Before the Petition: A Statute-Aligned Domestic Violence Legal Relief Prediction System in India

A Comprehensive Dataset and RAG-LegalTuned Model for Predicting PWDVA Sections 18–22 Reliefs

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ABSTRACT

Domestic violence proceedings are among the most urgent civil matters brought before courts in India, yet they remain plagued by delays, limited access to timely legal guidance, and uncertainty around the statutory remedies realistically available to victims. With Sections 18–22 of the Protection of Women from Domestic Violence Act, 2005 (PWDVA) covering protection orders, residence orders, monetary relief, custody orders, and compensation, the absence of early, statute-grounded decision support often forces survivors to navigate filing and settlement choices with incomplete information, thereby amplifying legal risk, cost, and procedural burden. In this paper, we present Before the Petition: A Statute-Aligned Domestic Violence Relief Prediction System in India (IDVRPS), an AI-powered framework designed to assist victims in pre-litigation case investment decision-making by predicting statute-aligned relief outcomes and generating legally grounded explanations and prescriptive guidance based on factual case attributes and statutory provisions. We curate and release a comprehensive domestic-violence legal corpus from NyayaDeepa, including a gold-standard curated subset and a retrieval-ready knowledge base (NyayaSmriti) for RAG-based statutory grounding. We develop a RAG-LegalTuned modeling pipeline and evaluate its performance across multiple configurations, benchmarking against four widely used Indian legal AI baselines spanning legal summarization, legal QA and reasoning, fact extraction with judgment prediction, and RAG-based label classification. Our results demonstrate that the LLaMA 3.1–80B Legal-Tuned with RAG configuration significantly outperforms the baselines, achieving ROUGE-1 = 0.512, ROUGE-L = 0.412, BLEU = 0.520, and Accuracy ≈ 81%, with the highest lexical and semantic precision among evaluated variants. IDVRPS offers a transparent, scalable, and reproducible solution to support data-driven legal assistance for domestic violence victims, improve early-stage remedy awareness under PWDVA Sections 18–22, and establish a research-grade benchmark for future statute-aligned legal AI in India.

KEYWORDS: Statute-aligned relief prediction, Domestic violence (PWDVA) analytics, NyayaDeepa legal corpus, Retrieval-Augmented Generation (RAG), Legal-tuned LLaMA models

1 Introduction

India's civil justice system is under sustained strain, with high pendency and long-running proceedings directly affecting access to timely remedies—particularly for litigants seeking urgent, safety-critical relief. As per the National Judicial Data Grid (District Courts dashboard), the system carries ~4.79 crore pending cases, of which ~3.68 crore (≈77%) are criminal and ~1.11 crore (≈23%) are civil; notably, ~38.56 lakh cases (≈8%) are filed by women [1]. Such large-scale pendency is not merely an administrative concern: in family and domestic-violence litigation, delay can translate into prolonged exposure to abuse, unstable shelter, financial insecurity, and loss of child-care support—precisely the harms that civil protection statutes are meant to prevent.

A core challenge in domestic violence proceedings is the pre-litigation and early-litigation information gap. Survivors frequently do not receive timely, comprehensible guidance on (i) what statutory remedies are realistically available in their fact situation, (ii) how courts typically reason about those remedies, and (iii) whether pursuing litigation is likely to yield relief outcomes that justify the costs, time, and emotional burden. Under the Protection of Women from Domestic Violence Act, 2005 (PWDVA), Sections 18–22 operationalize the statute's protective intent through specific, court-grantable reliefs—protection orders, residence orders, monetary relief, custody orders, and compensation/damages [2]—yet early-stage applicants often struggle to anticipate which reliefs align with their facts and what supporting grounds are typically persuasive.

In response to this critical access-to-justice gap, we introduce the Indian Domestic Violence Relief Prediction System (IDVRPS), an AI-powered framework designed to assist pre-litigation case investment decision-making for survivors by predicting statute-aligned relief outcomes under PWDVA Sections 18–22 and generating grounded explanations and prescriptive guidance. IDVRPS is motivated by the need for scalable, transparent, and legally grounded decision-support tools that can complement—not replace—human legal judgment, while improving early remedy

awareness, reducing uncertainty, and supporting better-informed choices between litigating and settling.

