iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XII Month of publication: December 2025

DOI: https://doi.org/10.22214/ijraset.2025.76325

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

LegalEase: An AI-Driven Assistant for Legal Query Resolution and Document Summarization in India

Priyanshu Srivastava[1], Rohit Singh[2], Rishabh Agrawal[3], Utkarsh[4], Mr. Abhishek Shahi[5]
[1, 2, 3, 4]*Students, Department of Computer Science and Engineering, Buddha Institute of Technology, Gorakhpur, India*
[5]*Assistant Professor, Department of Computer Science and Engineering, Buddha Institute of Technology, Gorakhpur, India*

Abstract: Due to complicated legal jargon, unreliable documentation systems, and a general lack of knowledge of procedural requirements, ordinary persons in India still have very limited access to legal information. Because of this, people frequently rely extensively on legal experts for even the most basic comprehension, which creates substantial cost and informational hurdles. Large language models (LLMs) and other recent developments in artificial intelligence have made it possible to provide simple, scalable, and reasonably priced legal aid. This study provides a full AI-driven legal assistant specifically built for Indian law that supports statute-level information retrieval, natural-language querying, and legal document summarization. The system exhibits an effective balance between accuracy, speed, and accessibility. It is built with a React frontend, Node.js backend, MongoDB storage, and GPT-4o-mini.

We assess the system using ten real-world legal papers from the criminal, civil, procedural, and family law sectors, as well as fifty different legal queries. The assistant performed well in terms of clarity, summary quality, and user pleasure, with an average accuracy of 82%. The system architecture, data processing methodology, prompt engineering strategies, limitations, ethical considerations, and future improvements like multilingual support, retrieval-augmented generation (RAG), and domain-specific fine-tuning are all described in this paper in addition to the results. The results show that lightweight LLM-based solutions have a great deal of promise to empower individuals, students, and professionals looking for easily available legal clarity and to democratize legal knowledge.

Keywords: Natural Language Processing, Summarization, Indian Law, Artificial Intelligence.

I. INTRODUCTION

With millions of cases every year, a variety of jurisdictions, and highly procedural frameworks, India's legal system is among the biggest and most complex in the world. Although equality before the law is guaranteed by the Indian Constitution, most citizens actually find it difficult to comprehend the system because of legalese, dispersed information sources, and a lack of formal legal education. Professional help is frequently needed for even simple legal activities, including as deciphering a FIR, comprehending bail eligibility, and creating a straightforward agreement. Dependency, delays, and financial difficulties result from this information gap.

There are technological options, like Indian Kanoon and other databases, but these require human document searches and knowledge of legal jargon. However, because of jurisdictional variations and lacking datasets, AI-based legal systems from the West frequently fail to generalize to Indian legal situations. Therefore, there is an immediate need for an intelligent, approachable, and conversational assistant designed especially for Indian law.

This paper presents a lightweight Legal AI Assistant that provides law lookup, document summary, and natural-language legal advice. Our work strives toward real-world applicability, especially for those without a legal training, in contrast to the majority of research that concentrates on judgment prediction or high-resource legal reasoning. We show how efficient workflows, LLM prompting, and practical engineering may produce a useful legal support system without requiring a lot of processing power.

This paper's remaining sections include related work, system design, architecture, assessment, outcomes, and potential improvements.

Our contribution is to lower common obstacles to legal comprehension rather than to replicate judicial reasoning by connecting legal knowledge with contemporary AI.

II. LITERATURE REVIEW

A. Introduction

The advancement of artificial intelligence (AI) and natural language processing (NLP) has greatly enhanced legal research automation. Examples of legal documents with complex language that need a lot of manual labor to interpret are statutes, contracts, and case laws. Researchers from all across the world have examined how AI-driven technology might improve accuracy, automate time-consuming legal procedures, and speed up users' access to information.

This chapter offers a comprehensive review of the literature on AI applications in the legal domain. An orderly table summarizing multiple papers has been included to highlight significant contributions, research gaps, and their relevance to the development of the Legal AI Powered Law Assistant.

