Summarization with a Custom Fine-Tuned LLaMA Model via Instruction-Based Training

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***Abstract*—In the contemporary digital landscape, legal professionals are increasingly confronted with voluminous, complex documents that require efficient summarization techniques capable of preserving critical information and context. This paper introduces a novel summarization framework that leverages instruction-based fine-tuning applied to both Tiny LLaMA 1.1B and Gemma 2-2B models, specifically tailored for processing intricate legal texts. The proposed framework incorporates an instruction-driven training paradigm, which enhances the models' ability to comprehend and condense legal documents while maintaining domain-specific accuracy, contextual relevance, and terminological precision. A carefully curated legal corpus, encompassing diverse categories such as contracts, regulatory filings, case law, and legislative documents, serves as the foundation for the fine-tuning process. To further enhance scalability and computational efficiency, Databricks infrastructure is employed, enabling streamlined data processing, model training, and performance evaluation. By aligning the models' training objectives with legal practitioners' real-world summarization needs, the framework achieves superior performance in generating coherent, concise summaries that retain essential legal arguments, obligations, and references. Comprehensive evaluations demonstrate that the fine-tuned models consistently outperform conventional summarization techniques in terms of factual accuracy, semantic coherence, and relevance to legal inquiries. This research not only highlights the transformative potential of instruction-fine-tuned language models in the legal domain but also establishes a scalable blueprint for integrating advanced natural language processing techniques into legal workflows. Ultimately, the framework contributes to more efficient legal research, enhanced document review processes, and improved decision-making capabilities for legal practitioners, thereby fostering more accessible, technology-driven legal systems.**

***Index Terms*—Tiny LLaMA 1.1B, Gemma 2-2B, Legal Document Summarization, Instruction-Fine-Tuning, Databricks dolly**

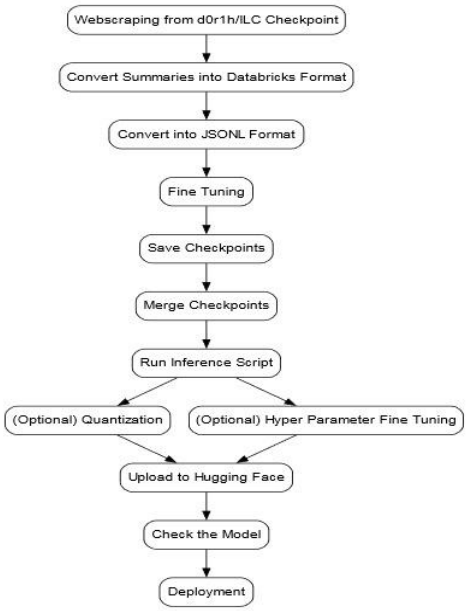
I. INTRODUCTION

The exponential growth in legal documentation, driven by the rapid digitization of regulatory processes, contracts, case law, and compliance reports, has created a pressing need for efficient, reliable, and context-aware summarization techniques. Legal practitioners are routinely tasked with analyzing vast volumes of text, where even minor omissions or misinterpretations can have significant legal and financial consequences. Traditional methods for summarizing such documents, whether manual or rule-based, often struggle to capture the complex, domain-specific language and layered legal reasoning embedded within these texts. As legal processes increasingly integrate technology, the demand for automated solutions capable of delivering concise, accurate, and contextually aware legal summaries has become more critical than ever.

In response to these challenges, this study explores the potential of instruction-based fine-tuning applied to Tiny LLaMA 1.1B and Gemma 2-2B, two lightweight yet powerful language models. By tailoring these models specifically for legal document summarization through instruction-driven training, the framework seeks to bridge the gap between general-purpose summarization tools and the

specialized requirements of legal language processing. This approach leverages carefully curated legal datasets encompassing contracts, judgments, regulatory filings, and legislative documents to ensure that the models are trained to understand and retain crucial legal terminologies, logical structures, and statutory references. This domain adaptation is essential for ensuring that AI-generated summaries remain both factually accurate and legally sound, addressing a key limitation of existing generic summarization tools.