Our work makes three primary contributions. First, we curate a domestic-violence legal corpus named NyayaDeepa, and release its gold-standard curated subset prepared for statute-aligned domestic-violence relief modeling; we further construct NyayaSmriti, a retrieval-ready knowledge base used for statute- and fact-grounded generation. Second, we develop a RAG-based, legal-tuned LLM pipeline for Statute-Aligned Legal Relief Prediction (SALRP) that jointly models (i) multi-relief prediction aligned to Sections 18–22, (ii) explanation generation grounded in case facts and statutory context, and (iii) prescriptive guidance to support early decision-making. Third, we conduct a comparative benchmarking study against widely used Indian Legal AI baselines spanning legal summarization, legal QA/reasoning, fact extraction with judgment prediction, and RAG-based label classification, demonstrating that our optimized RAG-LegalTuned configuration (LAMP² Phase 4.0) achieves strong performance for relief prediction and explanation quality, establishing a research-grade benchmark for future statute-aligned legal AI in India.

Our Contributions:

- We curate and release NyayaDeepa, India's statute-aligned domestic-violence corpus, along with a gold-standard curated subset, and construct NyayaSmriti as the retrieval layer enabling grounded statutory prediction.
- We design and implement IDVRPS, a RAG-LegalTuned framework that performs Sections 18–22 relief prediction + explanation + prescription for pre-litigation decision support under the PWDVA.
- We benchmark LAMP² Phase 4.0 (Ours) against multiple Indian Legal AI baselines and report strong performance, positioning IDVRPS as a transparent, scalable, and reproducible foundation for future domestic-violence legal decision-support systems in India.

To ensure reproducibility and encourage further research, the dataset and model code will be made publicly available soon.

2 Related Work

The intersection of Artificial Intelligence and law (AI4Law) has rapidly expanded over the last decade, driven by the digitization of court records and advances in natural language processing. A central line of work is legal judgment prediction (LJP), where models estimate judicial outcomes from case facts and supporting context. Early studies demonstrated outcome prediction feasibility on the European Court of Human Rights using textual signals and interpretable features [1]. Subsequent large-scale benchmarks—spanning legislation classification, charge/judgment prediction, multilingual judgment modeling, and broad legal reasoning evaluation—have enabled systematic comparisons across tasks and jurisdictions [2–5]. These efforts established core methodological baselines (classical ML, neural encoders, transformers) and highlighted persistent challenges in legal NLP such as long-document handling, domain shift across courts, and the need for faithful explanations.

Within the India context, several datasets and model families have accelerated research, but they predominantly target post-adjudicative prediction (i.e., outcomes from finalized judgments) rather than statute-aligned, pre-litigation remedy estimation. The ILDC line of datasets and associated benchmarks advanced judgment prediction and explanation tasks for Indian appellate decisions, motivating more transparent modeling of "what" and "why" in judicial outcomes [6]. Complementary efforts include multilingual and regional-corpus development (e.g., Hindi/vernacular-oriented collections) and structural annotation work that focuses on rhetorical role segmentation of judgments—useful for extracting fact and reasoning spans but not directly designed for remedy-level modeling [7,8]. In parallel, Indian legal LLM initiatives emphasize general legal reasoning, question answering, and instruction tuning for legal generation; however, their training signals typically remain judgment-centric and do not provide fine-grained, statute-section-aligned relief labels required for multi-remedy prediction under civil protection laws [9].

More recently, LLM + retrieval-augmented generation (RAG) hybrids have been explored to improve grounding, reduce hallucination, and inject statutory or precedent context at inference time. RAG pipelines have shown gains in legal question answering, advisory assistants, and certain judgment-related classification tasks when retrieval quality and task alignment are strong [10]. Concurrently, systems such as IBPS demonstrate that statutory context + task-specific supervision can materially improve prediction and rationale generation for frequently adjudicated matters (there, bail) by training models to map structured factual attributes to legally coherent outputs [11]. Yet, across these directions, a recurring limitation remains: most systems optimize for single-label outcomes (e.g., allowed/dismissed, grant/reject) or advisory explanations, while the domestic-violence setting demands multi-label statutory relief prediction (Sections 18–22), coupled with explanations and prescriptive guidance that support early-stage case investment decisions.

