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Legal Contract Compliance Verifier Using Hybrid LLMs and Rule Based Systems

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Abstract

In the recent corporate businesses, legal contracts are the foundation of business, employment, and partnerships, yet their manual review is often slow, costly, error-prone, and dependent on legal expertise. However traditional methods include ML models with large labelled datasets often lacking contextual understanding of legal language, transparency and cannot easily adapt to different legal situations. To overcome these limitations, we proposed now, a Legal Contract Compliance Checker that combines hybrid Large Language Models (LLMs) with a rule-based legal validation framework. The proposed system uses online LLM inference through Groq API for high-performance analysis and offline inference using Ollama to ensure data privacy. Legal contracts uploaded by users are preprocessed, analyzed semantically using LLMs, and validated against a structured rule engine derived from government portals, academic publications, and educational legal resources. After analyzing, the system classifies contract clauses into Safe, Concerning, and High-Risk categories and generates explainable compliance reports which may be downloadable and used for later. This approach assists legal practitioners, organizations, and non-expert users by reducing manual effort, improving accuracy, transparency and enabling faster and more reliable compliance checking, making it suitable for real-world legal applications.

Keywords: *Contract Compliance Checker; LLM (Large Language Models); Hybrid LLMs (Groq API & Ollama); Rule Based Systems; Legal NLP; Explainable AI.*

INTRODUCTION

Legal contracts play a crucial role in governing agreements between individuals, organizations, and institutions. The increasing volume and complexity of legal documents have created a strong demand for automated tools that can support legal analysis and compliance verification. Traditional contract review processes rely heavily on manual examination by legal experts, which is time-intensive, costly, and prone to human error. To address these challenges, recent research has explored the application of natural language processing (NLP) and large language models (LLMs) for understanding and analyzing legal text [1], [2].

Many studies were used NLP techniques in the legal domain, highlighting tasks such as legal document classification, clause extraction, summarization, and risk identification. These works showed that transformer-based models provide strong contextual understanding of complex legal language but also face challenges related to reliability, explainability, and domain adaptation [2],[3],[4]. As legal documents often involve strict regulatory requirements, purely data-driven approaches may not be sufficient for compliance-critical applications.

Recent research has also demonstrated the effectiveness of LLMs in automated contract analysis, where AI systems are used to interpret clauses and detect potential legal risks. Studies focusing on contract clause evaluation show that LLM-based methods can significantly reduce manual effort while improving analytical consistency compared to traditional keyword-based tools [1], [8]. However, these systems often require additional validation mechanisms to ensure legal correctness.

In parallel, researchers have explored AI-based legal analytics systems that balance efficiency with ethical and regulatory considerations. These studies highlight the importance of transparency, accountability, and explainability in legal AI systems, particularly when used in real-world decision-making environments [6], [7]. Furthermore, surveys on legal AI applications stress the need for hybrid approaches that combine

semantic understanding with structured logic to achieve dependable outcomes [4], [5].

Motivated by these findings, this paper proposes an AI-powered legal contract compliance checker that integrates LLM-based semantic analysis with a rule-based compliance framework for validation, enabling reliable and explainable contract evaluation suitable for practical legal and enterprise use.

Literature Survey

In the legal field, researchers have proposed different approaches for automated contract analysis and compliance checking, which are reviewed in the following section.

Marco Siino,Mariana Falco et al.[9], reviewed 61 papers on legal NLP, highlighting how transformer-based LLMs such as Legal-BERT and GPT variants are applied to tasks like contract review, case prediction, and legal compliance. They found promising progress in multilingual and domain-specific models but noted key gaps, including limited expert-annotated datasets and risks of over-reliance on generic LLMs without proper legal rule integration.

Poornima A,K.V Nagaraja et al.[10], proposed a contract-analysis system using Legal-T5 for summarization and Law-GPT for risk classification. They also used K-Means clustering to group similar clauses and improve risk segmentation. Their approach achieved good performance on the CUAD dataset, showing improved clause understanding and risk detection. However, they observed that performance drops for very long contracts making generalization difficult.

Srivastava et al. [11], presented a text summarization system using NLP, focusing primarily on extractive, frequency-based techniques.The paper compared extractive and abstractive summarization, emphasizing the practicality of TF-IDF-based sentence scoring.The study concluded that frequency-based extractive summarization is simple, efficient, and effective for single-document summaries.