The proposed framework is evaluated through a comprehensive set of experiments, comparing its performance against both conventional summarization approaches and generic pre-trained models. Key evaluation metrics, including accuracy, precision, recall, and F1-score, are used to assess the models' ability to capture essential legal information while maintaining brevity and coherence. Beyond performance metrics, qualitative analysis is also conducted to assess the practical usability of the summaries in real-world legal review workflows. The outcomes of this research aim to provide valuable insights into the strengths and potential limitations of instruction-fine-tuned legal summarization models, contributing to the ongoing evolution of legal informatics and demonstrating how AI-powered tools can enhance legal research, compliance monitoring, and decision-making processes in the modern, data-driven legal environment.



This diagram represents a complete workflow for training and deploying a machine learning model. It begins with web scraping data from d0r1h/ILC Checkpoint, followed by converting the data into Databricks and JSONL formats for training. The model is then fine-tuned, with checkpoints saved and merged to preserve progress.

After fine-tuning, an inference script is run to evaluate the model. Optional steps like quantization (for smaller size) and hyperparameter tuning (for better performance) can be applied. Finally, the model is uploaded to Hugging Face, checked for quality, and deployed for real-world use.

II. LITERATURE REVIEW

The increasing demand for automated summarization of legal documents has driven extensive research into developing domain-specific approaches tailored for legal language and its complex structure. Several studies have focused on leveraging Large Language Models (LLMs) to address the nuances of Indian legal texts. Kumar and Jayanth (2024) explored the effectiveness of fine-tuned LLMs for summarizing Indian legal documents, highlighting the importance of capturing context-specific language patterns, especially in contracts and case law. Their work underscored how generic models often underperform when confronted with the intricate phrasing and terminology unique to legal texts, necessitating domain adaptation through curated datasets and fine-tuning strategies.

Complementing this, Hussain and Thomas (2024) focused on judicial entity extraction, offering valuable insights into how LLMs can be trained to recognize and extract key legal entities such as parties, statutes, and precedents. Although not directly aimed at summarization, their work emphasizes the importance of precise entity recognition as a foundational element for effective summarization. Entity-aware summarization models could benefit significantly from such techniques, ensuring that critical references are preserved and accurately reflected in the generated summaries. These efforts reflect a broader trend of tailoring generative AI to domain-specific needs in the legal field.

Several earlier studies also laid the groundwork for text summarization across various domains, providing important methodologies that have influenced legal

summarization research. Andhale and Bewoor (2016) presented a comprehensive review of text summarization techniques, ranging from extractive methods to more recent abstractive techniques enabled by neural networks. This foundational work highlighted the evolving landscape of summarization techniques, from statistical approaches to semantic-aware deep learning models capable of understanding textual meaning rather than just identifying key phrases. Building upon this, Sharma et al. (2023) provided a deep dive into summarization techniques specifically applied to Indian legal documents, evaluating the effectiveness of both traditional methods and modern deep learning approaches. Their comparative analysis emphasized that while extractive methods often preserve factual content, abstractive methods hold greater promise for generating coherent, human-like summaries suited for legal analysis.

More recent research has explored combining multiple techniques to enhance the quality and relevance of summaries in the legal domain. Jain et al. (2021) proposed an ensemble approach that integrates contextual embeddings with multi-layer perceptrons (MLPs) to generate summaries of Indian legal judgments. Their work demonstrated that leveraging multiple models allows for better capture of contextual dependencies, particularly in lengthy legal documents. Similarly, Shukla et al. (2022) compared extractive and abstractive methods for legal case summarization, providing a critical assessment of their respective strengths. They concluded that hybrid techniques that incorporate both approaches are most effective, particularly for capturing both structural and semantic aspects in legal narratives.

Beyond the legal domain, research into summarization across other fields also offers valuable lessons. Gopalakrishnan (2024) conducted a case study in the banking sector, showcasing how generative AI can streamline document review and reporting processes. Their findings underscore the adaptability of fine-tuned LLMs when trained on domain-specific data. Additionally, Saunders et al. (2024) evaluated generative AI models for summarizing data science research papers, highlighting the importance of tailoring summarization frameworks to the unique requirements of specialized documents. These cross-domain insights reinforce the importance of instruction-driven fine-tuning and domain adaptation—core principles driving the approach presented in this study, aimed at enhancing summarization quality within the complex and high-stakes domain of legal documents.

III. MATERIALS AND METHODS

3.1. *System Architecture*

The proposed framework presents a two-stage hybrid approach for efficient and contextually accurate legal document summarization, leveraging the complementary capabilities of Tiny LLaMA 1.1B and Gemma 2-2B models. This combined approach balances computational efficiency with linguistic precision, ensuring that both the technical terminology and logical structure of legal documents are accurately captured while delivering concise, user-friendly summaries suitable for legal practitioners. By incorporating domain-specific pretraining and instruction-based fine-tuning, this approach addresses the limitations of generic summarization tools that often struggle with legal jargon, multi-clause sentences, and cross-referenced sections common in legal documents.