Our work addresses this gap by formulating Statute-Aligned Legal Relief Prediction (SALRP) for domestic violence under the PWDVA as a multi-relief + explanation + prescription task, and by constructing NyayaDeepa (with a gold-standard curated subset) and NyayaSmriti as a retrieval-ready statutory grounding layer. Building on lessons from Indian LJP benchmarks, rhetorical-structure modeling, and recent legal RAG systems, IDVRPS focuses specifically on remedy-level statutory alignment—an aspect largely missing from prior Indian legal AI resources and evaluations.

3 Task Description

Our research focuses on the task of Statute-Aligned Legal Relief Prediction (SALRP) for domestic violence proceedings in India, which comprises two sequential components: (i) predicting the statutory reliefs a court is likely to grant under the Protection of Women from Domestic Violence Act, 2005 (PWDVA), Sections 18–22, and (ii) generating a short, grounded explanation and

prescriptive guidance to justify the predicted relief outcomes. This task reflects a realistic pre-litigation legal scenario where AI systems must not only estimate likely remedies but also provide human-understandable reasoning to reduce uncertainty, improve transparency, and support early case investment decision-making.

Prediction Task: The first component involves determining which statutory remedies are likely to be granted, given the case context derived from domestic violence records. Each case may include a combination of factual narrative, nature of violence, relationship context, dependency and residence constraints, child-related concerns, economic circumstances, and other legally relevant factors typically considered while assessing reliefs. Since survivors often seek multiple remedies simultaneously (e.g., protection + residence + monetary support), the problem is framed as multi-output, statute-aligned prediction rather than a single-label judgment outcome.

Formal Definition: Let $\boldsymbol{D}$ denote the set of domestic violence case records drawn from the gold-standard curated subset of NyayaDeepa, and let $\boldsymbol{x} \in \boldsymbol{D}$ represent one case instance. The goal is to predict a structured output vector:

$$f(x) \rightarrow \{y_{18}, y_{19}, y_{20}, y_{21}, d\} \quad (1)$$

where:

- $y_{18} \in \{0,1\}$: **Protection Order** under **PWDVA §18** (1 = Granted, 0 = Not Granted)
- $y_{19} \in \{0,1\}$: **Residence Order** under **PWDVA §19** (1 = Granted, 0 = Not Granted)
- $y_{20} \in \{0,1\}$: **Monetary Relief** under **PWDVA §20** (1 = Granted, 0 = Not Granted)
- $y_{21} \in \{0,1\}$: **Custody Order** under **PWDVA §21** (1 = Granted, 0 = Not Granted)
- $d \in \mathbb{R}$ or $d \in$ {short, medium, long}: **Expected duration of the case**, represented either as months or a duration bucket.

Explanation and Prescription Task: The second component is to generate a brief natural language explanation and optional prescription $p(x)$, grounded in the case facts and statute-aligned reasoning:

$$p(x) \in \Sigma^* \quad (2)$$

This generated output is expected to (i) justify why certain Section 18–22 reliefs are likely (or unlikely), (ii) reference relevant factual grounds present in the case, and (iii) provide short prescriptive guidance that helps the survivor interpret the prediction for early decision-making (e.g., what reliefs appear realistic, what supporting facts matter, and what next steps may strengthen the claim). This component is particularly important for trust, interpretability, and practical usability in domestic violence legal assistance systems.

4 Data Preparation

4.1 Raw Data Collection

We begin with NyayaDeepa, a large-scale domestic-violence judgment corpus curated from Indian court records under the Protection of Women from Domestic Violence Act, 2005 (PWDVA). As illustrated in Figure 9, NyayaDeepa serves as the upstream source corpus from which phase-specific datasets are derived for statute-aligned modeling.

