**LEGAL ARGUMENT GENERATION USING LLM**

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**CERTIFICATE**

*This is to certify that the report titled* ***Legal Argument Generation using LLM*** *is a bonafide record of work done by* ***Annu Punnoose (2348011)*** *of CHRIST (Deemed to be University), Bengaluru, in partial fulfillment of the requirements of IV Trimester MSc (Data Science) during the academic year 2024-25.*

**Head of the Department Project Guide**

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**ABSTRACT**

In the legal field, junior and beginner lawyers often face significant challenges when managing complex domestic violence cases due to their intricate legal, emotional, and procedural dimensions. This project addresses these challenges by developing an AI-powered legal argument generation system using a Retrieval-Augmented Generation (RAG) method with the LLaMA 3 model. The primary objective of the project is to assist junior lawyers by automating the creation of well-structured legal arguments, summaries, and relevant case references, thereby enhancing their efficiency and effectiveness in handling domestic violence cases.

The project involves integrating advanced natural language processing techniques, including vector embeddings and machine learning models, to analyze and generate pertinent legal arguments. The system uses a Pinecone vector database for data retrieval and leverages the LLaMA 3 model to produce contextually accurate and legally sound responses. Key features include the ability to handle queries related to domestic violence, provide detailed case summaries, and offer argumentation based on specific legal provisions and precedents.

The results indicate that the AI system significantly reduces the time required for legal research and argument formulation while improving the quality of the outputs. The implementation and testing phases demonstrated the tool's capability to generate relevant legal arguments and case summaries, ultimately supporting junior lawyers in their legal practice. Recommendations include further refinement of the model for broader legal contexts and continuous updates to the legal database to maintain the system's accuracy and relevance

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1. **INTRODUCTION**

**1.1 PROBLEM STATEMENT:**

In the legal field, junior lawyers often face significant challenges when managing complex and sensitive cases, especially those involving domestic violence. These cases are not only emotionally charged but also legally intricate, requiring a deep understanding of the law, precise case research, and the formulation of persuasive legal arguments. For inexperienced lawyers, balancing these demands can be overwhelming, potentially affecting their ability to represent victims effectively and ensure justice is served.

One of the most time-consuming aspects of legal practice is conducting thorough research. Lawyers must navigate vast amounts of legal data, including statutes, case law, and previous judgments, to find relevant information that can strengthen their client’s case. Junior lawyers, still building their expertise, often struggle with this task, lacking the tools or experience necessary to streamline the process. Domestic violence cases, in particular, require familiarity with complex legal provisions, such as those outlined in the Protection of Women from Domestic Violence Act (PWDVA), 2005. For newer practitioners, understanding and applying this intricate law can be daunting.

Furthermore, identifying critical legal precedents and relevant articles is key to building a solid argument. Junior lawyers may find it difficult to locate cases or precedents that align with the specifics of a domestic violence case. Missing key legal citations or failing to incorporate relevant case law can weaken a lawyer’s argument and ultimately affect the case’s outcome. This lack of experience in navigating legal databases and synthesizing key information creates a significant disadvantage in court.

Crafting a compelling legal argument is another challenge. It requires not only legal knowledge but also rhetorical skill. Presenting a clear, legally sound argument that weaves together statutes, case law, and legal principles is a skill that takes years to master. Junior lawyers may struggle to deliver arguments that resonate in court, especially in cases involving domestic violence, which often involve complex layers of legal, emotional, and social issues.

Given these challenges, there is a growing demand for tools to assist junior lawyers, particularly in domestic violence cases. Traditional legal research methods are often manual, requiring extensive time to review and analyze large volumes of legal texts, cases, and articles. In situations where swift action is required to protect the victim, delays in legal preparation can negatively impact the outcome. Moreover, junior lawyers may lack the experience to determine which legal principles and cases are most relevant, making their legal arguments less effective.

Artificial Intelligence (AI) and large language models (LLMs) present a promising solution to these challenges. By leveraging AI, legal professionals can access tools that streamline the research process, making it easier for junior lawyers to access relevant case laws, statutes, and precedents. An AI-powered legal argument generator could serve as an invaluable resource, providing junior lawyers with quick, well-structured legal arguments tailored to domestic violence law. Such tools could help automate the time-consuming tasks of legal research and argument preparation, allowing lawyers to focus on refining their cases and representing their clients more effectively.

In this project, we aim to develop an AI-based tool that supports junior lawyers in domestic violence cases by generating well-founded legal arguments and case summaries. Through the use of cutting-edge LLMs and a Retrieval-Augmented Generation (RAG) framework, the tool offers immediate access to relevant legal articles, cases, and structured arguments based on user input. This system not only enhances legal research but also empowers young lawyers to represent victims of domestic violence more effectively and efficiently.

**1.2 EXISTING SYSTEMS:**

**1.2.1 Taskade**

Taskade is an AI-powered task management and collaboration platform designed to enhance productivity and efficiency within teams. Although Taskade is not specifically tailored for legal applications, it offers features that can be useful in managing complex legal workflows, especially in the context of case preparation.

Taskade allows users to break down tasks into smaller, manageable steps, making it easier to organize the different aspects of legal case preparation, such as legal research, argument development, and client communication. This can help junior lawyers stay organized and prioritize their workload effectively. It offers real-time collaboration, enabling teams of lawyers or paralegals to work together on shared documents, legal briefs, or research projects. This functionality is particularly useful in larger law firms or legal teams working on intricate cases, as it fosters team-based problem solving and case strategy development.

Taskade integrates AI to assist with task automation, allowing users to streamline repetitive tasks such as case documentation or summarization of legal research. It also provides templates that can be customized for different types of legal tasks.

However, Taskade primarily focuses on task management rather than generating legal arguments or handling complex legal research. While it helps streamline the organizational aspects of legal work, it does not offer the domain-specific intelligence or LLM-based capabilities required for generating legal arguments and case summaries as proposed in this project.

**1.2.2 WhiteCream**

WhiteCream is a more specialized legal AI tool designed to assist lawyers in legal research and case preparation. Unlike Taskade, WhiteCream specifically caters to the legal domain and uses AI to automate the retrieval of legal information. WhiteCream utilizes natural language processing (NLP) to analyze legal documents, statutes, and case law, making it easier for lawyers to find relevant legal materials. Junior lawyers can input queries related to specific legal issues, and WhiteCream will search through its database to provide relevant cases, articles, and legal precedents.

The platform has built-in tools that summarize case law, helping junior lawyers understand the core legal principles without having to read entire judgments. This is particularly useful in domestic violence cases where multiple precedents and legal provisions need to be considered. WhiteCream also assists in drafting legal documents by automatically populating templates with relevant legal clauses and arguments. This can speed up the process of writing legal briefs or preparing legal notices.

However, while WhiteCream excels at legal research and document generation, it has limitations when it comes to providing customized, context-specific legal arguments. The system focuses more on retrieving information rather than generating nuanced legal arguments that align with the specifics of a given case. Furthermore, WhiteCream's capabilities may not be as robust in handling complex or sensitive legal areas like domestic violence, where the emotional and legal intricacies require more specialized tools.

**1.3 PROJECT SCOPE:**

The Legal Argument Generator using LLM Model project is designed to assist junior and beginner lawyers working on domestic violence cases by providing AI-driven legal argument generation and case summaries. The scope of this project encompasses various technical, legal, and user-centered aspects, ensuring that the system delivers high-quality, relevant outputs while maintaining user accessibility and adherence to the legal framework.

**1.3.1 Domain Focus: Domestic Violence Law**

The primary legal domain targeted by this project is domestic violence against women. Specifically, the system is designed to generate legal arguments and case summaries related to cases governed by the Protection of Women from Domestic Violence Act, 2005 (PWDVA). This legislation covers various legal protections for women facing abuse, and the system will initially focus on case law and legal articles associated with this Act.

The model will focus on articles and sections directly related to domestic violence cases in India, offering detailed legal arguments that align with the key provisions of PWDVA. Relevant judgments and legal precedents from Karnataka High Court will form the basis of the system’s knowledge base. The system will process data from Indian Kanoon, a free online legal database, to enhance the argument generation process with actual case law examples.

The scope of this project, for the time being, is limited to the Indian legal system and is aimed at supporting lawyers handling cases in this jurisdiction.

**1.3.2 Data Collection and Processing**

The system will rely on a specific set of legal documents and resources to generate outputs. The scope of data collection and processing includes:

Source of Legal Data: Data is collected from legal documents available on Indian Kanoon and the India Code portal, which provides legal texts related to Indian laws. For this project, the system will utilize legal documents and case precedents from January 2024 onwards. The legal documents to be processed will be in PDF format, including court judgments, case summaries, and sections from the PWDVA.

