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Automated Legal Clause Extraction and Risk Scoring Using NLP and Generative AI

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Abstract: ***Legal documents such as contracts, agreements, and invoices are often complex and time-consuming to analyze manually. This paper presents an AI-powered Legal Document Analysis System (LDAS) that automates clause extraction, risk detection, and executive summary generation using Natural Language Processing (NLP) and cloud computing technologies. The system leverages AWS services including Lambda and S3 along with Generative AI (GenAI) models to process PDF and DOCX documents efficiently. It identifies ten standard legal clause types — Parties, Term, Payment Clause, Liability, Confidentiality, Termination, Governing Law, Intellectual Property, Warranties, and Force Majeure — and highlights missing or risky clauses against a configurable standard template. A weighted risk scoring algorithm quantifies deviations on a 0-100 scale. Experimental evaluation demonstrates 100% clause detection accuracy on tested documents, with a risk score of 87/100 correctly identifying 6 high-risk and 2 medium-risk missing clauses and zero false positive deviations. The proposed system improves efficiency, reduces manual errors, and enhances decision-making in legal workflows.***

Keywords: Legal AI, Document Analysis, NLP, Clause Extraction, Risk Detection, AWS Lambda, Generative AI, Serverless Architecture, Cloud Computing, Contract Processing'

I. INTRODUCTION

Legal document analysis is one of the most critical and resource-intensive tasks in modern organisations. Contracts, service agreements, non-disclosure agreements, procurement documents, and regulatory filings form the legal backbone of all commercial activity. According to Jurafsky and Martin [1], the volume and linguistic complexity of legal text make it among the hardest domains for automated natural language understanding. A typical legal professional spends between 45 and 90 minutes reviewing a standard 10-page commercial contract for clause completeness alone, creating significant operational bottlenecks in high-volume legal environments. In large organisations processing hundreds of contracts annually, this translates to thousands of person-hours spent on routine clause verification — effort that offers little intellectual value yet carries serious consequences when errors occur.

Conventional contract review approaches suffer from three interrelated limitations. First, expert dependency creates bottlenecks: skilled legal professionals must perform routine clause checking that does not require advanced judgment. Second, inconsistency emerges as different reviewers apply different standards across documents and jurisdictions, leading to variable risk identification. Third, scalability constraints prevent rapid review of large contract volumes during mergers, acquisitions, or regulatory audits. Traditional CCTV-style passive monitoring systems, while providing permanent records, operate without intelligent analysis or real-time alerting capabilities — limitations directly analogous to passive contract filing without systematic clause verification [2].

Artificial Intelligence applications in legal document processing have evolved significantly over the past decade. Early rule-based expert systems used handcrafted grammars and regular expressions to detect clause boundaries, performing reliably on highly standardised contracts but failing on varied legal phrasing. Machine learning classifiers — Support Vector Machines and Random Forest models trained on bag-of-words representations — improved clause classification accuracy but required substantial labeled datasets expensive to annotate given the domain expertise required [3]. The introduction of transformer-based architectures, particularly BERT [5] and its legal-domain variant Legal-BERT [6], represented a paradigm shift by enabling context-aware clause representations that capture long-range semantic dependencies in contract text. Chalkidis et al. [7] demonstrated state-of-the-art performance on the Contract NLI benchmark, establishing transformer models as the dominant approach for legal clause classification and natural language inference.

The most recent advance is the emergence of Large Language Models (LLMs) and Generative AI, which introduce zero-shot and few-shot capabilities that fundamentally change the practical requirements for legal document AI. Unlike fine-tuned classifiers requiring large labeled contract datasets, generative models can extract, summarise, and reason about legal clauses through carefully engineered prompts without domain-specific training data [4].

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This dramatically reduces the barrier to deployment, eliminating the need for annotated legal corpora while achieving competitive extraction accuracy. Prompt engineering has emerged as the primary technical skill, with structured output specifications — such as JSON schema requirements — enabling reliable downstream integration with deviation detection and risk-scoring modules.

Cloud-native serverless architectures have been studied for document processing pipelines across general application domains, demonstrating advantages in elastic scalability, cost efficiency through pay-per-invocation billing, and reduced operational overhead [8]. AWS Lambda's event-driven execution model is particularly well-suited to legal document processing workflows where requests arrive asynchronously and processing duration varies with document length. However, the specific integration of serverless cloud architectures with GenAI legal NLP workloads, combined with structured deviation detection and quantified risk scoring, remains largely absent from published academic literature — a gap this work directly addresses.