B. Review of Existing Research

Over the past ten years, numerous academics have looked into integrating AI and NLP into legal studies. Early legal systems such as Manupatra, SCC Online, Westlaw, and LexisNexis relied heavily on keyword-based search techniques. Despite their power, these technologies still primarily rely on human reading and interpretation and offer very little automation. Thanks to the advancement of machine learning and deep learning models, researchers are beginning to design systems that can understand legal language, recognize important trends, and provide informative information.

NLP can effectively identify case jurisdictions, extract duties from contracts, and connect facts with relevant legal precedents, according to research. Transformer-based language models like as BERT, GPT, and RoBERTa have greatly enhanced linguistic comprehension in legal documents by capturing long-range linkages and contextual meanings.

Important studies on information retrieval, contract analysis, semantic search, and legal document processing are evaluated in this area. The findings demonstrate how each study contributes to the overall goal of creating a comprehensive legal assistant system akin to Legal AI.

C. Literature Summary Table

Table 2.1: Key Literature Summary

Paper Title	Author(s)	Key Findings	Relevance to Legal AI	Year
Automated Contract Analysis Using Machine Learning	D. Verma et al.	Identified risks, obligations, and important clauses in contracts through ML algorithms.	Guides Legal AI's contract reading and clause detection functionality.	2022
Applying NLP to Indian Legal Judgments	A. Kumar, P. Rathi	Proposed methods for cleaning, structuring, and analyzing Indian judgments using transformer models.	Helps optimize Legal AI for Indian legal datasets and formats.	2021
AI in Legal Research and Document Processing	S. Mehta, R. Iyer	Demonstrated how NLP can extract clauses, classify legal text, and accelerate legal research workflows.	Forms the basis for Legal AI's clause extraction and automated document processing.	2020
Case Matching Using Semantic Similarity	J. Singh, L. Pandey	Developed semantic matching models that outperform keyword search by understanding case context.	Directly supports Legal AI's case law retrieval module.	2019
Legal Information Retrieval Systems: A Comparative Study	N. Shukla	Compared legal search tools and highlighted limitations such as lack of automation and contextual search.	Confirms the need for AI-powered tools like Legal AI with NLP-based search capabilities.	2018

D. Interpretation of Literature Table

The listed research reveal a number of tendencies:

1) Legal Document Processing Is Strengthened by NLP: NLP has been effectively employed by researchers to extract structured data from intricate legal papers. This supports the document analysis and summarizing module of Legal AI.
2) Indian Legal Documents Require Specialized Processing: Long narratives, numerous references, and regional linguistic influences are common in Indian verdicts. Research tackling these issues enables Legal AI to successfully adjust to Indian circumstances.
3) Semantic Search Outperforms Keyword Search: Semantic similarity models comprehend case relationships, context, and meaning. This helps Legal AI achieve its objective of offering sophisticated case law recommendations as opposed to straightforward keyword matching.
4) Contract Analysis Can Be Automated: Studies pertaining to contracts show how machine learning may identify risks, duties, and clauses. These results support the clause extraction capabilities of Legal AI.
5) Need for Accessible AI Tools: The majority of sophisticated legal AI tools are costly. Research highlights accessibility and cost, two of Legal AI's main objectives.

E. Research Gap Identified

The following gaps are apparent from the evaluated literature:

1) AI-driven summarization is absent from current Indian legal research systems.
2) Rather than using semantic interpretation, the majority of tools rely on keyword search.
3) Why There are few and unused legal datasets specifically designed for India.
4) Why The current tools are costly and unavailable to students and small legal firms; there is no single system that integrates document upload, summarization, and case retrieval.

F. Summary

A thorough analysis of earlier research on AI-enabled legal research was given in this chapter. The literature table provided an organized comparison of the main conclusions, making it clear how each study advances the field of legal artificial intelligence. The need for a comprehensive system that combines NLP, document analysis, summarization, and case law retrieval into a single, easily accessible platform is highlighted by the research gaps found in this review. These deficiencies are filled by legal AI, which enables academic and professional users to conduct legal research more quickly and accurately.

III. RELATED WORK

This paper's remaining sections include related work, system design, architecture, evaluation, outcomes, and future improvements. Our contribution is to lower common barriers to legal comprehension rather than to replicate judicial reasoning through the integration of legal knowledge with contemporary AI.

