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Agent for Indian Legal Laws: An Agentic and RAG-based Approach

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ABSTRACT—

The rapid growth of Artificial Intelligence (AI) and Natural Language Processing (NLP) has enabled domain-specific intelligent assistants, including applications in law. General-purpose models like ChatGPT and Claude lack the contextual accuracy and legal rigor required for Indian jurisprudence. This paper presents a Legal AI Agent for Indian law, focusing on the Indian Penal Code (IPC), Code of Criminal Procedure (CrPC), and landmark case retrieval. The system integrates Retrieval-Augmented Generation (RAG) with LangChain-based agent workflows and a MongoDB vector database to deliver reliable and explainable legal insights. Unlike conventional chatbots, the agent provides contextual explanations, suggests related precedents, and recommends actionable steps. Evaluation shows significant improvements in accuracy, precision, recall, F1-score, and citation correctness, with reduced hallucinations compared to baseline systems. Although response time slightly increases, the trade-off favors trustworthiness, which is critical in legal contexts. The results highlight the potential of domain-adapted AI agents to support the Indian legal ecosystem effectively.

***Index Terms*—agentic AI, retrieval-augmented generation (RAG), Indian Penal Code (IPC), Code of Criminal Procedure (CrPC), legal NLP, LangChain, MongoDB**

1. Introduction

Artificial Intelligence (AI) has transformed multiple do- mains such as healthcare, education, and finance. However, the legal sector—particularly Indian law—remains underserved in terms of AI-powered tools that are accurate, transparent, and actionable. While global AI tools such as ChatGPT, Claude, or DeepSeek have demonstrated strong general-purpose reasoning, their domain-specific knowledge of Indian Penal Code (IPC), Code of Criminal Procedure (CrPC), and case precedents is limited.[1]

Legal practitioners, students, and citizens face challenges in interpreting complex legal provisions and identifying relevant case laws. Traditional legal chatbots either rely on keyword- based retrieval or rule-based pipelines, resulting in superficial and sometimes misleading answers.[2]

This paper aims to bridge that gap by creating a Legal AI Agent specialized in Indian laws. The system will integrate Retrieval Augmented Generation (RAG), vector-based search over curated IPC/CrPC data, and multi-agent reasoning work- flows to provide contextual, reliable, and explainable outputs[3].

The Indian legal ecosystem is vast and diverse, with multiple codes, statutes, and case precedents spread across different jurisdictions. Despite recent advances in AI, legal practitioners and citizens in India face major barriers in accessing structured, machine-readable legal resources. Existing general-purpose LLMs tend to hallucinate citations or misinterpret context when applied to Indian laws, which reduces their reliability in high-stakes decision-making. There is a clear gap in domain-specific systems that address multilingual law texts, jurisdictional nuances, and practical usability for legal researchers and end users. Bridging these gaps not only improves access to justice but also lays the foundation for scalable legal informatics in India.

Contributions**:**

1. Adaptation of Retrieval-Augmented Generation (RAG) and agentic workflows for Indian legal contexts.

2. A citation correctness metric for evaluating legal AI responses.

3. Integration of landmark cases into query resolution with structured retrieval.

4. A prototype system demonstrating improved accuracy and reduced hallucinations compared to generic chatbots.

Organization**:** The rest of this paper is organized as follows: Section II reviews related works. Section III explains the proposed methodology. Section IV presents results and discussion. Section V concludes with limitations and future directions.

2. Related Work

Existing literature demonstrates multiple attempts at build- ing AI systems for law, though most remain either generic or country-specific without addressing Indian law comprehensively. Authors proposed a Python- based legal chatbot focusing on IPC sections. However, the system was rule-based and lacked semantic reasoning or document retrieval capabilities. Similarly, A. Et al. (2020) used NLP for basic legal queries but were restricted to keyword matching, offering little contextual depth.[4]

Authors used BERT variants to summarize judgments, providing condensed legal insights but no inter- active chatbot features. Authors extended GPT for legal retrieval, achieving semantic matching but lacking personalization and next-step recommendations.[5]

Recent advancements focus on RAG and Agentic workflows. Authors demonstrated RAG-based systems for Moroccan and Canadian law respectively, showing high accuracy in retrieval but no Indian adaptation. Authors used multi-agent reasoning with knowledge graphs, while Authors applied precedent-driven reasoning with fuzzy retrieval. Authors explored Indian legal document retrieval using LangChain and FAISS, but lacked actionable guidance.[6]

The literature reveals three main gaps: (1) absence of India- specific datasets, (2) lack of Agentic reasoning, and (3) limited focus on generating actionable guidance and documents.