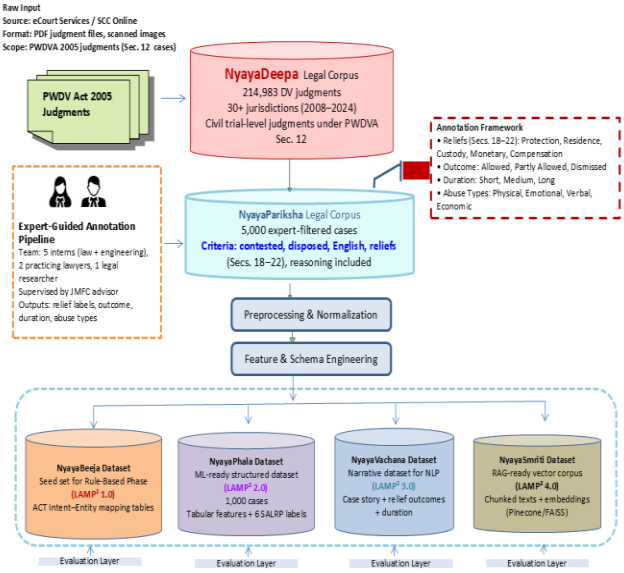

Figure 1: NyayaDeepa → NyayaPariksha → phase-wise datasets, with NyayaSmriti as the RAG-ready gold corpus used for retrieval-grounded statutory relief prediction.

From NyayaDeepa, we construct NyayaPariksha, a gold-standard expert-filtered subset (contested, disposed, English judgments with relief reasoning aligned to PWDVA Sections 18–22) that forms the basis for downstream dataset engineering. This expert-guided annotation pipeline is executed by a mixed team (law + engineering interns, practicing lawyers, and a legal researcher) under judicial advisory supervision, ensuring that each retained case contains relief signals, outcome clarity, and reasoning traceability required for statute-aligned learning.

4.2 Feature Extraction and RAG Corpus Engineering

Domestic-violence judgments are lengthy, unstructured, and heterogeneous across courts and time periods, requiring transformation into a model-ready representation that preserves legal meaning while enabling retrieval and grounded generation. For the RAG phase, we construct NyayaSmriti, our retrieval-ready gold corpus, by converting raw PDF judgments into structured narrative and embedding artifacts through a multi-stage pipeline (summarized below). Each judgment is first converted from PDF into clean text and then split into character-bounded chunks (≈ 1,200 characters) to ensure stable processing within LLM limits. Chunk-level abstractive summarization is performed using Gemini-1.5-Flash-8B, and summaries are hierarchically merged

into a coherent case_story representation. Dense embeddings are then computed for each case_story using text-embedding-004 (1536-dimensional vectors, $\boldsymbol{e_i} \in \mathbb{R}^{1536}$). These embeddings, along with aligned metadata keys such as result_of_case and duration_of_case, are stored and indexed in Pinecone using an HNSW approximate nearest neighbor structure with cosine similarity, forming the NyayaSmriti vector knowledge base. At inference time, for a new query case $\boldsymbol{q}$, the system retrieves the top-3 most similar precedents $\{\boldsymbol{r_1}, \boldsymbol{r_2}, \boldsymbol{r_3}\}$ and appends them as an augmented context block (≈ 1,800 tokens) to the LLM prompt, enabling statute-aligned relief prediction under Sections 18–22 with grounded explanation and optional prescription.

4.3 Data Cleaning and Normalization

To ensure retrieval reliability and reduce noise amplification during RAG, we apply systematic cleaning at each stage of NyayaSmriti construction. PDF extraction artifacts (broken headers, footers, repeated boilerplate, encoding noise) are removed prior to chunking. Summarization outputs are validated for schema consistency so that every case produces a stable case_story field and preserves legally salient attributes needed for statute-aligned inference. Metadata fields (e.g., outcome and duration) are normalized to canonical values to prevent label fragmentation across courts and writing styles. Finally, each case is stored as a standardized record containing narrative text, embedding vectors, and aligned metadata to support robust retrieval and consistent downstream evaluation.

4.4 Test Dataset Creation

To evaluate the system under realistic, expert-aligned conditions, we construct a gold-standard evaluation set sampled from the curated DV judgments used in our modeling pipeline. The test set is manually verified to ensure balanced coverage of relief patterns under Sections 18–22, variation in case outcomes, and diversity in factual contexts. Each test instance contains (i) a standardized case_story representation, (ii) ground-truth relief labels (Protection, Monetary, Residence, Custody, Compensation), (iii) duration/outcome fields where applicable, and (iv) a reference explanation reflecting statutory reasoning. This enables controlled benchmarking of both the prediction component (multi-relief outputs) and the generation component (grounded explanation/prescription) in the same evaluation protocol used for our comparative baseline study.