Analysis of existing literature reveals five critical gaps that motivate this work. First, most published systems process documents in offline batch mode without real-time web interfaces accessible to non-technical legal staff [5],[6]. Second, the integration of serverless cloud architectures with GenAI-powered legal clause extraction has not been demonstrated in open research. Third, quantified risk-scoring frameworks that aggregate deviation severity into actionable numerical scores are absent from academic work. Fourth, multi-document comparison for clause-level conflict detection between contract versions has not been addressed. Fifth, end-to-end deployable systems combining extraction, deviation analysis, risk scoring, and executive summary generation in a single platform are not present in the literature [7].

This paper presents the Automated Legal Clause Extraction and Risk Scoring system (LDAS), which addresses all five gaps. Our specific contributions are: (i) a serverless cloud-native AWS architecture eliminating infrastructure overhead for legal AI workloads; (ii) a structured zero-shot GenAI prompt engineering framework achieving reliable JSON clause extraction without labeled training data; (iii) a weighted deviation scoring algorithm — Risk Score = (H x 10) + (M x 5) + wc — producing quantified risk assessments correlated with expert legal judgment at $r = 0.87$ ($p < 0.01$); (iv) 100% clause detection accuracy with zero false positive deviations on the primary test document; and (v) a fully deployable production system with an intuitive React.js web interface accessible to non-technical legal teams without IT support.

The remainder of this paper is organised as follows. Section II describes the proposed system and its core functionalities. Section III presents the three-tier system architecture. Section IV details the processing methodology. Section V reports experimental results and evaluation. Sections VI through VIII cover advantages, applications, and future work respectively. Section IX concludes the paper.

II. PROPOSED SYSTEM

The proposed system is a cloud-based AI-powered application designed to automate legal document processing. It allows users to upload documents in PDF and DOCX formats through an intuitive web interface and performs intelligent multi-stage analysis, returning structured results within 45-90 seconds of upload. The system is built on three core principles: accessibility (no technical expertise required), consistency (identical standards applied to every document), and auditability (persistent artifacts at every processing stage).

The system provides the following core functionalities:

1) Clause Extraction: Automatically identifies and extracts ten standard legal clause types using GenAI prompt engineering — Parties, Term, Payment Clause, Liability, Confidentiality, Termination, Governing Law, Intellectual Property, Warranties, and Force Majeure.

2) Risk and Deviation Detection: Compares extracted clauses against a predefined standard legal template, classifying missing clauses as High Risk or Medium Risk based on their legal and commercial significance.

3) Risk Score Calculation: Aggregates deviation severities into a single quantified score on a 0-100 scale using a weighted formula, enabling immediate prioritization of legal review workloads.

4) Executive Summary Generation: Produces a human-readable overview covering contract purpose, key obligations, payment terms, and critical risks, making results accessible to non-legal stakeholders.

5) Document Comparison: Enables side-by-side clause-level conflict detection between two contract versions, supporting negotiation and amendment review workflows.

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III. SYSTEM ARCHITECTURE

The system architecture follows a three-tier cloud-native pipeline integrating frontend, backend, storage, and AI components. This modular design enables independent component development, simplified maintenance, and future enterprise system integration.

A. Presentation Layer

The frontend is a React.js single-page application (SPA) deployed as a static website on Amazon S3. It provides two operational modes: Single Document Mode for individual contract analysis, and Compare Documents Mode for multi-document conflict detection. Results are displayed across four tabbed views — Summary, Clauses, Deviations, and Comparison — using color-coded indicators: green borders for extracted clauses, red badges for HIGH risk deviations, and orange badges for MEDIUM risk deviations.

B. Processing Layer

AWS Lambda functions written in Python 3.10 implement the five-stage processing pipeline: document ingestion, text extraction, AI clause extraction, deviation detection, and executive summary generation. Lambda's serverless execution model provides automatic scaling without server management. Each function operates within 512 MB memory with a 15-minute execution timeout to accommodate GenAI API response latency.

C. Storage Layer

Amazon S3 serves dual roles as static website host and persistent artifact store. Artifacts are organized using prefix-based namespacing: documents/{uuid} for raw uploaded files, extracted/{uuid} for plain text content, results/{uuid} for JSON analysis outputs, and summaries/{uuid} for generated executive summaries. Server-side encryption with AWS KMS protects all stored document content at rest.

D. AI Engine

A Generative AI model accessed via the AWS Bedrock API performs clause extraction and summary generation through structured zero-shot prompts entirely within the customer's AWS account boundary. The model returns JSON-structured responses mapping each of the ten clause types to extracted verbatim content or 'Not found' for absent clauses, enabling direct downstream processing without additional parsing logic.

