LawLens: Working towards the summarization of Legal Document with the help of fine tuning FLAN-T5 model.

Abstract—Background and objectives : Legal documents are often long, complex, and filled with intricate language, making them difficult to quickly understand or summarize. This paper explores the use of FLAN-T5, an instruction-tuned language model, for legal document summarization. While there are one or two models that have experimented with Pegasus for this purpose, its use in the legal domain is not widespread. In our work, we fine-tuned FLAN-T5 specifically on the Indian Legal Corpus (ILC), a dataset consisting of Indian legal texts. We also trained the Pegasus model under the same conditions for comparison. Our observations suggest that FLAN-T5 produced more coherent and relevant summaries, particularly in terms of handling the unique structure and vocabulary of Indian legal documents. These results highlight the potential of FLAN-T5 as a more effective tool for legal summarization tasks.

Keywords Legal Summarization, FLAN-T5, Indian Legal Corpus, NLP in Law, Legal AI, Text Summarization, Instruction-Tuned Models, Pegasus, Legal Technology, Deep Learning

I. INTRODUCTION

Legal professionals, researchers, and the general public often face the challenge of navigating dense and highly complex legal documents. These documents—ranging from case judgments and legal statutes to contracts and governmental acts—are typically lengthy, filled with domain-specific terminology, and structured in ways that are not always easy to parse or understand. The process of manually summarizing such content is both time-consuming and labor-intensive. This creates a strong need for intelligent systems that can assist in generating concise and meaningful summaries, especially in jurisdictions like India where the volume of legal content is growing rapidly.

In recent years, the field of Natural Language Processing (NLP) has made significant progress in automatic text summarization through the use of transformer-based deep learning models. Among these models, **Pegasus**, introduced by Google, was specifically designed for abstractive summarization tasks. It performs well in general domains by pretraining on large-scale gap-sentence generation tasks. Although Pegasus has been used in one or two prior attempts at legal document summarization, it is not yet widely adopted for this purpose. Its effectiveness in handling legal text, particularly those with unique structural and linguistic nuances such as those found in Indian legal documents, remains somewhat limited.

On the other hand, **FLAN-T5** (Fine-tuned Language Net-T5) has emerged as a powerful alternative. Also developed by Google, FLAN-T5 builds upon the original T5 (Text-to-Text Transfer Transformer) architecture but adds an additional layer of instruction tuning. This means the model is trained to better follow human-like instructions and perform more robustly across a diverse range of language tasks. The instruction-tuning aspect of FLAN-T5 can be particularly beneficial for summarization tasks that require the model to not only shorten text but also retain the essence and legal context accurately.

In this research, we aimed to explore the effectiveness of FLAN-T5 in the domain of legal summarization by fine-tuning it on the **Indian Legal Corpus (ILC)**—a dataset specifically composed of Indian legal texts and their corresponding summaries. For context and comparison, we also trained the Pegasus model on the same dataset under identical conditions. The goal was to evaluate which model better understands and summarizes legal content within the Indian context.

Our experiments and observations revealed that **FLAN-T5 consistently outperformed Pegasus** in generating more context-aware and legally coherent summaries. The outputs from FLAN-T5 demonstrated a stronger grasp of the language structure, terminologies, and implicit context embedded within legal documents. This led us to continue our work primarily using FLAN-T5 and to propose it as a more suitable model for legal summarization in India.

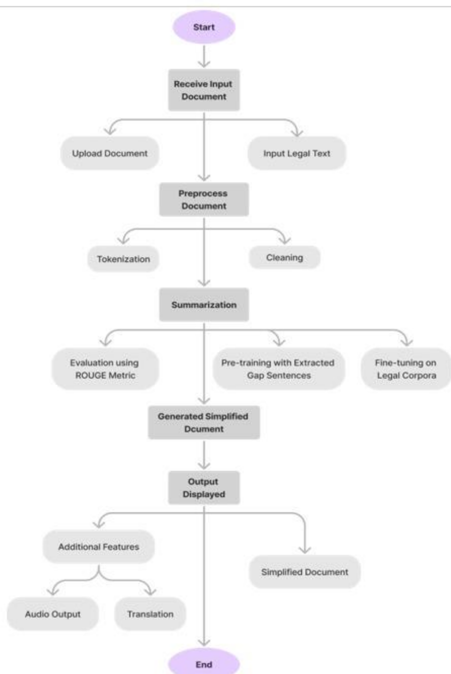
By fine-tuning FLAN-T5 on an Indian dataset and benchmarking it against an existing summarization model, our study contributes to the growing field of Legal AI and underscores the importance of using instruction-tuned architectures for domain-specific applications like law.