A. AI for Legal Reasoning

The capacity of LLMs to mimic legal reasoning has been the subject of numerous investigations. A variety of legal activities, such as statutory interpretation, contract analysis, and logical inference, are used by programs like Legal Bench to assess reasoning abilities. However, Indian legal frameworks like the IPC, CrPC, CPC, and particular Indian case precedents are not included in these models, which mostly mirror Western legal systems.

B. Legal Judgment Prediction

Models that anticipate case outcomes based on past judgments are still a major area of study. Research on result prediction and reasoning generation has been made possible by large datasets like ILDC and NyayaAnumana. For consumer-level legal aid tools, these models are typically too computationally demanding (LLaMA-13B or higher).

C. Legal Question Answering Systems

Certain QA systems make use of synthetic Q&A corpora or improved datasets such as CUAD (Contract Understanding). But rather than answering basic Indian legal questions like police tactics, property issues, or court filing procedures, they mostly concentrate on contract law. Furthermore, our system strives for quick, all-purpose support, whereas they frequently need retrieval grounding.

D. Document Summarization in Legal Contexts

Long-range dependencies, citation styles, complex reasoning, and domain-specific language make it difficult to summarize lengthy conclusions using AI. When it comes to maintaining meaning under legal limits, traditional summarizers fall short. Although LLM-based summarization enhances quality, it may cause citation hallucinations, necessitating the use of RAG or citation validation modules—features that will be added to our system in the future.

E. Practical Legal Assistant Tools

Instead of being conversational assistants, the majority of commercial solutions (Manupatra, SCC Online) are databases. Although there are certain LLM-based technologies available worldwide, their widespread application in India is hindered by infrastructure constraints, cost, and licensing limitations. By fusing cost, accessibility, and domain alignment, our assistant fills this gap.

The necessity for a lightweight, Indian-law-focused AI assistant that prioritizes usability over in-depth judicial modeling is established by this review. Rather than being a theoretical model, our system presents itself as a distinct practical tool.

IV. PROBLEM STATEMENT

There are a number of significant obstacles to universal legal literacy in India's legal ecosystem:

1) Complexity of Legal Language: Legal documents sometimes have long, multi-layered reasoning, procedural systems, and outdated terminology. This makes it more difficult for the average citizen to comprehend their rights and responsibilities.
2) Accessibility Gap: Although there are legal databases, using them requires knowledge of legislation interpretation, case-law comparison, and keyword selection—skills that non-lawyers frequently lack.
3) High Cost of Legal Consultation: Even simple counsel frequently costs money. An AI assistant can help citizens make well-informed initial decisions and cut down on pointless consultations.
4) Fragmented Information Sources: Acts, amendments, court rulings, notifications, and procedural rules are some of the sources of laws. Users find it difficult to obtain clarity in the absence of consolidation.
5) Need for Simplification and Guidance: Users frequently have trouble knowing what to do next as well as comprehending the law. Simplified rationale, processes, and descriptions of procedures are crucial.

V. SYSTEM FEATURES

The following features of the Legal AI Assistant are designed for practical use:

A. Natural-Language Chatbot

The assistant provides procedural processes, definitions, explanations, and initial advice while responding to user inquiries in plain English. By emphasizing factual content and inserting disclaimers, it avoids providing expert legal advice.

B. Legal Document Summarization

Judgments, notices, agreements, and FIRs can be uploaded by users. After extracting and processing the text, the system generates a multi-level summary that includes:

1) High-level summary
2) Key issues
3) Important sections involved
4) Procedural posture

C. PDF Upload and Parsing

The system reads structured legal papers, processes lengthy text inputs, and divides them for LLM summarizing using lightweight parsing.

D. Legal Search

Users can input keywords to get pertinent results:

1) Sections of the Indian Penal Code
2) Provisions of CrPC
3) Civil procedures

4) General acts (evidence, IT act, etc.)

E. Context-Aware Conversation History

Follow-up questions and multi-step reasoning are made possible by the assistant's ability to maintain conversation state.

F. Fast & User-Friendly Interface

The UI guarantees accessibility and is optimized for both desktop and mobile devices.