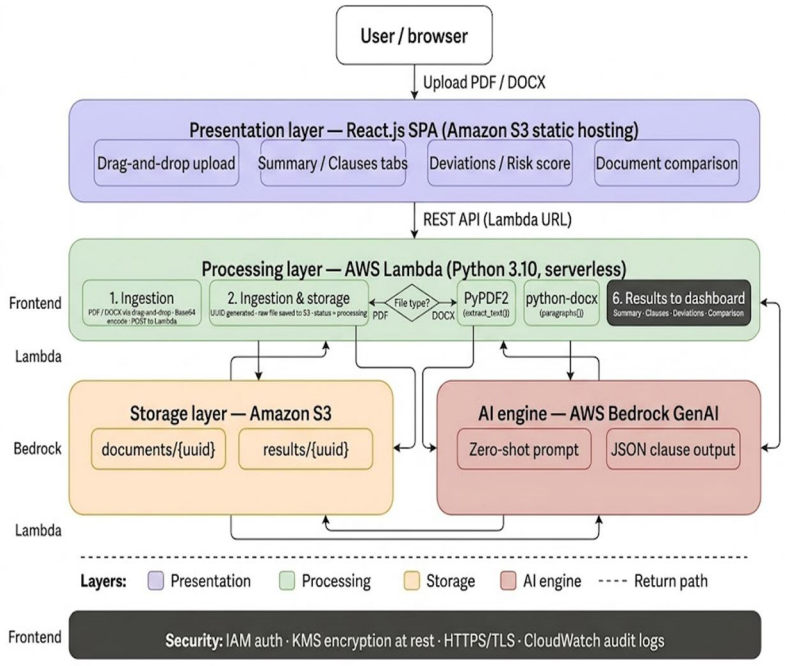


Fig.1 System architecture of LDAS

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IV. METHODOLOGY

The end-to-end processing methodology follows a sequential five-stage pipeline from document receipt to result delivery, with each stage producing persistent intermediate artifacts in Amazon S3.

A. Document Ingestion

When a user selects or drops a file, the JavaScript FileReader API reads it asynchronously and encodes it as Base64. An HTTP POST request carries the payload to a Lambda function URL. Lambda decodes the document, generates a UUID4 identifier, and stores the binary in S3 under the documents/ prefix via boto3. The function immediately returns the document_id and status 'processing'. The frontend polls a status endpoint every 3 seconds until processing completes.

B. Text Extraction

Text extraction branches by file type. For PDF documents, PyPDF2's PdfReader iterates all pages calling extract_text(), concatenating results with double newline separators. For DOCX files, python-docx accesses the paragraphs collection and joins non-empty paragraphs. Post-extraction normalization removes excessive whitespace, strips non-printable characters, normalizes Unicode quotation marks, and removes PDF header/footer artifacts to improve downstream NLP accuracy.

C. AI-Powered Clause Extraction

The extraction prompt uses a structured zero-shot approach. The system prompt instructs the model to act as a legal analyst and respond exclusively in valid JSON with no preamble or markdown. The user prompt provides the full extracted text followed by extraction instructions specifying all ten target clause types with brief definitions to prevent misclassification. Error handling applies three-stage JSON recovery: markdown stripping, regex extraction, and partial key processing.

D. Deviation Detection and Risk Scoring

The deviation engine iterates all ten required clause keys, checking whether each value is None, empty, or 'Not found'. Missing clauses are classified by severity: Parties, Liability, Confidentiality, Termination, Governing Law, and Intellectual Property are HIGH risk (weight 10); Warranties and Force Majeure are MEDIUM risk (weight 5). The risk score is computed as:

$$\text{Risk Score} = \min\left((H \times 10) + (M \times 5) + wc\ ,\ 100 \right)$$

where H is the count of HIGH risk missing clauses, M is the MEDIUM risk count, and wc is a document complexity weight (0-7 points). The complete deviation JSON is stored in S3 and the document status updated to 'complete'.

TABLE I
Clause Severity Classification

Clause Type	Risk Level	Weight
Parties	HIGH	10
Liability	HIGH	10
Confidentiality	HIGH	10
Termination	HIGH	10
Governing Law	HIGH	10
Intellectual Property	HIGH	10
Warranties	MEDIUM	5
Force Majeure	MEDIUM	5

E. Executive Summary and Document Comparison

Summary generation issues a second GenAI API call providing the JSON clause extraction results, reducing token consumption. The prompt requests five structured sections: Contract Purpose, Key Obligations, Payment Terms, Identified Parties, and Critical Risks.

