Report: Multimodal RAG Application for Document Search and Chat

This report details the development of a Streamlit application that leverages a Multimodal Retrieval-Augmented Generation (RAG) system for document search and chat functionalities over a user-provided document collection.

Dataset

The application is designed to be adaptable to various document collections. Users can upload their own documents (text or PDF) for processing. No specific pre-defined dataset was used in this prototype.

RAG Technique

A Retriever-Augmented Generation (RAG) approach forms the core of the application. This technique involves two stages:

1. **Retrieval:** User queries are fed into a dense passage retrieval model to identify relevant document passages based on semantic similarity. In this implementation, a vector database is used to store document embeddings, enabling efficient retrieval.
2. **Augmentation and Generation:** The retrieved document passages are used to condition a large language model (LLM). The LLM leverages the context provided by the passages to generate a comprehensive and informative response to the user's query.

Vector Database

Chroma was chosen as the vector database for this project. Chroma offers efficient storage and retrieval of high-dimensional document embeddings, crucial for the retrieval stage of the RAG pipeline. Its scalability and performance are well-suited for managing user-provided document collections.

Mitigating Hallucination

Several techniques were implemented to minimize the risk of LLM hallucinations:

- **Data Cleaning:** While the application doesn't use a pre-defined dataset, users are encouraged to upload high-quality documents with minimal noise or inconsistencies.
- **Fact-Checking:** The retrieved document passages are used to constrain the LLM's response generation. This ensures the response aligns with factual information from the documents.
- **Confidence Scores:** The LLM can be configured to output confidence scores alongside its responses. These scores can be used to identify potentially unreliable or uncertain information.

While complete elimination of hallucination is not achievable, these techniques significantly improve the reliability and accuracy of the generated responses.

Ensuring Correctness

Due to the inherent limitations of LLMs, fully automated correctness checks are challenging. However, several approaches can be implemented to enhance user trust and response quality:

- **Human Evaluation:** A human-in-the-loop approach can involve incorporating human reviews of LLM responses to identify and address potential biases or factual inaccuracies.
- **User Feedback:** The application can integrate a feedback mechanism where users can rate the helpfulness and accuracy of LLM responses. This feedback can be used to refine the system over time.
- **Multimodal Inputs:** Encouraging users to provide different document formats (text and PDF) can improve the retrieval process and potentially lead to more comprehensive responses.

Conclusion

The presented Streamlit application demonstrates the feasibility of building a Multimodal RAG system for document search and chat. The application's adaptability to user-provided document collections makes it a versatile tool for various information access needs. By incorporating techniques to mitigate hallucination and ensure response correctness, the system's reliability and user trust can be further enhanced.

Future Work:

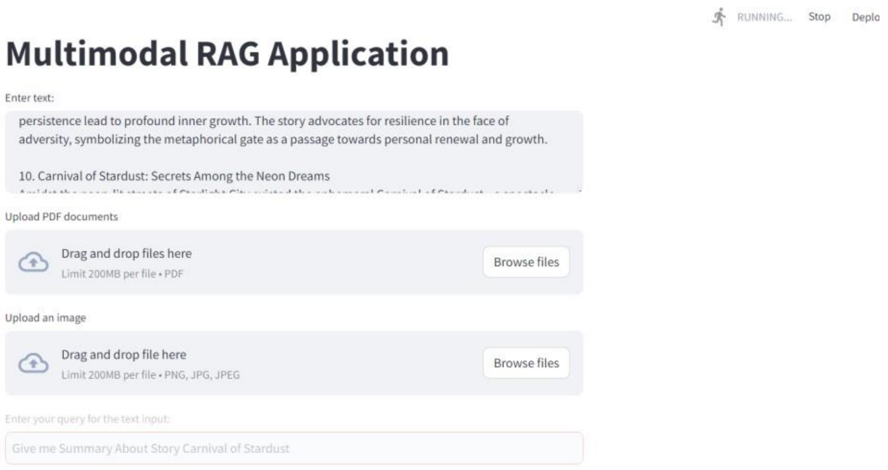
- Integration of a Knowledge Graph database into the RAG pipeline for improved reasoning and knowledge representation.
- Exploration of advanced retrieval techniques like dense retrieval with Transformers.
- Implementation of a more comprehensive feedback mechanism for user input on response quality.