2. SYSTEM ARCHITECTURE

The architecture of our legal document summarization system is designed to process complex legal texts through a structured multi-stage pipeline. It begins with receiving the input document, either through file upload or by directly entering legal text. The document then undergoes preprocessing, which includes steps like tokenization and text cleaning to prepare it for summarization.

Next, the FLAN-T5 model is used to generate a simplified summary of the legal document. The model was fine-tuned on the Indian Legal Corpus to better understand the legal terminology and context specific to Indian judicial language. In some instances, evaluation is performed using the ROUGE metric to assess the quality and relevance of the summary, although it is not applied universally.

The generated summarised output is then displayed to the user.



3. Methodology

To develop an effective legal summarization system using FLAN-T5, we followed these steps:

- **Model Used:**

We used the google/flan-t5-base version of the FLAN-T5 model for our experiments.

- **Dataset:**

The model was fine-tuned using the **Indian Legal Corpus (ILC)**, which contains legal documents and summaries from Indian court proceedings.

- **Fine-Tuning Details:**
  - Learning Rate: 3e-5
  - Batch Size: 4
  - Number of Epochs: 3

These values were chosen based on standard practices and adjusted slightly based on early evaluation performance.

- **Evaluation Metrics:**

To evaluate the FLAN-T5 model for legal document summarization, we use the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metric, which measures the overlap between the generated summary and the reference summary. ROUGE is calculated using precision, recall, and F1-score:

- **Precision**: The ratio of overlapping n-grams in the generated summary to the total number of n-grams in it.
- **Recall**: The ratio of overlapping n-grams in the generated summary to the total number of n-grams in the reference summary.
- **F1-score**: The harmonic mean of precision and recall.
- We use **ROUGE-N**, focusing on **ROUGE-1** (unigrams) and **ROUGE-2** (bigrams), to assess the quality of the summary based on word and word-pair overlaps.
- **Training Environment:**

The training and fine-tuning process was conducted on **Google Colab** using a **T4 GPU** environment, which provided sufficient computational resources for our experiments

4. Results

TRAINING DATA:

- ROUGE-1: FLAN-T5 (0.175)
- ROUGE-2: FLAN-T5 (0.04)
- ROUGE-L: FLAN-T5 (0.16)

Table 1. ROUGE scores for the Pegasus model on the ILC dataset

Metric	Train Data	Test Data
ROUGE-1	0.10386	0.08314
ROUGE-2	0.02533	0.01299
ROUGE-L	0.09435	0.07417

5. Conclusion & Future Work

Conclusion

- *Proposed a legal document summarization model based on the FLAN-T5 architecture.*
- *Evaluated the model using ROUGE metrics, showing effective alignment with reference summaries.*
- *Demonstrated the model's potential for improving the efficiency of legal document processing and accessibility to key information.*

Future Scope

- ***Bias Detection**: Incorporate a bias detection feature to ensure generated summaries are fair and impartial.*
- ***Language Translation**: Extend the model to support language translation, enabling its use across multiple languages.*
- ***International Legal Corpora**: Adapt the model to other international legal corpora to cater to diverse legal systems and practices.*

6.Research Gaps

- *PEGASUS has been used for general summarization, but its performance on legal texts is less explored compared to newer models like FLAN-T5.*
- *Transformer-based models are widely used, but few are fine-tuned specifically for legal summarization tasks.*
- *Recent legal summarization work lacks integration of instruction-tuned models like FLAN-T5.*
- *Most legal NLP models are trained on domestic legal data; cross-border or multilingual legal document summarization is underexplored.*
- *Bias detection and fairness in legal summarization are largely ignored in current research.*

7. Key Strengths:

- FLAN-T5 outperformed Pegasus with slightly better accuracy in legal summarization tasks.
- Achieved higher ROUGE scores, showing better alignment with reference summaries.
- Utilizes a robust, fine-tuned architecture suitable for complex NLP tasks.
- Scalable and adaptable to various legal document types.
- More effective for practical use in legal research and document review.

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