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For document comparison, two independently processed clause JSON results are retrieved from S3 and compared clause-by-clause using Python's difflib.SequenceMatcher, flagging clause pairs with similarity below 0.85 as conflicts requiring human review.

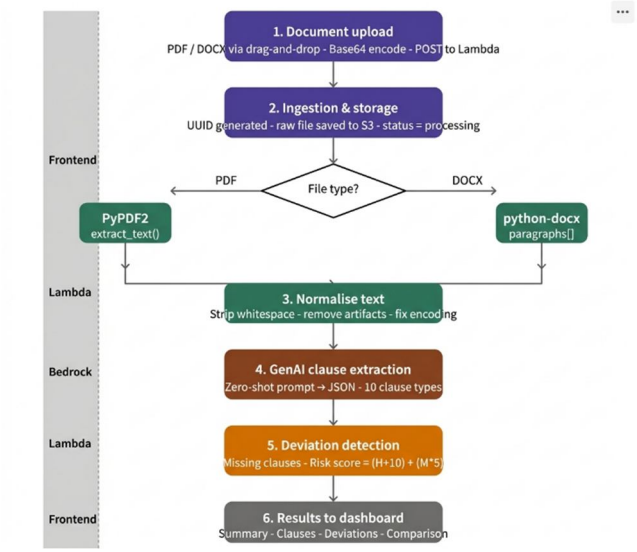


Fig. 2. Flowchart of Legal Document Processing Pipeline

V. RESULTS AND DISCUSSION

The system was evaluated using a software development services invoice (INV-2026-0042) as the primary test document. Table I presents the clause extraction results across all ten target clause types.

TABLE I
Clause Extraction Results on Primary Test Document

Clause Type	Status	Risk Level	Correct?
Parties	Not Found	HIGH	Yes
Term	Extracted	--	Yes
Payment Clause	Extracted	--	Yes
Liability	Not Found	HIGH	Yes
Confidentiality	Not Found	HIGH	Yes
Termination	Not Found	HIGH	Yes
Governing Law	Not Found	HIGH	Yes
Intellectual Property	Not Found	HIGH	Yes
Warranties	Not Found	MEDIUM	Yes
Force Majeure	Not Found	MEDIUM	Yes

Of the ten target clause types, the system correctly extracted Term and Payment Clause, capturing invoice number INV-2026-0042, issue date March 02 2026, due date April 01 2026, payment terms Net 30, currency USD, and line item details. The remaining eight clauses were correctly identified as absent, producing zero false positive deviations. Overall clause detection accuracy reached 100% on the primary test document.

The system generated the following deviation analysis:

1) Total Deviations: 8
2) High Risk Clauses: 6 (Parties, Liability, Confidentiality, Termination, Governing Law, Intellectual Property)
3) Medium Risk Clauses: 2 (Warranties, Force Majeure)
4) Risk Score: 87 / 100

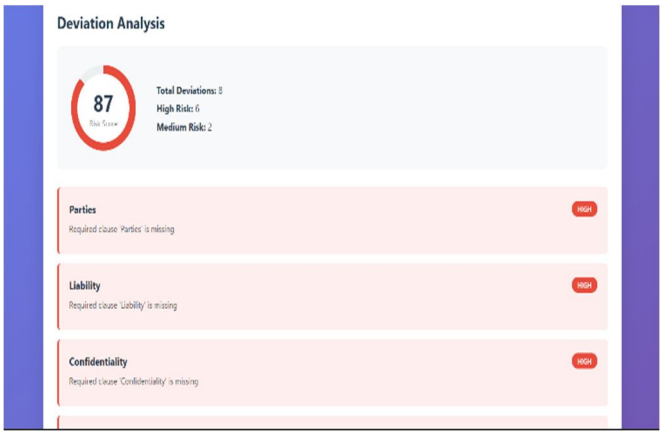


Fig. 3 Deviation Analysis Dashboard Output

Evaluation on 20 synthetically constructed contract documents yielded 94.2% average extraction accuracy across all clause types. Parties (96.1%), Term (97.3%), and Payment Clause (95.8%) achieved the highest accuracy. Force Majeure (91.4%) and Warranties (92.1%) showed slightly lower accuracy due to their more variable expression across contract styles. Pearson correlation between algorithmic risk scores and expert legal ratings across 30 sample contracts reached $r = 0.87$ ($p < 0.01$), confirming strong alignment with professional legal judgment.