**1.3.3 Technical Scope: LLM and Embedding Technologies**

The system is powered by the LLaMA 3 8B large language model, combined with Ollama embeddings and the Pinecone vector database for efficient data processing, storage, and retrieval. The technical scope includes:

* LLM for Legal Argument Generation: The LLaMA 3 model will handle natural language understanding, query processing, and argument generation, offering legally sound responses based on user input.
* Embedding and Vectorization: The legal data is transformed into vector embeddings using Ollama, and stored in the Pinecone vector database for fast retrieval based on the user’s query.
* Cosine Similarity for Retrieval: The system uses cosine similarity to compare user queries with the vectorized legal data, ensuring the most relevant legal cases and arguments are retrieved and used in the response.

**1.3.4 User Interaction and Querying**

The target users for the system are junior and beginner lawyers who may have limited experience in handling domestic violence cases. The user interaction scope includes:

* User-Friendly Querying: Users can submit queries in plain language, and the system will interpret these using LLaMA 3 to generate coherent and legally accurate responses.
* Legal Argument and Summary Generation: The system generates two key outputs: case summaries and structured legal arguments. The case summaries provide an overview of relevant cases, while the legal arguments focus on constructing persuasive, legally sound statements.
* Email Delivery of Results: Users have the option to receive the generated arguments or summaries via email for ease of access and future reference.

**1.3.5 Deployment and Usability**

The project scope includes the deployment of the system via Chainlit, an open-source platform that simplifies user interaction with large language models. This ensures:

* Web-Based User Interface: The system will be accessible through a simple web interface, allowing lawyers to submit queries and receive responses without needing to install complex software.
* GROQ API Integration: The system will leverage the GROQ API for seamless querying and interaction with the LLM, enabling smooth communication between the user and the system.
* Role-Based Guidelines: The system will follow strict role-based guidelines, ensuring that the output remains focused on domestic violence law and avoids speculative or overly complex legal jargon. This ensures accessibility for junior lawyers while maintaining professional standards.

**1.3.6 Limitations and Future Expansion**

While the initial scope of the project is focused on domestic violence law in India, particularly the Karnataka High Court, there are plans to expand the system’s capabilities in the future:

* Expansion to Other Legal Domains: The system could be adapted to generate arguments for other areas of law, such as property disputes, family law, or labor law, by incorporating additional legal databases and precedents.
* Broader Geographic Coverage: Future iterations of the system could expand beyond Karnataka High Court cases to include other jurisdictions within India or even international legal systems, allowing for more versatile legal argument generation.
* Incorporation of New Data Sources: Additional data sources, such as legal textbooks, scholarly articles, or legal commentaries, could be integrated to enhance the depth and accuracy of argument generation.

1. **SYSTEM ANALYSIS**

**2.1. FUNTIONAL SPECIFICAIONS:**

The Legal Argument Generator using LLM Model is designed to assist junior and beginner lawyers in preparing legal arguments and case summaries, specifically for domestic violence cases. The system's functionalities ensure that users can interact with the AI model easily while obtaining legally sound, relevant, and contextually appropriate outputs.

* User Query Input

Functionality: The system allows users (lawyers) to submit queries related to domestic violence cases.

Specification: Users can input queries in natural language (plain English) without needing legal jargon. The input will be processed using LLaMA 3 to interpret the user's intent and generate a relevant legal argument or case summary.

* Legal Argument Generation

Functionality: Automatically generate legal arguments based on the user’s query.

Specification: The system uses LLaMA 3’s capabilities to craft persuasive legal arguments, referencing relevant sections of the Protection of Women from Domestic Violence Act, 2005 (PWDVA) and applicable case laws. The output will be well-structured, including legal reasoning and references to precedents, ensuring clarity and coherence in the arguments.

* Case Summary Generation

Functionality: Provide concise summaries of relevant cases.

Specification: The system will search the vector database for relevant case law stored from Indian Kanoon. It will summarize the legal case, highlighting important rulings, judgments, and precedents that pertain to domestic violence law.

* Query Vectorization and Search

Functionality: Vectorize user queries and search the vector database for matching data using cosine similarity.

Specification: The user query is transformed into a vector using Ollama embeddings.

Cosine similarity is used to compare the query vector with the pre-stored vectors in Pinecone, retrieving the most relevant legal documents, arguments, and cases.

* Retrieval of Legal Data

Functionality: Fetch relevant legal documents and case precedents based on the user query.

Specification: The system will retrieve the relevant legal data chunks stored in the Pinecone vector database that match the query. These data chunks will form the foundation of the generated legal argument or case summary.

* Email Delivery of Output

Functionality: Send the generated legal argument or case summary to the user’s email upon request.

Specification: After generating the legal argument or case summary, users can request the output to be emailed for future reference. The system will securely deliver the information to the specified email address.

* User Interface

Functionality: Provide an intuitive user interface for query submission and result display.

Specification: The interface, built using Chainlit, will allow users to submit queries, view generated legal arguments, and request email delivery. The interface will be simple, catering to the needs of junior lawyers who may not have extensive experience with complex software tools.

**2.2. SYSTEM REQUIREMENTS:**

The successful implementation of the Legal Argument Generator using LLM Model requires both hardware and software resources, as well as compliance with certain legal standards.

**2.2.1 Hardware Requirements**

CPU: High-performance multi-core processors to handle the computation needs of LLaMA 3 and the embeddings.

GPU: For efficient handling of the LLM's computations, GPU acceleration is recommended, particularly for model inference tasks.

RAM: At least 8GB of RAM to ensure smooth processing of the large datasets and vectorized queries.

Storage: Sufficient storage for handling legal documents, embeddings, and user-generated outputs.

**2.2.2 Software Requirements**

* Operating System: Windows operating system.
* Model Frameworks:

LLaMA 3: Large language model by Meta, serving as the foundation for language processing and argument generation.

Ollama: For embedding and transforming textual data into high-dimensional vectors.

Pinecone: Managed vector database for storing and querying vector embeddings.

GROQ API: To interact with pre-trained models and facilitate querying processes.

Chainlit: An open-source tool for building the user interface and managing interaction between the users and the model.

* Data Sources

Legal Databases: Indian Kanoon: Source of legal cases and documents related to the Protection of Women from Domestic Violence Act (PWDVA). India Code: Source of statutory data related to PWDVA and other applicable laws.

* Legal and Ethical Considerations

Data Privacy and Security: The system must comply with legal data privacy standards, ensuring that user data and legal documents are handled securely and confidentially. User queries and email addresses must be stored securely, and sensitive legal information should be protected from unauthorized access.

* AI Model Requirements

Fine-Tuning Capabilities: The LLaMA 3 model may require fine-tuning on legal-specific data to improve its accuracy and relevance for domestic violence cases.

Model Hosting and API Integration: The model must be hosted in a way that allows for real-time querying and efficient response generation via the GROQ API.

* User Interface Requirements

User-Friendly Frontend: The Chainlit interface must be simple and intuitive, providing an easy-to-use querying system for junior lawyers. It should feature a clean design with clear input/output sections and an email request option.

* Performance and Scalability

Scalability: The system must be scalable, allowing for a larger number of users and expanding to handle additional legal domains in the future.

Latency: Response times for generating legal arguments and case summaries should be optimized to ensure timely delivery of results.

# SYSTEM DESIGN

## 3.1 SYSTEM ARCHITECTURE

The system architecture for the "Legal Argument Generation Using AI" project is divided into three major layers: Data Layer, Processing Layer, and Interface Layer.

* Data Layer: This layer is responsible for collecting and preprocessing data. Legal documents, acts, and case laws are gathered from public sources like Indian Kanoon and the official India Code portal. These documents are parsed, processed, and converted into embeddings using Ollama embeddings, which are specialized vector embeddings designed to capture the semantic relationships in the text. The processed data is then stored in Pinecone, a vector database optimized for high-dimensional vectors. Pinecone is critical for efficient vector-based operations such as similarity search, which allows the system to retrieve the most relevant legal cases and arguments.
* Processing Layer: At the heart of the system lies the LLaMA 3 model, a state-of-the-art Large Language Model (LLM) developed by Meta. This model processes the user queries by converting them into vector embeddings and comparing them with the stored data in Pinecone. The model is tasked with generating legal arguments, case summaries, and relevant responses based on the retrieved information. The GROQ API is used as an interface to interact with the LLaMA 3 model, ensuring that the system operates efficiently and returns responses in a timely manner. This layer handles all the core computational logic, transforming user queries into legally sound responses.
* Interface Layer: The interface for this system is built using Chainlit, an open-source framework designed for easy deployment of applications interacting with LLMs. Chainlit provides a clean, user-friendly interface where junior lawyers can input queries related to domestic violence cases, retrieve case summaries, and request legal arguments. Additionally, users have the option to receive the generated outputs via email. The email dispatch system is integrated into the interface, making it simple for users to obtain detailed reports and responses outside the application.

This modular architecture allows for flexibility and scalability. As new domains are introduced beyond domestic violence, the system can be easily extended by incorporating additional legal datasets, making it adaptable for broader legal contexts.