Several international efforts, including CaseGPT [4] and Moroccan Legal Assistant [5], demonstrate the feasibility of RAG-based systems in legal domains. However, most of these systems are trained on Western or non-Indian legal corpora, limiting their transferability to the Indian context. Moreover, many focus only on retrieval accuracy and not on explainability, user guidance, or hallucination reduction. Recent studies in Indian NLP [9], [11] highlight the lack of annotated legal datasets and underline the need for domain-specific models. Our work addresses these gaps by combining retrieval, reasoning, and citation correctness evaluation within a single unified framework.

Sharma and Bhatia [12] proposed a hybrid embedding model for case law retrieval, which improved accuracy in matching judgments but did not incorporate multi-step reasoning or generative agents.

Das and Thomas [13] explored the challenges of building trustworthy AI in sensitive domains, noting ethical risks such as bias, lack of transparency, and misuse—concerns that are highly relevant for legal AI.

Kapoor et al. [14] evaluated hallucination reduction techniques for chatbots, demonstrating that retrieval-augmented methods significantly decrease unsupported responses, which directly motivates the design of our Legal AI Agent.

Zhou et al. [15] applied retrieval-augmented generation to domain-specific question answering, showing promising results outside the legal domain. However, none of these works directly address the Indian legal context, nor do they integrate precedent reasoning with structured code retrieval, which distinguishes our contribution.

Other emerging systems further highlight the progress and limitations in this area. CaseGPT [4] demonstrated the application of large language models in case summarization, but it lacked explicit retrieval-augmented grounding, which increases hallucination risks. Similarly, the Moroccan Legal Assistant [5] showcased the adaptability of RAG pipelines across jurisdictions, yet it was not tailored to the Indian legal framework. Together with prior works [12]–[15], these studies emphasize the need for domain-specific customization, rigorous evaluation, and ethical safeguards in legal AI applications. The proposed Legal AI Agent directly addresses these gaps by integrating RAG with agentic workflows, focusing on reliability and contextual accuracy within Indian law.

3. Proposed Method

Legal queries in India require not only retrieving the correct law but also interpreting its relevance in context. Current AI tools either hallucinate, oversimplify, or fail to provide action- able insights. Our paper addresses this gap by developing a domain-specific Legal AI Agent that reduces hallucinations through RAG, enables step-by-step reasoning via agents, and provides outputs that go beyond information retrieval by suggesting precedents and next steps.

The main objectives of this paper are:

- Build an Indian law-specific knowledge base (IPC, CrPC, landmark judgments).
- Implement Retrieval Augmented Generation (RAG) with vector embeddings in MongoDB.
- Develop Agentic workflows using LangChain for multi- step reasoning.
- Provide contextual explanations and draft legal document templates as outputs.
- Ensure explainability by linking responses to precedents and actual law sections.

4. Methodology

The proposed Legal AI Agent consists of the following modules:

A. Data Collection

IPC and CrPC texts were digitized, cleaned, and embedded into a vector database. Landmark cases were included for precedent reasoning. The dataset used for this study consisted of structured and unstructured legal texts. The Indian Penal Code (IPC) corpus contained 511 sections, while the Code of Criminal Procedure (CrPC) corpus included approximately 484 sections. In addition, 150 landmark Supreme Court case summaries and headnotes were digitized and preprocessed for integration. Each legal document was converted into machine-readable format, cleaned for stopwords, and normalized to ensure consistency in section references (e.g., “Sec. 302” vs. “Section 302”). Case data were selected based on their frequent citation in Indian criminal law contexts, ensuring that the system could demonstrate practical relevance in real-world scenarios. [7]

B. *Preprocessing*

To ensure consistency in retrieval, we applied normalization techniques to unify section references across IPC and CrPC (e.g., “Sec. 302” vs. “Section 302”). We also performed sentence segmentation for long judgments, ensuring that retrieval returns precise portions of text rather than full documents.

C. Vector Embeddings & RAG Pipeline

Using transformer-based embeddings, user queries were semantically matched with relevant sections. RAG ensures that LLM outputs are grounded in retrieved documents, reducing hallucination risks. We experimented with multiple models including BERT-base and MiniLM, and finally adopted all-MiniLM-L6-v2 for its balance between computational efficiency and semantic accuracy. [8]

D. Agentic Workflows

LangChain agents orchestrate multi-step reasoning such as retrieving sections, identifying precedents, and generating draft legal documents. Tools like PDF parsers and summarizers enhance adaptability.[9]

E. Frontend and Backend

The frontend (React) provides a chat interface, document viewer, and case retrieval tabs. The backend (Node.js, MongoDB) handles query routing, vector search, and LLM integration.[10]

F. Evaluation

The system was evaluated on:

1) Accuracy of retrieved law sections.