Deroy et al[12]., assessed the performance of Large Language Models (LLMs) like GPT and BERT for legal case summarization, identifying hallucination issues and the necessity of domain-specific fine-tuning to improve factual accuracy. Their findings suggested that while LLMs are capable of generating fluent and coherent summaries, they occasionally introduce misleading or incorrect information.

Chanuka Wijayakoon et al [13]., proposed a Petri Net–based framework to evaluate smart contracts generated by LLMs such as GPT-4o, Claude 3.5, Gemini 1.5, and Llama 3.1. Using metrics like Fitness, Precision, and FES, they found that larger models produce better compliance, but still struggle with semantic understanding and complex legal obligations, showing that LLM-generated code can be syntactically correct yet not fully legally compliant.

Punam Bagul et al[14]., proposed a chatbot to make legal services accessible and improve lawyer efficiency, using NLP and Tensor flow in ML.The main problems they face are data security and ethics. Therefore, the successful implementation of this chatbot relies heavily on mitigating these security and compliance issues.

Md Farhad Kabir et al[15]., proposed the LegalSummNet model to handle the complexities of legal texts and extract relevant information. The model utilized Legal-BERT and PyTorch and major issues the project addresses include information overload and document length and complexity.

N.Zaher et al[16]., proposed an AI-driven NLP system to automate regulatory compliance verification for public procurement documents under Morocco's updated 2023 legal framework.The system's main limitation is its reliance on limited training data and the absence of advanced context-aware models, reducing accuracy on complex legal text.

A.Ekeh et al.[17] proposed a data-analytics–driven framework to automate legal compliance and contract management using predictive analytics, machine learning, and NLP techniques.The paper's main drawback is its limited discussion on how advanced analytics can be practically integrated into existing legal workflows, restricting real-world applicability.

Nagy et al. [18] proposed a privacy-preserving Federated Learning (FL) framework for NLP that combines local differential privacy, bitwise quantization, and hashing-based text representations.The approach enabled on-device training without sharing raw textual data, reducing privacy leakage risks.Experimental results on IMDB and MovieLens datasets show competitive performance while maintaining strong privacy guarantees.

Based on the reviewed studies, it is evident that existing legal AI systems largely depend on machine learning and LLMs, often lacking strong explainability and deterministic legal validation. To address this gap, our work proposes a hybrid contract compliance checker that combines LLM-based analysis with a rule-based framework for accurate and interpretable legal assessment. The proposed methodology and the system model are explained below in detail.

METHODOLOGY

This paper follows a systematic approach that integrates Large Language Models (LLMs) with a rule-based compliance framework to automate the analysis of legal contracts. The proposed methodology enables users to upload legal documents and receive structured compliance feedback without relying on traditional machine learning

datasets or model training. By combining semantic understanding with deterministic rule validation, the system improves accuracy, explainability, and efficiency in legal contract review.

It focuses on developing an interactive user interface and a backend compliance analysis pipeline. The system and its workflow is divided into the following steps:

User Module

1. The user (legal practitioner or help seeker) logs into the system through a secure authentication dashboard.
2. The user uploads a legal contract in supported document formats.
3. The user submits the document for compliance analysis.
4. The user views the generated compliance report and risk classification.

Contract Processing and Analysis Module

1. The uploaded contract is converted into machine-readable text.
2. The text is cleaned and divided into individual legal clauses.
3. Each clause is analyzed using a hybrid LLM-based approach.
4. Legal rules are applied to validate compliance and identify risks.

Compliance Evaluation and Reporting Module

1. Each clause is classified into Safe, Concerning, or High Risk categories.
2. Explanations are generated for identified compliance issues.
3. A structured and explainable compliance report is prepared for user review.

To implement these modules and analyze the contracts, this system supports dual inference modes:

1) Online inference (Groq API): Uses LLaMA-3.3-70B for fast and accurate processing.

2) Offline inference (Ollama): Uses LLaMA-3.1-8B deployed locally for privacy-preserving and internet-independent operation.