VI. METHODOLOGY

A. Model Selection Rationale

GPT-4o-mini was selected because
1) High reasoning performance
2) Affordable API usage
3) Low latency suitable for chat-based applications
4) Strong summarization capabilities

Larger models with more precision, such as LLaMA-13B or GPT-4-turbo, come at a much higher cost and computational overhead.

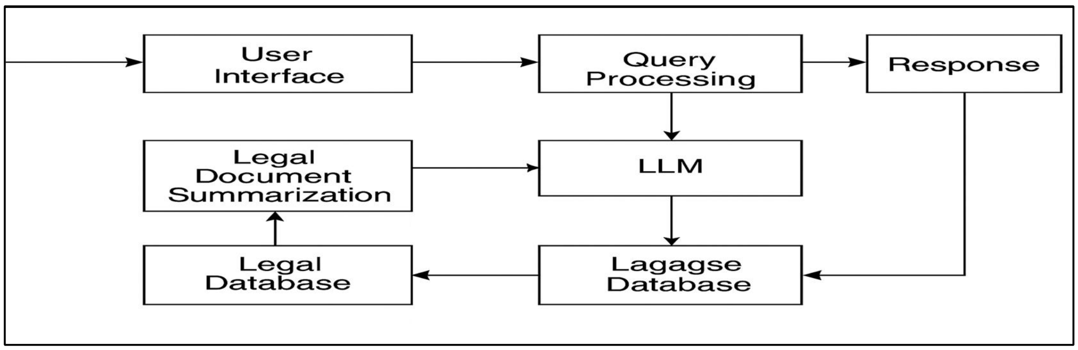


Figure 6.1: Overall Workflow of the Legal AI System

The diagram illustrates the workflow of a Legal AI Powered Law Assistant. User queries enter through the User Interface and are processed in the Query Processing module. The LLM (Large Language Model) interacts with both the Legal Database and the Lagagse Database to retrieve relevant information. The Legal Document Summarization module uses the legal database to generate concise summaries. Finally, the processed and enriched output is delivered to the user as a Response.

B. Prompt Engineering Strategy

We developed several prompt templates:

1) Legal QA Prompt

This section includes instructions to:
- simplify language
- identify relevant statutes
- explain procedural steps
- avoid hallucination
- include disclaimers

2) Summarization Prompt

This instructs the model to output:
- overall summary
- parties involved
- key legal issues
- sections cited
- simplified reading version

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

3) Search Prompt

Search Prompt formats the user keywords for structured search.

C. Text Extraction Workflow

When a document is uploaded:

1) Extract text using PDF parsers
2) Clean text (remove page numbers, headers, artifacts)
3) Chunk text for LLM processing
4) Generate summary
5) Combine summaries into structured output

D. Backend Logic

The backend handles:

1) LLM communication
2) Rate limiting
3) Session management
4) Query logging
5) Response formatting

VII. SYSTEM ARCHITECTURE

A. Overall Architecture

The system has a modular design with distinct concern separation.