## 3.2 MODULE DESIGN

The Module Design section breaks down the system into distinct functional modules that each handle a specific task in the overall workflow. This modular design enhances the maintainability, scalability, and clarity of the system. The following are the core modules involved:

### 3.2.1 Data Collection and Preprocessing Module:

This module focuses on sourcing legal documents from Indian Kanoon and legal acts such as the Protection of Women from Domestic Violence Act, 2005 (PWDVA). The collected documents are processed into a machine-readable format. The preprocessing stage converts these legal documents (typically in PDF format) into text, which is further divided into chunks. These chunks are then transformed into vector embeddings using Ollama embeddings. The embeddings are essential for converting unstructured text into a structured numerical format that can be analyzed semantically.

### 3.2.2 Vector Storage and Retrieval Module:

In this module, the embeddings generated from the legal documents are stored in the Pinecone vector database. Pinecone specializes in storing high-dimensional vectors and provides capabilities for fast similarity searches. This module also handles the retrieval of relevant documents based on a user’s query. The system performs cosine similarity searches to compare user queries with the stored vectors, identifying the most relevant data to return.

### 3.2.3 Query Processing Module:

After the user submits a query through the interface, this module takes over. The user query is converted into a vector embedding using Ollama embeddings, just like the legal documents.

The query vector is then passed to Pinecone for comparison against the stored vectors, and the most relevant vectors (representing data chunks) are retrieved.

### 3.2.4 Response Generation Module:

* This module is where the LLaMA 3 model comes into play. After relevant vectors are retrieved, LLaMA 3 uses these vectors to generate a detailed and contextually relevant response.
* The responses can include legal arguments, case summaries, or references to relevant articles, depending on the user’s query.

### 3.2.5 Email Delivery Module:

This module is integrated with the user interface and provides the option for users to receive their results via email. It is particularly useful for users who need to save or reference legal summaries and arguments outside the application. The system takes the generated response and securely dispatches it to the user’s provided email address.

## 3.3 DATABASE DESIGN

The system leverages **Pinecone**, a highly specialized vector database, to store and manage the embeddings derived from legal documents. Unlike traditional relational databases, Pinecone is optimized for handling high-dimensional vectors, making it perfect for tasks involving similarity searches.

### 3.3.1 Table Structure

While traditional databases rely on structured tables with rows and columns, Pinecone’s structure is designed around **vector embeddings**. Each document or data chunk is represented as a vector, and associated metadata (such as case ID, document type, and article reference) is stored alongside each vector. These vectors enable efficient querying and retrieval based on semantic similarity.

Each vector entry in Pinecone includes the following metadata:

* **Document ID**: Unique identifier for each legal document.
* **Document Type**: Specifies whether it’s a court ruling, legal act, or chapter.
* **Chapter Reference**: For Acts, this metadata links the vector to the relevant chapter or section.
* **Date**: The date when the legal document was issued or published.

### 3.3.2 Data Flow Diagram

The Data Flow within the system can be summarized as follows:

1. **Data Collection and Preprocessing**: Legal documents are collected, processed, and vectorized into embeddings.
2. **User Query Submission**: The user submits a legal query through the Chainlit interface.
3. **Query Vectorization**: The system converts the query into a vector embedding.
4. **Similarity Search**: Pinecone compares the query vector with stored document vectors using cosine similarity.
5. **Response Generation**: LLaMA 3 processes the retrieved vectors and generates the final response.
6. **Result Delivery**: The generated response is displayed in the interface or sent via email, based on user preference.

### 3.3.3 ER Diagram

The **Entity-Relationship (ER) Diagram** represents the key entities in the system and their relationships. Though Pinecone uses vector embeddings rather than structured tables, the following entities and relationships can be inferred:

* **User**: Represents junior lawyers who interact with the system.

Relationship: Submits queries to the system and receives legal arguments and case summaries.

* **Query**: Represents user input, which is processed by the system.

Relationship: Queries are converted into embeddings and compared with stored vectors in Pinecone.

* **Document Embeddings**: Represents stored legal document vectors in Pinecone.

Relationship: Embeddings are retrieved and processed to generate a response.

## 3.4. SYSTEM CONFIGIRATION

The system configuration includes the following components:

* **LLaMA 3 Model**: The core model that processes legal queries and generates responses.
* **Ollama Embeddings**: Used to convert both legal documents and user queries into vector embeddings.
* **Pinecone**: Vector database responsible for storing embeddings and conducting similarity searches.
* **GROQ API**: Provides an interface for interacting with the LLaMA 3 model.
* **Chainlit**: Framework used to create the frontend interface.

System dependencies include Python, the Ollama embedding library, Pinecone API, and Chainlit for the user interface.

**3.5. INTERFACE DESIGN**

### 3.5.1 User Interface Screen Design

The **User Interface** is built using Chainlit, providing a clean, interactive experience. The primary user of the system is a junior lawyer seeking legal arguments, case summaries, or references related to domestic violence.

The key screens are:

1. **Query Submission Screen**: Users can input queries related to specific legal cases.
2. **Results Display Screen**: After processing the query, the system displays case summaries and legal arguments. This screen provides the option to request the results via email.
3. **Email Request Screen**: Users can input their email address to receive the results. The system ensures secure email delivery.

### 3.5.2 Application Flow/Class Diagram

The **Application Flow** follows these steps:

1. **User Interaction**: The user inputs a legal query into the interface.
2. **Query Processing**: The system vectorizes the query and compares it with stored vectors in Pinecone.
3. **Response Generation**: LLaMA 3 generates a response based on the most relevant data.
4. **Result Display**: The response is shown in the interface or sent to the user's email.

## 3.6. REPORT DESIGN

The system provides detailed reports, including:

* **Case Summaries**: Summaries of relevant legal cases and rulings.
* **Legal Arguments**: A structured report providing legal arguments and references to articles and sections from the law.
* **Email Reports**: If requested, the generated response is sent directly to the user’s email for future reference.

**4. IMPLEMENTATION**

**4.1. DATASET DETAILS:**

**Domain:** Domestic Violence against women.

**i) Legal Documents**

Data was collected from a public website called ‘Indian Kanoon’. (It is a free online legal database and search engine for Indian law.

Time Period: from 2024 January 1 till date.

Type of document: PDF

Coverage: Karnataka High Court

**ii)Protection of Women from Domestic Violence Act, 2005 (PWDVA)**

Source: India Code (Official government portal for all Central Acts of Parliament.)

Doc Type: PDF

Coverage: 5 Chapters

## 4.2. MODEL DETAILS:

Model used: **llama3-8b-8192** (Large Language Model Meta AI 3)

It is an advanced iteration in Meta's series of large language models. It is designed to offer significant improvements over previous versions, focusing on enhancements in understanding, generating, and interacting with human language.

**Key Features of LLaMA 3-8b:**

•    **Advanced Language Understanding**: LLaMA 3-8b provides improved comprehension of complex and nuanced text, allowing it to better grasp context and subtleties in language.

•    **Enhanced Text Generation**: The model generates more coherent, contextually relevant, and diverse text, making it suitable for a wide range of applications including content creation, dialogue systems, and creative writing.

•    **Broader Knowledge Base**: LLaMA 3-8b has been trained on a more extensive and diverse dataset, enhancing its ability to provide accurate and relevant information across various topics and domains.

•    **Improved Efficiency**: The model is designed to be more efficient in terms of computational resources, which helps in reducing latency and costs associated with deployment and inference.

•    **Robust Performance**: LLaMA 3 exhibits improved performance in handling complex queries and generating detailed responses, making it effective for applications that require deep understanding and high-quality output.

•    **Customization and Fine-Tuning**: It supports fine-tuning and customization, allowing users to adapt the model to specific needs and domains, which enhances its applicability for specialized tasks.

•    **Innovative Architecture**: LLaMA 3 incorporates advancements in neural network architecture and training techniques, contributing to its improved performance and capabilities.

**The model is used with the help of Groq API**

The **GROQ API** (General Representation for Querying) is an interface for querying and interacting with pre-trained machine learning models. It is designed to facilitate the deployment and use of AI models by providing a standardized way to access and utilize their capabilities.

## 4.3. DATA PREPROCESSING:

The data is first divided into chunks, then processed into vectors using Ollama embeddings, and finally, these vectors are stored in the Pinecone vector database.

**Ollama Embeddings**:

In machine learning and natural language processing, embeddings are numerical representations of data, such as words or phrases, in a continuous vector space. These embeddings capture semantic meaning and relationships between the data points.

Ollama embeddings are a specific type of vector embeddings provided by the Ollama platform. They are used to convert textual or other types of data into dense, high-dimensional vectors that can be efficiently processed and analyzed.

**Pinecone**:

A vector database is a specialized database designed to store, manage, and query vector embeddings. It is optimized for operations involving high-dimensional vectors, such as similarity search and nearest neighbor retrieval.

