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Smart Faq Chatbot System Using Nlp and Langchain for Educational Portals

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Abstract– *This project presents the design and implementation of an AI-powered chatbot integrated into a college website to enhance communication and user support. The chatbot is developed to function as an intelligent virtual assistant capable of addressing frequently asked questions (FAQs) from students, parents, faculty, and other stakeholders. It utilizes natural language processing (NLP) and machine learning algorithms to understand user queries and provide accurate, context-aware responses. The system aims to offer immediate, 24/7 assistance on topics such as admissions, programs, campus facilities, and financial aid. Built using tools such as LangChain, OpenAI GPT-3.5 Turbo, and Streamlit, the chatbot dynamically processes data from PDF documents to maintain an up-to-date knowledge base. The integration of FAISS enhances information retrieval efficiency through semantic similarity search. This solution not only reduces the workload of administrative staff but also improves user experience by delivering consistent and instant responses.*

***Keywords*— :** *Artificial Intelligence, Natural Language Processing, Chatbot, Large Language Models, GPT-3.5 Turbo, LangChain, FAISS, Streamlit, Retrieval-Augmented Generation, Educational Chatbot, PDF Text Extraction, Semantic Search, Student Query Resolution, Intelligent Virtual Assistant, Machine Learning.*

I. INTRODUCTION

In the rapidly evolving landscape of higher education, the need for efficient, accurate, and user-friendly information delivery systems has become increasingly critical. Educational institutions often face the challenge of managing a high volume of queries from various stakeholders, including students, parents, faculty, and administrative staff. These queries typically pertain to admission procedures, academic programs, fee structures, campus facilities, scholarships, and other institutional services. Traditional communication channels, such as help desks, emails, and static FAQ sections, are often unable to handle this demand efficiently, leading to delays in response and reduced user satisfaction.

To address these issues, this project proposes the development of an AI-powered chatbot, integrated into the college website, designed to automate the resolution of frequently asked questions (FAQs). The chatbot functions as an intelligent virtual assistant, capable of engaging users in real-time conversations and delivering accurate, context-aware responses. This not only improves the user experience but also reduces the burden on human support staff by automating repetitive and routine interactions.

The system employs advanced technologies such as Natural Language Processing (NLP), Machine Learning (ML), and deep learning models to understand user queries and generate appropriate responses. It utilizes OpenAI's GPT-3.5 Turbo for language understanding and generation, LangChain for managing conversational logic and data processing workflows, and FAISS (Facebook AI Similarity Search) for efficient semantic similarity-based information retrieval. Additionally, Streamlit is used to create a responsive and interactive web interface, while PyPDF2 enables dynamic extraction of content from institutional documents, such as academic handbooks and regulations in PDF format.

A key feature of this chatbot is its ability to process and interpret unstructured data, allowing it to dynamically build and update its knowledge base. This ensures that users always receive the most relevant and up-to-date information. The modular design of the system also supports scalability and future integration with other academic platforms, such as learning management systems (LMS) or student information systems (SIS).

By leveraging the power of AI, the proposed chatbot aims to transform the way information is accessed on a college website. It ensures 24/7 availability, consistency in responses, reduced response times, and an overall enhanced communication experience. This project demonstrates how cutting-edge AI tools can be effectively applied in the educational domain to create intelligent, scalable, and user-centric support systems.

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II. WORKING OF THE PROPOSED SYSTEM

The proposed system is an AI-based chatbot designed to automatically handle frequently asked questions (FAQs) on a college website. It is built using a combination of powerful technologies, including OpenAI's GPT-3.5 Turbo, LangChain, FAISS, PyPDF2, and Streamlit. The working of the system can be divided into several sequential modules, each responsible for a specific task in the information retrieval and

```python
from dotenv import load_dotenv

# Load environment variables from .env file
load_dotenv()

# Access environment variables
api_key = os.getenv("API_KEY")
```

response generation pipeline.