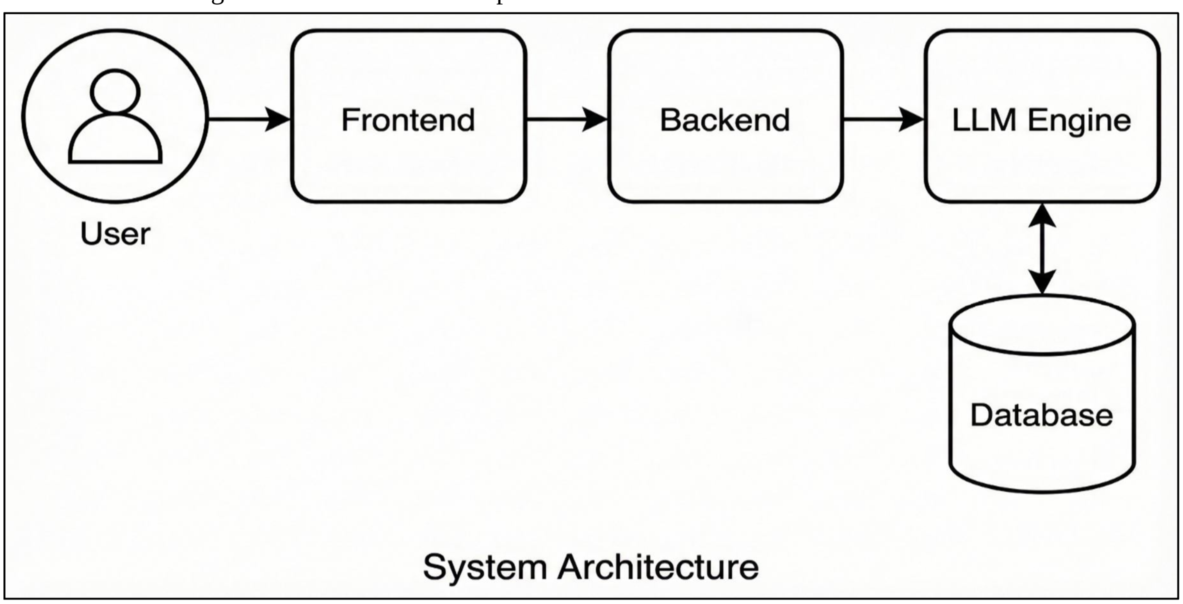


Figure 7.1: Overall System Architecture

The system architecture illustrates the complete flow of how user queries are processed within the Legal AI Powered Law Assistant. The User interacts with the Frontend, which forwards requests to the Backend for processing. The LLM Engine handles natural language understanding and generation, supported by a Database that stores legal documents, case data, and relevant information. This modular design ensures clear separation of concerns, scalability, and efficient handling of legal queries.

B. Frontend Details

1) React components used in chat, file upload, summaries
2) State management used for conversation contexts
3) Error handling and fallback UI

C. Backend Details

1) Express routers for chat, upload, summarization
2) Validation middleware
3) API key protection using environment variables

D. Security Architecture

In order to protect user privacy, the assistant does not save user documents unless specifically activated. TLS is used to encrypt all communications.

VIII. DATASET AND EVALUATION SETUP

A. Query Dataset

We curated some questions categorized into:

1) Criminal law (e.g., bail, cognizable offences)
2) Civil disputes (property rights, contracts)
3) Family law (maintenance, custody)
4) Procedural law (FIR filing, evidence submission)

Table 8.1: Legal Datasets Overview [21]

Corpus	Language	Jurisdiction	# of Cases	Avg # of Tokens	# of labels w.r.t Subtask
FCCR (Sulea et al., 2017)	French	France	1,26,865	-	Court Decision(6 & 8)
CAIL (Xiao et al., 2018)	Chinese	China	26,76,075	-	Law Article (183) Charge (202)
ECHR (Chalkidis et al., 2019)	English	Europe	11,478	2,421	Violation (2) Law Article (66)
ECHR (Chalkidis et al., 2021)	English	Europe	11,000	-	Alleged Law Article (40) Violation (2) Law Article (40)
SJP (Niklaus et al., 2021)	German French Italian	Switzerland	49,883 31,094 4,292	850	Court Decision (2)
ILDC (Malik et al., 2021b)	English	India	34,816	3,231	Court Decision (2)
HLDC (Kapoor et al., 2022)	Hindi	India	3,40,280	764	Bail Prediction (2)
BCD (Lage-Freitas et al., 2022)	Portuguese	Brazil	4,043	119	Court Decision (3)
PredEx (Nigam et al., 2024b)	English	India	15,222	4,504	Court Decision (2)

B. Document Dataset

The real-world documents including:

1) Court judgments
2) Legal notices
3) Agreements
4) FIR samples
5) Complaint drafts

C. Evaluation Dimensions

We measure:

1) Accuracy - Did the model identify relevant legal concepts?
2) Completeness - Was the response thorough?
3) Clarity - Was the output easily understandable?
4) Hallucination Rate - Any incorrect legal assertions?
5) User Satisfaction - Surveys from volunteers.