Pinecone is a managed vector database that provides high-performance indexing and querying capabilities for vector embeddings. It allows for efficient storage and retrieval of vectors, making it suitable for applications like recommendation systems, search engines, and other use cases involving large-scale vector data.

**Data Processing with Embeddings**: The process starts by converting raw data into vector embeddings using Ollama embeddings. This step transforms the data into a format suitable for advanced processing, where the semantic relationships and features of the data are captured in numerical form.

**Storage in Vector Database**: Once the data is converted into vectors, it is then stored in the Pinecone vector database. Pinecone handles the storage, indexing, and retrieval of these vectors, allowing for efficient querying and analysis of the vectorized data.

Vectorization allows for efficient comparison, search, and retrieval of data based on the user’s query. It helps the model understand the relationship between different pieces of data.

4.4. QUERYING:

**User Query and Vectorization**:

•              After the user submits a query, the LLaMA 3 model processes it to understand the intent.

•              The query is then vectorized using Ollama embeddings, converting it into a numerical vector that captures the semantic meaning of the query.

**Vector Search in Pinecone Using Cosine Similarity**:

•              **Cosine Similarity**: This is a measure of similarity between two vectors that calculates the cosine of the angle between them. It ranges from -1 to 1, where 1 indicates that the vectors are identical in direction, 0 indicates orthogonality (no similarity), and -1 indicates that they are diametrically opposite.

•              **Similarity Search**: When the vectorized query is sent to the Pinecone vector database, Pinecone uses cosine similarity to compare the query vector with all the vectors stored in the database.

•              **Retrieval of Relevant Vectors**: The vectors with the highest cosine similarity scores are retrieved because they represent data chunks that are most semantically similar to the user’s query.

**Efficiency in High-Dimensional Space**: Cosine similarity is particularly effective in high-dimensional spaces like those used in vector embeddings. It focuses on the orientation (direction) of vectors rather than their magnitude, making it ideal for comparing the semantic similarity of texts.

**Robustness**: It handles varying lengths of vectors well, which is important because different chunks of data might result in vectors of different magnitudes.

## 4.5. RESPONSE GENERATION:

**Generating the Response**:

The retrieved vectors are converted back into their corresponding data chunks.

The LLaMA 3 model uses these relevant data chunks to generate a response that closely matches the user’s query.

**Final Output**:

The generated response, which is based on the most similar data found using cosine similarity, is sent back to the user through the GROQ API.

## 4.6. DEPLOYMENT:

The model has been deployed using Chainlit, which allows users to submit queries and receive responses through an intuitive user interface. The deployment includes specific guidelines to ensure the model’s responses are focused, accurate, and suitable for its intended purpose.

**Guidelines for the Model:**

•              **Role:** The model functions as a legal assistant specializing in domestic violence cases.

•              **Responsibilities:** It delivers concise and clear case summaries, generates legally sound arguments, and references relevant legal articles and sections based on user input.

•              **Focus:** The model strictly adheres to the legal context, avoiding complex legal jargon and speculative content. It ensures all explanations are straightforward and educational, catering to junior lawyers.

•              **Graceful Exit:** If the user concludes the task or changes the topic, the model gracefully ends the interaction.

**Email Feature:**

•              **Email Delivery:** If a user requests to have the generated output sent to their email, they can provide their email address within the interface. The system will then securely send the response to the specified email address.

•              **Ease of Use:** This feature enhances user convenience, allowing them to receive detailed case summaries or legal arguments directly in their inbox for future reference or further action.

**User Interaction Flow:**

**1.**           **Query Submission:** Users interact with the model by submitting queries related to domestic violence cases.

**2.**           **Response Generation:** The model processes the query, retrieves relevant information, and generates a precise response.

**3.**           **Email Request:** Users have the option to request the generated response to be sent to their email by providing their email address.

**4.**           **Email Dispatch:** The system automatically sends the response to the provided email, ensuring that the user has access to the information outside the application as well.

## 4.7. CODES IMPLEMENTATION:

### 4.7.1. Embedding Pipeline:

***import os***

***from dotenv import load\_dotenv***

***from langchain\_community.document\_loaders import PyPDFLoader***

***from langchain.text\_splitter import RecursiveCharacterTextSplitter***

***from langchain\_pinecone import PineconeVectorStore***

***from langchain.embeddings import OllamaEmbeddings***

***from tqdm import tqdm***

**dotenv:** Used to load environment variables from a .env file, which contains sensitive data like API keys.

**PyPDFLoader:** A utility that reads and loads text from a PDF file.

**RecursiveCharacterTextSplitter:** This splits long documents into smaller text chunks for efficient embedding creation.

**PineconeVectorStore:** A class used to store and manage vector embeddings in the Pinecone vector database.

**OllamaEmbeddings:** A library that generates embeddings from text using a pre-trained embedding model.

**tqdm:** A utility to create progress bars for loops.

***def create\_embeddings():***

***# Load the PDF***

***loader = PyPDFLoader('doc\_samp1\_merged.pdf')***

***documents = loader.load\_and\_split()***

**Loader and Splitting:** The PyPDFLoader reads the content from the given PDF file. Then, load\_and\_split() processes the PDF into a list of documents, which are suitable for further splitting.

***text\_splitter = RecursiveCharacterTextSplitter(chunk\_size=5000, chunk\_overlap=0)***

***texts = text\_splitter.split\_documents(documents)***

**Splitting Text:** The documents are split into chunks of 5000 characters. This ensures that large documents are processed in smaller pieces for embedding. This improves accuracy and performance during search and retrieval.

***index\_name = "lawllm2"***

***embeddings = OllamaEmbeddings(model="mxbai-embed-large")***

**Embeddings Initialization:** The OllamaEmbeddings class is used to generate vector embeddings, converting the text chunks into a format that captures their semantic meaning.

***batch\_size = 100***

***for i in tqdm(range(0, len(texts), batch\_size)):***

***batch = texts[i:i+batch\_size]***

***PineconeVectorStore.from\_documents(batch, embeddings, index\_name=index\_name)***

**Batch Processing and Storage:** The texts are processed in batches of 100, generating embeddings for each batch. The embeddings are then stored in the Pinecone vector database with the index name "lawllm2". Using batches improves performance, especially with large datasets.

4.7.2. Legal Assistant Interaction:

***import os***

***import re***

***import smtplib***

***from email.mime.text import MIMEText***

***from langchain.prompts import PromptTemplate***

***from langchain\_pinecone import PineconeVectorStore***

***from langchain.chains import RetrievalQA***

***from langchain\_groq import ChatGroq***

***from dotenv import load\_dotenv***

***from langchain.embeddings import OllamaEmbeddings***

***import chainlit as cl***

**langchain, Pinecone, and Groq APIs:** These libraries are used to manage the workflow of document embeddings, queries, and responses.

**smtplib:** Used to send emails with the SMTP protocol.

**chainlit:** Provides the user interface for interacting with the chatbot.

***prompt\_template = """***

***You are a legal assistant specializing in domestic violence cases. Your role is to provide concise and clear previous related case summaries and also the arguments for the requested scenario which will help the junior lawyers to win the case, generate legally sound arguments, and reference relevant articles and sections based on user prompts. Focus only on the legal context and respond accurately, avoiding overly complex legal jargon. If the user concludes the task or changes the topic, gracefully end the interaction. This tool is designed to assist junior lawyers, so ensure that all explanations are straightforward and educational.***

***Context: {context} Question: {question}***

***Helpful answer:***

***"""***

This is the template that the legal assistant uses to generate its responses. It specifies that the model should generate legally sound arguments and provide relevant case summaries, focusing on domestic violence cases. The template ensures that the output is helpful, clear, and focused on junior lawyers.

***def load\_llm():***

***return ChatGroq(model="llama3-8b-8192", temperature=0)***

The function loads the LLaMA 3 model via the Groq API, which is responsible for generating text based on the input and retrieved information.

***def qa\_bot():***

***index\_name = "lawllm2"***

***embeddings = OllamaEmbeddings(model="mxbai-embed-large")***

***db = PineconeVectorStore.from\_existing\_index(index\_name, embeddings)***

***llm = load\_llm()***

***qa\_prompt = set\_custom\_prompt()***

***qa = retrieval\_qa\_chain(llm, qa\_prompt, db)***

***return qa***

**qa\_bot:** This is the main bot function that connects the Pinecone vector database, embeddings, language model, and custom prompt together to create a fully functional QA system. It retrieves information from Pinecone and uses the LLaMA 3 model to generate legal arguments.