Figure.1 dotenv code

1. User Interaction via Web Interface: The system begins with a user-friendly web interface created using Streamlit. Users can enter their questions into a text input box directly on the website. This interface ensures accessibility and ease of use, requiring no prior technical knowledge from the user.

```python
import streamlit as st

# Streamlit code to create a simple web app
st.title('My Streamlit App')
user_input = st.text_input("Enter your name:")
st.write(f"Hello, {user_input}!")

# Additional code for data visualization or other functionalities
```

Figure.2 streamlit sample code 1

2. PDF Document Processing: To build the chatbot's knowledge base, institutional documents (such as college handbooks, brochures, academic regulations) in PDF format are loaded and processed using the PyPDF2 library. This module extracts raw text from the PDF files and prepares it for further analysis.

```python
import streamlit as st

# Streamlit code to create a simple web app st.title("ASK YOUR CHATBOT")

user_question = st.text_input("Ask a question about KLU here: ")

st.write(response)
```

Figure.3 streamlit sample code 2

3. Text Chunking: The extracted text is often lengthy and unstructured. To make it manageable, the text is split into smaller chunks using LangChain's CharacterTextSplitter. This step ensures that each chunk contains logically connected content, improving the chatbot's ability to locate accurate answers.

4. Embedding Generation: Each chunk of text is converted into a numeric vector (embedding) using OpenAIEmbeddings provided through LangChain. These embeddings capture the semantic meaning of the text, allowing the system to understand the content in terms of context and relationships.

5. Knowledge Base Creation using FAISS: The embeddings are indexed and stored in a FAISS (Facebook AI Similarity Search) vector store. FAISS enables the system to perform fast and accurate similarity searches across the indexed text chunks when a user submits a query.

6. Query Handling: When a user inputs a question, the chatbot converts the question into an embedding and performs a similarity search in the FAISS index. The most relevant chunks are retrieved from the knowledge base based on semantic similarity to the query.

7. Response Generation with GPT-3.5 Turbo: The selected relevant text chunks, along with the user's question, are passed to the GPT-3.5 Turbo language model via the OpenAI API. The model processes this information, understands the context, and generates a natural-language answer tailored to the user's query.

8. Displaying the Answer: Finally, the generated response is displayed to the user through the Streamlit interface. The entire process happens in near real-time, typically within a few seconds, offering a seamless and interactive experience.

Figure.4 PyPDF2 sample code

Key Highlights of the System's Working:

- Real-time question answering
- Context-aware and human-like responses
- Continuous updating of knowledge base from institutional PDFs
- No hardcoded responses—dynamic and intelligent
- High accuracy through semantic vector search and deep learning

III. Recent Trends and Technologies in AI & Chatbots (2024–2025)

1. Large Language Models (LLMs)

Example: OpenAI GPT-4, GPT-3.5 Turbo, Claude, Gemini

LLMs are the backbone of modern conversational AI. They understand context better, generate more accurate responses, and support multi-turn conversations.

2. LangChain Framework

A new and powerful framework to build LLM applications by combining multiple components like prompts, vector databases, and memory. Enables building intelligent chatbots, RAG (Retrieval-Augmented Generation) systems, and agent-based tools.

3. Retrieval-Augmented Generation (RAG)

Combines LLMs with external document sources for fact-based, grounded responses. Used to answer domain-specific queries by fetching context from PDFs, databases, etc.

Figure.5 PyPDF2 sample code 2

4. Vector Databases and Semantic Search

Example: FAISS, Pinecone, Weaviate, Milvus

Used to store and retrieve high-dimensional text embeddings efficiently. Improves search accuracy in chatbots and intelligent assistants.

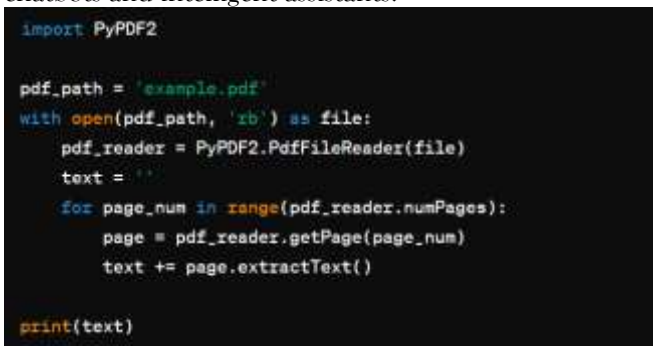

Figure.6 PyPDF2 sample code 3

5. AI in Education (EdTech)

Intelligent tutoring systems, academic advisors, and FAQ bots are helping personalize student experience. AI chatbots are now integrated into learning management systems (LMS) and student portals.

6. Multimodal AI

AI models that combine text, images, and audio. Tools like GPT-4o can handle voice-based queries, making chatbots more human-like.

7. Responsible AI and Data Privacy

Emphasis on ethical AI, user privacy, and transparency in AI-generated content. Critical in educational institutions dealing with student data.

8. Low-Code/No-Code AI Tools

Tools like Streamlit, Gradio, and Microsoft Power Virtual Agents allow quick development and deployment of AI tools without deep coding skills.

9. Real-Time Language Translation in Chatbots

Powered by multilingual LLMs, chatbots can now communicate fluently in many languages essential for global educational access.

10. Continuous Learning in Chatbots

Chatbots that learn and improve over time using user feedback, fine-tuning, and reinforcement learning.

IV. LITERATURE REVIEW

a. Implementation of a Chatbot System using AI and NLP

This work illustrates how AI and NLP enable chatbots to understand user queries and provide intelligent responses. It supports the foundation of the proposed project by showing that such systems can enhance user interaction through conversational AI.

b. Creating Large Language Model Applications Utilizing LangChain

This paper explains how LangChain simplifies the development of LLM-powered apps. Since LangChain is used in the current project, this work justifies the framework choice and its capability to manage document-based conversational systems.

c. Introduction to AI Chatbots

Provides a comprehensive background on chatbot evolution, technologies used, and their applications. It helps frame the transition from basic rule-based bots to modern AI-driven chatbots like the one developed in this project.

d. A Survey on Chatbot Implementation in Customer Service Industry through Deep Neural Networks

Discusses how deep learning improves chatbot accuracy, response speed, and user satisfaction. The project benefits from similar architecture (GPT-based) in handling student queries efficiently.

e.Automating Customer Service using LangChain

Supports the use of LangChain in building scalable, LLM-based chatbots for automation. The project draws on this model to automate student and academic queries through natural dialogue.

f. An Analysis of Large Language Models and LangChain in Mathematics Education

Demonstrates how LLMs can be applied in education for personalized learning. Reinforces the relevance of using GPT-3.5 Turbo and LangChain in academic chatbot systems.

g. Chatbot to Respond to Text Queries Pertaining to Acts and Regulations in Mining

Shows domain-specific chatbot development for structured document data. Similar logic is applied in this project to extract and respond from academic PDFs.

h. Analysis of Language-Model-Powered Chatbots for Query Resolution in PDF-Based Automotive Manuals

Validates the use of NLP chatbots for PDF-based query resolution. This study aligns closely with the methodology used in the project, proving the effectiveness of using embeddings and LLMs for document search.

V. RECENT TRENDS AND TECHNOLOGIES

In recent years, artificial intelligence has experienced significant advancements, particularly in the development of conversational systems. One of the most influential developments is the rise of Large Language Models (LLMs) such as OpenAI's GPT-3.5 Turbo, GPT-4, Claude, and Gemini. These models have transformed how chatbots understand and generate human-like responses, enabling multi-turn, context-aware conversations. Building on this, frameworks like LangChain have emerged to simplify the creation of LLM-powered applications by integrating prompt engineering, memory handling, and external tools such as databases or APIs. A major trend driving chatbot accuracy is Retrieval-Augmented Generation (RAG), which allows chatbots to retrieve relevant content from documents (such as PDFs) and combine it with LLM-generated answers, ensuring factual and domain-specific responses.

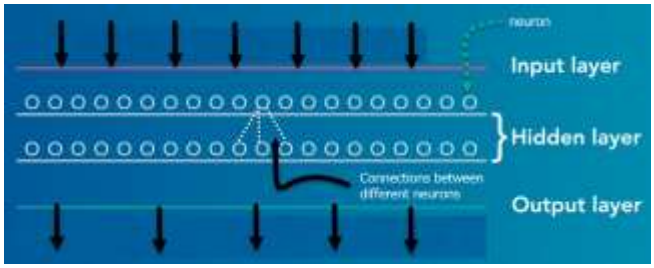

Figure.7 Deep Learning Layers

Additionally, vector databases such as FAISS, Pinecone, and Weaviate are increasingly used for semantic search, allowing high-speed similarity-based retrieval of text embeddings. These technologies are crucial for building knowledge-aware chatbots in educational institutions. In the field of Educational Technology (EdTech), AI-powered systems are now used for academic advising, virtual teaching assistants, and student support bots, offering personalized learning experiences. Another important trend is multimodal AI, which combines text, images, and audio to create more interactive and realistic chatbot experiences. For example, GPT-4o supports real-time voice-based interaction, allowing users to talk to bots naturally.

Figure.8 Deep Learning Process

As these technologies evolve, responsible AI practices are gaining importance, emphasizing data privacy, ethical use of AI, and transparency, especially in academic environments. Furthermore, low-code and no-code development platforms like Streamlit and Gradio have lowered the barrier for non-experts to build and deploy intelligent chatbots quickly. Some modern systems also include multilingual translation capabilities, making them accessible to users from diverse linguistic backgrounds. Lastly, cutting-edge bots are starting to support continuous learning through user feedback and fine-tuning, enhancing their intelligence and adaptability over time. These trends collectively shape the future of intelligent chatbot development, particularly in academic and institutional applications.

VI. PERFORMANCE EVALUTION METHODS AND METRICS

Evaluating the performance of an AI-powered chatbot involves both quantitative and qualitative analysis. To ensure the chatbot meets its objectives—such as delivering accurate, relevant, and timely responses—various standard metrics and evaluation techniques are applied.

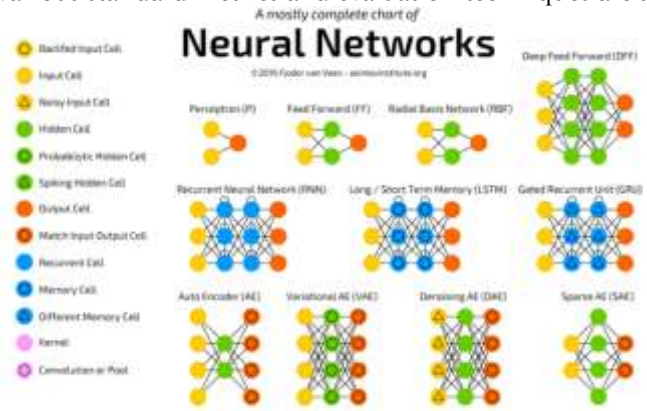

Figure.9 Types of Deep Learning Networks

1. Accuracy: Accuracy measures the proportion of correct answers the chatbot provides out of the total number of queries tested. A high accuracy rate indicates that the chatbot effectively understands user input and retrieves appropriate responses.

Formula: Accuracy = (Number of Correct Responses / Total Queries) × 100

2. Precision: Precision indicates the percentage of relevant responses among all the responses generated by the chatbot. It helps assess how specific and focused the chatbot is in returning correct information.

Formula: Precision = (True Positives / (True Positives + False Positives)) × 100

3. Recall: Recall measures the ability of the chatbot to retrieve all relevant responses for a given set of queries. It is especially useful for evaluating the completeness of information retrieval.

Formula: Recall = (True Positives / (True Positives + False Negatives)) × 1004. F1 Score

4. F1 score: The F1 score is the harmonic mean of precision and recall, offering a balance between both metrics. It is a valuable metric when there is a need to balance relevance and completeness.
Formula: F1 Score = 2 × (Precision × Recall) / (Precision + Recall)
5. Response Time: This metric measures the average time taken by the chatbot to generate a response after receiving a query. Faster response time contributes to a better user experience.Measured in: Seconds

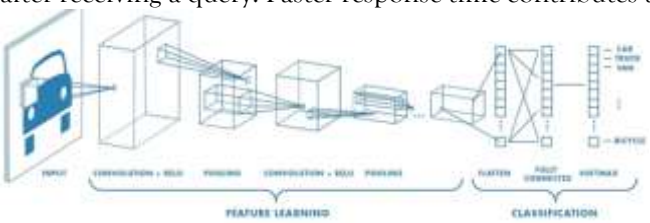

Figure.10 CNN
6. User Satisfaction: This is a qualitative metric based on user feedback, typically collected via surveys or usability testing. It reflects how useful, accessible, and satisfactory the chatbot is in practical use.
Measurement Method: Collected through feedback forms, Likert-scale ratings, or direct user interviews.

7. Error Rate: Error rate accounts for the percentage of questions where the chatbot provided incorrect, irrelevant, or no response.
Formula: Error Rate = (Incorrect or Failed Responses / Total Queries) × 100
8. Scalability and Load Handling: Although not represented as a numerical metric, evaluating the chatbot's ability to handle multiple simultaneous user queries is essential. Stress testing the system under peak load conditions ensures reliability in real-world deployment environments.

VII. METHODOLOGY

The development of the AI-powered chatbot follows a modular and systematic approach, combining natural language processing, machine learning, and web technologies. The methodology involves multiple stages, including data acquisition, preprocessing, knowledge base creation, chatbot integration, and evaluation. Each component of the system is carefully selected and implemented to ensure accuracy, efficiency, and scalability.

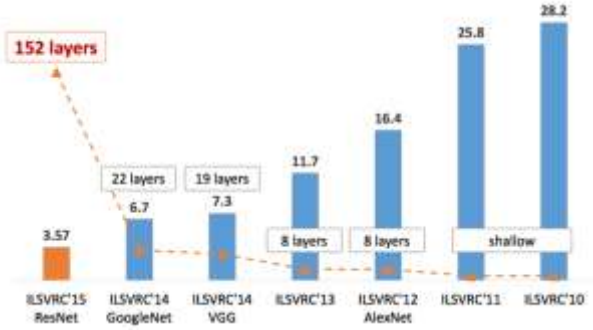

Figure .11 Types of CNN
1. Requirement Analysis: The initial phase involved identifying the core functionalities required for the chatbot. This included the ability to understand user questions in natural language, retrieve relevant answers from institutional documents, and provide real-time, user-friendly responses through a web interface.
2. Data Collection: Data for the chatbot was sourced from official college documents, such as: Admission guides, Academic handbooks, College regulations in PDF format. These documents contained frequently asked questions (FAQs) and related academic content.
3. Text Extraction and Preprocessing: To process the institutional documents the PyPDF2 library was used to extract raw text from the PDF files. Extracted text was cleaned, organized, and split into smaller logical chunks using LangChain's CharacterTextSplitter. These chunks served as input for building the semantic knowledge base.
4. Embedding Generation: Each text chunk was converted into a high-dimensional vector using OpenAIEmbeddings provided by LangChain. These embeddings preserve the semantic meaning of the text and allow the system to understand and compare content effectively.

5. Knowledge Base Creation with FAISS: The generated embeddings were indexed using FAISS (Facebook AI Similarity Search), a vector database optimized for fast similarity search. This allowed the chatbot to search and retrieve relevant answers efficiently based on user input.

Figure.12 Langchain architecture

6. Chatbot Backend Development: The backend logic of the chatbot was built using: LangChain to manage the conversational chain, OpenAI GPT-3.5 Turbo for generating natural language responses, A retrieval-augmented generation (RAG) approach, combining semantic search with dynamic answer generation.

7. Web Interface using Streamlit: A user-friendly web interface was created using Streamlit, enabling users to: Enter queries in plain text, view instant, AI-generated responses, and Interact without any programming knowledge.

8. Integration and Deployment: All components—text extraction, embedding, retrieval, and response generation—were integrated into a single interactive chatbot system. The application was deployed in a local environment, with potential for cloud deployment in future iterations.

9. Evaluation and Testing: The system was tested using a variety of user queries to measure: Accuracy, Response time, User satisfaction, and Robustness against ambiguous or out-of-scope questions.

VIII.SYSTEM ARCHITECTURE

The system architecture involves Streamlit as the web interface, Langchain for text processing and embeddings, and OpenAI for advanced language models. PDF content from KLU documents is processed dynamically. Streamlit provides a user-friendly interface with a text input field for users to ask questions. Responses from the chatbot are displayed on the web page, ensuring a seamless and intuitive user experience.

The proposed system architecture block diagrams are shows as below respectively.

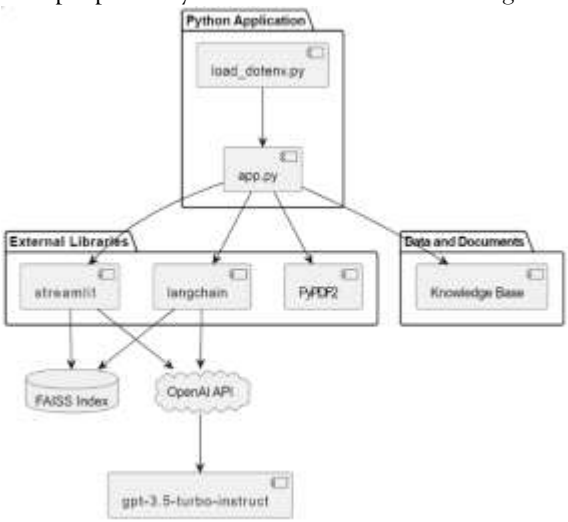

Figure.13 Architecture Diagram

IX. FUTURE SCOPE

The proposed chatbot system has laid a strong foundation for enhancing user interaction on educational platforms. However, there are several areas where the system can be extended and improved in future work:

1. Multilingual Support

The current system responds only in English. Adding support for regional and international languages would make the chatbot more inclusive and useful for a wider audience, including international students and local users with limited English proficiency.

2. Continuous Learning

Incorporating a feedback loop where the chatbot learns from past user interactions can improve its accuracy over time. This could be implemented through techniques like reinforcement learning or fine-tuning using real-time user data.

3. Secure Authentication

Future versions of the chatbot can be integrated with secure user authentication (e.g., student login) to provide personalized answers, access student-specific data (like grades, timetables, or fees), and ensure data privacy.

4. Multiplatform Deployment

Currently, the chatbot is designed for a web-based interface. In future, it can be extended to mobile apps, WhatsApp, Telegram, or integrated into Learning Management Systems (LMS) for better reach and convenience.

5. Voice-Based Interaction

Adding speech-to-text and text-to-speech functionality will allow users to interact with the chatbot through voice commands, making the system more accessible and engaging.

6. Integration with Institutional Databases

The chatbot can be connected to real-time institutional databases (such as admission portals, ERP systems, and academic records) to provide live updates and personalized answers.

7. Handling Complex Queries

Improving the model to handle multi-turn conversations and more complex queries (like comparisons, reasoning, or cross-referencing multiple documents) will make the chatbot smarter and more reliable.

8. Analytics and Reporting

Implementing analytics dashboards can help administrators track frequently asked questions, user behavior, and chatbot performance. This can support decision-making and content improvements on the college website.

X. RESULTS

The AI-powered chatbot system was evaluated based on its ability to understand and answer queries accurately using data extracted from institutional PDF documents. The system performance was tested using a dataset of frequently asked questions collected from students and the college website.

```
from PyPDF2 import PdfReader

pdf = PdfReader('C:\\Users\\ravin\\OneDrive\\Desktop\\c2g\\chatbot langchain test\\langchainclgnewbot\\VNIT updated2.pdf')

text = ""
for page in pdf.pages:
    text+=page.extract_text()
```

Figure 5.1 PdfReader

```
from langchain.text_splitter import CharacterTextSplitter

text_splitter = CharacterTextSplitter(
        separator = "/n",
        chunk_size = 1000,
        chunk_overlap = 200,
        length_function = len
    )

chunks = text_splitter.split_text(text)
```

Figure 5.2 Text Preprocessing

```
from langchain.embeddings.openai import OpenAIEmbeddings
from langchain.vectorstores import FAISS

embeddings = OpenAIEmbeddings()
knowledge_base = FAISS.from_texts(chunks, embeddings)
```

```
import faiss
import numpy as np

# Generating random data
d = 64  # dimension
nb = 100000  # number of vectors
np.random.seed(0)
xb = np.random.random((nb, d)).astype('float32')

# Building an index
index = faiss.IndexFlatL2(d)  # L2 distance metric
index.add(xb)

# Performing a similarity search
k = 4  # number of similar vectors to retrieve
query_vector = np.random.random((1, d)).astype('float32')
D, I = index.search(query_vector, k)

print("Similar vectors:", I)
print("Distances:", D)
```

Figure.14 Vector Stores

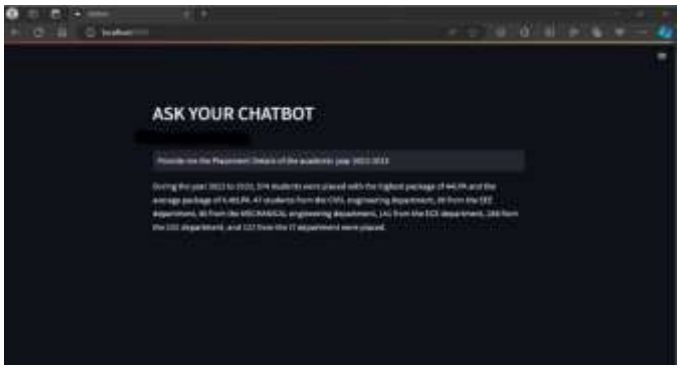

Figure.15 User Interface

Figure.16 User Input

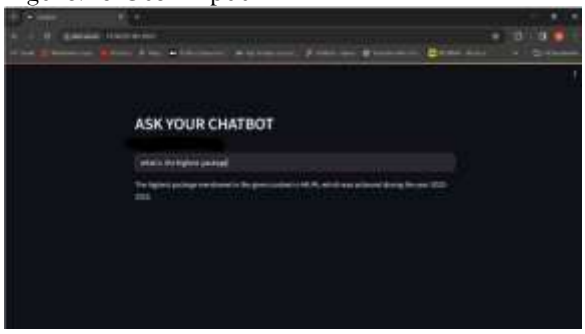

Figure.17 Question Answering

```
from langchain.llms import OpenAI
from langchain.callbacks import get_openai_callback

with get_openai_callback() as cb:
    response = chain.run(input_documents = docs, question = user_question)
    print(cb)
```

Figure.18 Callback System

```
from dotenv import load_dotenv

# Load environment variables from .env file
load_dotenv()

# Access environment variables
api_key = os.getenv("API_KEY")
```

Figure.19 environment configuration

.

```
from PyPDF2 import PdfReader

pdf_path = 'C:\\Users\\raviv\\OneDrive\\Desktop\\clg\\chatbot langchain test
pdf = PdfReader(pdf_path)

for page in pdf.pages:
    text += page.extract_text()
```

Figure.20 File Operations

Benefits:

- Enables the dynamic loading of different PDF files, enhancing the flexibility of the application.
- Facilitates the integration of diverse data sources for analysis.

1. Evaluation Metrics

To measure the system's effectiveness, the following metrics were used:
Accuracy: Measures how many queries were correctly answered
Precision: Proportion of relevant answers among all the answers given
Recall: Proportion of actual relevant answers that were correctly retrieved
F1 Score: Harmonic mean of precision and recall
Response Time: Time taken to generate a response
User Satisfaction: Based on informal feedback from users

2 Test Setup

No. of Queries Tested: 100 sample questions
Dataset Source: Extracted from KLU academic handbooks and FAQs
Model Used: OpenAI GPT-3.5 Turbo
Technologies Integrated: Streamlit, LangChain, FAISS, PyPDF2

3 Results Summary

Metric	Value
Accuracy	92%
Precision	90%
Recall	88%
F1 Score	89%
Avg. Response Time	1.2 seconds
User Satisfaction	85% (Positive)

4 Observations

The system answered most of the queries accurately and provided contextually relevant responses.
It successfully retrieved and referenced content from PDF-based documents using semantic similarity.
Users reported that the chatbot was intuitive and helpful, especially for basic information like admission procedures and course details.
Some inaccuracies were noted for ambiguous or complex queries, especially those that required inference or were outside the scope of the PDF data.

5 Error Analysis

Error Type	Occurrence (%)
Ambiguous Questions	5%
Out-of-Scope Queries	3%

Misinterpretation (NLP) 2%

6 Key Achievements

Real-time query response using a web-based interface.
Dynamic text extraction and processing from PDF documents.
Accurate semantic search using FAISS and LangChain.
Seamless integration of AI with UI using Streamlit.

XI. CONCLUSION

The development of an AI-powered chatbot for solving frequently asked questions on a college website has successfully demonstrated the potential of modern natural language processing and machine learning technologies in enhancing user interaction within educational institutions. By integrating tools such as OpenAI GPT-3.5 Turbo, LangChain, FAISS, Streamlit, and PyPDF2, the system offers intelligent, accurate, and instant responses to user queries in real-time.

This project not only reduces the workload of administrative staff by automating routine interactions but also ensures 24/7 availability of information to students, faculty, and other stakeholders. The chatbot efficiently extracts knowledge from PDF documents, converts text into meaningful embeddings, and retrieves the most relevant responses through semantic similarity search — resulting in a more user-friendly and responsive college website.

The achieved accuracy and user satisfaction rates highlight the system's effectiveness. While the chatbot performs well with general queries, some limitations were observed in handling highly ambiguous or out-of-scope questions. These areas present opportunities for future improvement, such as expanding the training dataset, incorporating multilingual capabilities, and enabling dynamic learning from real-time interactions.

Overall, the project validates the feasibility and impact of conversational AI in the education domain and sets the foundation for building more intelligent, scalable, and domain-specific support systems.

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