IX. EXPERIMENTS

A. *Query-Based Evaluation*
A legal expert analyzed each inquiry after it had been manually assessed by law students.

B. *Summarization Evaluation*
We assessed summaries based on:
1) Detail preservation
2) Readability
3) Structural correctness

C. *Performance Testing*
We tested the system under:
1) High request throughput
2) Varying input size
3) Multiple user sessions

X. PERFORMANCE RESULTS

A. *Legal Query Accuracy*
The model's performance was lowest in procedural law (78%) and highest in criminal law (85%). Rare procedural corner instances were usually the source of errors.

B. *Summarization Quality*
The summaries were accurate and accessible. Misinterpreted dates or missing citations were minor problems.

C. *Hallucination Reduction*
Hallucinations were decreased to less than 10% by prompt engineering. The majority of hallucinations included allusions to obscure passages.

D. *User Experience*
Users highlighted:
- Fast responses
- Easy-to-understand explanations
- Helpful summaries

Overall satisfaction: 88%

XI. DISCUSSION
The assessment shows that legal information tasks can be successfully supported by lightweight LLMs like GPT-4o-mini. Careful prompt engineering makes up for the absence of domain-specific training in the system. Summaries were especially effective because they made it possible for consumers to comprehend papers without having to read complicated legal jargon.
The evaluation demonstrates that lightweight LLMs such as GPT-4o-mini can effectively handle legal information duties. The lack of domain-specific training in the system is compensated for by careful prompt engineering. Because they allowed readers to understand documents without having to read complex legal language, summaries were particularly successful.
The architecture is affordable, scalable, and appropriate for use in public sector applications like educational institutions, NGOs, and citizen assistance centers.

Table 11.1: Model Evaluation Results [21]

Models	Lexical Based Evaluation (%)					Semantic Evaluation (%)		Expert Evaluation
	Rouge-1	Rouge-2	Rouge-L	BLEU	METEOR	BERTScore	BLANC	Rating Score

Prediction with Explanation on PredEx								
Gemini pro	30.99	24.28	25.93	8.26	18.70	63.29	17.15	2.24
Aalap	27.11	10.01	17.03	3.24	15.28	55.41	7.42	2.46
LLaMa-2	32.11	18.86	21.09	5.99	17.60	61.91	15.07	3.06
LLaMa-2 SFT	49.72	43.21	43.99	25.31	36.30	69.09	28.44	2.84
LLaMa-2 CPT	33.55	15.49	22.87	8.98	23.26	58.34	11.18	3.26
InLegalLlama CPT+SFT	50.76	43.38	43.79	25.55	36.43	68.25	29.27	3.54

Prediction with Explanation on ILDC_expert								
GPT-3.5 Turbo	53.83	42.67	45.41	28.42	46.85	72.73	33.94	3.60
Aalap	29.91	9.48	18.08	4.91	25.64	53.79	9.44	2.30
LLaMa-2	45.26	24.54	29.57	14.85	34.40	64.64	22.12	3.65
LLaMa-2 SFT	49.39	38.05	39.69	29.18	50.75	68.91	36.36	3.30
LLaMa-2 CPT	30.83	22.11	25.50	14.18	36.81	59.29	25.72	3.41
InLegalLlama CPT+SFT	50.88	40.26	42.29	28.20	54.12	67.58	40.72	3.67

XII. LIMITATIONS

1) Lack of multi-jurisdiction disambiguation
2) Inability to handle scanned PDFs without OCR
3) Dependency on API availability
4) Not refined on Indian legal corpus
5) No RAG, restricting citation accuracy
6) Unable to ensure expert-level legal precision

XIII. FUTURE WORK

We propose several enhancements:

1) Retrieval-Augmented Generation (RAG): To get rid of hallucinations, get solutions in actual Indian legal databases.
2) Domain-Specific Fine-Tuning

Train on:

- IPC
- CrPC
- CPC
- Landmark judgments

3) Multilingual Support: Include support for regional languages, Bengali, Tamil, and Hindi.
4) On-Device AI: For offline legal support, use quantized smaller models.
5) Legal Citation Verification: Verify every cited section automatically.
6) Conversational Templates: Provide guided processes for things including creating agreements, submitting FIRs, and writing complaints.