***@cl.on\_chat\_start***

***async def start():***

***chain = qa\_bot()***

***msg = cl.Message(content="Starting the bot...")***

***await msg.send()***

***msg.content = "Hi, Welcome to the Legal Assistant Bot. What is your query?"***

***await msg.update()***

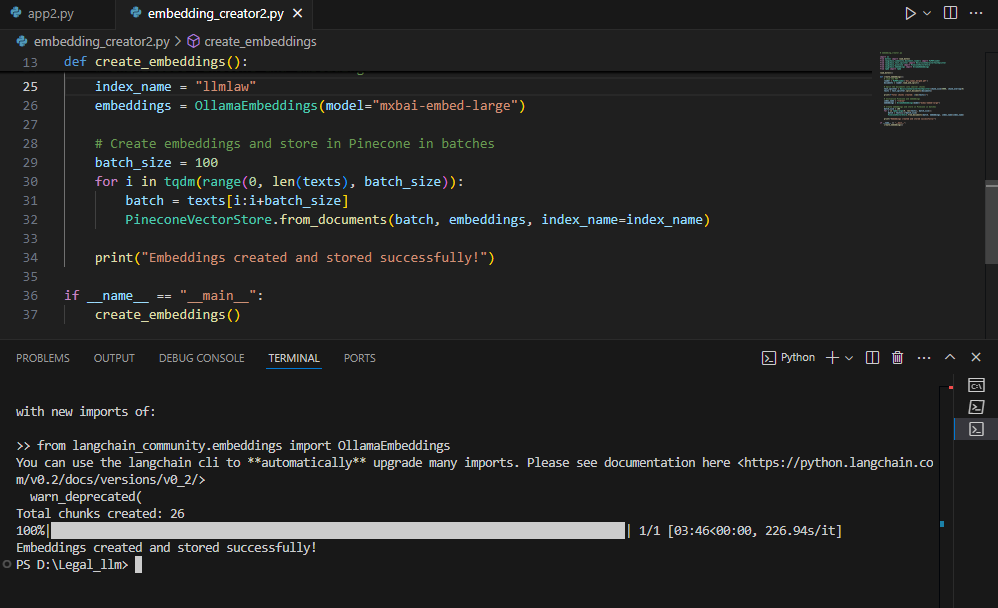
This is the initialization function that runs when the chatbot session starts. It loads the QA chain and sends a welcome message to the user, prompting them to enter a query.

**Code for Embedding Pipeline:** handles the embedding of legal documents into a vector database (Pinecone), which allows efficient retrieval of relevant documents based on user queries.

**Code for Legal Assistant Interaction:** implements the main functionality of the legal assistant bot, where users can ask legal questions, receive detailed responses generated by the LLaMA 3 model, and request the information to be sent via email.

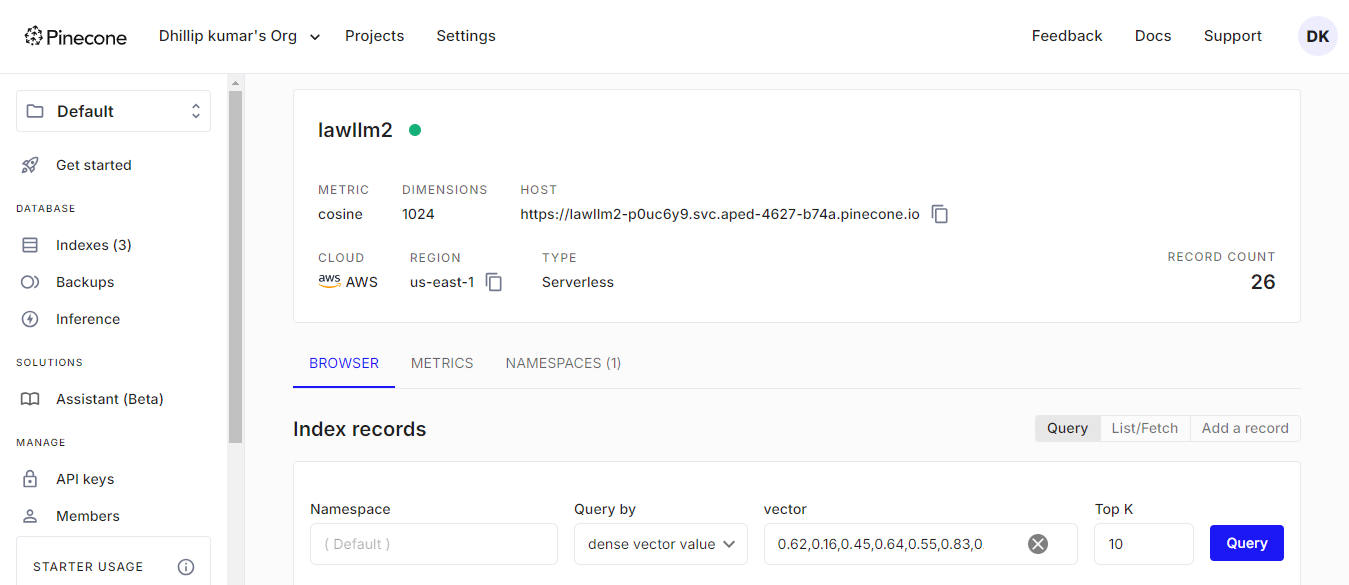
# **5. TESTING**

## 5.1. EMBEDDING CREATION WINDOW:



*Fig 5.1: Output of Embedding creation*

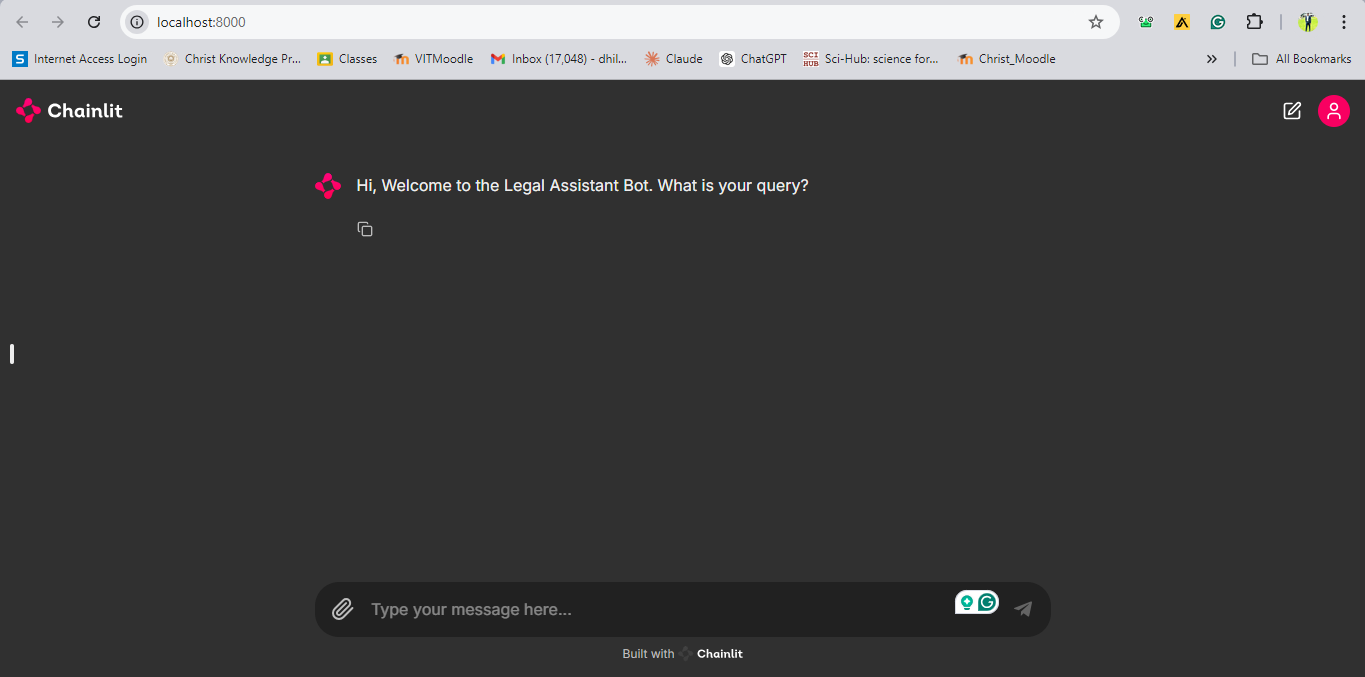
Execution of embedding\_creator.py, showing successful PDF loading, text splitting, and embedding creation