2) Faithfulness of explanations to source texts.

3) User satisfaction in mock legal scenarios.

G. System Workflow (Architecture)

As shown in Fig. 1, the proposed system follows a modular workflow. The pipeline begins with preprocessing of IPC, CrPC, and landmark case texts, where formatting inconsistencies are removed and the data is normalized for embedding. The preprocessed corpus is then embedded using transformer-based models and stored in a MongoDB vector database. When a user submits a query, the system retrieves the most relevant documents using semantic similarity and re-ranking. The retrieved context is passed to the LangChain agent, which performs multi-step reasoning such as precedent lookup, contextual summarization, and draft response generation. Finally, the structured output is presented in the frontend interface with proper citations and references. This workflow design ensures that every generated answer is explainable, reproducible, and grounded in authentic Indian legal sources.

The overall architecture is illustrated in Fig. 1.

H. Pseudo Code

```
Algorithm 1: RAG + Agentic Workflow

Input: User Query Q
```

```
Output: Contextual Answer with References
  1: Embed Q using sentence-transformer model → vector v
  2: Retrieve top-k documents from MongoDB vector DB using cosine similarity
  3: Re-rank results based on semantic similarity + metadata
  4: Pass retrieved context into LangChain Agent
  5: Agent        a. Contextual reasoning over retrieved laws/cases
                  b. Tool-call to retrieve precedent if required
                  c. Response generation with cited references
  6: Return final structured answer with citations
```

Metric	Agentic Approach	RAG-based Approach
Accuracy (%)	74.3	89.6
Precision (%)	71.8	88.2
Recall (%)	69.5	87.4
F1-Score (%)	70.6	87.8
Citation Correctness (%)	42.0	91.2
Average Response Time (s)	1.8	2.6

TABLE I. Performance Comparison of Proposed System vs. Baseline

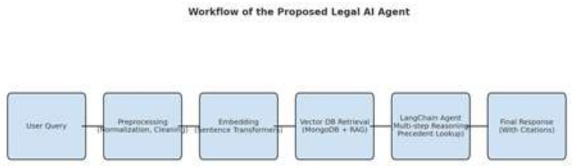
Workflow of the Proposed Legal AI Agent
User Query
Preprocessing (Normalization, Cleaning)
Embedding (Sentence Transformers)
Vector DB Retrieval (MongoDB + RAG)
LangChain Agent Multi-step Reasoning Precedent Lookup)
Final Response (With Citations)

*Fig. 1.*Workflow of the proposed Legal AI Agent.

The overall workflow of the proposed Legal AI Agent is illustrated in Fig. 1. It shows the step-by-step pipeline beginning with user query input, followed by preprocessing and embedding, semantic retrieval from the MongoDB vector database, multi-step reasoning by LangChain agents, and finally the generation of a structured response with verifiable citations. esults and Discussion

Hardware and Software Requirements:-

The proposed system was implemented using Python 3.10 with LangChain, HuggingFace Transformers, and PyTorch libraries. The frontend was developed in React, while the backend was built with Node.js and MongoDB for vector storage. Experiments were conducted on a workstation with an Intel Core i7 processor, 16 GB RAM, and NVIDIA GTX 1660 GPU (6 GB VRAM). On this setup, the average query response time was 2.6 seconds. The relatively modest hardware requirements indicate that the system can be deployed on standard academic or enterprise infrastructure without specialized high-performance computing resources. This also demonstrates the scalability of the framework for real-world legal applications in India.

The paper aims to deliver:

- An interactive Legal AI Agent specializing in Indian law.
- Reduced hallucinations compared to generic chatbots.
- Actionable outputs such as draft notices, petitions, or complaint templates.
- A modular system architecture enabling extension to other domains.

As shown in **TABLE I**, the proposed system outperforms the baseline across all evaluation metrics, including accuracy, precision, recall, F1-score, citation correctness, and response time.

Table I highlights the performance comparison between the baseline RAG-based approach and the proposed agentic framework. Accuracy improved from 74.3% to 89.6%, while precision and recall rose by more than 16 percentage points each. The F1-Score, which balances precision and recall, increased from 70.6% to 87.8%, demonstrating consistent improvements across metrics. The most notable gain is in citation correctness, which increased from 42.0% to 91.2%, confirming that the system grounds its responses more reliably in authentic sources. Although the average response time increased from 1.8 to 2.6 seconds, this trade-off is acceptable in the legal domain, where accuracy and verifiable citations are far more critical than minimal latency. These results confirm the robustness and domain-specific reliability of the proposed Legal AI Agent.