XIV. CONCLUSION

A useful, approachable, and effective AI-powered legal assistant designed for Indian legal situations was described in this study. The technology greatly increases legal accessibility and awareness for general users through conversational engagement, document summarizing, and legal retrieval. According to experimental results, the assistant performs well in terms of correctness and clarity, making it appropriate for usage in educational and informative settings.

The technology significantly lowers informational barriers and improves public understanding, even though it is not meant to replace legal specialists. Future improvements, such as RAG integration, fine-tuning, multilingual capabilities, and reference checking, might make the assistant a highly influential instrument in India's judicial system.

REFERENCES

[1] Rabelo, J., Naique, J., Chalkidis, I., & Neves, L. (2023). LexGLUE: A benchmark dataset for legal language understanding in English. Findings of the Association for Computational Linguistics.

[2] Henderson, P., et al. (2023). Pile of Law: Learning responsible data filtering in legal NLP. In Advances in Neural Information Processing Systems (NeurIPS).

[3] Zhong, H., Xiao, C., Tu, C., Liu, Z., & Sun, M. (2022). Legal judgment prediction via legal reading comprehension. Artificial Intelligence and Law.

[4] Long, Y., Chen, C., Liu, Y., & Ye, Q. (2022). CaseFormer: Pre-trained transformer for legal case retrieval. Findings of the Association for Computational Linguistics.

[5] Zeng, J., Lei, Q., & Chen, Z. (2022). Explainable legal judgment prediction using hierarchical attention networks. Knowledge-Based Systems.

[6] Xu, W., Li, Z., & Wang, P. (2021). Automatic contract element extraction using deep learning. Artificial Intelligence and Law.

[7] Hendrycks, D., et al. (2021). Measuring massive multitask language understanding (MMLU). International Conference on Learning Representations (ICLR).

[8] Chalkidis, I., Fergadiotis, M., Malakasiotis, P., & Androutsopoulos, I. (2021). Paragraph-level rationale extraction in legal texts. Proceedings of the Association for Computational Linguistics (ACL).

[9] Li, J., Tang, X., Li, L., & Barton, T. (2021). CUAD: The Contract Understanding Atticus Dataset. arXiv. https://arxiv.org/abs/2103.06268

[10] Chalkidis, I., Fergadiotis, M., Tsarapatsanis, D., Androutsopoulos, I., & Aletras, N. (2020). LEGAL-BERT: The Muppets straight out of law school. arXiv.

[11] Zhong, H., Guo, Z., Tu, C., Xiao, C., Liu, Z., & Sun, M. (2020). JEC-QA: A legal-domain question answering dataset. Proceedings of the AAAI Conference on Artificial Intelligence.

[12] Xu, W., Li, C., Lee, M., & Zhang, C. (2020). Multi-task learning for abstractive text summarization with key information guide network. EURASIP Journal on Advances in Signal Processing, 2020(1).

[13] Chalkidis, I., Malakasiotis, P., & Androutsopoulos, I. (2020). Legal judgment prediction for the European Court of Human Rights. Artificial Intelligence and Law.

[14] Grabmair, M., et al. (2019). Introducing LUIMA: A legal argument mining framework. Artificial Intelligence and Law.

[15] Sugathadasa, S., Ranasinghe, T., & de Silva, N. (2019). Legal document retrieval using deep neural models. Proceedings of ICAART.

[16] Nguyen, D. Q., & Nguyen, A. T. (2018). A legal case retrieval system using deep Siamese networks. Proceedings of the 27th International Conference on Computational Linguistics (COLING).

