IT5712
PROJECT I

Smart Legal Judgment Prediction System using Multi-Level Attention and Graph Augmented Reasoning

Progress Report - I

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1. Abstract

The Legal Judgment Prediction (LJP) module integrates multi-level attention and graph-augmented reasoning to predict legal outcomes from case facts. The model first preprocesses raw case documents and encodes them using a contextual language model, while a parallel graph construction stage organizes facts, statutes, and legal keywords into a heterogeneous knowledge graph. A Graph Attention Network refines node representations, and a cross-attention layer fuses textual and structural features to produce statute, charge, and sentence predictions. The JudgEx sub-module then generates human-readable explanations for these predictions, ensuring interpretability and transparency. This hybrid design outperforms traditional text-only models by combining semantic understanding with explicit legal relational reasoning, offering a step toward explainable AI-assisted judgment systems.

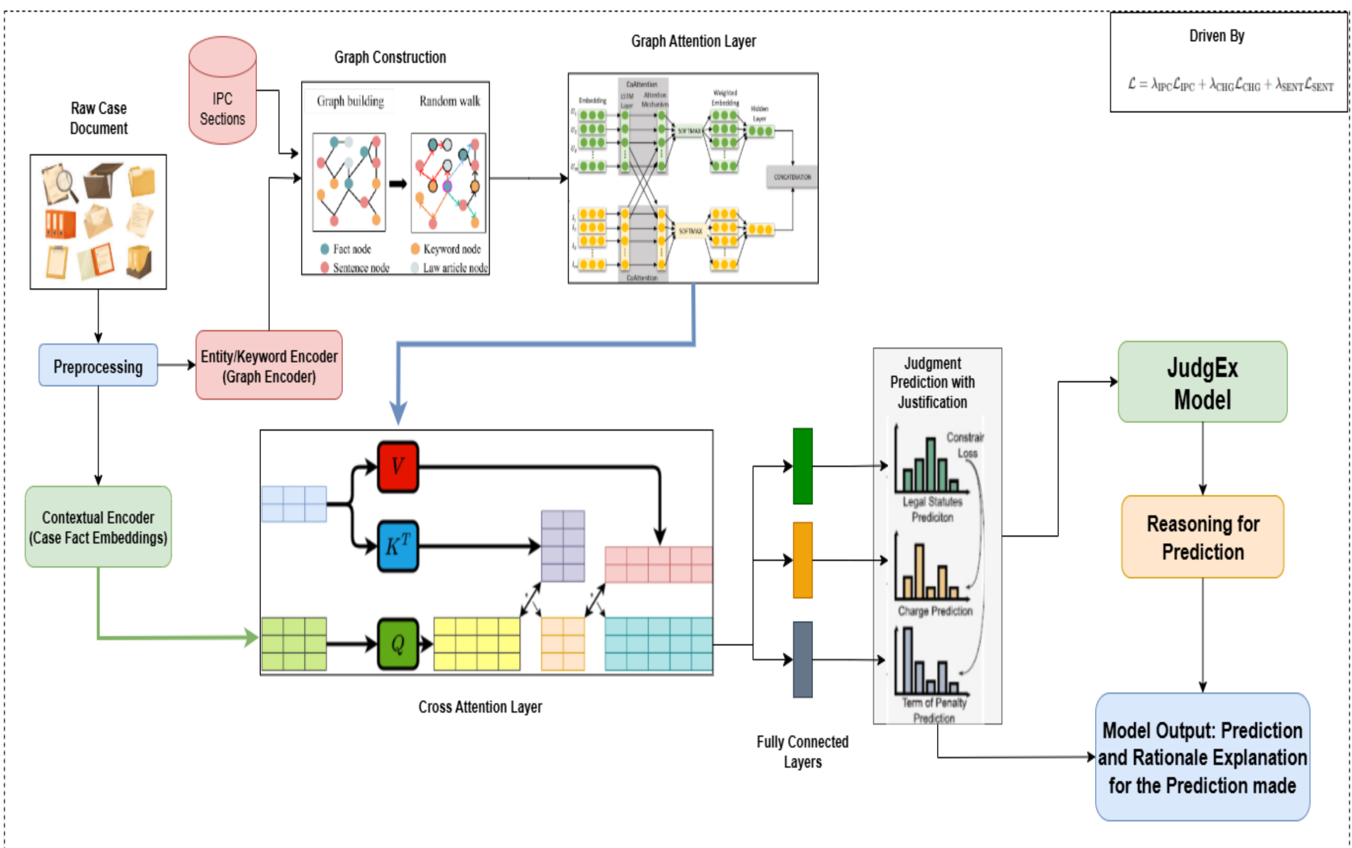
2. Introduction

The Legal Judgment Prediction (LJP) module is designed to assist judicial decision-making by automatically predicting legal outcomes such as statutes, charges, and sentence durations based on factual case descriptions. Traditional models often rely solely on textual data, overlooking the intricate relational dependencies between facts, laws, and precedents that underpin real-world legal reasoning. To address this limitation, the proposed system employs a multi-level attention and graph-augmented reasoning framework that combines deep contextual understanding with structured relational knowledge. The model preprocesses legal documents to extract relevant entities and facts, encodes them using contextual language models like LegalBERT or Legal-LLaMA, and constructs a heterogeneous graph linking facts, statutes, and legal keywords. A Graph Attention Network (GAT) refines these graph embeddings by modeling interdependencies among legal entities, while a Cross-Attention Fusion layer aligns textual and structural representations for context-aware prediction. The JudgEx sub-module then generates coherent, human-understandable explanations that justify each prediction, ensuring interpretability and transparency. By integrating semantic comprehension, graph-based reasoning, and explainable inference, this approach establishes a robust and trustworthy AI framework for legal judgment prediction, bridging the gap between automated analysis and judicial reasoning.