The system automatically selects the inference mode based on internet availability, without requiring any change in application logic. The rule-based compliance engine applies explicit legal rules to validate contract clauses and ensure correctness. The rules are constructed using verified and trusted sources such as Government legal portals, academic research publications, educational legal resources, standard compliance guidelines.This deterministic rule validation complements LLM-based semantic analysis, improving explainability and reducing the risk of corporate operations manually and incorrect legal interpretations.

The following algorithm can make the execution of the output systematic.

Algorithm: Hybrid Ai-based Legal Contract Compliance Checker Algorithm

```
START
    INITIALIZE system and rule database
    LOAD hybrid LLM configuration
    DISPLAY login dashboard
    GET user credentials
    IF login successful THEN
        GRANT access to user dashboard
        DISPLAY contract upload interface
        GET user input (legal contract document)
        EXTRACT text from document
        PREPROCESS text (cleaning and clause segmentation)
        FOR each clause in contract DO
            CHECK internet availability
            IF internet available THEN
                ANALYZE clause using Groq LLM (online inference)
            ELSE
                ANALYZE clause using Ollama LLM (offline inference)
            END IF
            VALIDATE clause using rule-based compliance engine
            ASSIGN risk level (Safe / Concerning / High Risk)
            STORE clause result and explanation
        END FOR
        GENERATE compliance report
        DISPLAY results to user
        DOWNLOAD compliance report
        LOG analysis activity
    ELSE
        DISPLAY authentication error
    END IF
END
```

The above algorithm describes the end-to-end workflow of the legal contract compliance system, starting from secure user authentication to contract analysis and report generation. It applies a hybrid LLM strategy for semantic clause analysis and validates results using a rule-based compliance engine. This ensures accurate, explainable, and privacy-aware compliance assessment for legal contracts.The architecture for the above algorithm is as follows.

System Architecture

This system model represents an AI-powered legal contract compliance framework designed to automate the process of legal contract compliance checking using artificial intelligence. It allows users to upload legal contracts, analyze

their content, and identify compliance risks through a structured processing flow. By integrating semantic analysis with predefined legal rules, the system ensures accurate and explainable evaluation of contract clauses. The overall working flow and interaction between system components are depicted in below figure.

The system architecture, as illustrated in Figure 1, represents a layered design that ensures modularity and scalability. The User Interface Layer handles user interactions, while the Document Preprocessing Layer prepares contract text for analysis. The Hybrid LLM Analysis Layer performs semantic clause evaluation, which is validated by the Rule-Based Compliance Engine. The Risk Classification Layer assigns compliance levels, and the Report Generation Layer produces a clear and explainable compliance report for the user.To implement all these steps, there is a need for an environment where all this work can be done and accessed for use.