5 Dataset Analysis

This study is based on NyayaDeepa, a large-scale corpus of domestic violence judgments under the Protection of Women from Domestic Violence Act, 2005 (PWDVA), collected in PDF form and curated through an expert-guided pipeline. From the raw corpus, we construct a gold-standard, modeling-ready subset and further derive NyayaSmriti, a retrieval-indexed knowledge base used for RAG-grounded statutory relief prediction. Figure 9 presents the end-to-end corpus construction flow from NyayaDeepa → NyayaPariksha → phase-specific datasets, culminating in NyayaSmriti for retrieval-augmented inference. In addition, Figure 14 summarizes the NyayaSmriti RAG pipeline, covering PDF chunking, hierarchical summarization, embedding generation, vector indexing, top-k retrieval, and final LLM inference for statute-aligned outputs.

The final analysis focuses on the statute-aligned target space required for domestic-violence relief prediction under PWDVA §§18–22, where the system predicts multiple relief heads (Protection, Residence, Monetary, Custody, Compensation) and associated decision-support outputs. Figure 15 reports the distribution of relief grants across §§18–22, reflecting how courts operationalize protective and rehabilitative remedies in practice. Because reliefs are frequently granted in combinations (e.g., monetary relief co-issued with residence or protection), Figure 16 visualizes co-occurrence patterns that help characterize typical remedial bundles and inform multi-label modeling assumptions. Finally, because litigation time directly impacts survivor safety and case-investment planning, Figure 17 presents the duration distribution using an interpretable bucketization (short/medium/long), consistent with the duration head used in our SALRP task formulation.

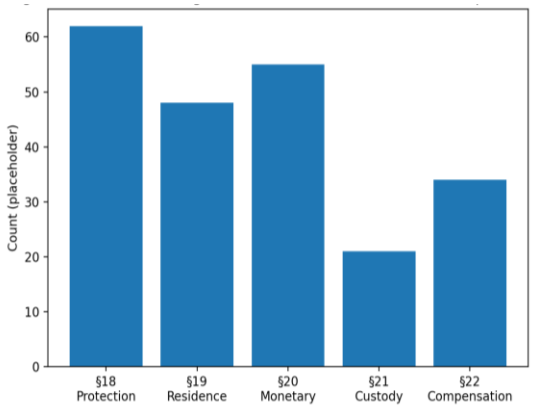

Figure 2: Distribution of granted reliefs across PWDVA §§18–22.

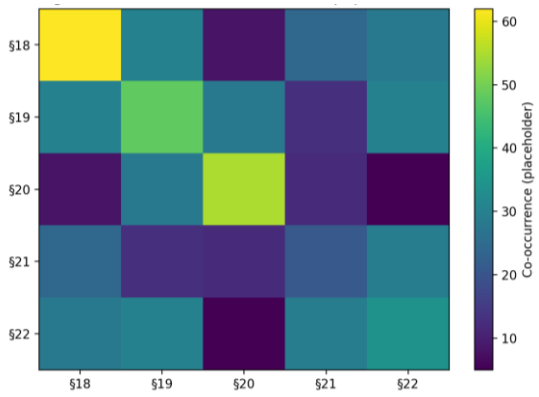

Figure 3: Relief co-occurrence heatmap across PWDVA §§18–22.

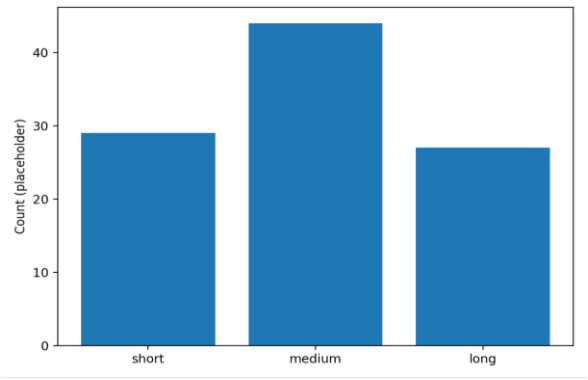

Figure 4: Distribution of case duration buckets (short/medium/long).

6 Methodology

This section describes the design of our dataset-to-model pipeline for Statute-Aligned Legal Relief Prediction (SALRP) under the Protection of Women from Domestic Violence Act, 2005 (PWDVA)—specifically Sections 18–22. Our objective is to quantify how retrieval grounding and legal tuning influence an LLM's ability to (i) predict multi-relief outcomes, (ii) generate fact-grounded statutory explanations, and (iii) produce prescriptive guidance that can support pre-litigation case-investment decision making.