3. Proposed Work

The proposed work introduces a hybrid Legal Judgment Prediction framework that integrates multi-level attention with graph-augmented reasoning to enhance both accuracy and interpretability. The system preprocesses case documents, extracts key entities and statutes, and constructs a heterogeneous graph capturing relationships between facts, keywords, and legal provisions. A Graph Attention Network refines these relationships, while a Cross-Attention layer fuses graph and textual embeddings for joint reasoning. The JudgEx module then generates natural-language explanations for the predicted statutes, charges, and sentence durations, ensuring transparency and explainability. This design bridges data-driven learning with structured legal logic, enabling more reliable and interpretable judgment predictions.

3.1. Architecture



4. Implementation

The implementation involves preprocessing legal case documents to extract facts, entities, and statutes, followed by encoding them using a contextual model like LegalBERT or Legal-LLaMA. A heterogeneous graph is then constructed to represent relationships among facts, keywords, and legal sections, and processed through a Graph Attention Network (GAT) to learn relational embeddings. These graph embeddings are fused with textual features using a Cross-Attention mechanism for joint reasoning. Finally, the JudgEx module generates predictions for statutes, charges, and sentence durations, along with human-readable explanations, forming a complete and interpretable legal judgment prediction pipeline.

4.1 Experimental Setup:

The experimental setup involves training and evaluation of the proposed Legal Judgment Prediction model on curated legal datasets such as IndianKanoon, NyayaAnumana, and PredEx, containing annotated case facts, statutes, and outcomes. The implementation is carried out in Python using PyTorch and Transformers, with LegalBERT or Legal-LLaMA as the contextual encoder. Graph-based reasoning is implemented through PyTorch Geometric (PyG), where each case is represented as a heterogeneous graph with fact, statute, and keyword nodes. The model is trained on a GPU-enabled environment (NVIDIA A100/Colab TPU) using the Adam optimizer, a learning rate of 2e-5, batch size of 8, and dropout of 0.3 to prevent overfitting. Multi-task loss weights (λ_IPC, λ_CHG, λ_SENT) are tuned empirically for balanced performance across statute, charge, and sentence predictions. Evaluation metrics include F1-score, Precision, Recall, and BLEU/METEOR for rationale generation, ensuring both predictive accuracy and interpretability.

4.2 Application:

Judicial Decision Support: Assists judges and legal practitioners by predicting relevant statutes, charges, and sentence durations from case facts.

Legal Research Automation: Enables quick retrieval of similar cases and related judgments to support precedent-based reasoning.

Case Classification and Management: Automatically organizes and categorizes legal documents according to offence type or IPC section.

Explainable AI in Law: Provides transparent, human-understandable explanations for each prediction, ensuring trust and interpretability in legal decision-making.

4.3 Algorithm

LEGAL JUDGMENT PREDICTION (D, S):

```
1: P ← PREPROCESS(D)
2: F ← CONTEXTUAL_ENCODER(P)
3: K ← KEY_WORD_ENCODER(G)
4: G ← GRAPH_CONSTRUCT(K, P, S)
5: H ← GRAPH_ENCODER(G)
6: Q ← LINEAR_PROJ(F)
   K ← LINEAR_PROJ(H)
   V ← LINEAR_PROJ(H)
7: S ← (Q × Kᵀ) / √d_k
   A ← SOFTMAX(S)
   C ← A × V
8: H_fuse ← RESIDUAL(C, F)
9: Y_statute, Y_charge, Y_term ← FC_LAYERS(H_fuse)
10: L ← λ_IPC L_IPC + λ_CHG L_CHG + λ_SENT L_SENT
11: R ← JUDGEX_REASONER(H_fuse, Y_statute, Y_charge, Y_term)
12: return (Y_statute, Y_charge, Y_term, R)
```

JUDGEX MODEL (X, P):

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1: M ← LOAD_BASE_MODEL(LLAMA2_BASE)
2: M_pre ← CONTINUED_PRETRAIN(M, SCI_HC_DATA)
3: M_fine ← SUPERVISED_FINETUNE(M_pre, PREDEX_DATA)
4: I ← CONCATENATE(X, P)
5: E ← TOKENIZE(I)
6: H ← M_fine.ENCODE(E)
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```
O ← M_fine.DECODE(H)
R ← FORMAT_EXPLANATION(O)
return R
```

5. Result Analysis

The result analysis demonstrates the effectiveness of the proposed Legal Judgment Prediction framework in improving both predictive accuracy and interpretability compared to traditional text-based models. The integration of Graph Attention Networks (GAT) and Cross-Attention Fusion significantly enhanced relational understanding between case facts and statutes, resulting in higher F1-scores for statute and charge prediction tasks. The model achieved superior macro F1, precision, and recall scores, indicating balanced performance across diverse case types. The inclusion of the JudgEx module further contributed to qualitative improvements, as the generated rationales closely aligned with real judicial reasoning. Evaluation using BLEU and METEOR metrics validated the fluency and relevance of explanations. Overall, the results confirm that combining textual and graph-based reasoning enables more accurate, explainable, and legally coherent predictions, outperforming baseline models like LegalBERT and SVM-based classifiers.

6. Future Work

Future work can focus on expanding the system's capabilities and improving adaptability across diverse legal contexts. The model can be enhanced by incorporating multilingual support to handle regional court judgments in Indian languages and by integrating domain-specific retrieval mechanisms for real-time precedent search. Further research may explore temporal graph learning to capture the evolution of legal interpretations over time and multi-modal integration of textual, audio, and evidential data for more holistic reasoning. Fine-tuning the JudgEx module with larger judicial explanation datasets can improve the quality and diversity of generated rationales. Additionally, deploying the system as a cloud-based legal assistant platform with interactive visualization and feedback loops from legal experts can bridge the gap between AI prediction and real-world judicial practice.