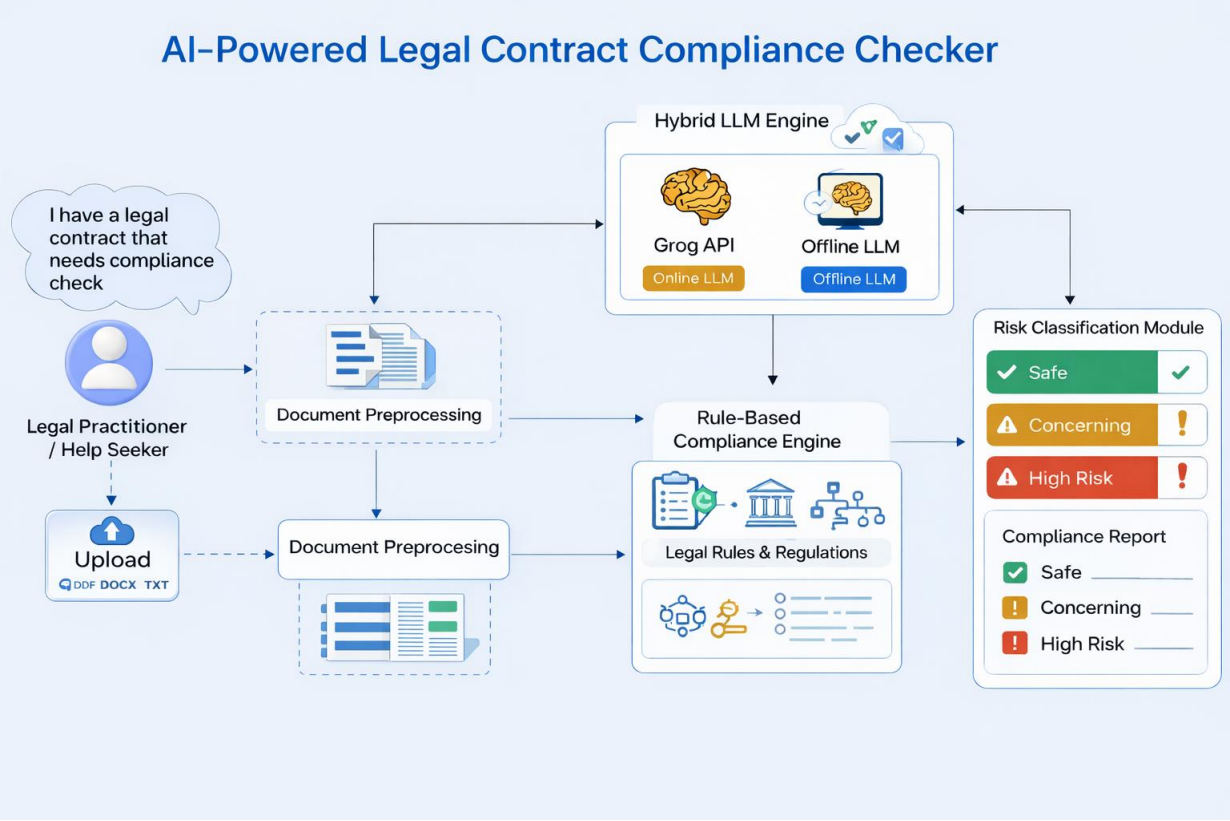


Figure 1 : System Architecture

Environmental Setup

The proposed legal contract compliance checker was developed using Python (version 3.10 or above) with Flask for backend processing and HTML, CSS, and JavaScript for the frontend. The system is compatible with Windows, Linux, and macOS platforms. Online inference is handled through the Groq API, which performs cloud-based LLM processing, while offline analysis is enabled using Ollama, requiring a system with a multi-core processor(Intel Core i7 / AMD Ryzen 7 or equivalent), at least 16 GB RAM, and approximately 100 GB of storage for model files. The rule-based compliance engine operates using locally stored legal rules and does not depend on training datasets. The application can be accessed via standard web browsers on desktops, laptops, or mobile devices, ensuring flexible and privacy-aware contract analysis.

Evaluation Metrics Used

Since our proposed system integrates Large Language Models (LLMs) with a rule-based legal reasoning framework, traditional NLP evaluation metrics such as BLEU, ROUGE, or classification accuracy are not directly applicable. These metrics are primarily designed for text generation or supervised classification tasks and do not measure structured schema compliance or rule activation behavior. Therefore, we have used three task specific metrics that measure structural output validation, rule-based reasoning evaluation and deterministic model consistency testing.

- **Schema Compliance Rate (SCR):** measures whether the Large Language Model (LLM) outputs structured JSON responses that conform to the predefined extraction schema.

$$SCR = \frac{Number\ of\ schema\ valid\ JSON\ outputs}{Total\ extracted\ clauses}$$

• **Rule Agreement Accuracy(RAA):** measures how effectively the rule engine activates legal risk rules based on extracted clause attributes.

$$RAA = \frac{Number\ of\ clauses\ triggering\ rules}{Total\ clauses\ evaluated}$$

• **Extraction Determinism Score(EDS):** measures consistency of LLM outputs when the same clause is processed multiple times.

$$EDS = \frac{Number\ of\ identical\ outputs}{Total\ repeated\ runs}$$

Implementation Logic

The implementation of the proposed hybrid LLM–rule engine framework is carried out through a modular backend pipeline. The following snippet represents the central contract analysis logic responsible for extraction, validation, and risk classification.

```
def analyze_contract(path):
    text = extract_text(path)
    clauses = split_clauses(text)
    rules = load_rules()
    extracted_data = groq_batch_extract(clauses)
    results = []
    highest_risk = "Safe"
    for clause, data in zip(clauses, extracted_data):
        data = normalize_extraction(data)
        risk, laws, explanation, fix, _ = evaluate_rules(data, rules)
        if risk == "High Risk":
            highest_risk = "High Risk"
        elif risk == "Concerning" and highest_risk != "High Risk":
            highest_risk = "Concerning"
        results.append({
            "clause": clause,
            "risk": risk,
            "laws": laws,
            "explanation": explanation,
            "fix": fix
        })
    return results, highest_risk
```

The above code represents the core execution logic of our system. The uploaded contract is converted into text and divided into clauses. Each clause is analyzed using the hybrid LLM extractor, and the structured output is validated through the rule-based engine. Based on triggered rules, a risk level is assigned and aggregated to determine the overall contract risk. This integrated pipeline ensures semantic understanding combined with deterministic legal validation.