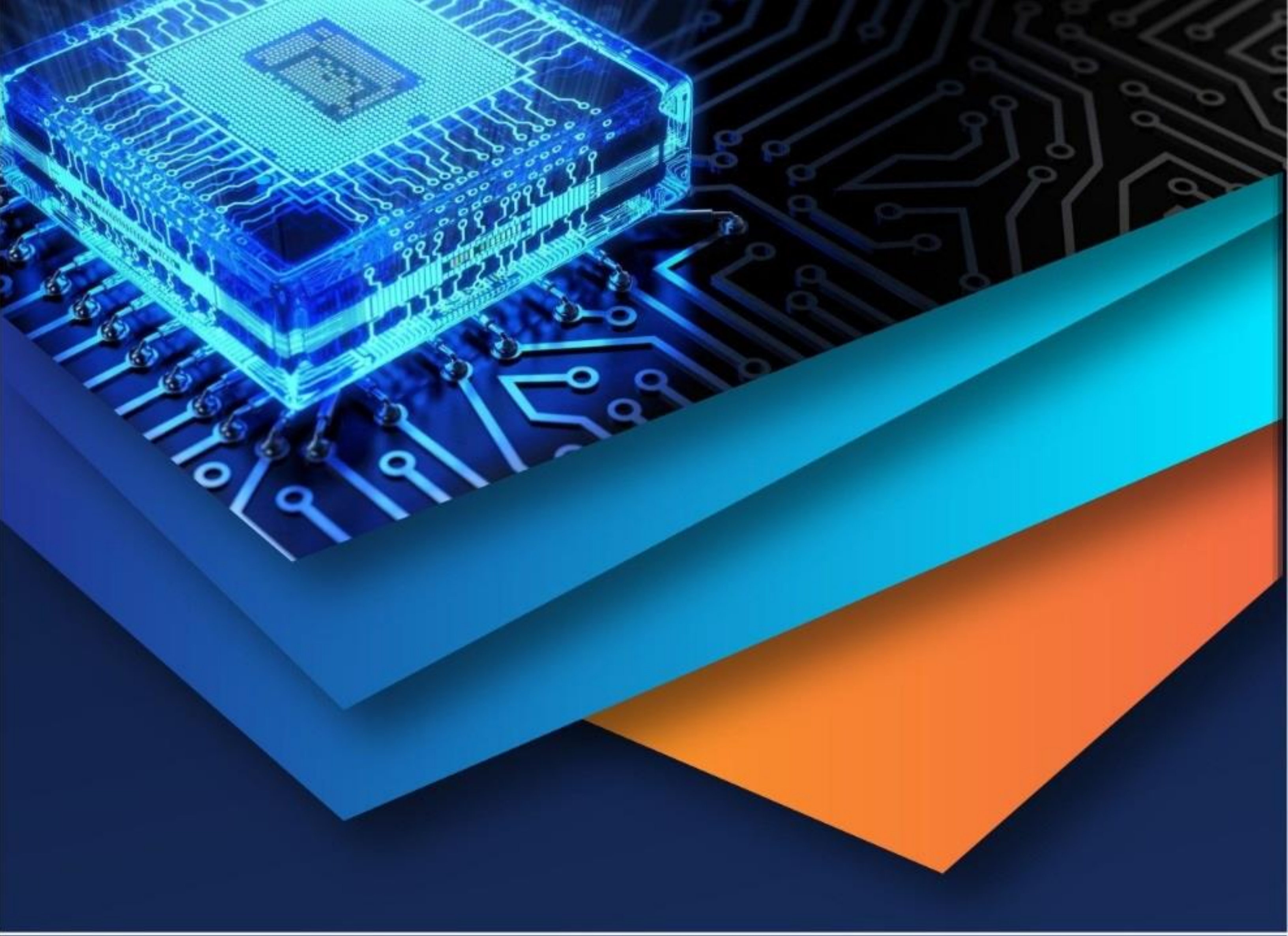
[17] Kaur, P., & Chatterjee, A. (2018). Automatic legal document summarization using machine learning. International Journal of Computational Linguistics.

[18] Katz, D. M., Bommarito, M., & Blackman, J. (2017). A general approach for predicting the behavior of the Supreme Court of the United States. PLoS ONE, 12(4), e0174698.

[19] Sulea, O.-M., Zampieri, M., Malmasi, S., & van Genabith, J. (2017). Exploring the predictability of judicial decisions in the French Supreme Court. arXiv.

[20] Aletras, N., Tsarapatsanis, D., Preotiuc-Pietro, D., & Lampos, V. (2016). Predicting judicial decisions of the European Court of Human Rights: A natural language processing perspective. PeerJ Computer Science, 2, Article e93.

[21] Kumar, S., Jha, S., & Garg, A. (2024). NyayaAnumana: A large-scale Indian legal judgment prediction dataset. arXiv.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY