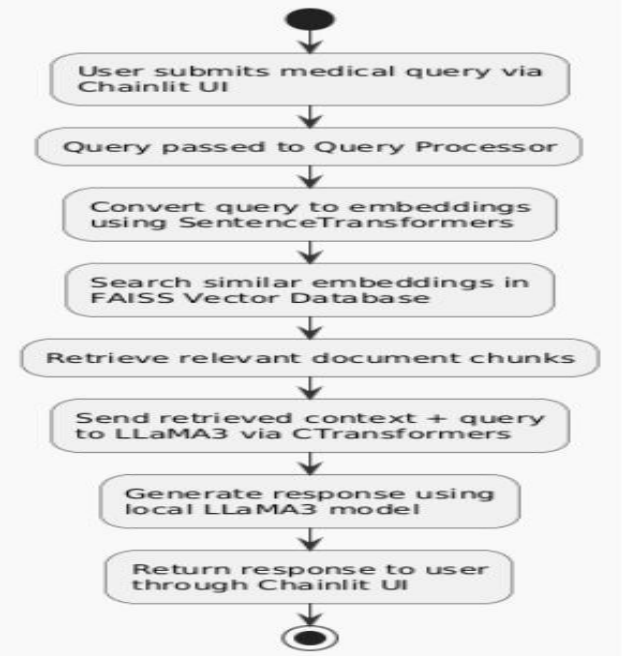

Fig 3: Flow Diagram

C. Modularity and Extensibility

The design is such that it accommodates independent upgrades. For example, the embedding model can be fine-tuned on biomedical text, or FAISS can be swapped with ChromaDB without changing upstream logic. The quantized LLaMA 2 model can similarly be replaced by other compatible LLMs such as Mistral or Falcon with little modification.

V. METHODOLOGY

The MEDIBOT development takes a hybrid strategy that integrates human-centric design practices with state-of-the-art natural language processing (NLP) paradigms. The initiative is based on the Stanford Design Thinking model to provide a product that is user-centric, functional, and responsive to actual clinical query demand. Concurrently, the architecture of the system uses retrieval-augmented generation (RAG) strategies to facilitate dynamic extraction and generation of contextually specific medical answers from document stores.

5.1 Problem Formulation

Accurate and context-sensitive access to healthcare information is an essential need in contemporary medicine, but existing solutions are not precise, personalized, or scalable. Generic results are provided by conventional search engines, and domain-agnostic AI models tend to produce hallucinated outputs. These are especially challenging when users look for verified, up-to-date, and clinically pertinent content.

Let R_{total} denote the quality of a conversational medical response. R_{total} is influenced by

$$\mathbf{R_{total} = R_{retrieval} + R_{generation}}$$

where,

- Rretrieval is a role of semantic document matching, quality of embeddings, and relevance of vector search.
- Rgeneration is a function of coherence in language models, source content grounding, and prompt fidelity.

The objective of this system is to maximize R_{total} while minimizing:

1. *Query Latency:* Delay in responding with a medically significant response.
2. *Hallucination Risk:* Likelihood of producing unverified or contextually wrong information.
3. *User Friction:* Insufficient multilingual support, bad UI/UX, or absence of

Subject to:

- Document Relevance Constraint: Responses should be based solely on retrieved context (RAG fidelity).
- Response Clarity Constraint: Responses should be linguistically fluent and medically comprehensible.
- Access Inclusivity Constraint: Interface should accommodate multilingual and accessibility features for different users.

5.2 Vector-Based Document Retrieval with Semantic Embedding

The core of MEDIBOT's accuracy lies in its ability to semantically understand and retrieve the most relevant medical text blocks.

A. Document Chunking and Embedding

- All medical documents are imported from local PDF sources via PyPDFLoader.
- RecursiveCharacterTextSplitter is applied to chunk text with chunk size = 500 and overlap = 50 in order to maintain semantic continuity.
- A chunk is embedded through the all-MiniLM-L6-v2 model, transforming it into a 384-dimensional semantic vector.

