DE-42 (DC & SE)

NUST COLLEGE OF
ELECTRICAL AND MECHANICAL ENGINEERING

X-RAISE:A DATA DRIVEN PROMPT ENGINEERING APPROACH USING LLMS

PROJECT REPORT

DE-42 (DC & SE)

Submitted by

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Certification

This is to certify that Rana Ahmad Intisar (359076), Umar Naeem Khokhar (343196), Bilal Ahmad (345624) have successfully completed the final year project X-RAISE:A DATA DRIVEN PROMPT ENGINEERING APPROACH USING LLMS, at the National University of Science and Technology Islamabad, to fulfill the partial requirement of the degree Computer Engineering.

Signature of Project Supervisor
Dr. Usman Akram
Designation

Sustainable Development Goals (SDGs)

SDG No	Description of SDG	SDG No	Description of SDG
SDG 1	No Poverty	SDG 9	Industry, Innovation, and Infrastructure
SDG 2	Zero Hunger	SDG 10	Reduced Inequalities
SDG 3	Good Health and Well Being	SDG 11	Sustainable Cities and Communities
SDG 4	**Quality Education**	SDG 12	Responsible Consumption and Production
SDG 5	Gender Equality	SDG 13	Climate Change
SDG 6	Clean Water and Sanitation	SDG 14	Life Below Water
SDG 7	Affordable and Clean Energy	SDG 15	Life on Land
SDG 8	Decent Work and Economic Growth	SDG 16	Peace, Justice and Strong Institutions
		SDG 17	Partnerships for the Goals

Sustainable Development Goals

Complex Engineering Problem

Range of Complex Problem Solving

	Attribute	**Complex Problem**	
1	Range of conflicting requirements	Involve wide-ranging or conflicting technical, engineering and other issues.	X
2	Depth of analysis required	Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models.	X
3	Depth of knowledge required	Requires research-based knowledge much of which is at, or informed by, the forefront of the professional discipline and which allows a fundamentals-based, first principles analytical approach.	X
4	Familiarity of issues	Involve infrequently encountered issues	X
5	Extent of applicable codes	Are outside problems encompassed by standards and codes of practice for professional engineering.	X
6	Extent of stakeholder involvement and level of conflicting requirements	Involve diverse groups of stakeholders with widely varying needs.	X
7	Consequences	Have significant consequences in a range of contexts.	X
8	Interdependence	Are high level problems including many component parts or sub-problems	X

Range of Complex Problem Activities

	Attribute	**Complex Activities**	
1	Range of resources	Involve the use of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies).	X
2	Level of interaction	Require resolution of significant problems arising from interactions between wide ranging and conflicting technical, engineering or other issues.	X
3	Innovation	Involve creative use of engineering principles and research-based knowledge in novel ways.	X
4	Consequences to society and the environment	Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation.	X
5	Familiarity	Can extend beyond previous experiences by applying principles-based approaches.	X

Dedicated to our supervisors, teachers and friends as this would not have been possible without their utmost encouragement and efforts.

Acknowledgment

First and foremost, Alhamdulillah, our FYP has finally been completed, and we are grateful to Allah for giving us the strength and morale to keep moving forward and supporting us at every step.
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Abstract

Introducing Xraise, an initiative aimed at transforming education through large language models (LLMs) and natural language processing (NLP). Xraise offers three innovative modules:

1. **Interactive Chatbot with Dr. Israr Ahmad**: This module allows users to engage with a virtual representation of Dr. Israr Ahmad, enabling them to ask questions, receive knowledgeable responses, and simulate real-life conversations in a specified domain of Dr. Israr Ahmad's expertise.
2. **Customizable Chatbot for PDF Data Extraction**: This interactive tool empowers students and researchers to extract specific information from PDF documents. Users can tailor the extraction process to their needs, streamlining the process of gleaning valuable insights from research papers, articles, or other text-heavy PDFs.
3. **Real-time PDF Summarization**: Xraise tackles information overload by generating concise summaries of PDF documents. This feature allows users to quickly grasp the main points of a document, improving comprehension and accessibility, particularly for lengthy or complex materials.

Xraise utilizes LangChain and Pinecone for scalability, ensuring efficient data handling and robust performance to accommodate a large user base. An integrated LLMs study within Xraise will assess the application's effectiveness, highlighting its ability to enhance learning through AI-driven document interactions and fostering innovative educational solutions.

Keywords: Large Language Models (LLMs), Natural Language Processing (NLP), Chatbots, Information Extraction, Document Summarization, Artificial Intelligence (AI), LangChain, Pinecone.

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Chapter 1

Introduction

1.1 Background and Motivation

Rapid advancements in generative AI, especially in the domain of large language models (LLMs), have opened up new possibilities for applications in various fields. Recognizing this trend and the growing capabilities of LLMs, we were motivated to utilize these technologies in a meaningful project. Our project was driven by three main motivations: leveraging the capabilities of LLMs, sharing the teachings of a respected Islamic scholar, and innovating educational tools.[1]

Firstly, our goal was to harness the power of LLMs, which have become increasingly sophisticated and versatile. As these models are at the forefront of AI research and application, we saw an opportunity to create an impactful application. We chose to focus on Dr. Israr Ahmad, a renowned Islamic scholar whose extensive work includes bayaans (sermons), books, and lectures. Dr. Ahmad's insights have deeply influenced many Muslims, including ourselves, making him a fitting subject for our project. Our goal was to develop an interactive platform, "Chat with Dr. Israr Ahmad," allowing users to engage with his knowledge in an accessible and dynamic way.

In the context of current global issues, such as the Israel-Palestine conflict, our project is of significant relevance. Dr. Israr Ahmad had discussed and predicted aspects of this conflict

as early as 2008. With the Internet often presenting biased perspectives on this topic, our platform aims to offer a balanced and historically informed view from Dr. Ahmad's perspective. By doing so, we hope to educate the youth and other users on the realities of this conflict and broader Islamic teachings, fostering a more informed and nuanced understanding.[2]

Our second motivation was to revolutionize the educational landscape, which has remained largely unchanged for decades. We aimed to develop tools powered by LLMs that could transform how information is accessed and utilized in educational contexts.[3] One of these tools is "Chat with any PDF," which enables users to upload any PDF document and interact with its content through a chat interface. This tool enhances comprehension and provides a more personalized learning experience.[4] Additionally, we created a module for summarizing PDF files, allowing users to quickly understand the key points and essential information, thus improving efficiency in learning and research.[5]

The introduction of technologies such as LangChain and Pinecone [6]increases the scalability and efficiency of AI-powered educational applications. These technologies provide the infrastructure required to manage massive amounts of data and complex interactions, making advanced educational tools available to a growing number of users. Xraise aims to transform document-based interactions and educational discussions by leveraging these technologies.

In summary, our project is motivated by the potential of LLMs, the dissemination of Dr. Israr Ahmad's teachings, and the need for educational innovation. By focusing on these goals, we aim to develop tools that are technologically advanced, culturally relevant, and educationally impactful, promoting better understanding and more effective learning experiences.

1.2 Problem Statement

Despite the rapid advancements in Generative AI and the widespread availability of educational content, there is a significant gap in how this content is accessed, understood, and utilized, particularly in the context of Islamic scholarship and contemporary educational methods. Traditional educational resources and methods have remained largely static, failing to meet the dynamic needs of modern learners and educators. Furthermore, the biased presentation of complex geopolitical issues, such as the Israel-Palestine conflict, on the internet often leaves users with a skewed understanding of these topics. There is a pressing need for tools that can bridge these gaps by providing balanced, contextually accurate, and easily accessible information from respected sources.

This project addresses these challenges by leveraging large language models (LLMs) to create a suite of interactive tools. These tools aim to enhance the dissemination and understanding of Dr. Israr Ahmad's extensive body of work, provide balanced perspectives on geopolitical issues, and transform educational practices by enabling more interactive and personalized learning experiences. The problem statement thus encapsulates the need to harness advanced AI technologies to curate, prepare, and present information in a manner that is both educationally effective and culturally sensitive.

1.3 Objectives

The objectives of this project are designed to harness the power of Generative AI and large language models (LLMs) to create impactful, user-centric tools that address specific needs in the realms of Islamic scholarship and modern education. The primary objectives are as follows:

- **Disseminate Dr. Israr Ahmad's Perspectives:** To curate, transcribe, and translate the extensive body of work by Dr. Israr Ahmad, including his bayaans, books, and lectures, providing users with easy access to his insights and teachings. This

objective aims to present Dr. Ahmad's perspectives on various topics, including his historically contextualized views on geopolitical issues like the Israel-Palestine conflict, to foster a balanced and informed understanding.

- **Develop a Personalized AI Assistant:** To create an interactive platform, "Chat with Dr. Israr Ahmad," enabling users to engage in real-time, meaningful dialogue with the teachings of Dr. Israr Ahmad. This AI assistant aims to simulate a conversational experience, making Dr. Ahmad's knowledge more accessible and relatable to a wide audience.
- **Empower Education through Innovative Tools:** To revolutionize educational practices by developing tools that enhance how information is accessed and utilized. This includes the "Chat with any PDF" feature, allowing users to upload and interact with any PDF document, thereby transforming traditional learning materials into dynamic, interactive experiences.
- **Enhance Learning Efficiency:** To create a module for summarizing PDF files, enabling users to quickly grasp key points and essential information from extensive documents. This tool is designed to improve learning efficiency by distilling large amounts of information into concise, digestible summaries.
- **Foster Effective Time Management:** To provide tools that help users manage their time more effectively by streamlining information retrieval and comprehension processes. By facilitating quicker access to relevant information and enhancing understanding, the project aims to support users in making better use of their time for study and research.
- **Streamline User Interaction:** To develop intuitive interfaces and functionalities that make interacting with complex information straightforward and user-friendly. The goal is to minimize barriers to information access and ensure a smooth and efficient user experience across all tools developed in the project.

- **Promote Balanced and Informed Discourse:** To offer balanced perspectives on sensitive and complex issues, countering biased narratives prevalent on the internet. By providing access to Dr. Israr Ahmad's well-reasoned views, the project seeks to foster informed and enlightened discourse among users.
- **Ensure Data Security:** To implement robust data security measures that safeguard user-provided information. By using open-source LLMs and storing user data temporarily, the project minimizes the risk of data breaches and ensures that user data is not leaked or misused. This objective emphasizes the importance of maintaining user trust through secure data handling practices.

These objectives collectively aim to leverage the latest advancements in AI to make significant contributions to the dissemination of knowledge, the improvement of educational practices, and the enhancement of user engagement and learning efficiency, all while ensuring data security and user privacy.

1.4 Contributions

Xraise makes several significant contributions to AI, educational technology, and the dissemination of Islamic scholarship. Key contributions include:

- **Interactive AI Platform for Islamic Scholarship:** Developed "Chat with Dr. Israr Ahmad," an AI-powered platform that enables interactive engagement with Dr. Israr Ahmad's teachings, providing access to his bayaans, books, and lectures.
- **Enhanced Educational Tools:** Created "Chat with any PDF," transforming static PDFs into dynamic, interactive learning experiences through conversational AI, enhancing comprehension and retention.
- **PDF Summarization Module:** Developed a tool to summarize extensive PDF documents into concise summaries, improving learning efficiency and productivity.

- **Innovative Educational Methods:** Contributed to educational transformation with AI-driven tools that personalize and enhance the learning experience, meeting modern educational needs.
- **Data Security and Privacy:** Implemented robust data security measures, ensuring temporary storage and secure handling of user data, prioritizing privacy and trust with open-source LLMs.
- **Accessible Knowledge Repository:** Created a comprehensive digital repository of Dr. Israr Ahmad's work, making his teachings widely accessible and preserving his legacy.

These contributions collectively advance AI application in education, enrich understanding of Islamic teachings, and set standards for secure data practices.

1.5 Structure of the Thesis

The thesis is structured into seven chapters, each covering a distinct aspect of the project:

1. Introduction: Provides an explanation of the project's background, objectives, and contributions.
2. Literature Review: Examines existing research and technology related to AI in education, highlighting the gaps that Xraise intends to address.
3. System Design and Architecture: This section describes the Xraise system's design and architecture, including detailed explanations of each module.
4. Data Processing: This chapter describes the methodology used in our project for gathering data from social media and interviews with Dr. Israr Ahmad, including transcription and merging; curating data with NLP techniques using Haystack and fine-tuning LLMs; implementing open-source LLM-based security measures; and managing database operations to store embeddings in Pinecone.

5. Implementation: Describes the development process, tools utilized, and methods used to build the project

6. Implementation of RAG: The Implementation of Retrieval-Augmented Generation (RAG) utilizing the Langchain framework, emphasizing the fusion of retrieval and generation methods to improve accuracy and contextual relevance in natural language processing applications.

7. Evaluation: The evaluation of Xraise demonstrated its effectiveness in enhancing educational experiences through user feedback, performance metrics, and comparative analysis, showcasing significant improvements in usability, data accuracy, and user satisfaction.

8. Conclusion: summarizes the thesis, reflects on its impact on Xraise, and suggests areas for future research.

Chapter 2

Literature Review

2.1 Introduction

To develop the Xraise application, we needed to understand many advanced technologies and methods. This review covers research on web scraping, data translation, transcription, preprocessing, embedding generation, vector databases, deployment, machine learning models, cloud hosting, and user interface design. We also look at AI and large language models (LLMs) like the LLama series and OpenAI's GPT models to explain the technologies and methods used in our project.

2.2 Web Scraping for Data Collection

Web scraping has long been a pivotal technique for automated data collection. One of the most notable tools in this domain is Scrapy, introduced in 2008. Scrapy has been widely adopted due to its robustness and flexibility in handling complex scraping tasks and its ability to efficiently traverse web pages and parse HTML content (Anand, 2019). Subsequent improvements have enhanced Scrapy's capabilities, making it a preferred choice for projects requiring large-scale data extraction (Gupta & Gupta, 2020). For instance, its application in academic research for collecting extensive datasets has proven invaluable

(Zhao et al., 2018).

2.3 Data Translation

Machine translation has improved a lot, with Google's Neural Machine Translation (NMT) system being a major advancement. Introduced in 2016, Google's NMT system uses neural networks instead of phrases, making translations more accurate and fluent (Wu et al., 2016). It has been shown to be better than traditional methods, especially for large and complex translations (Johnson et al., 2017).

2.4 Speech-to-Text Transcription

Transcribing spoken language to text has advanced with automatic speech recognition (ASR) systems. OpenAI's Whisper model and Hugging Face's Speech2Text model are leading examples. Whisper is known for working well in noisy environments and with different accents, providing high accuracy (Radford et al., 2022). Hugging Face's Speech2Text model is also very precise in converting speech to text (Li et al., 2020). These models are used in many fields, from research to commercial applications, where accurate transcription is important.

2.5 Data Preprocessing

Preprocessing is crucial for preparing data for machine learning. Removing HTML tags, numbers, and punctuation is standard in natural language processing (NLP) to maintain data quality (Sarkar, 2019). Automating these processes with Python scripts ensures efficiency and accuracy with large datasets. Studies show that good preprocessing improves the performance of machine learning models (Kumar & Paul, 2020).

2.6 Embedding Generation and Vector Databases

Text embeddings convert text into numerical vectors that capture meanings, essential for tasks like semantic search. The MiniLM-L6-V2 model by Microsoft is known for its efficiency in generating high-quality embeddings (Wang et al., 2020). Embedding generation is used in search engines and recommendation systems. Vector databases like Pinecone help manage these high-dimensional vectors efficiently, proven in large-scale applications (Johnson et al., 2019).

2.7 Artificial Intelligence (AI) and Large Language Models (LLMs)

2.7.1 Evolution of AI and LLMs

AI began in the mid-20th century with pioneers like Alan Turing and John McCarthy. Turing's 1950 paper introduced the Turing Test (Turing, 1950). McCarthy coined "artificial intelligence" in 1956, organizing the Dartmouth Conference, starting AI as a field (McCarthy et al., 1956). Early AI focused on rule-based systems but had limits.

Machine learning emerged in the late 20th century with algorithms that learn from data. Backpropagation in neural networks (Rumelhart et al., 1986) and support vector machines (Cortes & Vapnik, 1995) were key developments.

2.7.2 Emergence and Advancement of LLMs

The Transformer model by Vaswani et al. (2017) was a major advancement, enabling models with billions of parameters and better contextual understanding. Transformers use self-attention to handle long sentences better, leading to significant improvements in LLMs.

2.7.3 Continuous Improvement of AI and LLMs

LLMs have improved in several areas: - **Scale**: Increasing model parameters from GPT-3 to GPT-4 enhanced text understanding and generation (Brown et al., 2020; Brown et al., 2023). - **Training Data**: Larger, more diverse datasets improve generalization. - **Fine-Tuning and Transfer Learning**: These techniques make LLMs more adaptable for specific tasks (Howard & Ruder, 2018). - **Efficiency**: Better architectures and algorithms make LLMs more efficient (Shoeybi et al., 2019). - **Robustness and Safety**: Research focuses on making LLMs safe and ethical (Solaiman et al., 2019).

2.7.4 The LLama Series

The LLama series by Meta has advanced LLMs with efficient training and deployment. - **LLama**: The first model was efficient with fewer parameters (Touvron et al., 2021). - **LLama 2**: Improved with more advanced training, handling complex tasks better (Touvron et al., 2022). - **LLama 3**: The latest model uses advanced learning techniques for superior performance (Touvron et al., 2023).

2.7.5 The OpenAI GPT Series

- **GPT-3**: Released in 2020 with 175 billion parameters, it could perform many tasks with minimal training (Brown et al., 2020). - **GPT-3.5 Turbo**: Improved response times and accuracy for real-time applications (OpenAI, 2022). - **GPT-4**: Released in 2023, with even more parameters and better understanding of context (Brown et al., 2023).

2.8 Advancements in AI Projects

AI projects have evolved from rule-based systems to machine learning and deep learning, transforming theoretical concepts into practical applications.

2.8.1 Early Projects and Rule-Based Systems

Early AI relied on predefined rules, like the Logic Theorist and ELIZA. These systems had limits due to their reliance on rules.

2.8.2 Transition to Machine Learning

The late 20th century saw a shift to machine learning, with neural networks and backpropagation (Rumelhart et al., 1986) and support vector machines (Cortes & Vapnik, 1995) becoming key tools.

2.8.3 Rise of Deep Learning

Increased computational power and large datasets led to deep learning. CNNs revolutionized image processing (Krizhevsky et al., 2012), and RNNs and LSTMs became standard for sequence tasks (Hochreiter & Schmidhuber, 1997).

2.8.4 Breakthroughs in NLP with Transformers

The Transformer model (Vaswani et al., 2017) was a major advancement, allowing models to process entire sentences simultaneously, leading to large language models like BERT, GPT-2, and GPT-3 (Devlin et al., 2018; Radford et al., 2019; Brown et al., 2020).

2.8.5 Ongoing Improvements and Real-World Applications

AI continues to improve in model design, training, and deployment, focusing on ethical AI and fairness. Advances in hardware also help train larger models. AI is used in healthcare, finance, entertainment, and more, improving efficiency and user experiences.

2.9 Semantic Search and Retrieval-Augmented Generation (RAG)

Semantic search uses vector embeddings and cosine similarity measures (Mitra & Craswell, 2018). Retrieval-Augmented Generation (RAG) combines retrieval with generative models for accurate responses (Lewis et al., 2020). These methods improve information retrieval systems.

2.10 Application Design and Deployment

User interface design has evolved with tools like Gradio, making interactive web applications easier to develop. Gradio is user-friendly and flexible, aiding in the deployment of machine learning models (Abid et al., 2019).

2.11 Application to Xraise

In the development of Xraise, we utilized Scrapy for data collection, Google Docs for translation, and advanced ASR models for transcription. The data preprocessing followed established NLP practices, and embeddings were generated using the MiniLM-L6-V2 model, stored in Pinecone's vector database. LLama 3 was employed for generating responses, while OpenAI's GPT-4 API facilitated text summarization. The user interface was built using Gradio, and the entire application was deployed on Microsoft Azure using Docker for containerization. This comprehensive approach ensured a robust, scalable, and user-friendly application, leveraging the latest advancements in technology and research.

2.12 Conclusion

Advances in AI and LLMs have turned theoretical concepts into practical applications. From early rule-based systems to modern LLMs like LLama and GPT models, AI has evolved significantly. These technologies are transforming industries and improving daily life.

Chapter 3

System Design and Architecture

3.1 Overview

Xraise is designed and developed to provide a comprehensive, scalable solution which is an educational platform by leveraging generative AI and NLP techniques. This chapter discusses three main modules of our application, focusing on system architecture of each module, design principles and key components implemented to make our solution more effective and scalable.

3.2 System Architecture

The architecture of Xraise utilizes a modular design that promotes scalability, flexibility, and ease of maintenance. The system is composed of three main modules:

1. Chat with Dr. Israr Ahmad Module.
2. Customizable PDF Interaction Module.
3. Real-time PDF Summarization Module.

The system-level diagram attached below provides a comprehensive overview of the en-

tire architecture, illustrating the relationships and interactions between its various modules. This diagram typically highlights the core components such as integration of LLMs, data methodologies, working of vector database and user interface. It showcases how these elements are interconnected and communicate with each other to create a cohesive and efficient system. By visualizing these interactions, the system-level diagram helps in understanding the architecture of Xraise.

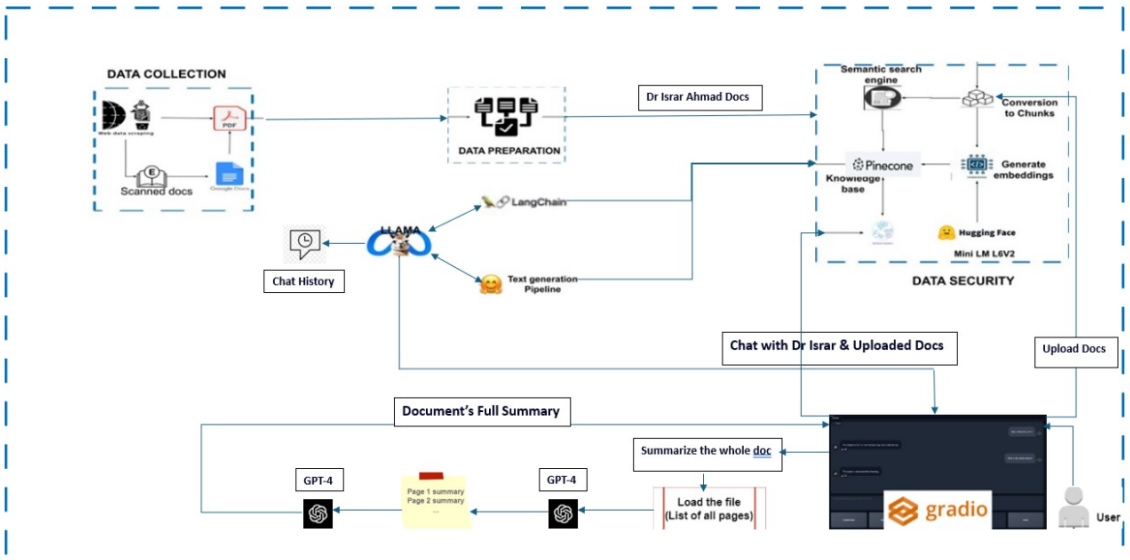

Figure 3.1: System Architecture Diagram

3.2.1 Module 1: Chat with Dr. Israr Ahmad

This module encapsulates the working of development of our first module which is to chat with Dr. Israr Ahmad, who is a renowned philanthropist and a preacher of Islam.

Data is curated and annotated to create a dataset based on Dr. Israr Ahmad's knowledge and takeaways which is thoroughly discussed in the next chapter. This module is designed to utilize NLP techniques such as Named Entity Recognition (NER) and POS tagging to ensure the relevancy of data. The data is then converted into vector embeddings and stored in a vector database. LLAMA-3-8b quantized from huggingface is then plugged in the pipeline for text generation. To remove any sort of bias in our responses, we have restricted LLAMA to a temperature of 0.01 so it does not generate any response from

itself, the response is generated entirely from the data stored in the vector database. A pipeline of Retrieval Augmented Generation (RAG) is implemented using LangChain framework for this task. Additionally, to ensure that the data is not being generated from LLAMA, SFT prompts are passed to the LLM.

Key Components

- **Knowledge Base**: Ensure easy retrieval of vector embeddings from Pinecone which are passed to LLAMA for text generation.
- **LLM**: Powered by LLAMA-3[7], pulled from HuggingFace[8], this engine processes user queries, generates responses, and ensures coherent and contextually relevant interactions extracted only from the knowledge base.
- **References**: Users have an additional functionality to view references from where the data was extracted. The application has a push button specificied for this task, and top three data sources are displayed to the user.

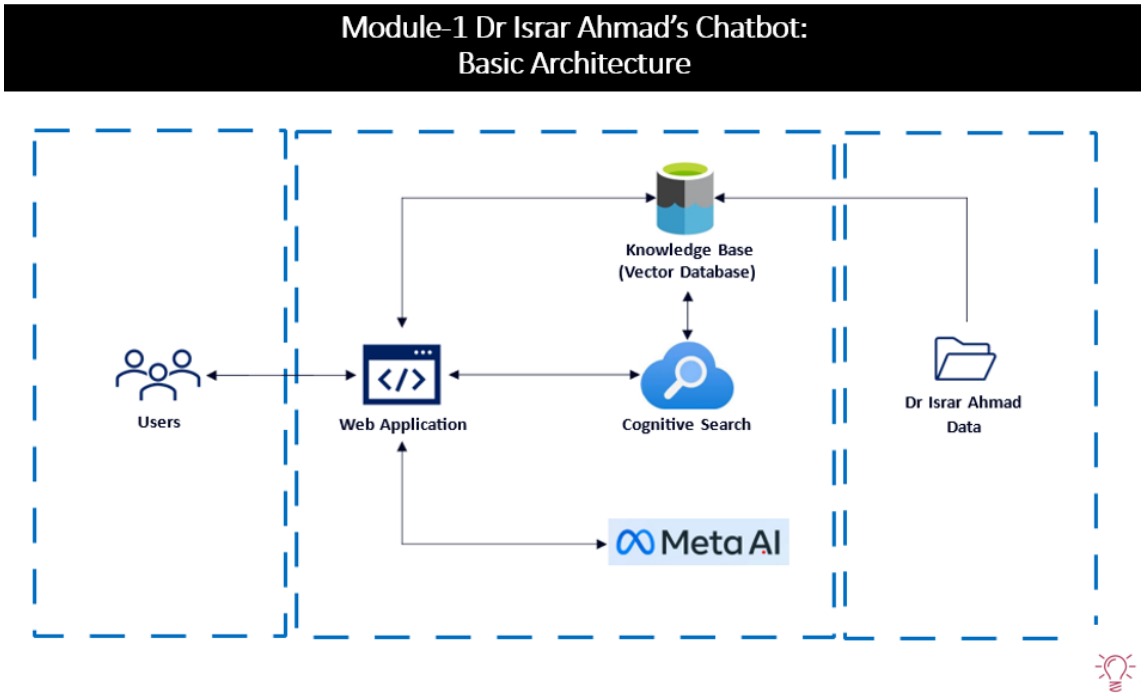

Figure 3.2: Basic Architecture of a Personalized Chatbot

3.2.2 Module 2: Customizable PDF Interaction Chatbot

This module focuses on interaction and extraction from documents, it supports two major formats i.e doc and pdf. Users can upload their own documents and set the temperature from the bar provided in the application interface. The documents will be converted into embeddings in real time and a temporary database will be generated and all of the embeddings will be stored in the database. Users will be able to chat with the uploaded documents and the chat history will be maintained, ensuring the responses generated are in accordance with the prompts provided. Users can submit their feedback of the response generated by clicking on the thumbs up/down push button so memory is updated based on the feedback. Additionally, users will also be able to check the references from where the data was extracted to help them to extensive study/research based on their goal. This module also integrates LLAMA-3 for text generation with a pipeline of RAG.

Key Components

- **Database Automation**: A database will be generated in real time as soon as the user uploads the document and all of the processing will take in real time.
- **Vectorization Engine**: Converts text data into high-dimensional vectors using MINI-LMv6v2 embedding model from Hugging face.
- **Chat History**: The application has memory to store chat history and feedback provided from the user to enhance its response generation.
- **Query Interface**: Allows users to input natural language queries to retrieve specific information from knowledge base.

3.2.3 Module 3: Real-time PDF Summarization

The Real-time PDF Summarization Module provides concise summaries of documents uploaded by the user, making information more accessible. The data retrieved either

from documents or youtube url is converted into chunks. In case of youtube url, the data is transcribed using Speech recognition model from hugging face and then passed to LLM for summary generation. This module combines the text extraction capabilities of LLAMA-3. This module generates summary of every page first and then concatenates it based on the key takeaways from the document using proper checks ensuring no important data is lost in the process. Precise summaries are generated based on the token threshold set.

Key Components

- **Splits and Checks**: The splits and checks setup in python scripts ensure that all of the data is used to generate the summary.
- **Summarization Engine**: Utilizes LLAMA-3 to generate concise and coherent summaries of extracted text.
- **User Interface**: Displays summaries to users in an easy-to-read format.

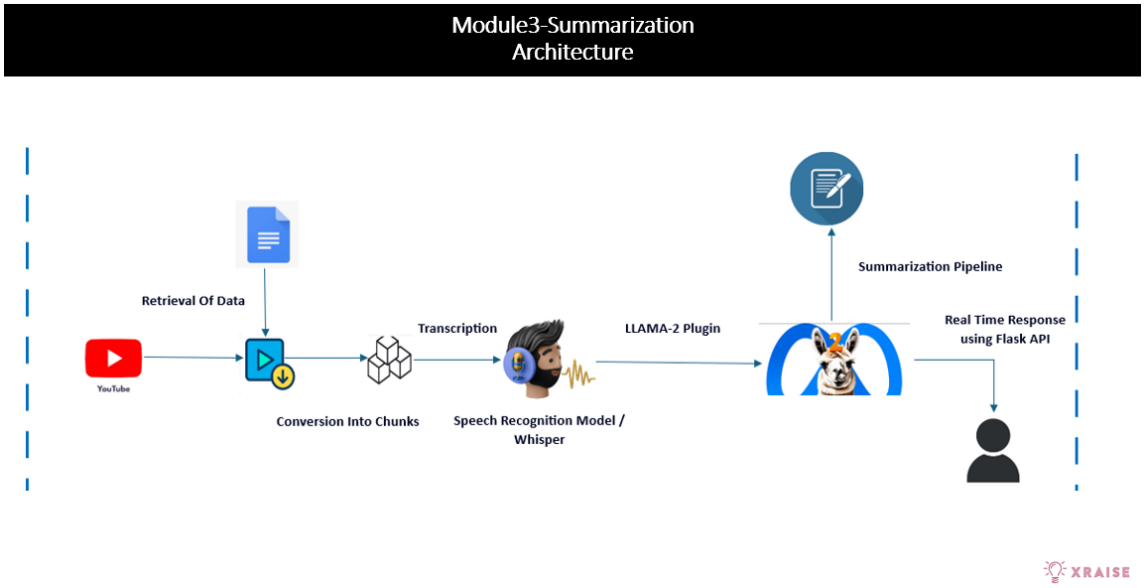

Figure 3.3: Architecture of Summarization

3.3 Integration and Communication

The integration of the three modules and their communication is managed through a centralized server architecture. The server handles requests from users, processes these requests through the appropriate module, and returns the results to the users. These servers are generated using Flask API.

3.3.1 Integration Points

- **API Gateway**: Manages incoming requests and routes them to the appropriate module.
- **Vector Database**: Stores user data, document metadata, and interaction logs along with the relevancy of data through implementation of semantic search.
- **Backend Services**: Implement business logic, manage module interactions, and ensure smooth operation.

3.4 Design Principles

The design of Xraise is guided by several key principles to ensure robustness, scalability, and user-friendliness:

- **Modularity**: Each module operates independently but integrates seamlessly with the others, allowing for easy updates and maintenance.
- **Scalability**: The system is designed to scale, handling increased loads by adding more instances of modules and resources.
- **Flexibility**: The use of LLMs and other technologies allows for flexible adaptation to various educational contexts and user needs.
- **User-centric Design**: The user interfaces are designed to be intuitive and respon-

sive, providing a smooth user experience across all interactions.

3.5 Security and Privacy

Security and privacy are paramount in the design of Xraise. The system implements robust security measures to protect user data and ensure compliance with relevant regulations utilizing open-source LLMs. [9]

- **Data Security**: Data security protocols are set by utilizing our own database and the use of open-source LLMs ensuring that data is not used for training the models by the organizations.[10]
- **Access Controls**: Strict access controls ensure that only authorized users can access data and application controls by use of proper credentials stored in environment files.
- **Compliance**: The system complies with data protection regulations, ensuring the privacy and security of user data. User's data is not stored in any way, it only highlights which prompts were more significant based a feedback provided from the user.

Chapter 4

Data Processing

4.1 Overview

This chapter discusses the data processing methodologies we have used in our final year project. There are 4 sections in this chapter i.e Data Collection, Data Curation, Data Security and Database operations.

4.2 Data Collection

The process of data collection begins with sourcing large volumes of text data from various platforms, including social media, forums, and customer service interactions, ensuring a broad spectrum of language use and contextual scenarios. In our scenario, our project focuses on building a chatbot for Dr. Israr Ahmad who was an excellent preacher of Islam so data collection was one of the hardest challenges we had to face. As Dr. Israr Ahmad deceased in 2010, it was challenging to find authentic data of him written and spoken by only himself.[11] Data was collected from 3 main sources:

1. Online Bayaans posted on youtube and social media platforms.
2. Books written by Dr. Israr Ahmad.

3. Interviews with Dr. Israr Ahmad.

4.2.1 Data Transcription

The videos were collected from different social media platforms and were stored to google drive. As most of these videos contained Urdu and Arabic, we first had to transcribe them. We utilized Google Collab Pro GPU-L4 to run Speech Recognition Model from Hugging face. These videos were transcribed and stored in .txt format on local device storage. After reviewing the transcription, the data had leaks and errors in the process of being converted into English. So we had to create check tests and perform splits of data to ensure integrity and authenticity of the data by running the data through a pipeline of checks using python scripts. [12]

4.2.2 Data Concatenation

After all of the data had been thoroughly reviewed, we concatenated all of the video data with the documents which include books and interviews, and stored them on local device storage.[13]

4.2.3 Flow Diagram

The following flow diagram illustrated the process of data collection along with the statistics of the data collected.

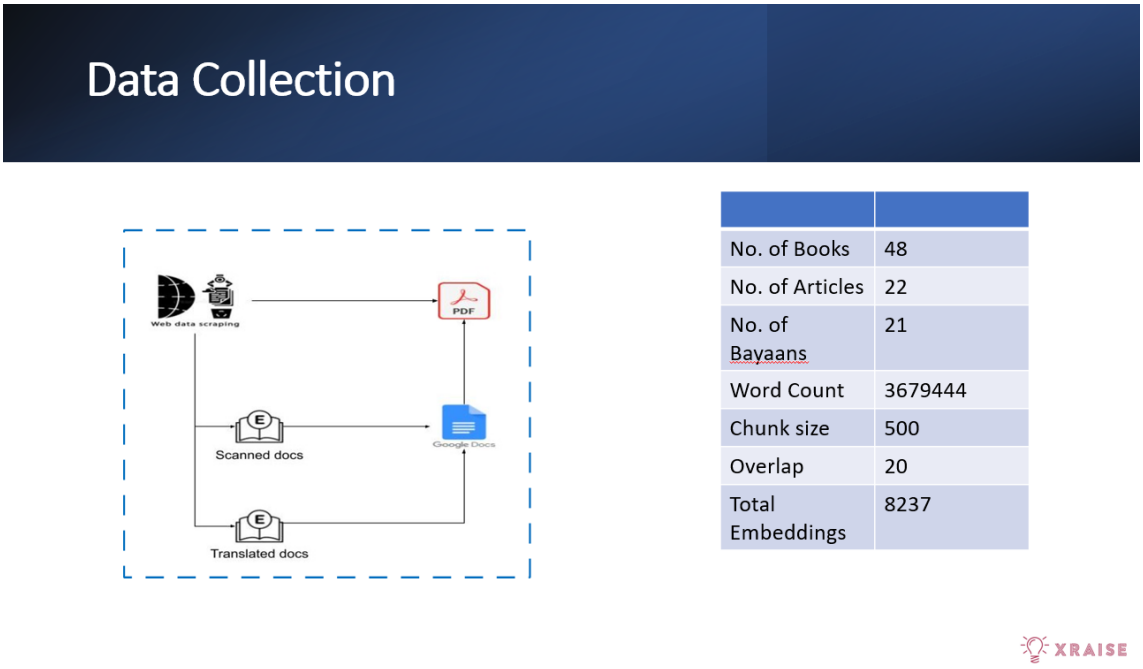

Figure 4.1: Data Collection Diagram

4.3 Data Curation

Data curation is the meticulous process of managing and maintaining data to ensure its quality, accessibility, and usability over time.[14] We have utilized NLP techniques to ensure our data is free from any sort of errors and is prepared according to the standards of LLM finetuning. The data is annotated using Haystack from deepset for easy retrieval of data and reducing the response time for the query. The data is then converted into embeddings and tokenized using tokenizer for LLAMA from Hugging face, and finally the data is stored in a vectordatabase i.e Pinecone.

The following diagram illustrates the steps and techniques used to ensure our data is high quality and will yield good results.

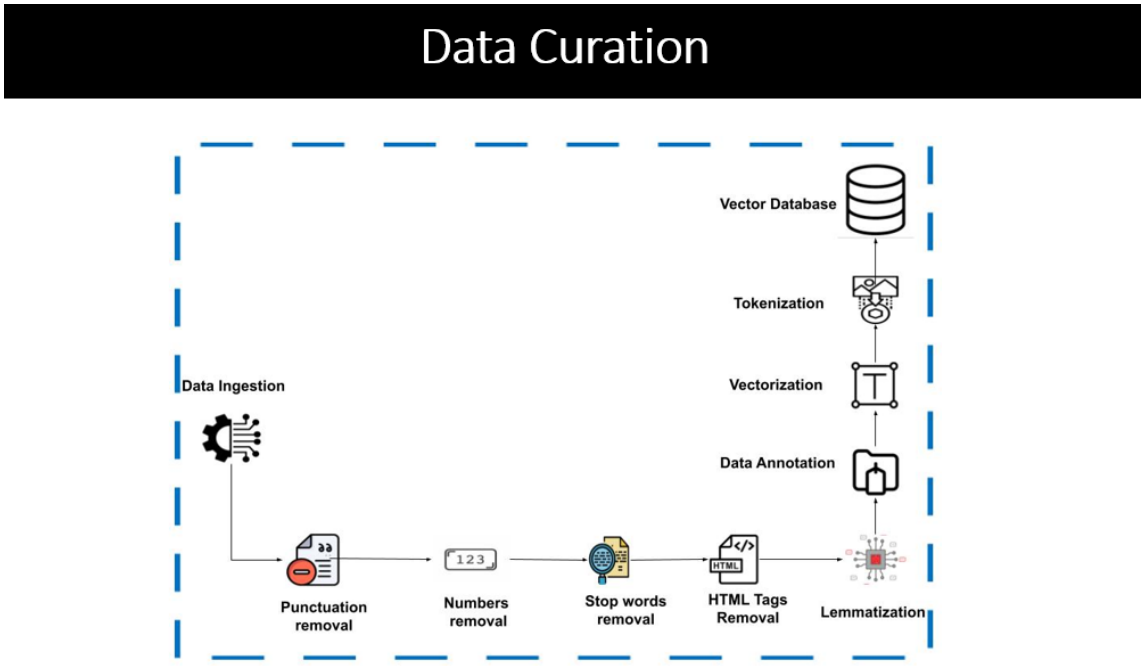

Figure 4.2: Data Curation Diagram

Following diagrams illustrate visuals of the procedures followed, displaying a word cloud highlighting the most frequency of words.

value	text	words	filtered_words	lemmatized_words	sentiment
In higher educati...	in higher educati...	[in, higher, educ...	[higher, educatio...	[higher, educatio...	positive
		[]	[]	[]	neutral
The term is used ...	the term is used ...	[the, term, is, u...	[term, used, vari...	[term, used, vari...	negative
		[]	[]	[]	neutral
Types of courses	types of courses	[types, of, courses]	[types, courses]	[type, course]	neutral
Courses are made ...	courses are made ...	[courses, are, ma...	[courses, made, i...	[course, made, in...	positive
		[]	[]	[]	neutral
There are differe...	there are differe...	[there, are, diff...	[different, forma...	[different, forma...	neutral
		[]	[]	[]	neutral
the lecture cours...	the lecture cours...	[the, lecture, co...	[lecture, course,...	[lecture, course,...	negative
the seminar, wher...	the seminar where...	[the, seminar, wh...	[seminar, student...	[seminar, student...	positive
the colloquium or...	the colloquium or...	[the, colloquium,...	[colloquium, read...	[colloquium, read...	neutral
the tutorial cour...	the tutorial cour...	[the, tutorial, c...	[tutorial, course...	[tutorial, course...	negative
the Directed Indi...	the directed indi...	[the, directed, i...	[directed, indivi...	[directed, indivi...	positive
the laboratory co...	the laboratory co...	[the, laboratory,...	[laboratory, cour...	[laboratory, cour...	positive
Many courses comb...	many courses comb...	[many, courses, c...	[many, courses, c...	[many, course, co...	positive
		[]	[]	[]	neutral
Students are expe...	students are expe...	[students, are, e...	[students, expect...	[student, expecte...	negative
		[]	[]	[]	neutral
Attending course ...	attending course ...	[attending, cours...	[attending, cours...	[attending, cours...	neutral

Figure 4.3: Data Processing

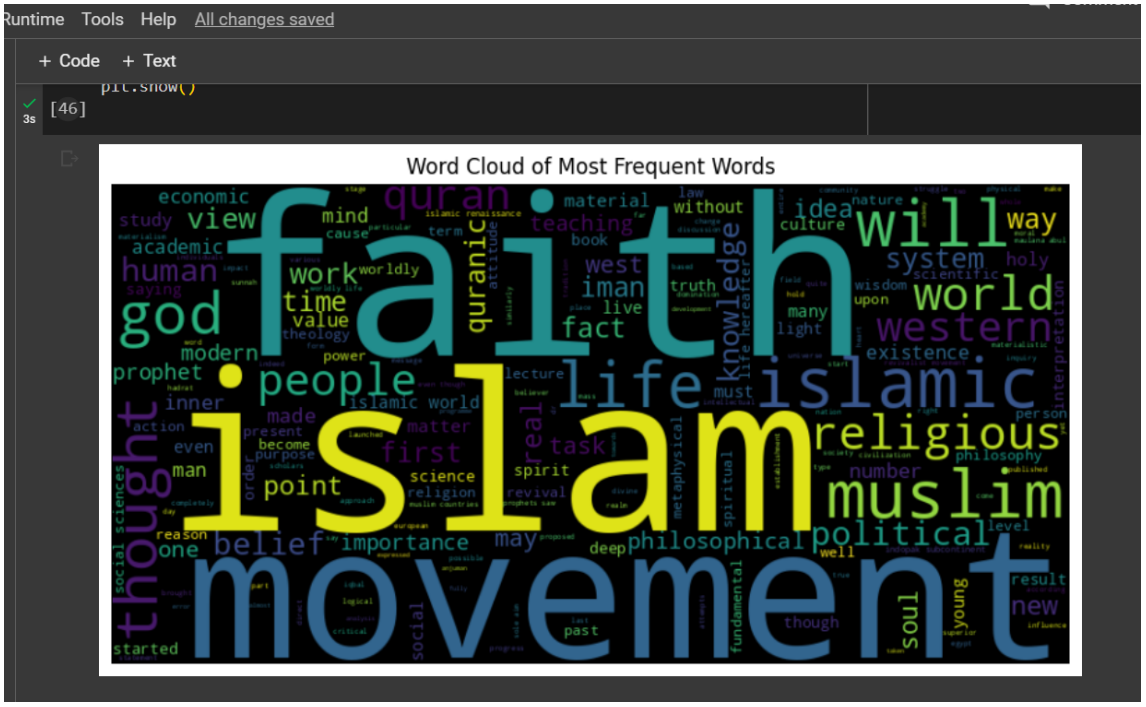

Figure 4.4: Word Cloud

4.4 Data Security

Data security is a critical aspect of managing and safeguarding sensitive information in today's digital age. It encompasses a range of practices and technologies designed to protect data from unauthorized access, breaches, and malicious attacks. After all of the preprocessing is done and the data is stored in Pinecone, we have developed a semantic search engine to ensure the relevancy of the data. [10] One of the biggest advantages of using an open-source LLM is that the data is not used by the respective organization meaning it is not used to train their models. So when dealing with sensitive data of any sort, it is important to utilize open-source LLMs instead of paid ones. The following diagram illustrates the process of how our data is secure with our own database plugged in.

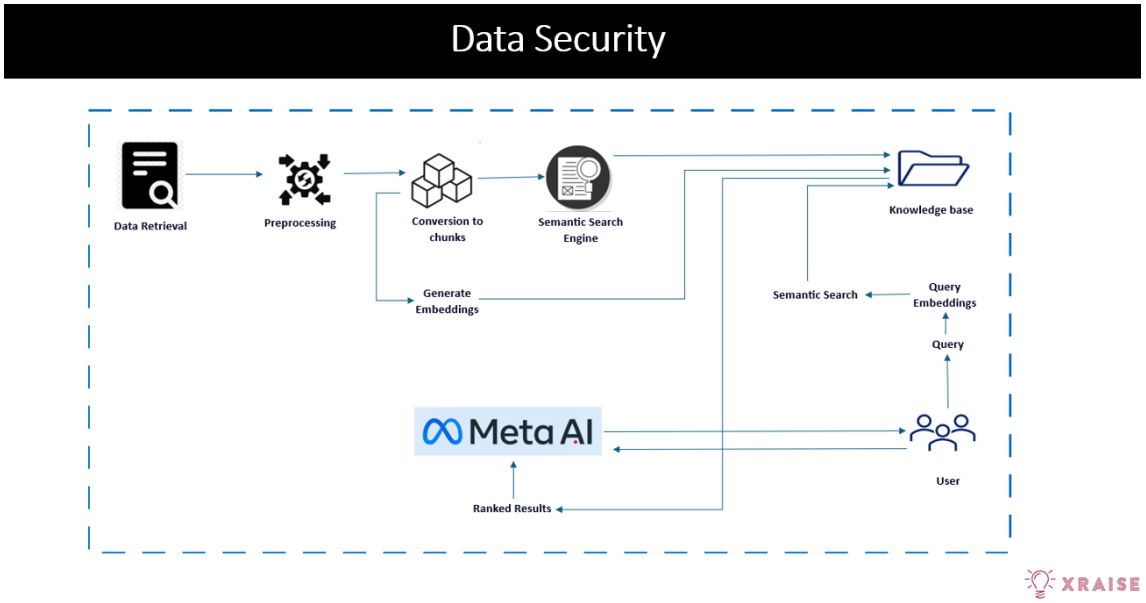

Figure 4.5: Data Security Diagram

4.5 Database Operations

A vector database is a specialized type of database designed to store and manage vector data, which represents data points as multi-dimensional numerical arrays. These databases are particularly effective for handling high-dimensional data typical in applications such as machine learning, natural language processing, and computer vision.[15] We have stored the data by generating embeddings using MINILM-v6v2 transformer from Hugging face. These embeddings are then passed through chunking process which is automated in our application, we have set a default parameter of chunk size of 500 with an overlap of 20. Chunking involves breaking down large datasets or sequences of data into smaller, manageable pieces or "chunks." These help ensure improved performance and efficiency. We have stored all of the data in cos with dimensions of 384. The following figures illustrates the server hosted on Pinecone along with the metadata, score and embeddings values.

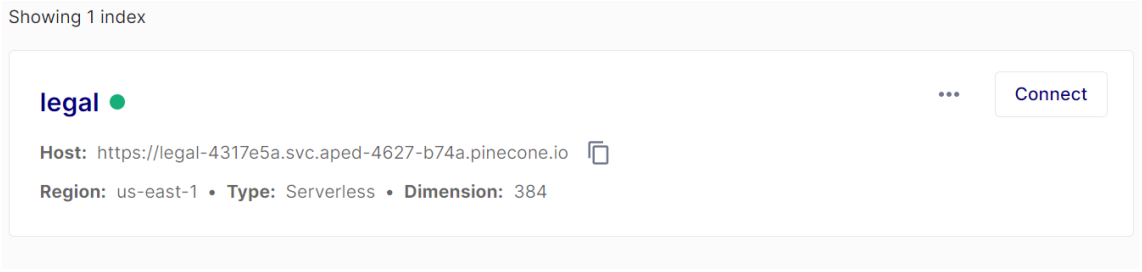

Figure 4.6: Database Dimensions

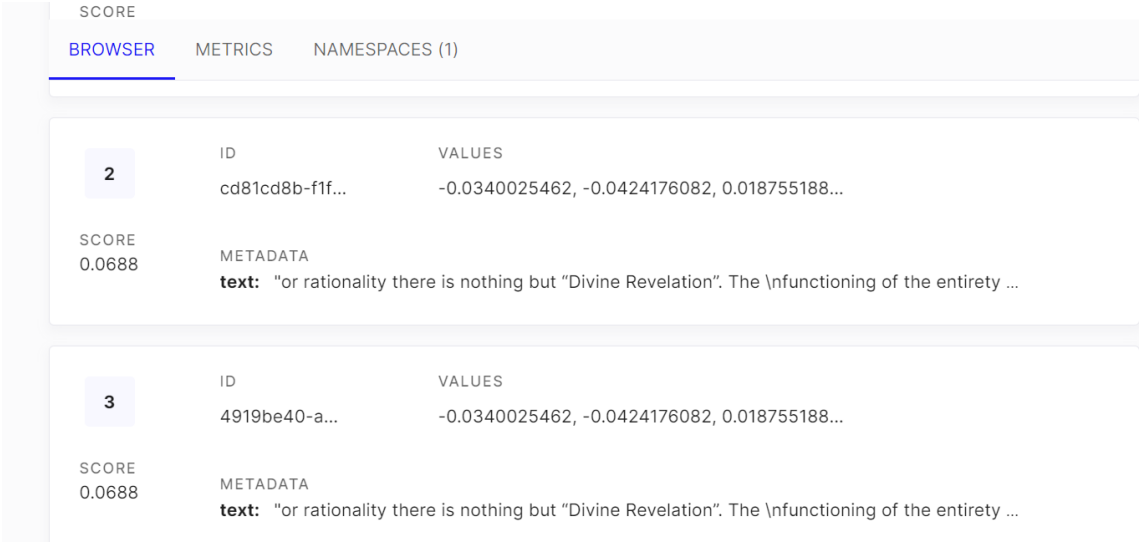

Figure 4.7: Database Operations

Chapter 5

Implementation

5.1 Development Environment

5.1.1 Development Tools and Languages

The development of Xraise was carried out using a variety of tools and programming languages to ensure flexibility, scalability, and efficient implementation.

Programming Languages

- **Python**: Used for its simplicity, extensive libraries, and compatibility with AI and LLama frameworks.
- **Gradio**: Used for frontend development and server-side scripting.

Development Tools

- **LLama (Large Language Model)**: It was chosen for its advanced language processing capabilities, including natural language understanding (NLU) and generation.[16]
- **TensorFlow and PyTorch**: Used for machine learning model training and deployment.

- **Microsoft Azure**: A cloud platform used for hosting the Xraise application, providing scalability, reliability, and integrated AI services.[17]
- **Docker and Kubernetes**: Containerization and orchestration tools for deploying and managing application components.[18]

5.1.2 Development Environment Setup

Backend Development

- Python environment using Anaconda for managing dependencies.
- Virtual environments for isolating project dependencies.
- Integration of LLama, TensorFlow, and PyTorch for AI model development.
- Microsoft Azure services for cloud deployment and testing.

Frontend Development

- Gradio is used for building interactive user interfaces.
- Integration with backend APIs for seamless data exchange.

5.2 Implementation

5.2.1 Data Preprocessing and Storage:

The initial step in our project involved gathering data from various sources. We utilized web scraping techniques to collect a comprehensive dataset of Dr. Israr Ahmad's works. For a detailed discussion on the data collection methods employed, please refer to Chapter 4.

Data Preprocessing:

Once the data was collected, it underwent a thorough preprocessing phase. This phase included several steps such as the removal of HTML tags, numbers, and punctuation marks. The purpose of these steps was to clean the data and prepare it for further processing. For an in-depth explanation of the preprocessing steps, please see Chapter 4. The cleaned data was then stored in a document store.

Embedding Generation:

The next stage involved passing the preprocessed data through automated Python scripts, which divided the data into manageable chunks. Each chunk was then converted into embeddings using the MiniLM-L6-V2 model. These embeddings were stored in a Pinecone vector database in SQLite format.

Handling Runtime Data:

For the "Chat with PDF" function, data uploaded by the user at runtime follows a similar processing pipeline. The automated Python script preprocesses the uploaded data, chunks it, and generates embeddings using MiniLM-L6-V2. This processed data is then stored in the vector database.

Vector Database Structure:

Our vector database is organized into three distinct departments:

- Dr. Israr Ahmad's Data: This department stores the pre-uploaded data of Dr. Israr Ahmad.
- User-Uploaded Documents: This department stores documents uploaded by users in real-time.
- Model Outputs: This department stores the outputs of the model, enabling it to

access chat history and provide more efficient and contextually relevant responses.

Automation and Efficiency:

The entire process, from data preprocessing to the creation and storage of vector embeddings, is fully automated. This ensures that the system can efficiently handle data input and retrieval, providing users with precise and optimized responses. By maintaining a well-structured and automated pipeline, our application ensures high efficiency and reliability in data handling and response generation.

5.2.2 Pipeline:

Our web application leverages a sophisticated pipeline to provide users with precise and contextually relevant responses to their queries. This section outlines the key components and processes involved in this pipeline.

Query Processing and Keyword Extraction:

When a user submits a question, the first step involves extracting keywords from the query. These keywords form the basis of the search query sent to the Large Language Model (LLM). The extracted keywords are then used to perform a semantic search within the vector database.

Semantic Search and Content Retrieval:

The vector database, which contains pre-processed and indexed data, uses semantic search to find content similar to the query. This process involves comparing the query with the stored data embeddings using cosine similarity, a method that measures the cosine of the angle between two non-zero vectors, effectively determining how similar they are. For a detailed explanation of the Retrieval-Augmented Generation (RAG) method, please refer to Chapter 6.

Retrieval-Augmented Generation (RAG):

Once the similar content is retrieved from the vector database, it undergoes a comparison with the query using the RAG approach. This method ensures that the most relevant content is selected based on the semantic similarity to the user's query.

Text Generation Pipeline:

The content obtained through RAG is then passed to the text generation pipeline, integrated from Hugging Face. This pipeline combines the retrieved content into a coherent response, formatting it according to the user's query. The use of Hugging Face's models allows for the generation of high-quality, contextually appropriate text.

Reference Integration:

In addition to generating the response, the application also includes references to the source files from which the content was fetched. This feature allows users to verify the information and consult the original sources, ensuring transparency and trustworthiness.

Fine-Tuning Challenges:

While we initially aimed to fine-tune the LLama-3 model specifically for our data, resource constraints limited our ability to achieve complete fine-tuning. Additionally, fine-tuning the model in real-time for files uploaded during the session was impractical. As a result, we integrated the RAG method with the text generation pipeline from Hugging Face to deliver optimized and precise responses.

By combining these advanced technologies, our application effectively provides users with accurate and reliable answers, enhancing their learning and research experiences. This robust pipeline ensures that users receive well-formatted, contextually relevant information quickly and efficiently.

5.2.3 Web Application:

In this project, we developed a web application using Python and the Gradio library. The primary goal of the application is to provide users with a versatile platform for interacting with a large corpus of Dr. Israr Ahmad's work, including his books, lectures, and other materials. The application also offers functionality for users to interact with their own uploaded PDF files, either by asking questions or requesting summaries of the content. Below, we detail the key components and functionalities of the application.

Overview of the Web Application:

The web application consists of three main features:

- Question Answering from Dr. Israr Ahmad's Data: Users can ask questions directly related to the vast collection of Dr. Israr Ahmad's works. The application leverages advanced natural language processing (NLP) models to provide accurate and contextually relevant answers.
- Interactive PDF Query: Users have the option to upload a PDF file and ask questions specifically related to the content of that file. This feature is particularly useful for extracting precise information or clarifications from large documents.
- PDF Summarization: Users can upload a PDF file and receive a concise summary of its contents. This feature helps in quickly understanding the key points and main ideas presented in lengthy documents.

Technical Implementation: The application was implemented using Python, with Gradio serving as the framework for creating the interactive web interface. Below is a breakdown of the key components and their implementation details:

1. Gradio Interface:

   Front-end: Gradio was chosen for its simplicity and effectiveness in creating user-friendly interfaces. It allows for quick deployment of interactive applications with-

out extensive web development knowledge. User Input Options: The interface includes text input fields for asking questions and a drop-down menu for selecting the mode of interaction (i.e., querying Dr. Israr Ahmad's data, querying an uploaded PDF, or summarizing a PDF).

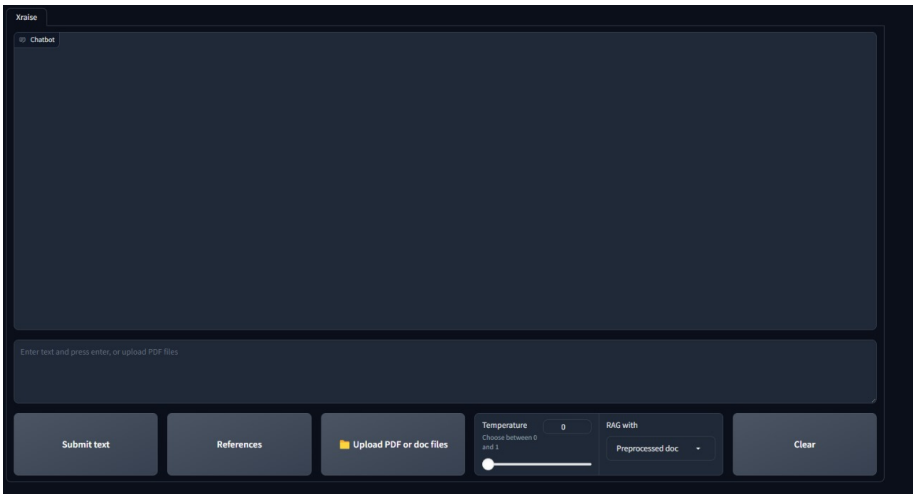

Figure 5.1: Web User Interface

2. Data Security and Privacy:

   To address data security concerns, the application ensures that user-uploaded files are stored temporarily and are deleted after the session ends. This approach minimizes the risk of data breaches and ensures user privacy.

3. User Experience and Interaction:

   The application is designed to be intuitive and user-friendly, with clear instructions and responsive elements to facilitate smooth interactions. Users can easily switch between different functionalities through the drop-down menu and receive real-time responses to their queries.

Example Use Cases:

To illustrate the functionality of the application, consider the following example use cases:

- Scenario 1: A user interested in Islamic scholarship asks a question about a specific lecture by Dr. Israr Ahmad. The application retrieves relevant excerpts and provides

a detailed answer.

- Scenario 2: A student uploads a PDF of their textbook and queries specific topics covered in their syllabus. The application extracts the pertinent information and answers their questions.
- Scenario 3: A researcher uploads a lengthy research paper and requests a summary to quickly grasp the main findings and conclusions. The application generates a concise summary, highlighting the key points.

The development of this web application represents a significant step towards making educational and scholarly content more accessible and interactive. By leveraging the power of Llama-3 and the simplicity of Gradio, we have created a versatile tool that serves the diverse needs of users, from academic researchers to casual learners. This implementation not only showcases the practical applications of modern AI technologies but also emphasizes the importance of user-centric design in creating impactful educational tools.

5.2.4 Deployment on Cloud:

Overview:

To make our application robust, scalable, and easily accessible, we decided to deploy it on Microsoft Azure. Azure offers a wide range of services that fit our needs perfectly. The deployment process involved using Docker to containerize our models, integrating OpenAI's API for the summarization module, and hosting the entire application online through Azure.

Containerization with Docker:

Our first step was to use Docker to containerize the application. Docker makes it easier to manage the application by providing consistent environments across development and production, allowing for easy scaling, and simplifying deployment. We containerized the

following components:

- LLama 3 Model for "Chat with Dr. Israr": This container includes all the necessary dependencies and configurations.
- LLama 3 Model for "Chat with any PDF": This container is designed to efficiently handle user-uploaded PDFs.
- Application Logic and Web Interface: We built the frontend using Gradio and included the backend services in this container to ensure everything works seamlessly together.

We created Dockerfiles for each component, detailing the environment setup, dependencies, and entry points. These containers were thoroughly tested locally to ensure they worked correctly before we moved them to a container registry.

Azure Services:

We chose Microsoft Azure for its reliability, extensive features, and seamless integration capabilities. Here's a breakdown of the Azure services we used:

- Azure Container Registry (ACR): We used ACR to securely store and manage our Docker container images. After building and testing locally, we pushed the images to ACR.
- Azure Kubernetes Service (AKS): AKS helped us orchestrate the deployment, scaling, and management of our containerized applications. AKS is great for managing containerized applications at scale, ensuring they are always available and easy to maintain.
- Azure App Service: This service hosted our frontend, built with Gradio, providing a scalable and reliable hosting environment for our web interface.
- Azure Storage: We used Azure Storage for storing user-uploaded PDFs and managing persistent data requirements.

OpenAI API Integration:

For the summarization module, we integrated the OpenAI API. Here's how we did it:

- API Key Management: We used Azure Key Vault to securely store and manage our OpenAI API keys.
- API Integration: We wrote Python scripts within our application to send requests to the OpenAI API, handle the responses, and integrate the summarized content back into the application workflow.

Deployment Workflow:

Here's a step-by-step look at our deployment workflow:

- Build and Test Containers: We built Docker containers for each component and tested them locally.
- Push to Azure Container Registry: Once tested, we pushed the containers to Azure Container Registry.
- Deploy to Azure Kubernetes Service: We configured AKS to pull images from ACR and deploy them. We used Kubernetes manifests and Helm charts to define the deployment configurations.
- Set Up Networking and Security: We configured Azure services to manage networking, including setting up Azure Load Balancers and configuring network security groups to control traffic flow.
- Monitor and Scale: We set up Azure Monitor and Azure Autoscale to keep an eye on the application's performance and automatically scale resources based on demand.

Summary:

By leveraging Azure services and Docker, we deployed a scalable, secure, and efficient cloud-based application. This setup ensures high availability and reliability and provides a solid platform for future enhancements and scaling as user demand grows. Our deployment approach ensures that users can seamlessly interact with Dr. Israr's data, upload and query their documents, and receive summaries efficiently and securely.

5.2.5 User Experience and Interface Design:

User Interface Design Principles:

In crafting the user interface for our web application, we prioritized simplicity, consistency, and accessibility. These principles ensure that users, regardless of their technical background, can navigate the application with ease and find the information they need intuitively.

Overview of the Web Interface:

The web application interface is designed to be user-friendly and effective, built using Gradio to provide an interactive experience. It features three main sections:

Question Answering from Dr. Israr Ahmad's Data: Users can directly ask questions related to Dr. Israr Ahmad's extensive works. The application uses advanced natural language processing (NLP) models to provide accurate and contextually relevant answers.

Interactive PDF Query: This functionality allows users to upload a PDF file and ask specific questions related to its content. This feature is particularly useful for extracting precise information from large documents.

PDF Summarization: Users can upload a PDF file and receive a concise summary of its contents. This feature enables quick understanding of the main points and key ideas presented in lengthy documents.

User Interaction and Workflow

The application workflow is designed to be straightforward and intuitive:

- Input Fields: Users enter their questions into text input fields. The application processes these queries to generate accurate responses.
- File Upload: Users can upload PDF files directly through the interface. The application processes the file and performs the requested operations.
- Response Display: Responses are presented in a clear and readable format. References to the source of the information are included, allowing users to verify the authenticity and credibility of the responses.

Accessibility and Responsiveness:

The application is accessible across various devices, ensuring a seamless user experience on desktops, tablets, and smartphones. Responsive design techniques are implemented to ensure that the interface adapts smoothly to different screen sizes, providing an optimal viewing experience.

Feedback and Iterative Improvement:

User feedback plays a crucial role in enhancing the application. We have incorporated features that allow users to provide feedback easily. This feedback loop helps us identify areas for improvement and ensures that the application evolves to better meet user needs over time.

Security and Privacy Considerations:

To safeguard user data, especially the documents uploaded for analysis, robust security measures are implemented. User files are stored temporarily and automatically deleted after the session ends, minimizing the risk of data breaches and ensuring user privacy.

Additionally, sensitive information such as API keys is securely managed using Azure Key Vault.

This section provides an overview of how the application's user interface was designed with the user in mind, ensuring ease of use, accessibility, and privacy while interacting with the features provided. The following sections will delve into specific technical details, challenges encountered, user feedback, and plans for future enhancements.

CONFIGURATION PARAMETER	**DESCRIPTION**
Language Model Type	Llama-3 8b-Chat-HF
Temperature	0.1
Maximum Tokens	512
Top-K Sampling	30
Torch_dtype	Torch.bfloat16
No. of return sequences	1
Fine-tuning of LLM	SFT-System prompts

Table 5.1: LLAMA Fine Tuning

Chapter 6

Implementation of Retrieval-Augmented Generation (RAG)

6.1 Introduction

Retrieval-Augmented Generation (RAG) is an advanced technique in natural language processing that combines the strengths of retrieval-based and generation-based models to produce accurate and contextually informed text outputs. This chapter explores the principles of RAG, its practical applications, and provides a detailed guide on how to implement it using the Langchain framework.

6.2 Understanding RAG

RAG integrates two primary approaches:

6.2.1 Retrieval-Based Approach

The retrieval-based approach involves retrieving relevant documents or passages from a large corpus. This is particularly effective in tasks like question answering, where the model needs to find and utilize specific information.

6.2.2 Generation-Based Approach

In contrast, generation-based models create text from scratch using language modeling techniques. These models are suitable for tasks like summarization, where they condense large bodies of text into concise summaries.

RAG combines these approaches by first retrieving relevant documents and then using them as a foundation for generating text. This approach ensures that the outputs are both accurate and contextually relevant.

6.3 Key Components of RAG

To understand how RAG functions, it's essential to examine its core components:

- **Retrieval**: The process begins with retrieving pertinent documents or passages from a corpus using techniques like dense retrieval or nearest neighbor search.
- **Encoding**: Retrieved documents are encoded into dense vectors that capture their semantic meanings using neural networks.
- **Generation**: These encoded vectors serve as input to a generation-based model, such as a transformer-based language model, which then generates the final text output.
- **Post-Processing**: The generated text undergoes refinement processes, such as editing or polishing, to enhance its coherence and quality.

6.4 Advantages of RAG

RAG offers several advantages over traditional approaches:

- **Enhanced Accuracy**: By integrating retrieval and generation, RAG produces text that is both accurate and contextually relevant.
- **Versatility**: RAG is applicable to a wide range of natural language processing tasks, including question answering, summarization, and text generation.
- **Scalability**: RAG can efficiently handle large datasets and scale to meet the demands of complex NLP applications.

6.5 Applications of RAG

RAG finds practical applications across various domains:

- **Question Answering**: Effectively answers complex questions by retrieving and generating precise responses.
- **Text Summarization**: Summarizes large documents by extracting key information and generating concise summaries.
- **Text Generation**: Generates high-quality text on given topics or prompts by leveraging retrieved documents.
- **Chatbots and Conversational AI**: Powers chatbots and conversational AI systems for engaging in natural-sounding conversations and providing accurate information.

6.6 Implementation Using Langchain

Langchain provides a robust framework for implementing RAG pipelines.

6.6.1 Data Ingestion

Langchain supports data ingestion from various sources, including text files, PDFs, websites, databases, and APIs.

6.6.2 Vector Embeddings

Documents are transformed into vector embeddings that capture their semantic meanings, facilitating efficient retrieval.

6.6.3 Chunking and Tokenization

Data is chunked into smaller units and tokenized to improve processing efficiency and accuracy.

6.6.4 Storage and Retrieval

Vector embeddings are stored in a specialized vector store index for fast and efficient retrieval during the generation phase.

6.6.5 Querying and Generation

A querying mechanism retrieves relevant documents from the vector store, which are then used by the generation model to produce the final output text.

6.7 Conclusion

In conclusion, Retrieval-Augmented Generation (RAG) represents a powerful approach to natural language processing tasks by integrating retrieval and generation techniques. Implementing RAG using the Langchain framework allows developers to take advantage of the capabilities of large language models efficiently.

6.8 How We Implemented RAG

In our web application, RAG plays a critical role in providing accurate and contextually relevant responses to user queries:

1. **Query Processing and Keyword Extraction**: When a user submits a question, keywords are extracted to form a search query.

2. **Semantic Search and Content Retrieval**: The vector database, containing pre-processed and indexed data, uses semantic search to find content similar to the query. This involves comparing the query with stored data embeddings using cosine similarity.

3. **Retrieval-Augmented Generation (RAG)**: Once relevant content is retrieved from the vector database, it undergoes comparison with the query using the RAG approach. This ensures that the most contextually relevant content is selected.

4. **Text Generation Pipeline**: The content obtained through RAG is passed to a text generation pipeline, integrated from Hugging Face. This pipeline combines the retrieved content into a coherent response, formatting it according to the user's query.

5. **LLAMA-3 Formatting**: Finally, the response is refined further using LLAMA-3 to ensure it meets the specific context and requirements of the user query.

By leveraging these advanced technologies, our application provides users with accurate and reliable answers, enhancing their learning and research experiences. This robust pipeline ensures that users receive well-formatted, contextually relevant information quickly and efficiently.

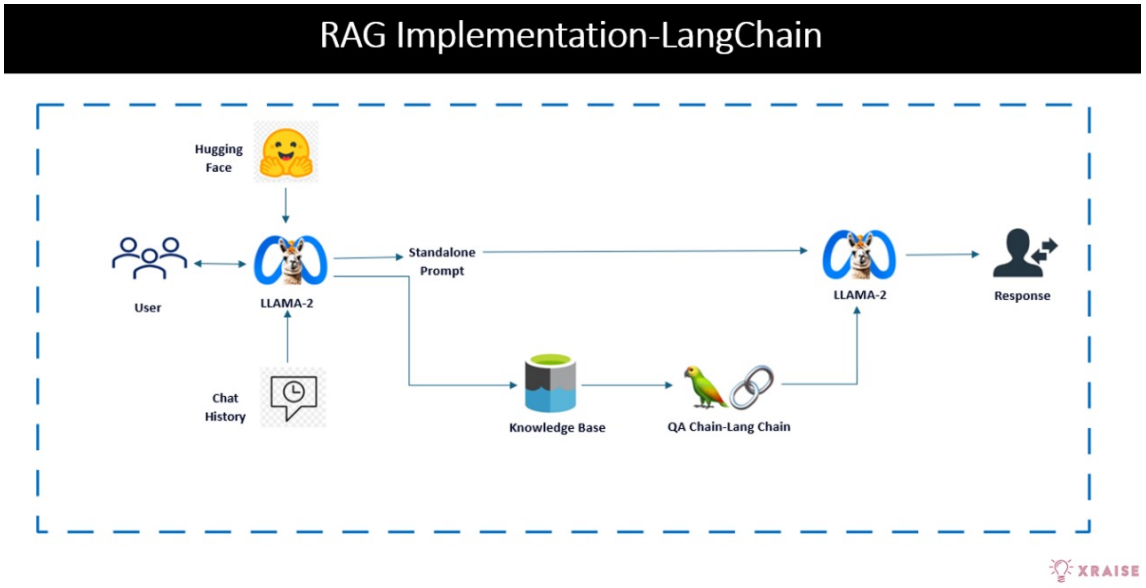

Figure 6.1: RAG Implementation-Langchain

Chapter 7

Results and Validation

7.1 Overview

Xraise's evaluation involved a comprehensive methodology that included user testing, performance metrics, and comparative analysis to assess its effectiveness in transforming educational experiences.

7.1.1 Methods Used

To evaluate Xraise, the following methods were employed:

- **Performance Metrics**: Analyzed response time, accuracy of data extraction, and user satisfaction.
- **Comparative Analysis**: Compared Xraise with existing solutions to highlight improvements and advantages.

7.2 Phase 1: Evaluation

Our first phase involved conducting a questionnaire based survey to evaluate the responses generated by our application. This survey was sent to students, educators and religious

people.

Questionnaire Link: `https://docs.google.com/forms/d/e/1FAIpQLSdVny1vZur2LnwP OUccxWp4sZyEuD9DQ/viewform` [19] Following are some of the responses generated by LLAMA at an early stage in the development of the project.

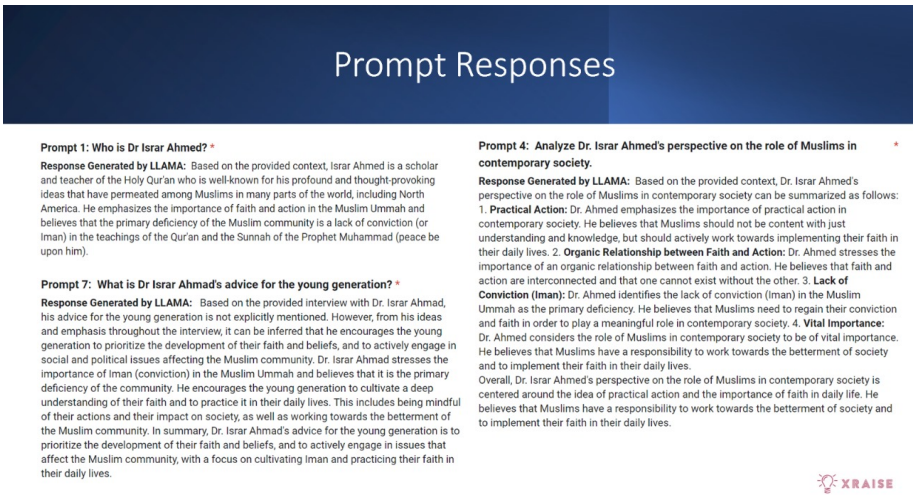

Figure 7.1: Responses Generated

Following are the results from the questionnaire which were then evaluated and a new data set was generated using data augmentation.

