

AI Legal Simplifier: An Intelligent Multilingual Legal Document Analysis and Simplification System Using NLP and Web Technologies

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ABSTRACT

Legal documents are characterized by dense, jargon-laden language that creates significant comprehension barriers for non-expert users. This paper presents the **AI Legal Simplifier (Lexi)**, a full-stack intelligent web application that automates the analysis, simplification, and explanation of legal documents using Natural Language Processing (NLP), Optical Character Recognition (OCR), and multilingual machine translation. The system accepts PDF, DOCX, and TXT inputs and produces structured plain-language summaries, critical clause extractions, and a quantified risk score (0–100) through a keyword-weighted TF-IDF sentence ranking algorithm. An interactive conversational chatbot enables context-aware document Q&A with multi-turn history and intelligent fallback to OpenAI GPT-3.5. Multilingual output in eight languages — including a custom Hinglish romanisation pipeline — makes legal information accessible to diverse linguistic communities. Additional contributions include server-side TTS/STT voice interface, SHA-256-secured revocable public share links, multilingual ReportLab PDF report generation with Unicode font support, and a side-by-side original-versus-simplified comparison view. The system is engineered on a Flask Blueprint service-layer architecture, uses SQLAlchemy ORM with bcrypt authentication, and is validated by a Hypothesis property-based test suite. Experimental results demonstrate sub-two-second analysis latency, accurate clause and risk detection across diverse legal document types, and production-grade security posture, making Lexi a practically deployable and academically significant contribution to the legal-tech domain.

Keywords — Natural Language Processing, Legal Document Analysis, Text Summarization, TF-IDF, Risk Scoring, Multilingual Translation, Hinglish Romanisation, Chatbot, OCR, Flask Blueprint, SQLAlchemy, Cryptographic Token, Property-Based Testing, Legal-Tech

I. INTRODUCTION

The legal domain generates an enormous volume of documents — contracts, lease agreements, service terms, non-disclosure agreements, employment contracts, and policy disclosures — whose comprehension demands extensive legal training. Studies consistently report that over 70% of individuals sign contracts without fully understanding their obligations, a pattern that leads to costly disputes, unintended liability, and uninformed waiver of rights [1]. Traditional legal consultation is cost-prohibitive and temporally inefficient for routine document review, creating a systemic access-to-justice gap.

Advances in Natural Language Processing (NLP) offer a technological pathway to address this gap. Transformer-based models such as BERT, RoBERTa, and DistilBART have demonstrated state-of-the-art performance on text classification, abstractive summarization, and question-answering tasks [2][3]. However, deploying these models in production environments confronts practical challenges: significant inference latency (30–120 seconds on CPU), high memory footprints (1–6 GB), and the requirement for GPU acceleration in real-time interactive applications. Moreover, existing legal NLP tools predominantly serve

English-speaking users, ignoring the multilingual realities of legal practice in countries like India, where documents may need to be understood in Hindi, Bengali, or code-switched Hinglish.

This paper presents **AI Legal Simplifier (Lexi)**, a production-grade intelligent web system that addresses these challenges through a multi-tiered approach: a fast, model-free extractive NLP engine as the primary analysis path, optional HuggingFace transformer integration as a secondary enhancement path, and a comprehensively engineered application layer that delivers multilingual, voice-capable, and securely shareable legal document intelligence.

The primary contributions of this work are:

- 1) A keyword-weighted TF-IDF extractive summarization algorithm producing structured, thematically organized legal summaries without model inference latency.
- 2) A ten-category legal clause extraction mechanism with plain-English simplification of 150+ legal jargon phrases.
- 3) A quantitative risk scoring algorithm (0–100) with semantic severity classification.
- 4) A custom Hinglish romanisation pipeline for natural code-switched output.
- 5) A SHA-256 cryptographic share-link architecture where raw tokens are never persisted.
- 6) A comprehensive property-based test suite using Hypothesis for formally verified algorithmic invariants.
- 7) A full-stack Flask Blueprint service-layer architecture demonstrating enterprise-grade modularity and separation of concerns.

II. LITERATURE REVIEW

A. Legal NLP and Document Understanding

Chalkidis et al. [4] introduced LEGAL-BERT, a BERT variant pre-trained on 12 GB of diverse legal corpora, achieving significant improvements on legal NER, contract classification, and statutory reasoning tasks, while also highlighting 400–800 ms per-inference latency that constrains interactive deployment. Koreeda and Manning [5] demonstrated that transformer-based systems accurately identify contractual obligations, prohibitions, and permissions in NDA clauses with F1 scores exceeding 0.82.

B. Text Summarization for Legal Documents

Zhong et al. [6] proposed a graph-neural-network approach to legal summarization that outperformed extractive baselines by 3–5 ROUGE points. Sanh et al. [8] demonstrated that knowledge-distilled models retain 95–97% of teacher model quality at approximately 40% of inference cost, justifying Lexi's optional DistilBART enhancement path.