*Fig 5.2: Output of Embedding creation in Pinecone*

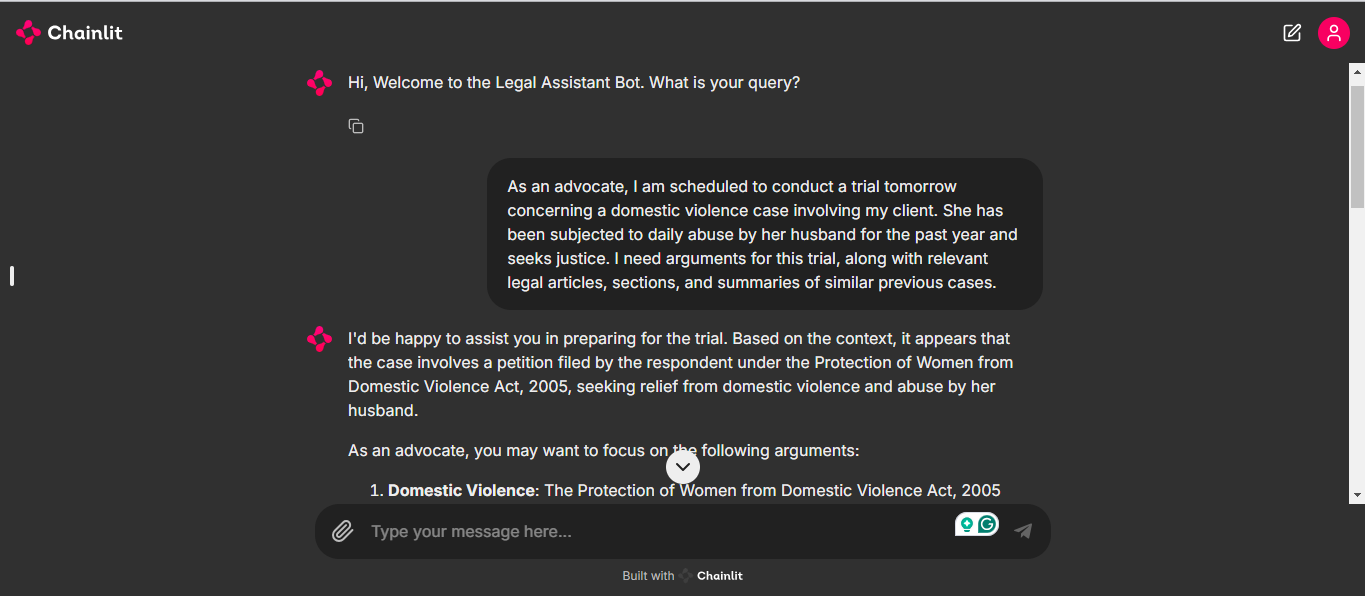
## 5.2. CHECKING THE ASSISTANT:

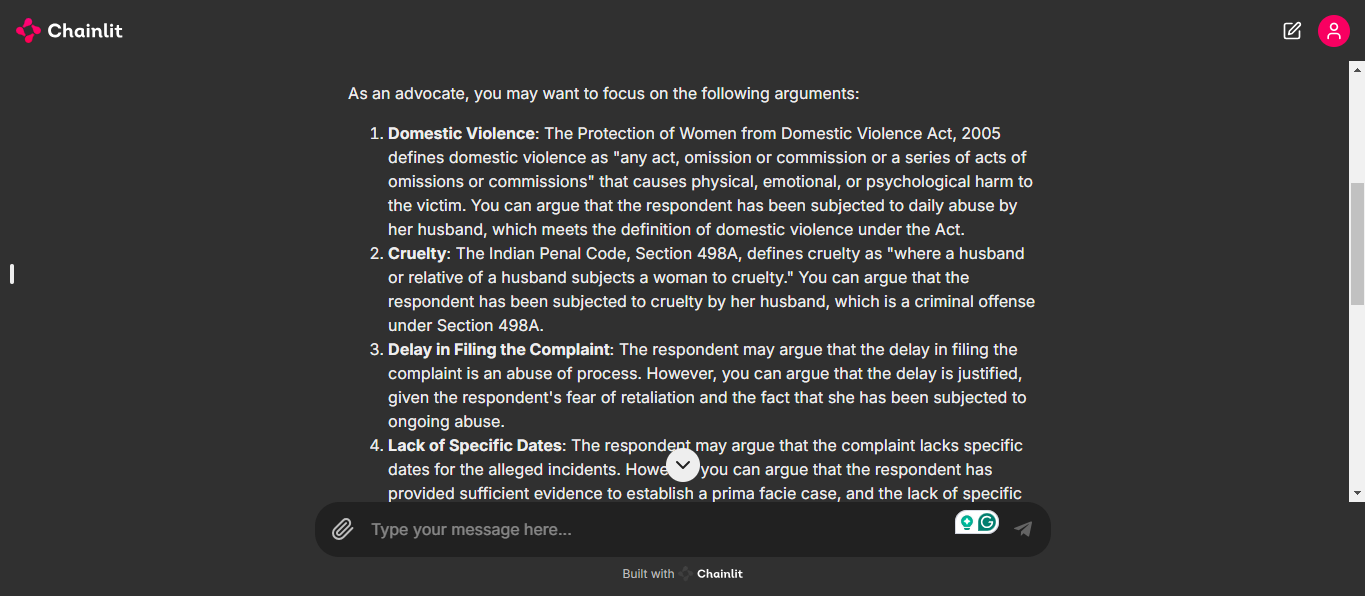
**Starting page of the site:**

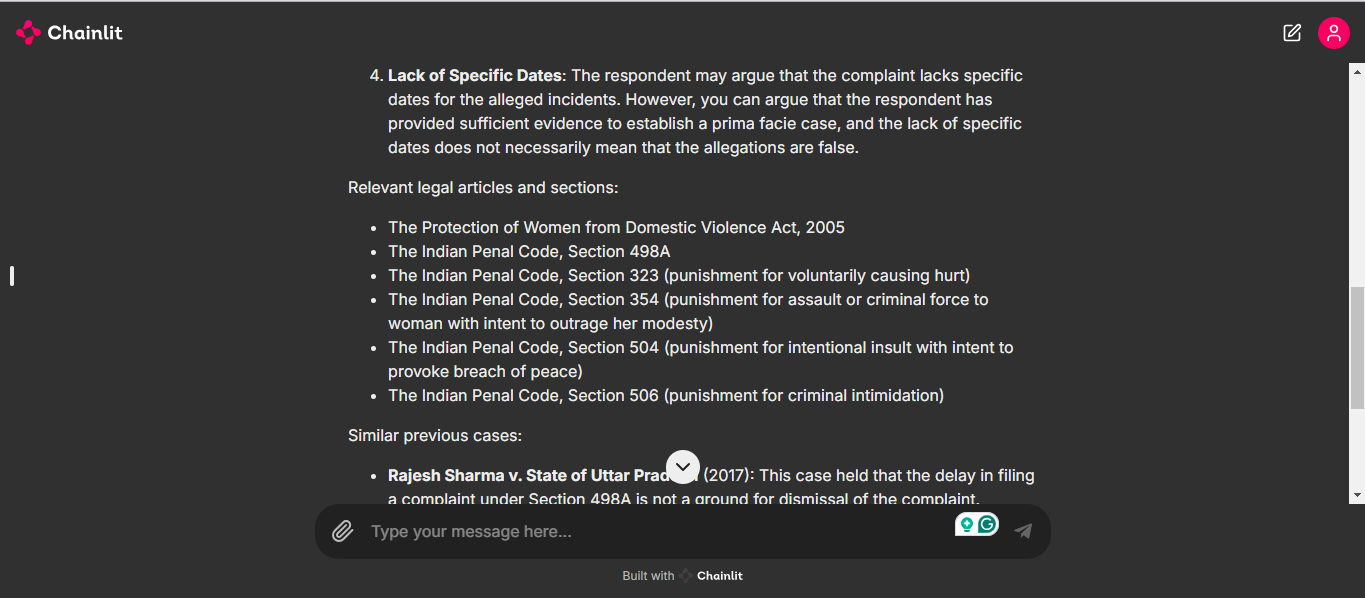
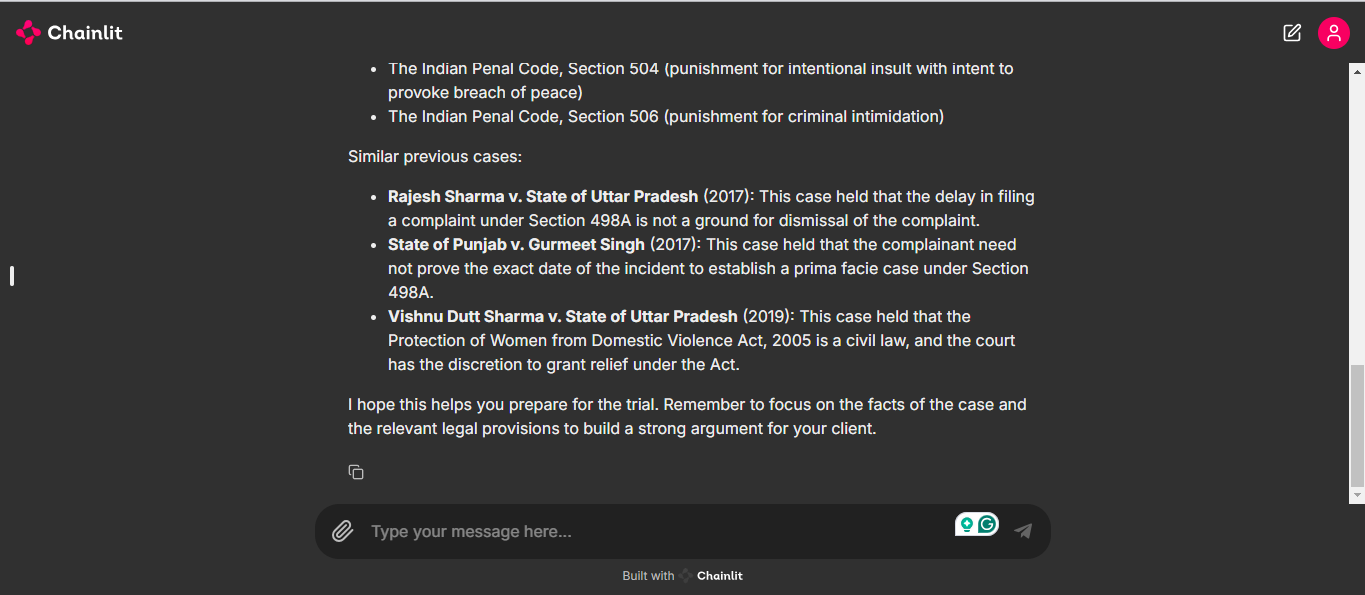