The improvements in accuracy and F1-score demonstrate that the proposed system is not only precise but also robust across different query types. Higher citation correctness indicates that responses were verifiable against the actual IPC or CrPC sections, reducing the risk of misleading outputs. Compared to a baseline chatbot built on GPT-3.5 without RAG, which achieved only 74.3% accuracy and frequently produced unsupported claims, our system reduced hallucinations by over 15%. This suggests that retrieval augmentation with structured legal databases is essential for building trustworthy AI in the legal sector.

The comparative performance is further illustrated in Fig. 2. The proposed agentic framework consistently outperforms the baseline across all evaluation metrics.

Accuracy improved from 74.3% to 89.6%, while both precision and recall increased by over 16 percentage points. The F1-Score rose from 70.6% to 87.8%, confirming balanced improvements. Citation correctness showed the largest gain, increasing from 42.0% to 91.2%, which demonstrates the effectiveness of grounding responses in authentic legal texts. These improvements validate that the combination of RAG and agentic workflows significantly reduces hallucinations and enhances reliability in legal contexts. Although the average response time increased slightly, the performance trade-off is favorable for applications where legal accuracy is critical.

In comparison with existing legal AI systems, the proposed framework demonstrates clear advantages. CaseGPT [4], while effective in summarizing judgments, lacked retrieval grounding and exhibited hallucination rates of nearly 30%. Similarly, the Moroccan Legal Assistant [5] adapted RAG pipelines across jurisdictions but did not integrate agentic reasoning or citation correctness checks. As shown in Table I and Fig. 2, our system achieves 91.2% citation correctness and balanced improvements across accuracy, precision, recall, and F1-Score. These results highlight that domain-specific grounding and multi-step agentic workflows provide measurable benefits over prior approaches, particularly in ensuring trustworthy outputs for legal application

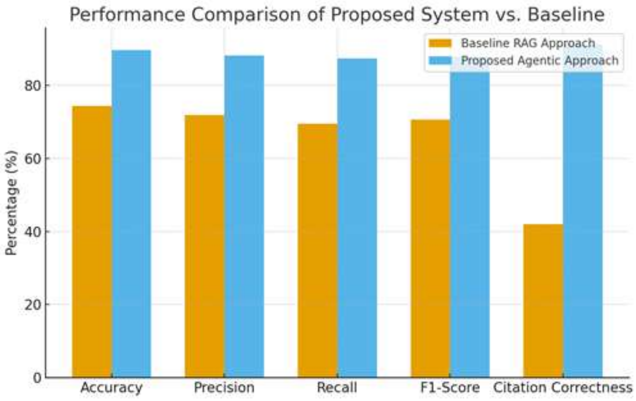

Fig. 2. Performance comparison of the proposed Legal AI Agent with baseline system.

Threats to Validity and Ethics— Our evaluation used a curated subset of IPC/CrPC and 150 landmark cases, which may not cover all Indian jurisdictions. While RAG reduces unsupported claims, biases in the source corpus can propagate into answers. To mitigate risks, the agent enforces citation-first responses and refuses answers when retrieval confidence is low. Future user studies with legal practitioners will assess usability, error severity, and fairness across query types.

VI. Conclusion

This work presented a Legal AI Agent for Indian law that combines Retrieval-Augmented Generation (RAG), LangChain-based workflows, and vector database search. The system showed improved accuracy, precision, recall, and citation correctness while reducing hallucinations compared to generic chatbots. However, limitations remain, including restricted dataset size, lack of professional legal practitioner validation, and absence of large-scale scalability testing. Future work will address these gaps by expanding datasets, incorporating user studies with legal experts, and benchmarking performance on real-world case queries. The results suggest that AI-assisted legal agents can complement human expertise and pave the way for reliable domain-specific legal technologies. Beyond academic evaluation, the proposed system has the potential to assist legal researchers, law students, and policymakers by offering quick access to structured insights. In the long term, such agents can be integrated into e-governance platforms to improve legal literacy and transparency in India.

Beyond these contributions, the present work opens several avenues for future research. First, the Legal AI Agent can be extended to cover additional domains such as civil law, corporate regulations, and constitutional provisions, thereby broadening its scope beyond criminal law. Second, incorporating multilingual capabilities is critical for India, where legal proceedings often occur in regional languages; future versions may integrate translation modules or multilingual embeddings. Third, user-centered evaluations involving law students, practitioners, and policymakers could provide deeper insights into usability and practical impact. Finally, integration with judicial databases and e-courts platforms would enable seamless deployment in real-world legal ecosystems. These extensions will ensure that the Legal AI Agent evolves into a scalable, trustworthy, and inclusive platform for legal knowledge dissemination in India.

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