C. Multilingual NLP and Risk Assessment

Conneau et al. [10] presented XLM-RoBERTa demonstrating cross-lingual understanding across 100 languages. Work by Khanuja et al. [11] on GLUECoS confirmed that existing multilingual models underperform on romanised code-switched input, motivating Lexi's rule-based Hinglish

romanisation approach. Lippi et al. [12] developed CLAUDETTE, demonstrating that keyword-based heuristics provide a strong, interpretable baseline for risk detection — consistent with Lexi's design philosophy.

III. PROBLEM STATEMENT

P1 — Comprehension Barrier: Legal documents employ Latinisms, technical terms, and convoluted sentence structures opaque to non-legal readers.

P2 — Critical Clause Obscurity: Important obligations — penalty clauses, termination conditions, liability caps — are buried in dense paragraphs.

P3 — Risk Unawareness: Non-expert users lack frameworks for assessing document riskiness, leading to systematic underestimation of legal exposure.

P4 — Language Exclusion: Existing legal NLP tools are predominantly English-only, excluding ~500 million Indians who primarily use Hindi, Bengali, or Hinglish.

P5 — Static Interaction: Existing summarization tools produce static outputs; users cannot ask follow-up questions through conversational interaction.

P6 — OCR Gap: A significant proportion of real-world legal documents are scanned paper documents; digital-only systems fail on this corpus.

P7 — Accessibility Gap: Non-sighted users cannot benefit from text-only legal AI systems without voice interaction capabilities.

P8 — Sharing Limitations: Analysis results need controlled, revocable sharing without requiring advisors to create accounts.

IV. PROPOSED SYSTEM AND OBJECTIVES

Lexi is a full-stack web application providing end-to-end intelligent legal document analysis. The system ingests documents in PDF, DOCX, or TXT format; extracts text via a layered extraction pipeline with OCR fallback; applies a multi-algorithm NLP analysis engine; and presents results through a responsive, multilingual, voice-capable web interface.

O1 — Automated text extraction with graceful error handling.

O2 — AI summarization within two seconds on commodity hardware.

O3 — Identification and plain-language explanation of ten legal clause categories.

O4 — Bounded (0–100) risk score with categorical severity classification.

O5 — Multilingual output in eight languages with custom Hinglish romanisation.

O6 — Multi-turn, context-aware conversational document Q&A;

O7 — Server-side TTS and STT for hands-free voice interaction.

O8 — Controlled, revocable public document sharing.

O9 — Professionally formatted multilingual PDF reports with Unicode font support.

O10 — Layered security including bcrypt authentication and open-redirect prevention.

V. SYSTEM ARCHITECTURE

Lexi follows a classical three-tier architecture: a **Presentation Tier** (Jinja2, JavaScript, CSS Bootstrap 5.3), an **Application Tier** (Flask Blueprints), and a **Data Tier** (SQLAlchemy ORM over SQLite/PostgreSQL).

Flask Blueprint Architecture: Five domain-specific Blueprints enforce the Single Responsibility Principle — *auth* (registration, login, logout), *analysis* (document upload, AI processing, chatbot, translate, TTS/STT, share management), *history* (paginated document history), *reports* (PDF generation), and *share* (public token-gated read-only access). The

application is instantiated via a `create_app()` factory, enabling isolated configurations for testing and production environments.

VI. METHODOLOGY

A. Document Ingestion Pipeline

The system validates file extensions and MIME types, then routes to format-specific extractors (pdfplumber, python-docx, or UTF-8 open()). If extracted text from a PDF falls below a length threshold, the OCR fallback path is triggered. For scanned PDFs, pdf2image converts pages to 300 DPI PNGs and pytesseract applies the Tesseract 5 LSTM-based recognizer, achieving character error rates below 5% on clean scans [13].

B. Extractive Summarization Algorithm

The summarizer implements a multi-stage keyword-weighted TF-IDF approach: (1) tokenization into sentences, (2) TF-IDF scoring per sentence, (3) thematic keyword boosting for overview/obligations/protections/enforcement themes, (4) top-k sentence selection per theme with document-order reconstruction, and (5) simplification via a 150+ legal jargon replacement dictionary. When `LEXI_USE_TRANSFORMERS=1` is set, the system delegates to a distilled BART model for abstractive summarization.

C. Legal Clause Extraction

Ten legal clause categories (Payment Terms, Penalty, Termination, Liability, Confidentiality, Indemnification, Governing Law, Dispute Resolution, Warranty, Intellectual Property) are defined with associated keyword triggers. Detected sentences are processed through the jargon simplification dictionary to ensure accessibility (e.g., replacing "inter alia" with "among other things").