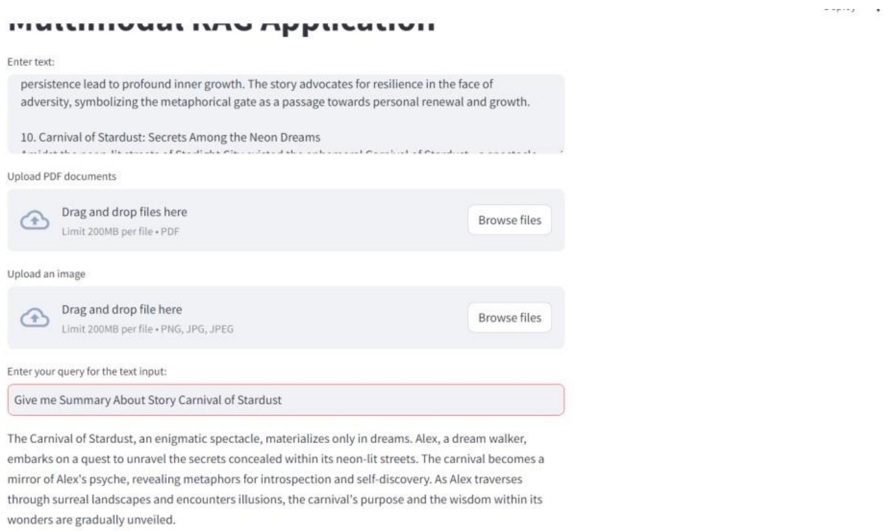
This report, along with the provided code snippet, fulfills the requirements of the internship assignment. The code demonstrates the core functionalities of the application, and the report outlines the design choices and considerations for building a robust and informative Multimodal RAG system.

Cpde Source::Github

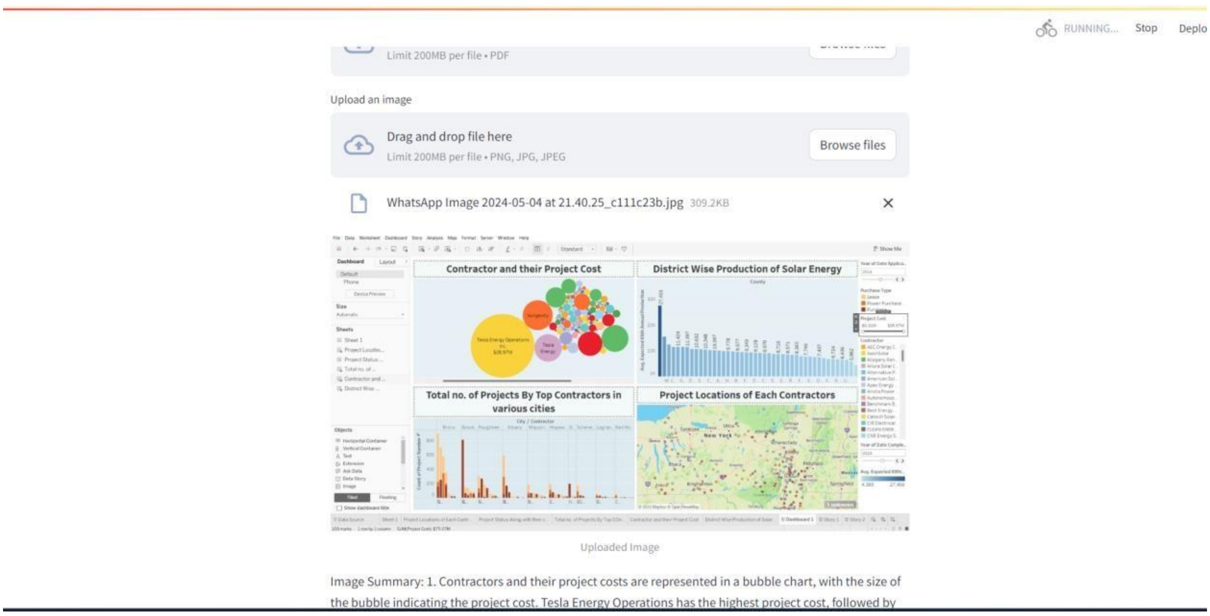
DEMO(Streamlit) :