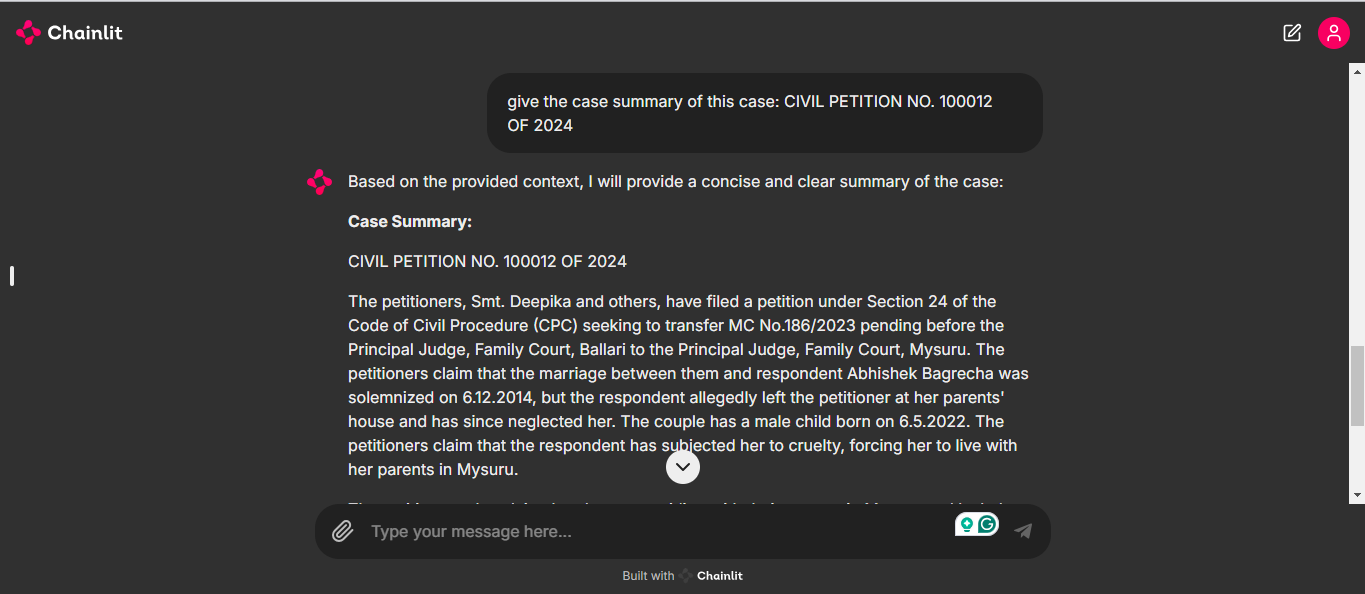
*Fig 5.3: Starting page of the Assistant*

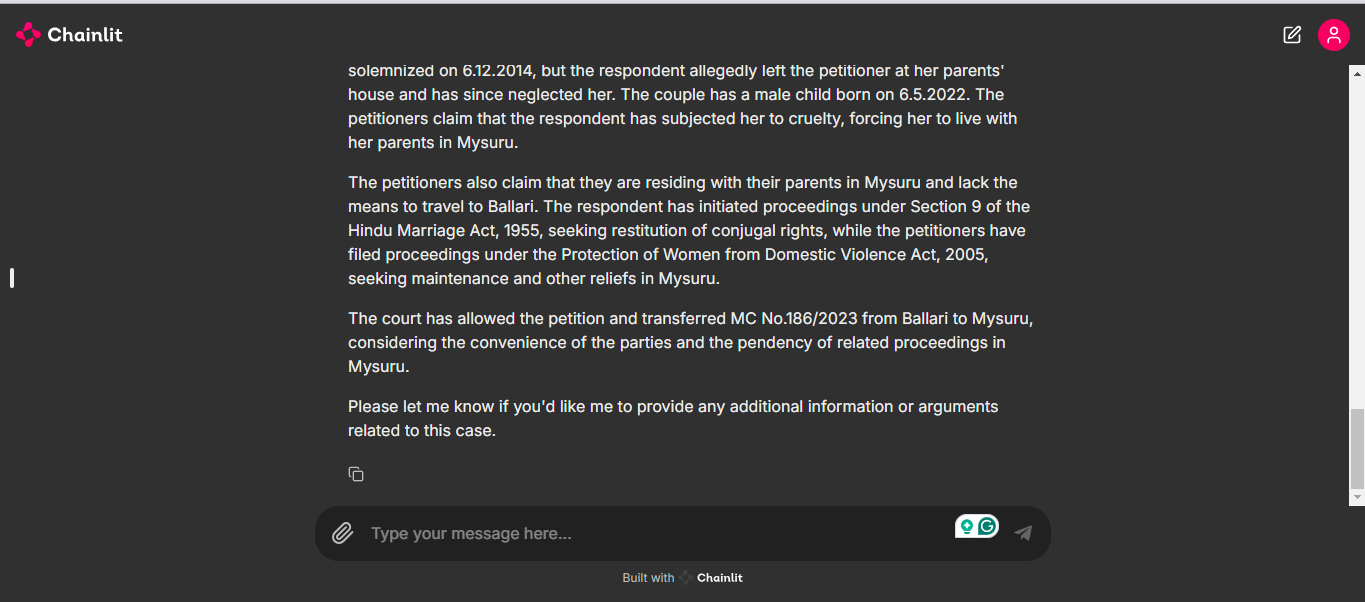
**User’s queries and the assistant responses:**

*Fig 5.4: User Query - 1*

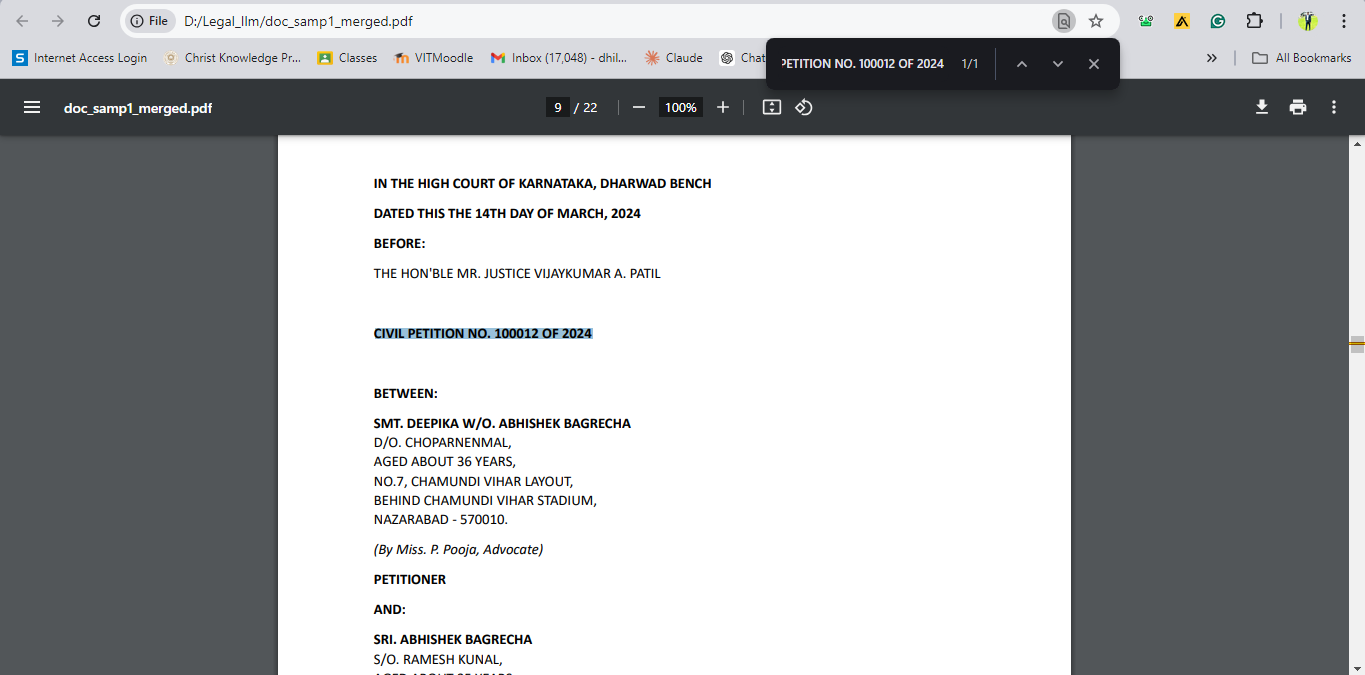
 *Fig 5.5: Assistant response for user query - 1*

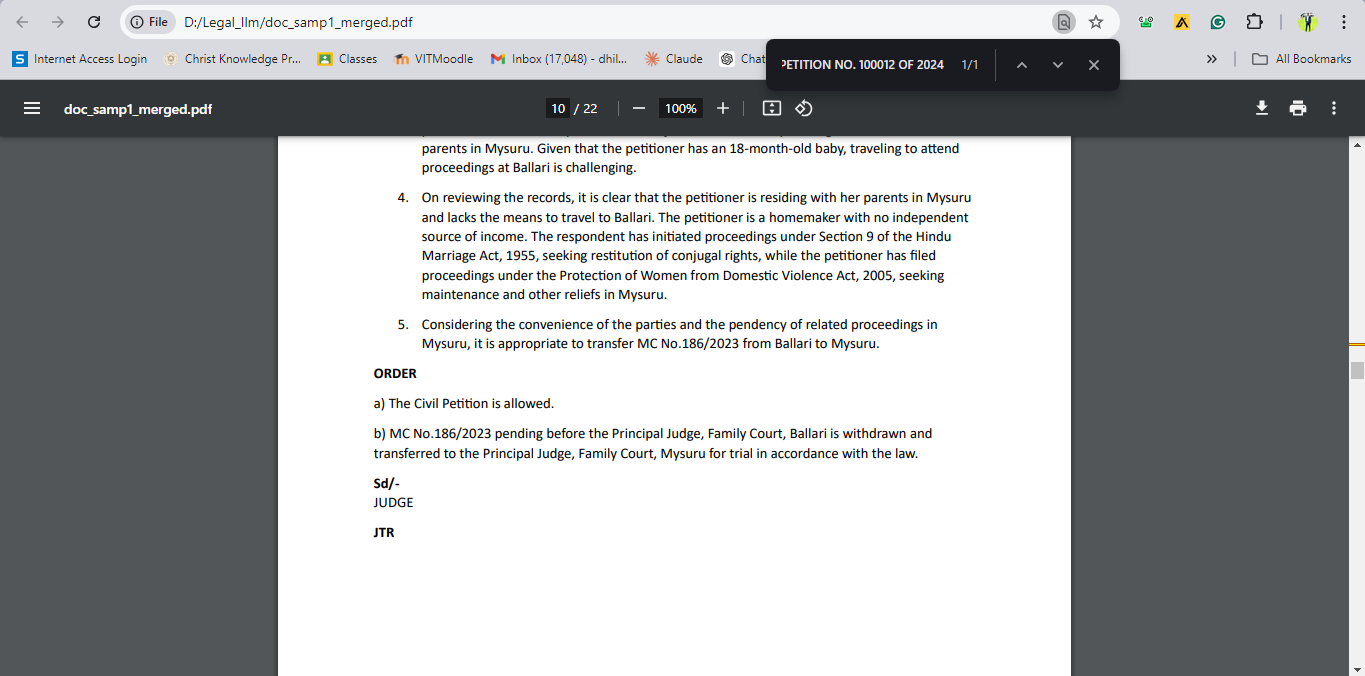
 *Fig 5.6: Assistant response for user query - 1* *Fig 5.7: Assistant response for user query – 1*

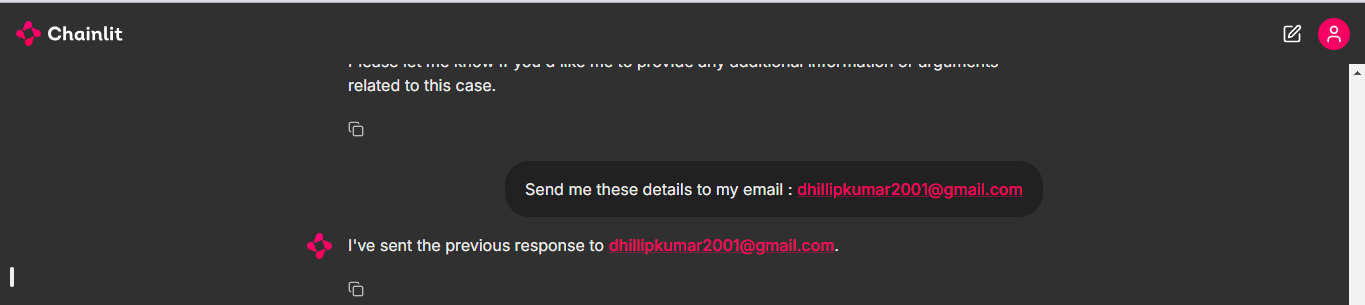
*Fig 5.8: User Query - 2*

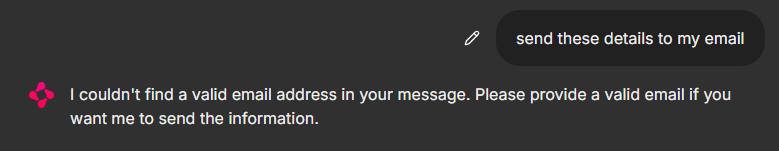
*Fig 5.9: Assistant response for user query - 2*

**Validating the Assistant’s response from the loaded data:**

 *Fig 5.10: Validation for response - 2*

*Fig 5.11: Validation for response – 2*

*Fig 5.12: User’s request for the content over the email*

*Fig 5.13: User’s invalid request handling*

The legal assistant model demonstrated strong capabilities throughout the testing phase. It effectively generated coherent, legally sound arguments and case summaries based on user queries, highlighting its practical application for junior advocates. The model's performance in retrieving relevant legal information, including laws and case precedents, proved essential for addressing domestic violence cases.

Key strengths observed during testing include:

* **Accurate Query Processing:** The model accurately understood user queries and provided well-structured legal arguments, relevant legal sections, and case summaries, as showcased in multiple test scenarios.
* **Email Functionality:** The system successfully identified email addresses in user queries and sent detailed responses to users via email, adding an important layer of utility for legal professionals needing to share case information quickly.
* **Handling of Large Documents:** The model efficiently processed and split large legal documents, generating embeddings without significant delay, ensuring that even complex cases can be handled seamlessly.
* **Error Handling:** The system managed invalid inputs gracefully, providing helpful error messages or prompts for the user to reformulate their query.

Overall, the legal assistant model provides significant value to junior lawyers, enhancing their productivity and supporting their legal research with timely and relevant information. The model's ability to generate concise and accurate case summaries, along with its integration with Pinecone for efficient retrieval of legal data, positions it as a powerful tool in the legal domain. Further improvements in response time and adaptability to more complex legal scenarios could push this model toward even greater utility.

# **6. CONCLUSION**

The AI-driven legal argument generation system presented in this project provides a transformative solution to the challenges faced by junior and less experienced lawyers, especially in handling intricate domestic violence cases. These cases often require deep legal knowledge, extensive research, and a nuanced understanding of relevant laws and precedents, all of which can be daunting for younger practitioners. By leveraging the power of advanced language models and integrating a comprehensive legal database, this system automates the most time-consuming aspects of legal research.

Through quick retrieval of case summaries, generation of legally sound arguments, and access to relevant statutes and precedents, the tool not only reduces the burden on lawyers but also ensures a higher standard of legal representation. This enables junior lawyers to focus on refining their courtroom strategies and presenting compelling arguments. The integration of this AI-driven tool significantly enhances the quality of case preparation, leading to more efficient trial proceedings and improved chances of securing justice for victims of domestic violence.

By providing faster access to legal information, the system bridges the gap between knowledge and practical application, empowering lawyers to handle even the most challenging cases with greater confidence and competence. Ultimately, this tool serves to improve both the efficiency and effectiveness of legal representation, reducing delays in justice and ensuring better outcomes for victims of domestic violence. The project demonstrates the potential of AI in transforming the legal profession by making expert-level legal assistance accessible to all.

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