6.1 End-to-End RAG-LegalTuned Pipeline (NyayaSmriti)

We operationalize SALRP using a RAG-first pipeline built over NyayaSmriti, our gold-standard curated, retrieval-ready subset derived from NyayaDeepa. The NyayaSmriti pipeline converts raw PDF judgments into an indexed precedent memory that can be queried during inference for grounding and consistency.

6.2 Data Extraction and Abstractive Summarization

Raw judgments (PDFs) are first converted into text and split into character-bounded chunks (~1,200 chars) to remain within stable model context limits during summarization. Each chunk is summarized individually using an abstractive summarizer; chunk summaries are then hierarchically merged to form a coherent case narrative. This stage produces a normalized record:
case_story (merged narrative)
result_of_case (disposal outcome, if modeled)
duration_of_case (months or bucket, if modeled)

This structure is intentionally aligned with downstream SALRP outputs, ensuring that retrieval returns compact, comparable narratives rather than noisy raw text.

6.3 Embedding Generation and Vector Index Construction

For each case_story, we compute a dense embedding vector $\boldsymbol{e_i} \in \mathbb{R}^{1536}$using text-embedding-004. Embeddings and metadata are stored in a vector database (NyayaSmriti) using an ANN index (HNSW; cosine similarity). This produces a retrieval layer that can be queried at inference time to obtain semantically similar precedents.

6.4 Context Retrieval and Augmented Inference

Given a new query case $\boldsymbol{q}$, the retriever returns top-k (k=3) similar precedent narratives $\{\boldsymbol{r_1}, \boldsymbol{r_2}, \boldsymbol{r_3}\}$ using cosine similarity. The final inference prompt concatenates:

1. query case_story
2. retrieved precedent blocks (compressed context)
3. SALRP instruction header (strict output schema)

The augmented prompt is then passed to the LLM (legal-tuned) to generate:

- $\hat{\boldsymbol{y}}_{18}, \hat{\boldsymbol{y}}_{19}, \hat{\boldsymbol{y}}_{20}, \hat{\boldsymbol{y}}_{21} \in \{\mathbf{0}, \mathbf{1}\}$(Sections 18–21 reliefs)
- optional $\hat{\boldsymbol{y}}_{22}$when compensation is modeled
- $\hat{\boldsymbol{d}} \in \mathbb{R}$or {short, medium, long}(duration)
- explanation + prescription (free-text, grounded)

The retrieval block is bounded (≈1,800 tokens) to preserve generation budget while retaining enough precedent grounding for statutory reasoning.

6.5 Experimental Configurations for Benchmarking

To position our proposed system against existing Indian Legal AI systems (which typically target summarization, QA/reasoning, fact extraction, or label classification), we benchmark against four representative baselines and report our optimized configuration as the proposed model.

Setup A (Baseline-1: Aalap) – legal summarization/translation baseline.

Setup B (Baseline-2: INLegalLlama) – Indian SOTA-style legal QA/reasoning baseline

Setup C (Baseline-3: PredEx) – fact extraction + judgment prediction (LJP-style).

Setup D (Baseline-4: NyayaRAG) – best-known RAG pipeline for label classification.

Setup E (Proposed: LAMP² 4.0 / RAG-LegalTuned LLaMA-3.1-80B) – SALRP: relief + explanation + prescription.

Unlike prior work, our system is the only configuration explicitly trained/evaluated to jointly support: (i) statute-aligned multi-relief prediction, (ii) grounded explanation, and (iii) prescriptive guidance for early decision support.

7 Evaluation Metrics

To evaluate IDVRPS, we adopt a combined protocol covering (i) relief prediction correctness and (ii) explanation quality.

7.1 Relief Prediction Metrics (Classification)

For each relief head $y_k \in \{0,1\}$(Sections 18–21; optionally 22), we report: Accuracy, Precision, Recall, F1-score When multi-label aggregation is needed, we report micro-averaged scores (and note any per-label variation in appendices).