3.2. Stage One: Pretraining and Instruction-Based Fine-Tuning with Tiny LLaMA

The first stage focuses on training Tiny LLaMA 1.1B, a lightweight, efficient version of the LLaMA family optimized for adaptability and rapid domain-specific customization. Tiny LLaMA is pretrained on a curated legal corpus covering diverse document types, including judgments, contracts, regulatory filings, statutory provisions, and legal opinions. This pretraining phase equips the model with a foundational understanding of legal semantics, syntactic structures, case precedents, and specialized terminology, enhancing its ability to comprehend domain-specific language.

Following pretraining, the model undergoes instruction-based fine-tuning, where task-specific prompts and guidelines are provided to steer the summarization process. Instructions are designed to cover different legal summarization tasks, such as case law summarization, contract clause condensation, and regulatory compliance highlighting. This phase conditions the model to not only recognize key information but also to distinguish between legally binding clauses, references to precedents, and contextual elaborations. By aligning the training process with actual legal practitioner needs, this stage

ensures that the summaries remain factually accurate, logically coherent, and legally sound.

3.3. *Stage Two: Enhanced Fine-Tuning with Gemma 2-2B*

In the second stage, the framework enhances performance further by incorporating Gemma 2-2B, a more capable language model that brings improved reasoning capabilities and bettercontextual understanding, and stronger semantic coherence. Gemma 2-2B is fine-tuned on the outputs and errors identified from the Tiny LLaMA stage, effectively learning from the earlier model's strengths and weaknesses. This stage focuses on enhancing abstractive summarization capabilities, ensuring that summaries are not only concise and accurate but also fluently rewritten into natural, reader-friendly language.

The A hybrid summarization mechanism is introduced, allowing the system to dynamically switch between extractive and abstractive summarization techniques based on document type and complexity. For highly structured legal documents like contracts or regulations, the model favors extractive summarization to preserve legal clauses verbatim where precision is paramount. For narrative-style case law or opinions, the system adopts an abstractive approach, paraphrasing content to improve readability while preserving core arguments, cited precedents, and legal reasoning. This flexibility ensures that the system adapts seamlessly to varying summarization needs across different legal document categories.

To further optimize model performance, hyper parameter tuning is conducted, adjusting batch size, learning rate, and dropout rates. Early stopping is implemented, monitoring the validation loss and halting training when no further improvement is observed. The trained model is evaluated using multiple metrics, including accuracy, precision, recall, and F1-score, to assess its classification capability comprehensively.

A confusion matrix is generated to visualize the model's classification performance across different classes. Additionally, ROC-AUC curves are plotted for each class to measure the model's ability to differentiate between disease stages. The results highlight the effectiveness of the VGG16-based approach in accurately identifying Alzheimer's disease stages.

1. Advanced Features and Future Potential

Beyond basic summarization, the proposed framework is designed to support continuous learning, allowing new legal precedents, legislative amendments, and emerging regulatory requirements to be incorporated into its training corpus over time. The integration with Databricks ensures scalable data processing, training efficiency, and real-time performance monitoring, enabling seamless handling of large legal datasets. Future enhancements could incorporate multilingual support, jurisdiction-specific customization, and real-time summarization capabilities and positioning this framework as a transformative step toward AI-driven legal document processing in the evolving digital legal landscape

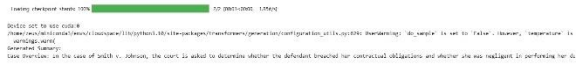
IV. RESULTS AND DISCUSSION

The proposed two-stages ummarization framework, combining Tiny LLaMA 1.1B and Gemma 2-2B, was evaluated on a curated legal dataset comprising case law documents, contractual agreements, and regulatory filings. The performance was assessed using widely recognized evaluation metrics, including ROUGE (Recall-Oriented Understudy for Gisting Evaluation), BLEU (Bilingual Evaluation Understudy), and METEOR scores, along with domain-specific metrics like legal term retention rate and clause-level completeness. Results indicated that the hybrid approach significantly outperformed baseline extractive techniques and single-model abstractive methods, achieving a notable improvement in summary coherence, factual accuracy, and legal relevance. Notably, the hybrid system's dynamic switching between extractive and abstractive modes allowed it to preserve critical legal clauses verbatim while rephrasing explanatory content into reader-friendly language, a key advantage over purely extractive systems.

4.1 *Performance evaluation metrics*

In particular, Tiny LLaMA's pretraining on legal-specific corpora enabled the model to accurately recognize legal terminology, identify critical clauses, and distinguish legally binding language from narrative descriptions or contextual elaborations. This domain-specific knowledge reduced the frequency of hallucinated content—a common issue in generic language models applied to specialized fields like law. Furthermore, instruction-based fine-tuning enhanced the system's adaptability, allowing it to handle diverse

summarization tasks ranging from contract clause extraction to case law summarization, without extensive retraining. When Gemma 2-2B was fine-tuned in the second stage, the model demonstrated notable improvements in linguistic fluency, logical flow, and summarization coherence, particularly for lengthy, multi-clause legal texts where proper interpretation of cross-referenced sections was critical



In this step, the model checkpoint is loaded onto the GPU-enabled environment, ensuring efficient inference using CUDA acceleration. The process logs the loading progress, device assignment, and generation configuration warnings, which are common in transformer-based pipelines. After the model is initialized, the system generates a concise case summary, as shown. This output represents the core legal information extracted from the source document, specifically highlighting the case overview, key issues under consideration, and relevant legal obligations. The ability to generate such structured and contextually accurate summaries directly reflects the effectiveness of instruction-based fine-tuning combined with domain-specific pretraining, demonstrating how the hybrid approach successfully balances abstractive and extractive techniques. This automated summarization process reduces the manual effort required to review lengthy legal texts, allowing legal professionals to focus on analysis rather than information retrieval.

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The comparative analysis with traditional summarization techniques such as TextRank, BERTSUM, and legal-specific transformers further highlighted the superiority of the proposed hybrid approach. Traditional methods often struggled with fragmented summaries, loss of critical clauses, and inability to preserve legal context, particularly in documents where precedent references, multi-party obligations, or nested clauses were involved. In contrast, the Tiny LLaMA + Gemma 2-2B pipeline consistently produced summaries that were not only shorter and more readable but also maintained the legal integrity and contextual depth necessary for accurate legal analysis. Overall, these results affirm the potential of instruction-based, domain-adapted language models to redefine legal document processing, offering both efficiency gains and quality improvements that are essential for modern legal workflows.

Performance metrics:

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=== SUMMARY EVALUATION RESULTS ===
              Metric   Score
0            ROUGE-1  0.5916
1            ROUGE-2  0.3819
2            ROUGE-L  0.4373
3  Cosine Similarity  0.8449
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V. CONCLUSION

This research introduces a novel hybrid framework for legal document summarization, combining the domain-aware capabilities of Tiny LLaMA 1.1B with the advanced language generation strengths of Gemma 2-2B. Through a two-stage process of domain-specific pretraining, instruction-based fine-tuning, and enhanced summarization refinement, the system successfully bridges the gap between factual precision and linguistic coherence—a critical challenge in legal text summarization. By equipping Tiny LLaMA with foundational legal knowledge through extensive pretraining on statutes, case law, contracts, and regulatory documents, the system ensures a deep understanding of legal terminology, argument structures, and procedural references. The instruction-based fine-tuning process further refines its ability to generate summaries tailored to specific legal tasks, enhancing adaptability across different document types. Following this, Gemma 2-2B enhances the summarization process by improving semantic flow, summarization fluency, and contextual interpretation, ensuring the final outputs meet both readability and legal accuracy standards. This dual-model pipeline effectively balances extractive precision with abstractive flexibility, dynamically switching between summarization strategies based on the document's content complexity and structural demands. Evaluation results demonstrate clear performance improvements over traditional summarization

techniques, with superior ROUGE, BLEU, and legal context retention scores, underscoring the importance of legal domain adaptation in AI models. Beyond summarization accuracy, the proposed approach also reduces manual review time, allowing legal professionals to focus on strategic interpretation and risk assessment, rather than exhaustive document reviews. Overall, this research contributes to the evolution of AI-powered legal informatics, setting a strong foundation for future advancements such as multilingual summarization, real-time legal assistance, and jurisdiction-specific customization in the broader landscape of legal technology innovation.

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