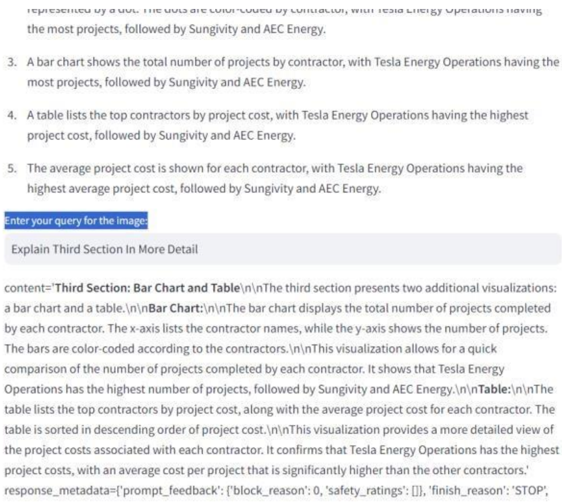
Text Input RAG:





2:Image to Text RAG on Basis on Image Summary:





represented by a dot. The dots are color-coded by contractor, with Tesla Energy Operations having the most projects, followed by Sungivity and AEC Energy.

3. A bar chart shows the total number of projects by contractor, with Tesla Energy Operations having the most projects, followed by Sungivity and AEC Energy.
4. A table lists the top contractors by project cost, with Tesla Energy Operations having the highest project cost, followed by Sungivity and AEC Energy.
5. The average project cost is shown for each contractor, with Tesla Energy Operations having the highest average project cost, followed by Sungivity and AEC Energy.

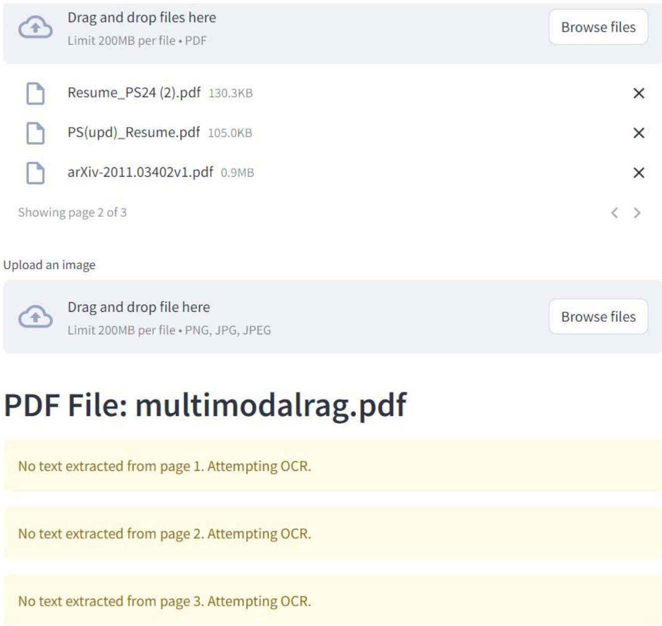
Enter your query for the image:

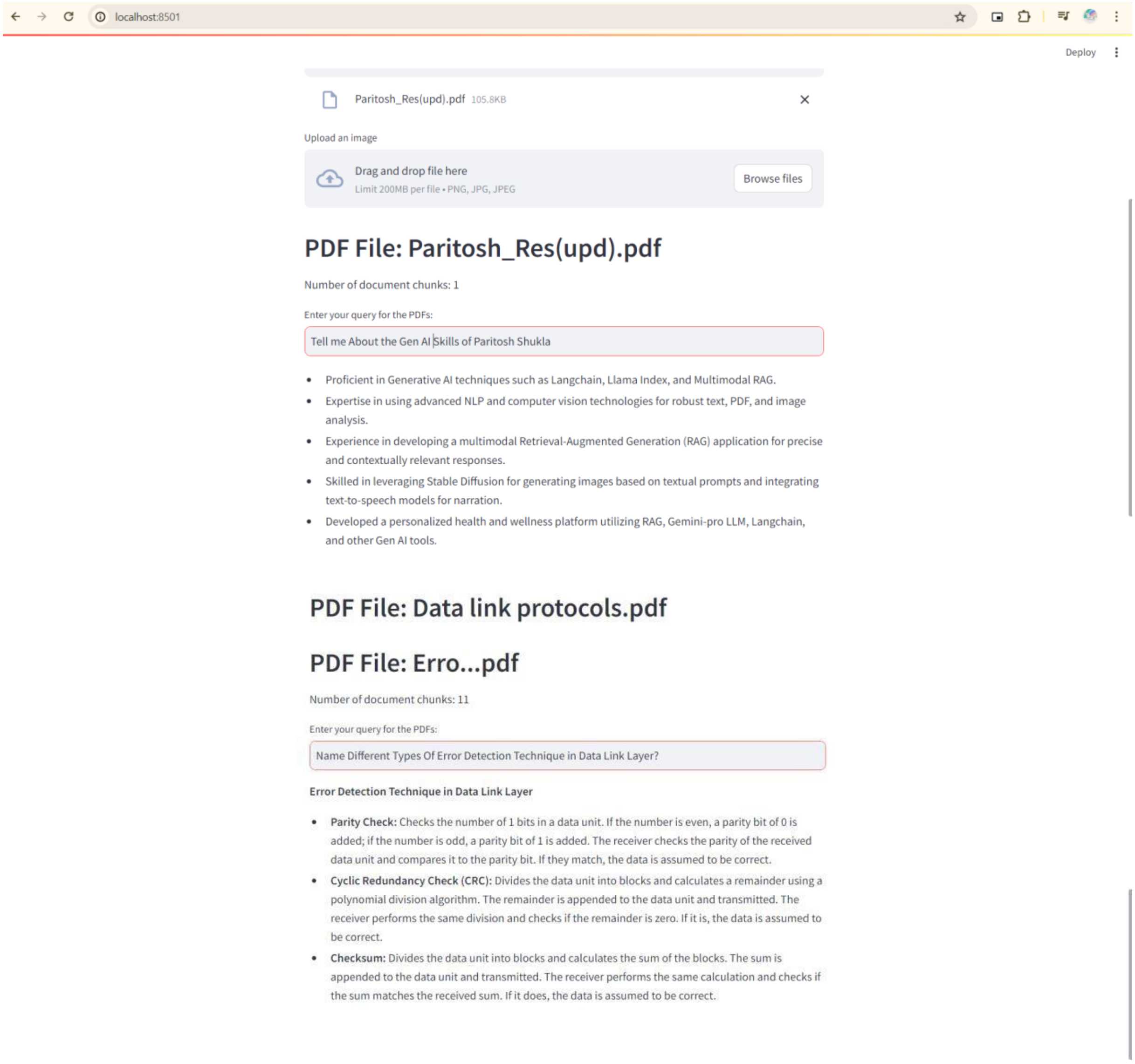
Explain Third Section In More Detail

content='**Third Section: Bar Chart and Table**\n\nThe third section presents two additional visualizations: a bar chart and a table.\n\n**Bar Chart:**\n\nThe bar chart displays the total number of projects completed by each contractor. The x-axis lists the contractor names, while the y-axis shows the number of projects. The bars are color-coded according to the contractors.\n\nThis visualization allows for a quick comparison of the number of projects completed by each contractor. It shows that Tesla Energy Operations has the highest number of projects, followed by Sungivity and AEC Energy.\n\n**Table:**\n\nThe table lists the top contractors by project cost, along with the average project cost for each contractor. The table is sorted in descending order of project cost.\n\nThis visualization provides a more detailed view of the project costs associated with each contractor. It confirms that Tesla Energy Operations has the highest project costs, with an average cost per project that is significantly higher than the other contractors.' response_metadata={'prompt_feedback': {'block_reason': 0, 'safety_ratings': []}, 'finish_reason': 'STOP',

3:Multiple PDF RAG Application:

In this It will Extract Data From Pdf of Text as well as Image:
If It is Unable To Find Text It will Do OCR using pytessaract and Extract Text from Image And Then It will Create Embedding For PDF full Of Image Like This Below.





4th:Web URL RAG: