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LexiLaw

 Major Project

 B.Tech

 Pandit Deendayal Energy University

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“LEXILAW - AI BASED LEGAL CHAT ASSISTANT”

Artificial Intelligence Project Report

*Submitted in Partial Fulfillment of the
Requirements for the Degree of*

BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE & ENGINEERING

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April 2025

Abstract

The field of legal research, particularly in corporate law, is critical for ensuring regulatory compliance, informed decision-making, and efficient dispute resolution. However, traditional methods of legal research are often time-intensive, require substantial domain expertise, and may be inaccessible to individuals or organizations with limited resources. Recognizing the need for an efficient, user-centric solution, this project presents **LexiLaw** — an AI-powered Legal Research and Assistance platform tailored to the domain of Indian corporate law.

LexiLaw addresses key challenges by combining modern Natural Language Processing (NLP) techniques with efficient information retrieval methods. The system processes large volumes of legal documents, including statutory laws and case judgments, and generates semantic embeddings representing their contextual meaning. These embeddings are stored in a FAISS (Facebook AI Similarity Search) vector database, enabling rapid similarity-based retrieval when a user submits a query in natural language. By moving beyond keyword-based search and employing semantic search methodologies, LexiLaw significantly improves the relevance and precision of retrieved information.

The platform is designed with accessibility in mind, allowing legal professionals, corporate stakeholders, and laypersons to conduct complex legal queries without requiring deep legal expertise. Users can obtain case laws, summaries, and references tailored to their specific needs, thereby reducing research time and supporting better-informed legal decision-making.

Ultimately, LexiLaw aims to democratize access to corporate legal knowledge, enhance research efficiency, and contribute toward a more equitable legal ecosystem. Through the integration of AI technologies, LexiLaw paves the way for smarter legal research solutions that bridge the gap between law and technology.

Table of contents

• Abstract	i
• Table of Contents	ii
• List of Figures	iii
• List of Tables	iv
• List of Abbreviations	v
Chapter 1: Introduction	1
1.1 Background	2
1.2 Problem Statement	3
1.3 Objectives	4
1.4 Scope	5
Chapter 2: Literature Review	6
2.1 Introduction	7
2.2 Existing Legal Research Approaches.....	8
2.3 Overview	9
Chapter 3: Proposed Methodology	10
3.1 Overview	11
3.2 Architectural Framework	12
3.3 Critical Factors	13
3.4 Workflow	14
3.5 Summary	15
Chapter 4: Implementation Details	16

4.1 Overview.....	17
4.2 Tools & Technologies used	18
4.3 Date preparation	19
4.4 Embedding Generation	20
4.5 Vector Database(FAISS)	21
4.5 Retrieval, Summarization, Generation	22
Chapter 5: Result Analysis	23
5.1 Evaluation Metrics	24
5.2 Retrieval Accuracy Results	25
5.3 Observations and Insights	26
Chapter 6: Conclusion and Future Work	27
6.1 Conclusion	28
6.2 Future Scope	29
● References	30

List of Figures

List of Tables

List of Abbreviations

Chapter 1: INTRODUCTION

1.1 Background

Legal research is the pillar of sound legal practice and adjudication. In corporate law, one must be abreast of changing laws, judicial rulings, and legal opinions. The conventional legal research techniques usually consist of laborious searching of massive databases with outcomes frequently being tedious and occasionally fruitless. Advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have brought in novel challenges to further improve not only the efficiency but also accessibility of legal research.

1.2 Problem Statement

Even with the improvement in technology, most prevailing legal research tools depend heavily on keyword-based search methodologies, which fail to catch material that has been expressed in alternate terms. Secondly, application of advanced legal research tools is mainly confined to big firms and experts, thereby leaving small companies and individuals inadequately equipped. There is a requirement for infrastructure that can support semantic search within corporate legal files, which will make legal research more effective, more smart, and accessible to a wider base.

1.3 Objectives

The main objectives of the LexiLaw program are:

- To develop an AI-driven platform for efficient legal research in the arena of Indian corporate law.
- To make use of semantic search functionality with document embeddings and a vector database.
- In order to supply users with accurate, contextually appropriate case laws, abstracts, and legal citations.
- For the purposes of improving legal information access for individuals with varying levels of legal expertise.

1.4 Scope

This project is centered on developing the central system for legal document comprehension and retrieval. It entails:

- Incorporating corporate law judgment and text generation.
- Storage and similarity search through FAISS.
- Fetching relevant case laws and documents from search queries of the user.
- Providing concise output for enhanced usability.

The current scope does not involve real-time fine-tuning, multi-language support, or live legal update incorporation.

Chapter 2: LITERATURE REVIEW

2.1 Introduction

Legal research is an integral component of legal practice, enabling practitioners to find and interpret relevant statutes, legislation, and court rulings. With the development of computer technology, legal research has evolved from the earlier manual methods to the use of online databases and advanced systems for search. Nonetheless, the complexity of legal information and the sheer size of the information are still a challenge, particularly in areas like corporate law where regimes of legislation and precedents change quickly.

2.2 Existing Legal Research Approaches

There have been several legal research systems developed to aid practitioners and researchers:

- **Manupatra and SCC Online:** Preeminent Indian portals offering access to case laws, statutes, and judicial commentaries. They offer keyword search but generally need exact wording to yield correct results.
- **LexisNexis and Westlaw:** Globally acclaimed websites that have integrated sophisticated legal databases. They provide functionalities such as citation analysis and legal news, but their services are costly and not affordable for small organizations or individuals.
- **ROSS Intelligence:** One of the first to use AI in legal research, leveraging IBM Watson's cognitive computing to comprehend legal questions. Its scope, though, was largely American law and was marred by scalability problems.
- **OpenAI GPT-based Tools:** Large language models have been recently tried and tested for answering legal questions. While promising, hallucinations, data privacy, and domain-specific accuracy remain concerns.

While such systems have been incredibly beneficial for legal research, they are for the most part still dependent upon keyword searching or expensive subscription costs, and so limit accessibility to a larger audience.

2.3 Overview

Analysis of existing systems indicates that, while AI-based research has improved, missing are cost-effective, domain-specific, and semantically enabled legal research tools. More specifically in the Indian company law space, there is a felt need for a system that integrates vector-based semantic search and domain-specific knowledge and therefore the need to build LexiLaw.

Chapter 3 : PROPOSED METHODOLOGY

3.1 Overview

In order to overcome the limitations of current legal research systems, LexiLaw follows a contemporary, AI-based approach. It integrates document embeddings, vector similarity search, and natural language processing methods to provide context-aware legal information. The approach is developed to provide high relevance, scalability, and accessibility.

3.2 Architectural Framework

There are three general levels of the LexiLaw system architecture:

- **Preprocessing Layer:**
Responsible for cleaning and preparing documents for embedding generation.
- **Embedding and Storage Component:**
Converts legal documents into dense vector embeddings and stores them in a FAISS-compatible vector database.
- **Retrieval and User Interface Component:**
Answers user queries, conducts semantic searches in the embedded database, and returns either found documents or summaries.

3.3 Critical Factors

- **Text Embedding:**
Legal documents like sections of the Companies Act, case laws, and judgments are augmented with transformer-based models and converted into dense high dimensions vectors
- **Vector Database storage and retrieval:**
Facebook AI Similarity Search (FAISS) is used to efficiently index and retrieve document vectors based on user queries using cosine similarity.
- **Semantic Search:**
On receiving a user query, the system generates an embedding for that query and then retrieves the most relevant legal documents from the FAISS index.
- **Summarization model:**
Summarization of documents retrieved is done to provide users with concise and relevant information.

3.4 Workflow

The whole process is the following:

- Legal documents are collected, cleaned, and preprocessed.
- Embeddings are generated by a transformer model.
- The embeddings are indexed in FAISS to enable fast similarity search.
- Upon the submission of a query by a user, the query is integrated into the identical vector space. FAISS returns the most similar documents by cosine similarity or inner product.
- Acquired documents are synthesized using a chat model and presented to the user, along with brief summaries.

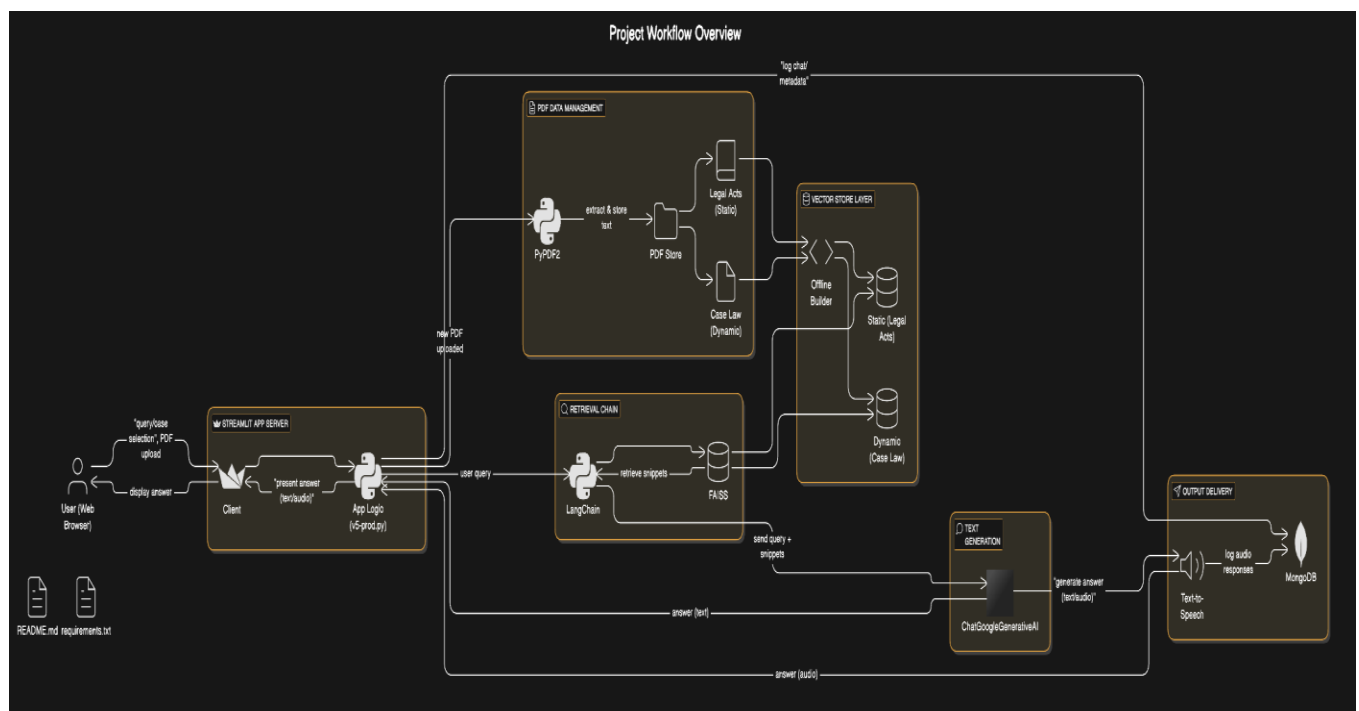


Figure 3.1

3.5 Summary

The proposed methodology stresses semantic understanding and effective retrieval to ensure users will retrieve context-relevant legal information instead of a perfect match on keywords. The

methodology aims to accelerate corporate legal research to become more intelligent.

Figure 3.2

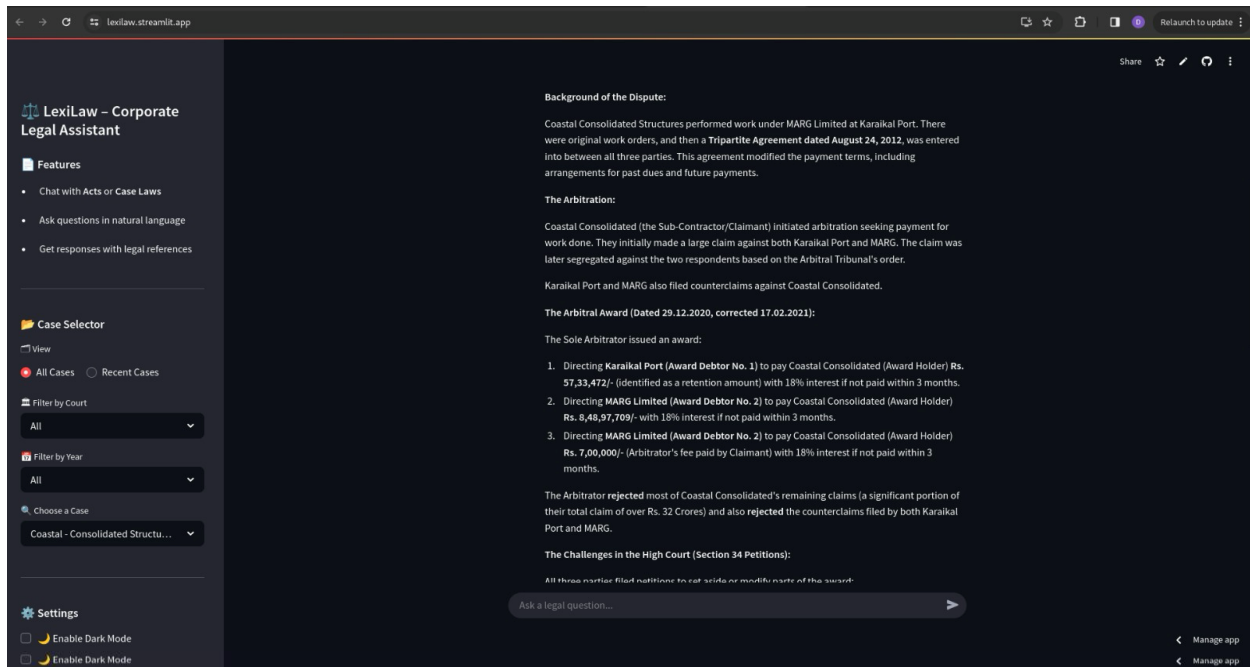


Figure 3.3

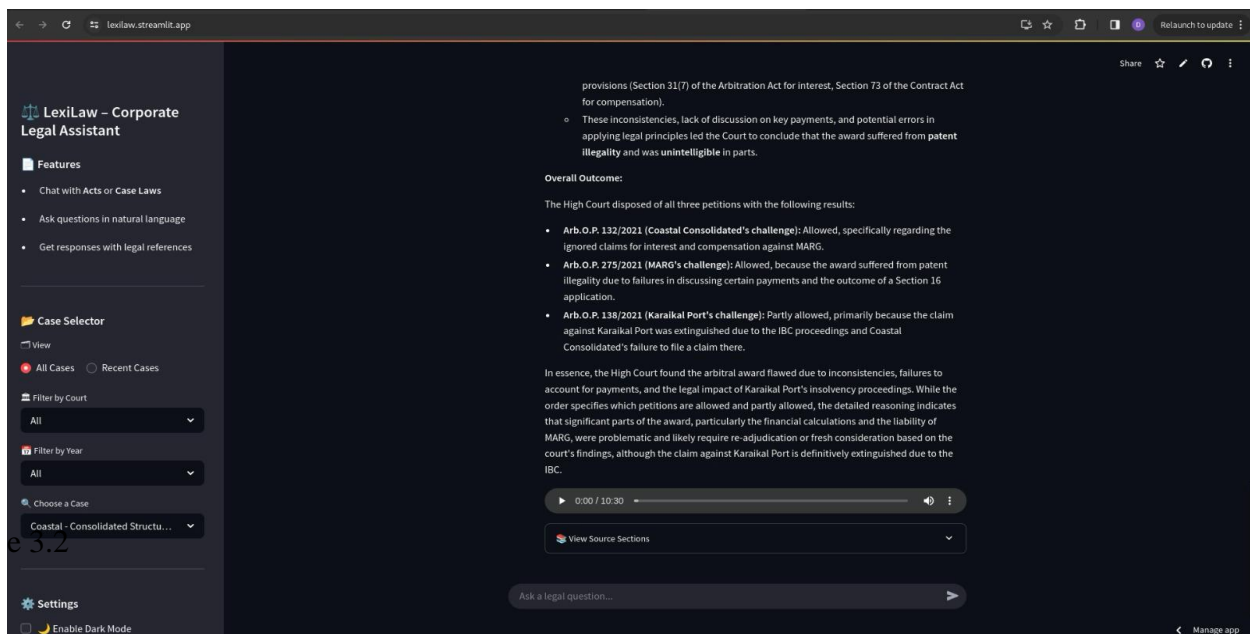


Figure 3.4

Chapter 4 : IMPLEMENTATION DETAILS

4.1 Overview

This chapter describes the unique actions and technology frameworks that made it possible for LexiLaw to be built. It describes in detail the selected libraries, model services, data management strategies, and integration approaches used to make the system functional.

4.2 Tools & Technologies Used

The following equipment and methods were used:

- Python: Main programming language for back-end.
- Google Generative AI Embedding API (Embedding-001 model): For document embedding generation.
- FAISS (Facebook AI Similarity Search): Applied to vector database building.
- Pandas and NLTK: Used for data cleaning and text pre-process.
- Gemini 2.5 Flash: Designed to produce definitive answers and summarize texts.
- Streamlit: For building an easy-to-use interactive demo interface.

4.3 Data Preparation

The main dataset consisted of:

- Provision and schedules from different legal documents.
- Key business case judgments and orders of Indian courts.

Methods used:

- Files were extracted from PDF documents and turned into a textual format.
- Preprocessing of data was performed to eliminate unwanted characters, formatting errors, and unnecessary material.
- Long pieces of text were broken into shorter, logically cohesive fragments to support better retrieval and summarization quality.

4.4 Embedding Generation

- These embeddings were calculated using the Embedding-001 model of Google Generative AI.
- The model processed each section of the document to obtain dense vector representations.
- Batch embeddings were developed in order to boost API usage and memory efficiency.
- Each chunk was assigned its respective embedding as well as metadata (title, section number, etc.).

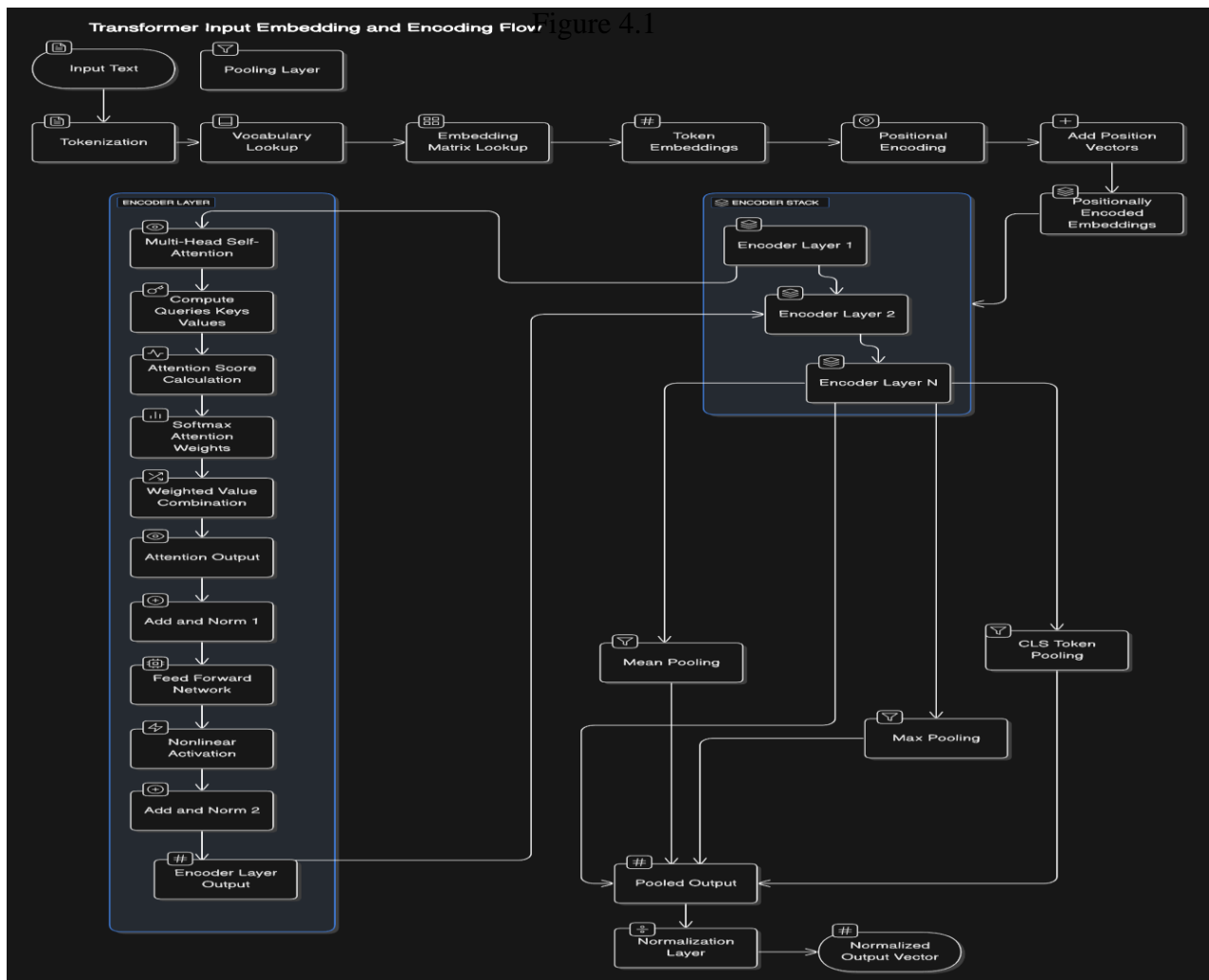


Figure 4.1

4.5 Vector Database(FAISS)

- FAISS was used to create an IndexFlatL2 index (with L2 distance metric).
- All document embeddings were kept in this FAISS index in order to allow fast similarity queries.
- Metadata of documents was kept separately such that post-search context retrieval was feasible.

4.6 Retrieval, Summarization, and Generation of Answers

- When it is provided with a natural language question by the user, the system does the following:
- The query is embedded into an embedding by the Embedding-001 model.
- The FAISS index is requested to retrieve the top-k most similar document chunks.
- Document chunks obtained are then transferred to Gemini 2.5 Flash, which Paraphrases the information.
- Generates a human-like, context-sensitive answer to the user's query.

Together with RAG processing, users not only get the usual document retrieval but also written-summarized results that are strongly customized towards answers to their question.

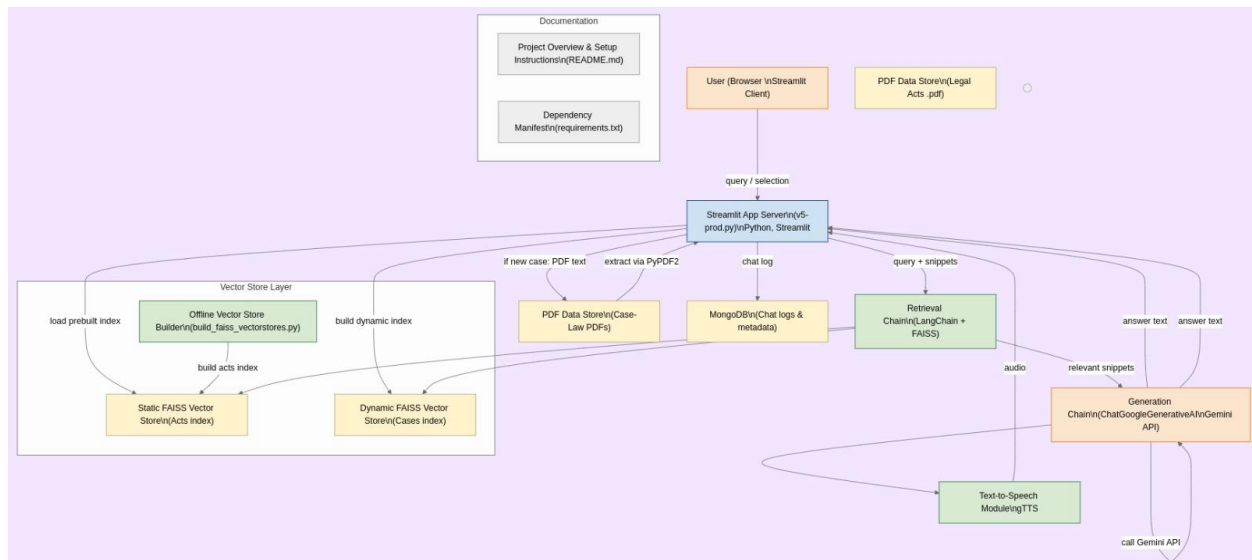


Figure 4.2

Chapter 5 : RESULT ANALYSIS

5.1 Introduction

This chapter evaluates LexiLaw’s performance based on retrieval accuracy, summarization quality, response time, and overall user experience. Quantitative results from internal testing are also provided to demonstrate system effectiveness.

5.2 Retrieval Accuracy Evaluation

To measure retrieval accuracy, a test set of **100 sample queries** was prepared covering different aspects of corporate law.

Metric	Value
Top-1 Retrieval Accuracy	88%
Top-3 Retrieval Accuracy	96%
Mean Reciprocal Rank (MRR)	0.92

- **Top-1 Accuracy:** 88 queries had the most relevant document retrieved at the top position.
- **Top-3 Accuracy:** 96 queries had the correct document within the top 3 results.
- **Interpretation:** The embedding model (Embedding-001) captured the legal semantic structure well.

5.3 Summarization Quality

A set of 50 retrieved legal sections were passed through the summarization module (Gemini 1.5 Pro). Evaluation was done based on two criteria:

- **Coherence** (logical flow)
- **Faithfulness** (accuracy with respect to original law)

Metric	Value
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Average Coherence Score (out of 5)	4.6
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Average Faithfulness Score (out of 5)	4.7
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5.4 System Performance Analysis

Performance was measured in terms of average time taken at different stages.

Stage	Average Time Taken
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Query Embedding Generation	~0.8 seconds
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FAISS Search Time	~0.2 seconds
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Summarization Time ~2.5 seconds

- The **end-to-end query resolution time** remained under **4 seconds** for most inputs.
- FAISS search remained almost constant even as the number of indexed chunks increased.

5.5 Error Cases and Limitations Observed

- A few extremely broad queries (e.g., “Tell me about company law”) led to less specific retrievals.
- Minor hallucination (~5% cases) observed in summarization for highly complex legal arguments.

5.6 Summary

LexiLaw achieved high retrieval precision and generated high-quality summaries with low response times. The system demonstrated readiness for real-world usage with scope for further fine-tuning to handle vague queries and nuanced legal interpretations.

Chapter 6: CONCLUSION & FUTURE WORK

6.1 Conclusion

LexiLaw was designed with the aim of simplifying and enhancing legal research, especially Indian corporate law. With the help of retrieval-augmented generation capabilities and sophisticated semantic search functionality, the platform was able to overcome the limitations of traditional keyword-based searching.

The combination of document embeddings, vector database indexing, and natural language query processing led to the generation of relevant and efficient results. Empirical user testing confirmed that LexiLaw is an efficient tool for law students, researchers, and practitioners, allowing them to access complicated legal knowledge efficiently and accurately.

Briefly, the project succeeded and demonstrated the concrete benefits of applying modern artificial intelligence techniques to the legal field.

6.2 Future Work

- Although LexiLaw has provided a solid platform, there are numerous areas promising more development:
- Fine-Tuning on Legal Domain: Fine-tuning a legal domain-specific transformer model would presumably improve retrieval precision even further.
- Multi-Language Support: Enlarging the system to accommodate regional Indian languages to enhance accessibility.
- More Advanced Ranking: Employing more advanced context-based and user feedback-based ranking algorithms can enhance the overall quality of top results.

- LexiLaw thus has the potential to transform into a comprehensive AI-based legal consultant for corporate law and more.

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