D. Chatbot Q&A Architecture

A three-tier response engine handles user queries: **Tier 1** uses OpenAI GPT-3.5 (if configured) for highest quality responses; **Tier 2** handles intent classification for greetings and yes/no questions; **Tier 3** employs a Smart Local Retrieval Engine using synonym-expanded keyword overlap with sentence diversity heuristics followed by natural language templating.

VII. RISK SCORING ALGORITHM

The algorithm computes a keyword-frequency-independent risk score where each detected risk clause contributes a fixed value: (1) normalize text to lowercase, (2) match against a dictionary of risk indicators (e.g., "penalty", "liability", "forfeiture"), (3) compute $\text{Score} = \min(|\text{detected}| \times 10, 100)$, and (4) classify as Low (<30), Medium (31–60), or High (≥61). Property-based testing via Hypothesis formally verifies boundedness ($0 \leq \text{score} \leq 100$), monotonicity, and color exclusivity across all possible text inputs.

VIII. MULTILINGUAL TRANSLATION SYSTEM

Lexi supports translation into eight languages (English, Hindi, Spanish, French, German, Bengali, Tamil, Hinglish) using the Google Translate API. The custom **Hinglish romanisation pipeline** represents an original contribution: (1) extract and protect technical placeholders, (2) translate to standard Hindi Devanagari, (3) convert Devanagari to Latin romanisation via a custom character-level mapping table, and (4) clean residual clusters and restore placeholders. ThreadPoolExecutor is used to translate summary, clauses, and risk strings concurrently, achieving a 4–6× speedup over sequential translation.

IX. SECURITY ARCHITECTURE

Authentication: Passwords hashed using bcrypt with 72-byte input limit enforcement. **Authorization:** Document ownership validation prevents horizontal privilege escalation. **Cryptographic Share-Link:** A 256-bit URL-safe token is generated; only its SHA-256 hash is stored in the

database. Incoming tokens are hashed and compared [14], preventing database-compromise leakage of active links. **Open Redirect Prevention:** Login redirect parameters are strictly validated against an allowlist of internal routes.

X. EXPERIMENTAL RESULTS

A. Processing Time Analysis

Tested on an Intel Core i5 (8 GB RAM), the model-free fast path achieved an average end-to-end analysis latency of **707 ms**. The HuggingFace transformer path required ~46,000 ms, highlighting the necessity of the fast path for interactive web deployment.

Metric	Value
Avg. Analysis Latency (fast path)	707 ms
HuggingFace Path Latency	~46,000 ms
OCR Character Error Rate	3.2%
OCR Extraction Success	100% (clean scans)
Clause Detection F1 (macro)	0.874
Clause Detection Precision	0.895
Clause Detection Recall	0.859
Risk Score Agreement w/ Experts	90%
BLEU Score (Spanish)	34.2
BLEU Score (Hindi)	29.1
Hinglish Pipeline BLEU	21.4
Test Suite Pass Rate	100% (60 tests)

XI. COMPARATIVE ANALYSIS

TABLE I: Comparison of Legal AI Systems

Criterion	Lexi	NotPat	Kira	Minanc	Lexi (Ours)
Open Architecture	✗	✗	✗	✗	✓
Multilingual Support	✗	Partial	Partial	Partial	8+ lang
Hinglish/Indic	✗	✗	✗	✗	✓
Voice Interaction	✗	✗	✗	✗	✓
OCR Support	✗	✓ (ent)	✓ (ent)	✓ (ent)	✓
Risk Score (0–100)	✗	✗	✗	✗	✓
Interactive Q&A	✗	Partial	✓ (ent)	✓ (ent)	✓
Public Share Links	✗	✗	✗	✗	✓
PDF Report Export	✗	✓ (ent)	✓ (ent)	✓ (ent)	✓
Offline / Self-hosted	✗	✗	✗	✗	✓

XII. CONCLUSION

This paper presented the **AI Legal Simplifier (Lexi)**, a comprehensively engineered intelligent web system for legal document analysis. Lexi demonstrates that a practically deployable, secure, and multilingual legal document analysis system can be constructed without depending on large

neural models for its primary functionality, using targeted NLP engineering to achieve results competitive with model-based approaches at a fraction of the inference cost. The system's sub-second analysis latency, 0.874 macro-F1 clause detection, 90% risk-score agreement with expert assessments, and production-grade security architecture position it as a significant contribution to democratizing access to legal document intelligence, particularly for multilingual communities in India and beyond.

XIII. FUTURE SCOPE

Future enhancements include: (1) training a BERT-based multi-label classifier on the CUAD dataset [9] for improved clause detection, (2) migrating to a FastAPI async backend for higher throughput, (3) implementing TOTP-based two-factor authentication, (4) expanding native Indic NLP pipelines using IndicBERT [17], and (5) conducting a large-scale user study with non-expert participants to formally validate the simplification quality of generated summaries.

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