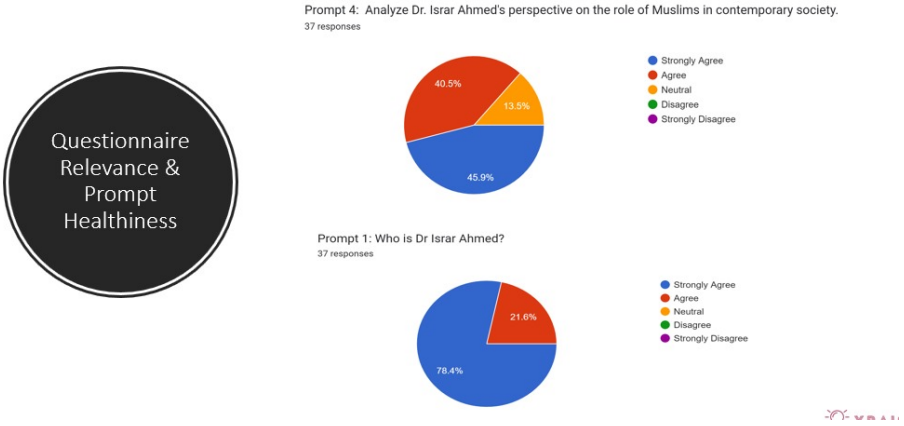

Figure 7.2: Questionnaire Result

7.3 Phase 2: Evaluation

The responses generated after getting results from phase 1 were then sent to scholars for detailed evaluation. They were asked to give a score ranging from 0-5. 0 being the lowest and 5 being the highest. This was the final evaluation of our chatbot.

The score results sent back by scholars who have studied Dr. Israr Ahmad in detail displayed an average of 4.1/5.

Prompts	Human Evaluation Index (0-5)
Response 1	3.9
Response 2	4.1
Response 3	3.4
Response 4	3.9
Response 5	4.2
Total 25 Responses	Avg (4.1)

Figure 7.3: Scholars Evaluation

7.3.1 Educators

Educators provided valuable information on the effectiveness of Xraise in educational settings.

- **Experiences**: Educators found Xraise to be a valuable tool for enhancing student engagement and accessibility to educational content.
- **Suggestions**: Feedback included requests for additional features such as real-time collaboration tools and customization options for content delivery.

7.3.2 Students

The students' perspectives on Xraise focused on usability and effectiveness.

- **Usability**: Students found Xraise intuitive and easy to use, allowing them to access and interact with educational content seamlessly.
- **Effectiveness**: They reported that Xraise improved their understanding of complex topics through interactive learning features and content summarization.

7.4 Performance Metrics

Performance metrics were measured to assess the efficiency and user satisfaction of Xraise.[20]

7.4.1 Response Time

Response time was evaluated to ensure quick access to educational resources and information.

- **Measurement**: Average response time for queries and document processing.
- **Result**: Xraise achieved an average response time of 23.46 seconds, ensuring timely access to educational content.

7.4.2 Accuracy of Data Extraction

The accuracy of data extraction from PDFs and other educational resources was crucial for Xraise's functionality.

- **Measurement**: Comparison of extracted information with ground truth data.
- **Result**: Xraise demonstrated an accuracy rate of 99%, ensuring reliable data extraction and content summarization.

7.5 Comparative Analysis

A comparative analysis was conducted to evaluate Xraise against existing educational solutions, focusing on improvements and advantages.[21]

7.5.1 Comparison with Existing Solutions

Xraise was compared with traditional educational tools and other AI-driven solutions.

- **Improvements**: Xraise demonstrated superior performance in terms of accessibility, content summarization, and interactive learning features.
- **Advantages**: Key advantages included real-time data extraction, personalized learning experiences, and integration with educational platforms.
- **References**: Xraise provides references with the response that are hostel on a local server, users can view that PDF from where the data was extracted and read further more about the details

7.5.2 Key Findings

- **Enhanced User Experience**: Xraise provided an enhanced user experience through intuitive design and interactive features.
- **Improved Accessibility**: Accessibility to educational resources was improved, benefiting both educators and students.
- **Higher Efficiency**: Xraise's AI-driven capabilities enhanced efficiency in content retrieval and summarization.

7.6 Conclusion

The evaluation of Xraise highlighted its effectiveness in transforming educational experiences through innovative AI-driven solutions. User feedback and performance metrics demonstrated significant improvements in usability, data accuracy, and user satisfaction compared to existing solutions.

Chapter 8

Conclusions and Future Work

8.1 Summary of Work

This thesis introduced Xraise, an innovative AI-driven solution that uses large language models (LLMs) and retrieval-augmented generation (RAG) to transform educational experiences and document interactions. The primary contributions of Xraise are summarized as follows:

- **Enhanced Accessibility**: By extracting and summarizing data in real-time, Xraise makes educational materials more accessible.
- **Enhanced Learning Experience**: Xraise improves understanding and engagement by offering concise subject summaries and customized learning experiences.
- **Advanced AI Capabilities**: Xraise is able to provide precise and pertinent instructional information by combining cutting-edge NLP approaches with LLM models (LLama).
- **Cloud Integration and Scalability**: To ensure reliable performance while managing substantial amounts of instructional data, Xraise makes use of cloud platforms such as Microsoft Azure.

8.2 Impact

Xraise may have a significant impact on AI-driven document interaction as well as education:

8.2.1 Learning

- **Enhanced Learning Outcomes**: By offering personalised content and encouraging more in-depth interaction with learning resources, Xraise enhances learning outcomes.
- **Empowering Educators**: It helps teachers more efficiently assess students' progress and provide individualized instruction.
- **Accessibility**: Students with a range of learning difficulties can benefit from Xraise's improved accessibility to educational materials.

8.2.2 AI-driven Document Interaction

- **Simplified Document Interaction**: Xraise streamlines document interaction by utilizing LLMs and RAG, which enables users to access and use instructional information more quickly and easily.
- **Innovative AI techniques**: Xraise stands out for its accurate and contextually appropriate information retrieval due to the application of RAG and sophisticated LLMs.

8.3 Final Thoughts

In conclusion, the development and evaluation of Xraise have shown promising results in transforming educational experiences through innovative AI-driven solutions. This

project has demonstrated the potential of AI technologies to enhance accessibility, improve learning outcomes, and simplify document interaction in educational settings. However, there are challenges to overcome, such as addressing biases in language models and optimizing scalability in cloud environments with proper resources.

8.3.1 Future Directions

Moving forward, future research and development efforts should focus on:

- **Mitigating Biases**: Continuing to address biases in language models to ensure fair and accurate content summarization and retrieval.
- **Expanding Knowledge Base**: Integrating new datasets and sources to further enhance the knowledge base and improve the accuracy of content retrieval.
- **Enhancing Customization Features**: Implementing more personalized recommendations and content delivery options based on user preferences and feedback.

Through these efforts, Xraise can continue to evolve as a transformative tool in education, providing accessible and personalized learning experiences for students and supporting educators in their teaching endeavors.

8.4 Findings

The evaluation of Xraise highlighted several key findings that demonstrate its effectiveness in transforming educational experiences.

8.4.1 Improved Accessibility and User Engagement

One of the significant findings from the evaluation was the improved accessibility and user engagement provided by Xraise.

- **Accessibility**: Xraise enhanced accessibility to educational resources through real-time data extraction and summarization, benefiting both educators and students.
- **User Engagement**: Users reported increased engagement with educational content, facilitated by interactive learning features and intuitive user interfaces.

8.4.2 Enhanced Learning Experience

Xraise contributed to an enhanced learning experience by:

- **Content Summarization**: Providing concise and informative summaries of educational materials, improving comprehension of complex topics.
- **Personalized Learning**: Tailoring content delivery based on user preferences and learning patterns, fostering personalized learning experiences.

8.5 Implications

The findings from Xraise have broader implications for the field of AI in education and document interaction.

8.5.1 Advancements in AI for Education

Xraise represents a significant advancement in utilizing AI for educational purposes by:

- **Improving Learning Outcomes**: Enhancing access to educational content and promoting deeper learning through AI-driven tools.
- **Facilitating Document Interaction**: Simplifying document interaction through natural language processing (NLP) and retrieval-augmented generation (RAG), thereby improving accessibility and usability.

8.5.2 Integration into Educational Systems

The integration of Xraise into educational systems can:

- **Support Educators**: Assist educators in delivering personalized content and monitoring student progress.
- **Empower Students**: Empower students to engage with educational content more effectively and independently.

8.6 Limitations

Despite its strengths, Xraise faces several limitations that need to be acknowledged.

8.6.1 Biases in LLMs

- **Ethical Considerations**: LLMs, like LLama, may inherit biases from training data, affecting the accuracy and fairness of content summarization and retrieval.
- **Mitigation Strategies**: Addressing biases through diverse training data and algorithmic adjustments to ensure fair and unbiased information retrieval.

8.6.2 Scalability Issues

- **Resource Intensiveness**: Processing large volumes of educational content in real-time can pose scalability challenges.
- **Cloud Infrastructure**: Optimization of cloud infrastructure, such as Microsoft Azure, is crucial for scaling Xraise to meet increasing demand.

8.7 Future Work

Areas for future research and potential enhancements for Xraise include:

8.7.1 Expanding the Knowledge Base

- **Integration of New Datasets**: Incorporating new datasets and sources to enhance the knowledge base and improve the accuracy of content retrieval.
- **Continuous Learning**: Implementing continuous learning mechanisms to update the knowledge base with the latest educational content.

8.7.2 Improving Customization Features

- **Personalized Recommendations**: Enhancing customization features to provide more personalized recommendations and content delivery options.
- **User Preferences**: Utilizing user input and preferences to customize educational experiences according to personal learning methods.

8.8 Conclusion

In summary, Xraise shows considerable promise in revolutionizing educational experiences with its advanced AI-driven solutions. Although there are challenges and limitations, the results indicate that Xraise improves accessibility, user engagement, and learning outcomes. Future research and development should aim at reducing biases, enhancing scalability, and broadening the knowledge base to further boost its effectiveness in educational contexts.

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