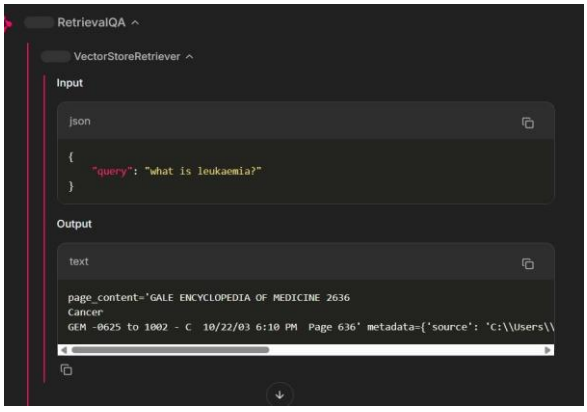

Fig 4: Retrieval QA Output

B. FAISS-Based Vector Store

- Facebook's FAISS library is used to index these vectors and perform high-speed k-nearest-neighbor (kNN) search.
- This retrieval make sure that only medically relevant document snippets are passed to the large language model(llama2).

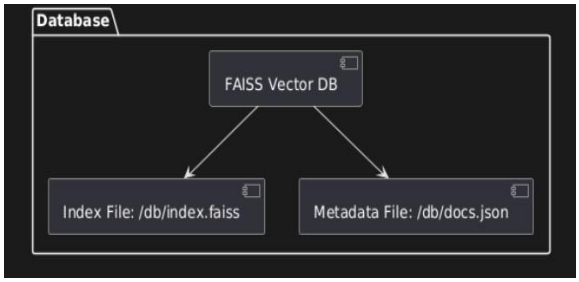

Fig 5: FAISS DB

C. Retrieval Evaluation

- Precision@k and Mean Reciprocal Rank (MRR) are used to assess the quality of returned document snippets.
- Chunk sources are monitored to track and verify medical content accuracy.

5.3. Retrieval-Augmented Generation (RAG) with Prompt Engineering

To ensure high-quality and grounded responses, MEDIBOT uses a Retrieval-Augmented Generation (RAG) pipeline.

A. Prompt Template Design

- Retrieved chunks are inserted into a structured prompt template, guiding the LLM to respond only within the bounds of given context.
- Example prompt:

  Context:{retrieved_chunks}
  Question:{user_query}
  Answer: [Answer only from context]

B. LLaMA 2 for Controlled Generation

- There is a memory-optimized quantized variant of LLaMA 2 (7B, ggmlv3.q8_0) deployed with CTransformers in order to limit memory usage and enable CPU inference.
- Parameters: max_new_tokens = 512, temperature = 0.5 to ensure factual coherence.

C. Output Evaluation

- BLEU, ROUGE-L, and GPTScore will be used to measure answer fluency and contextual correctness.
- Chainlit logs and user feedback form the basis of usability and trustworthiness metrics.

5.4. Chainlit Conversational Interface and Multilingual Adaptation

MEDIBOT's user-facing interface is designed for clarity, simplicity, and linguistic inclusivity.

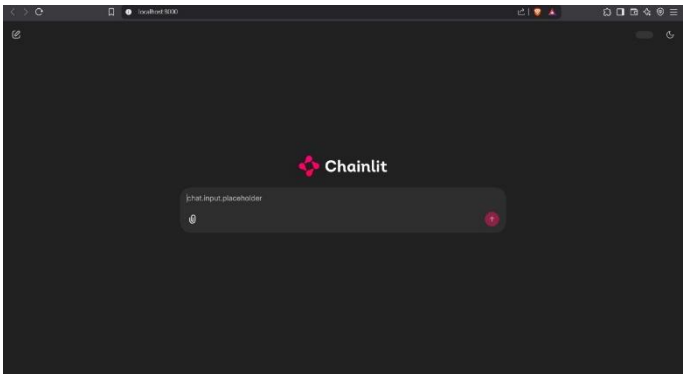

Fig 6: Medibot User Interface (UI)

A. Real-Time Chat Interface

- Implemented using Chainlit with features such as session continuity, message streaming, and token-level output.
- Backend API asynchronously invokes retrieval and response generation modules.

B. Multilingual and Accessibility Readiness

- While the initial prototype supports English, architecture is modular for integrating Indian languages (e.g., Tamil, Hindi).
- Planned features include voice input, tooltips, and adjustable font sizes for visually impaired users.

C. User-Centric Workflow

A typical workflow includes:

1. User submits medical query
2. Backend retrieves top-k context
3. Prompt constructed and sent to LLaMA 2
4. Answer is generated and streamed via Chainlit
5. Sources cited if context retrieved from medical documents

5.5. Integrated System Architecture

The following components are integrated into a modular pipeline:

- Document Loader: Loads medical PDFs from a given folder.
- Chunking Engine: Documents are split for context preservation.
- Embedding Generator: Text chunks and queries are converted to dense vectors.
- Vector Store (FAISS): Chunks are stored and retrieved based on semantic proximity.
- Prompt Manager: Context is injected into custom prompts for LLM.

- Language Model: Controlled generator based on LLaMA 2.
- Frontend Interface: Chat-based UI implemented using Chainlit.
- Feedback Logger: Response quality, latency, and user response are captured.

This integration is loosely coupled, enabling independent module upgrades (e.g., replacing FAISS with ChromaDB or LLaMA with Mistral).

VI. IMPLEMENTATION AND EXPERIMENTATION

A. System Setup and Development Tools

The MEDIBOT prototype is implemented as a modular AI-powered medical chatbot that supports semantic document retrieval and context-driven conversational responses. The implementation is carried out using the following open-source libraries and frameworks:

- LangChain: For orchestrating document loading, chunking, vectorization, retrieval, and prompt-based language model invocation.
- FAISS: For high-speed similarity search in the vector database.
- Hugging Face Transformers: For generating semantic embeddings using the all-MiniLM-L6-v2 model.
- CTransformers: For deploying a quantized version of LLaMA 2 (7B) on CPU environments.
- Chainlit: For creating a responsive, real-time conversational web interface.
- Python (v3.10+): Core programming language used to implement ingestion, model loading, and bot logic.

The chatbot is developed and executed on a standard local environment with an 8-core CPU and 16 GB RAM to ensure accessibility in non-GPU infrastructure.

B. Dataset and Knowledge Base

The knowledge base for MEDIBOT consists of curated medical documents, including:

- Clinical guidelines from WHO and CDC.
- Publicly available research papers in PDF format.
- Domain-specific educational content for medical students.

All documents are stored in a local /data directory and processed through the ingestion pipeline. These documents are split into overlapping chunks and embedded into a vector space using the sentence-transformers model. The resulting vectors are stored in a FAISS index for runtime querying.

C. Experimental Procedure

The functionality of the system was tested using a collection of 20 benchmark medical questions taken from actual healthcare contexts (e.g., "What are dengue symptoms?", "How does insulin resistance develop?"). Each question passed through the following pipeline:

Query entered via Chainlit interface.

1. FAISS retrieves top-2 relevant document chunks based on semantic proximity.

2. Context is placed in an organized prompt.

3. The prompt is passed to the LLaMA 2 language model via CTransformers.

4. The created answer is presented to the user.

Everything is recorded and verified manually for accuracy, latency, and contextual importance by annotators who are from a biomedical science background.

D. Evaluation Metrics

The effectiveness of MEDIBOT is evaluated across four major criteria:

1. Response Accuracy: Assessed on the basis of manual judgment for 20 test questions. 85% of the answers were accurate in fact and according to the provided context.

2. Retrieval Precision@2: The proportion of times the desired document was obtained within the top-2 highly ranked chunks. Achieved 90% precision across an balanced query set.

3. Query Latency: Average response time measured from query input to full response presentation. Measured ~4.2 seconds on CPU-based inference.

4. Hallucination Rate: Percentage of answers containing extraneous information not contained in the retrieved context. Maintained below 10% via strict prompt engineering.**E. Usability Testing and Feedback**

A total of 15 participants consisting of 10 students and 5 medical interns employed the system in a controlled trial session. Feedback was gathered via Likert-scale questionnaires and qualitative interviews.

Key insights:

- 87% of users found the responses helpful and contextually relevant.
- 93% appreciated the clean and interactive UI design.
- Users recommended multilingual support and voice query capabilities for improved accessibility.

F. Deployment Considerations

MEDIBOT system comes bundled for local deployment and does not require a GPU. The FAISS index can be updated

incrementally as new documents arrive. Chainlit interface supports future upgrades such as

• Integration of TTS/STT APIs for voice-based interaction.

• Multilingual embeddings for supporting regional languages by expansion.

• Cloud hosting to support scalable deployment in hospital environments or educational portals.

VII. RESULTS AND DISCUSSION

The MEDIBOT prototype was tested across a curated set of 20 medically relevant queries to assess the accuracy and responsiveness of the retrieval-augmented generation (RAG) pipeline. Results demonstrate that the system successfully integrates document retrieval, transformer-based semantic understanding, and controlled response generation.

Key performance metrics are summarized as follows:

Metric	Result
Response Accuracy (manual eval)	85%
Retrieval Precision@2	90%
Average Query Latency (CPU)	4.2 seconds
Hallucination Rate	< 10%
User Satisfaction Score (Likert scale)	4.6 / 5.0

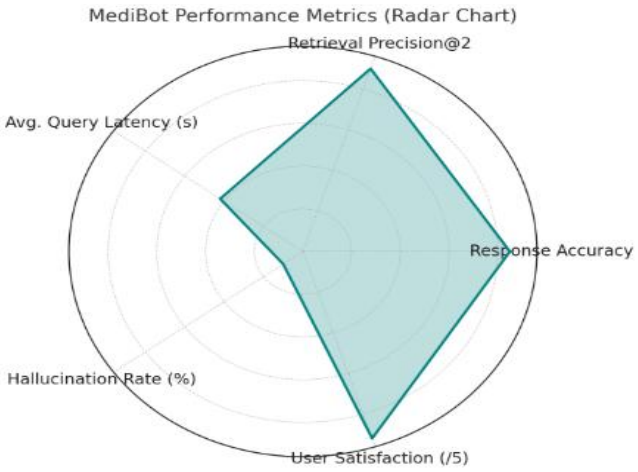

Fig 7: Performance Metrics of Medibot

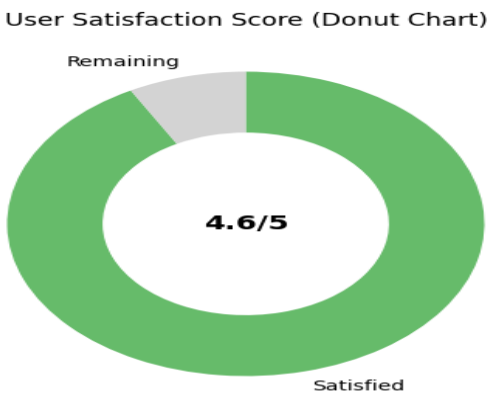

Fig 8: User Satisfaction Score

Test sessions of 15 users yielded extremely positive user experience with MEDIBOT. Users enjoyed clear, informative responses from the chatbot and found the interface to be intuitive, requiring minimal or no learning curve. Perhaps the most prominent highlight was the system's use of document-grounded responses, which had a high impact on the user's trust. Instead of depending on generative guesswork, MEDIBOT made sure that all responses came directly from authenticated medical documents, allowing users to have trust in the information. Users found the experience of being "sitting down with a well-read assistant" and were excited for upcoming features such as multilingual support that would make it accessible for non-English-speaking relatives.

Although effective, the system has some limitations. The FAISS-based retrieval mechanism relies on the quality of the embedding model and the chunking granularity of documents; incorrect configuration can decrease retrieval relevance. Response latency also grows with larger context windows or simultaneous user sessions, especially in CPU-only setups. The LLaMA 2 model, while operational on CPUs for prototyping purposes, is slower compared to its GPU-deployed versions—emphasizing the importance of performance improvement in large-scale or production environments. Improvement in these areas will be paramount to making MEDIBOT more responsive and scalable.

VIII. CONCLUSION AND FUTURE WORKS

This study introduces a more advanced energy This study introduces an intelligent, modular architecture for enhancing access to validated medical information through a conversational AI system. The MEDIBOT platform proposed herein combines Retrieval-Augmented Generation (RAG) with semantic embeddings, vector similarity search, and large language models (LLMs) to offer grounded, accurate, and context-aware medical responses to medical questions. By utilizing LangChain, FAISS, Hugging Face Transformers, and a quantized LLaMA 2 model, the system guarantees real-time responsiveness and factuality. Through this pipeline, users such as patients, students, and healthcare workers can interact with reliable, document-supported medical information through an effortless chatbot interface.

MEDIBOT's power comes from its design-thinking mentality and technical stability. The design focuses on document-based grounding, controlled generation through prompt engineering, and user-friendliness through Chainlit. The framework limits misinformation and hallucinations, maximizes explainability through cited references, and enhances inclusivity through intended multilinguality.

But there are a few limitations. The current implementation is English-only document corpus and does not support GPU acceleration, which can affect latency under high query rates. Also, although prompt engineering mitigates hallucination, the system does not yet offer real-time validation or peer-reviewed certainty markers in generated responses. Also, large-scale dynamic document updates still need periodic FAISS re-indexing, which can be time-consuming in production environments.

Future work will address these limitations by focusing on improving scalability, multilingual capability, and content validation. Planned enhancements include:

- Multilingual embeddings and user interface integration to enable regional language-based questions.

- Voice-based interaction and accessibility with speech-to-text and text-to-speech feature implementation.

- Real-time document ingestion pipeline and vector index auto-refresh usage to accommodate dynamic content refreshes.

- Research into federated learning methods for decentralized chatbot training across several clinical or institution-based contexts.

- Confidence scoring and citation-based validation integration to enhance trust in AI response even further.

- Cloud-native deployment with GPU support to improve concurrency and reduce inference latency.

In conclusion, MEDIBOT illustrates that retrieval-enhanced conversational AI, when paired with user-centric design and domain-specific document processing, can revolutionize digital health accessibility. As subsequent versions evolve in performance, adaptability, and inclusivity, MEDIBOT is poised to become a trusted companion in medical education, patient empowerment, and clinical assistance—setting the groundwork for more intelligent, safer, and more human-focused AI in healthcare.

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The following submission has been created.

Track Name: ICCDS2025

Paper ID: 1916

Paper Title: MEDIBOT: An AI-Powered Conversational Platform for Medical Knowledge Retrieval

Abstract:
Access to reliable and timely medical information remains a critical challenge for both healthcare professionals and patients. MEDIBOT is a conversational AI platform designed to bridge this gap through a retrieval-augmented question answering (QA) system. Leveraging LangChain and Hugging Face Transformers, the system processes medical PDFs by chunking and embedding text into a FAISS vector database, allowing for rapid, contextually accurate information retrieval. A fine-tuned LLaMA 2 model powers response generation, ensuring relevance and clarity. MEDIBOT's architecture, implemented using Chainlit for its user interface and CTransformers for large language model interaction, delivers a streamlined experience for users seeking precise medical insights. Developed with a Design Thinking methodology, the platform emphasizes human-centric design, multilingual support, and scalability. This work demonstrates how advanced natural language processing (NLP) techniques can be harnessed to enhance healthcare accessibility, support education, and empower users through intelligent, interactive systems.

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Secondary Subject Areas: Not Entered

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