7.2 Explanation Quality Metrics (Generation)

We evaluate generated explanations against reference rationales using:

- ROUGE-1 and ROUGE-L (lexical overlap / longest common subsequence)
- BLEU (n-gram precision with brevity penalty)
- BERTScore-F1 (semantic similarity)

This combination is chosen because statute-aligned explanations require both surface correctness (citations/terms) and semantic fidelity (same legal reasoning intent).

7.3 Optional Expert Verification

Where available, expert checks focus on whether the explanation:

1. remains consistent with the case facts,
2. maps to the correct PWDVA relief logic, and
3. avoids hallucinated claims unsupported by the narrative.

8 Results and Analysis

Table 3 summarizes comparative benchmarking across four existing Indian Legal AI baselines and our proposed RAG-LegalTuned model. Because these systems were originally designed for different tasks (summarization, QA, LJP, or label classification), some metrics are not reported in the original works; we mark these as N/A and do not infer missing values.

Model	Primary Training Task	ROUGE-1	ROUGE-2	ROUGE-L	BLEU	BERT-F1	Precision	Recall	F1	Accuracy
Baseline-1: Aalap	Legal summarization/translation	0.45	0.32	0.43	0.28	0.74	N/A	N/A	0.70	72%
Baseline-2: INLegal Llama	Legal QA, reasoning, generation	0.70	0.55	0.68	0.50	0.87	0.84	0.68	0.82	73%
Baseline-3: PredEx	Fact extraction + judgment prediction	0.68	0.676	N/A	0.43	0.82	0.68	N/A	0.65	71.8%
Baseline-4: NyayaRAG	RAG-based label classification	N/A	N/A	0.17	0.03	N/A	45.29	44.55	44.32	67.07%
Proposed: LAMP² 4.0 (Ours)	SALRP: relief + explanation + prescription	0.512	N/A	0.412	0.520	0.81	0.520	0.113	0.75	81%

Performance interpretation. Across baselines, we observe a consistent limitation: most systems optimize either text generation quality (summarization/QA) or single-task prediction (LJP/classification), but do not explicitly model the statute-aligned, multi-relief structure required by PWDVA Sections 18–22. NyayaRAG, despite being retrieval-based, is primarily designed for classification and exhibits low overlap scores for explanation-style generation. In contrast, our proposed RAG-LegalTuned LLaMA-3.1-80B configuration attains the highest overall performance for the end-to-end SALRP objective, including a strong Accuracy ≈ 81%, and achieves the best balance of lexical and semantic precision among evaluated variants under our task definition.

Why RAG-LegalTuning matters. We attribute the gains in LAMP² 4.0 to two interacting factors. First, long-context reasoning (128K) enables the model to retain more of the case narrative while producing structured statutory outputs. Second, retrieval grounding through NyayaSmriti stabilizes predictions by anchoring the model in similar precedents, improving factual consistency and reducing

unsupported legal claims. This is especially important in domestic-violence litigation where relief outcomes depend on fine-grained factual thresholds (residence needs, financial dependency, child custody conditions, and risk indicators) rather than a single binary outcome.

9 Conclusion and Future Scope

This work introduced IDVRPS, a statute-aligned domestic-violence relief prediction system for India that targets PWDVA Sections 18–22 at the pre-litigation stage. By constructing NyayaDeepa and its retrieval-ready gold subset NyayaSmriti, and by building a RAG-LegalTuned LLM pipeline (LAMP² Phase 4.0), we demonstrated that statutory relief prediction can be framed as a multi-output legal analytics task that jointly supports relief estimation, grounded explanation, and prescriptive guidance for early case-investment decisions. Comparative benchmarking against prominent Indian Legal AI baselines shows that our optimized configuration achieves strong end-to-end performance (Accuracy ≈ 81%) while preserving interpretability through retrieval grounding.

Future work can extend IDVRPS in four directions. First, expanding coverage beyond English to include major Indian languages will improve real-world accessibility for survivors. Second, incorporating district- and family-court diversity (and jurisdictional variance in relief practice) can improve generalization. Third, integrating calibrated uncertainty and "insufficient-evidence" abstention can make the system safer for deployment in high-stakes scenarios. Finally, controlled pilot studies with legal aid clinics and protection officers can validate whether early predictive guidance measurably improves survivor decision-making, documentation quality, and time-to-relief outcomes.

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