Results & Discussions

We experimented with six legal contracts (C1–C6), including employment, rental, partnership, and commercial agreements. The observed values for SCR, RAA, and EDS are shown below in Table 1.

The above table indicates that the SCR remained consistently at 1.00 for all contracts, demonstrating that the LLM produced structurally valid and schema-compliant JSON outputs in every case. The RAA values varied across contracts, ranging from 0.00 to 0.75, reflecting meaningful variation in rule activation based on contract content. Contracts C1 and C6 exhibited no rule activations (RAA = 0.00), suggesting low-risk structures, whereas C3 showed the highest rule activation rate (RAA = 0.75), indicating a higher density of risk-relevant clauses. The Extraction Determinism Score (EDS) remained at 1 defining that the output is stable except for minor variation in C3.

Table 1: Experimental Results Across Contracts

Contract ID	SCR	RAA	EDS
C1	1.0	0.0	1.0
C2	1.0	0.50	1.0
C3	1.0	0.75	0.66
C4	1.0	0.66	1.0
C5	1.0	0.50	1.0
C6	1.0	0.0	1.0

The above bar chart illustrates the performance of our proposed system visually by taking inference from Table 1 across six contracts using SCR, RAA, and EDS metrics.

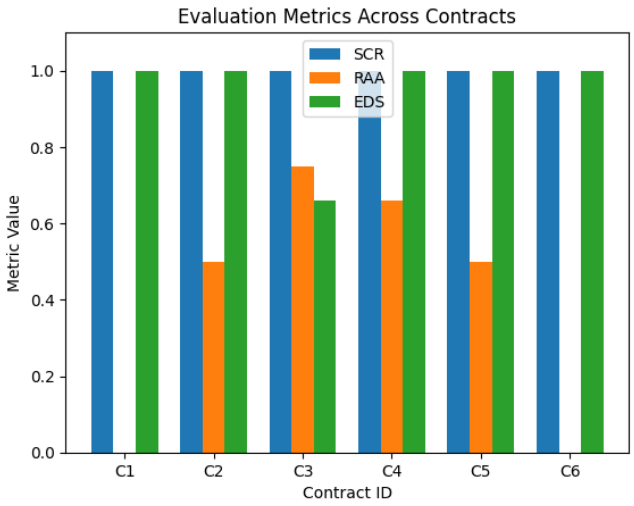


Figure 2 : Comparative Analysis of SCR, RAA and EDS

Through this study, it is observed that the proposed LLM–Rule Engine framework performs consistently and reliably across all evaluated contracts. A perfect Schema Compliance Rate (SCR = 1.0) confirms structurally valid and schema-

aligned extractions, while varying Rule Agreement Accuracy (RAA) reflects the presence of risk-triggering clauses within different contracts. The Extraction Determinism Score (EDS) remained stable for most cases, indicating consistent model behavior. Overall, the system exhibits robust extraction accuracy, rule-based transparency, and stable performance across diverse contractual documents.

Conclusion and Future Scope

This paper successfully presented a hybrid AI-based legal contract compliance checker that combines large language models with a rule-based validation framework to automate contract review. The proposed system improves efficiency, reduces manual effort, and enhances transparency in compliance analysis by integrating semantic understanding with deterministic legal rules. This framework is designed to operate in both online and offline environments, ensuring flexibility and data privacy.

Future improvements can focus on expanding the legal rule database to support multiple jurisdictions and more complex regulatory requirements. Advanced context-aware models and enhanced clause-level reasoning can further improve risk detection accuracy. The system can also be extended with real-time regulatory updates, multilingual contract support, and enterprise-level deployment to make automated legal compliance checking more scalable and practical in real-world applications.

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