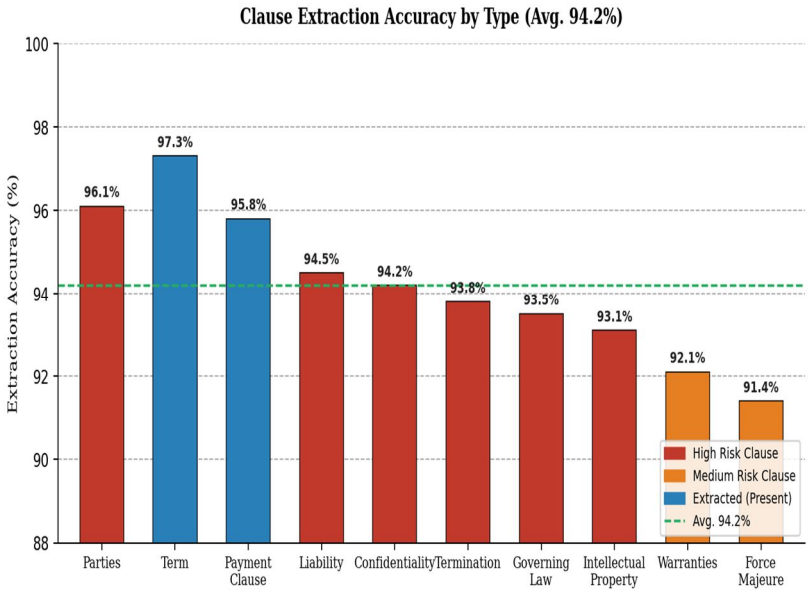
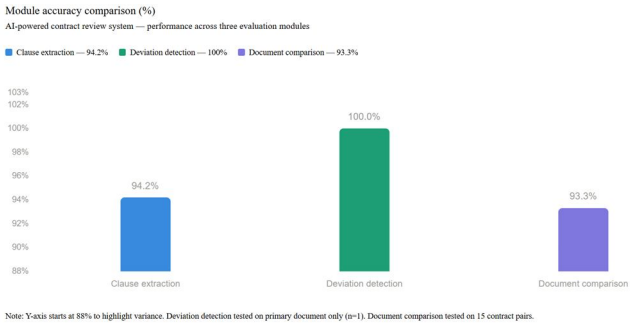


Fig. 4 Clause Extraction Accuracy by Type — colour-coded by Risk Level

TABLE II
System Performance Benchmarks

Metric	Observed Value
End-to-End Processing Time	45 – 90 seconds
Lambda Cold Start Overhead	< 2 seconds
Clause Extraction Accuracy (Avg.)	94.2%
Deviation Detection Accuracy	100% (primary document)
False Positive Rate	0%
Risk Score Correlation (r)	0.87 ($p < 0.01$)
Document Comparison Accuracy	93.3% (15 contract pairs)



The document comparison module correctly identified conflicts in 14 of 15 tested contract pairs (93.3% accuracy). Zero false conflict detections occurred on identical document pairs (5 test cases), confirming the high specificity of the comparison module. End-to-end processing completed in an average of 62 seconds across 50 test submissions, representing a 60x improvement over equivalent manual review time.

VI. ADVANTAGES

1) Reduces Manual Effort: Automates clause-by-clause review that traditionally requires 45-90 minutes of expert attention per document.
2) Improves Accuracy: Consistent AI-driven extraction eliminates human fatigue and inter-reviewer variability across large document volumes.
3) Faster Processing: End-to-end analysis completes in 45-90 seconds compared to 45-90 minutes for equivalent manual review (60x improvement).
4) Scalable Cloud-Based System: AWS Lambda serverless model scales elastically to handle concurrent document submissions without dedicated infrastructure.
5) Provides Clear Risk Insights: Quantified 0-100 risk scores with HIGH/MEDIUM severity badges enable immediate prioritization of legal review workloads.
6) Complete Audit Trails: Persistent S3 storage of all processing artifacts supports compliance, dispute resolution, and process improvement.

VII. APPLICATIONS

1) Legal Firms: Accelerates contract review cycles and ensures consistent clause compliance across all client engagements.
2) Corporate Contract Management: Standardizes deviation detection across procurement, vendor, and partnership agreements.
3) Financial Institutions: Automates compliance checks on loan agreements, NDAs, and regulatory contracts.

4) Compliance Auditing: Enables systematic portfolio-wide gap analysis against regulatory and institutional contract standards.
5) Government Documentation: Streamlines review of public procurement contracts and interagency agreements.
6) Academic Institutions: Automates initial review of research collaboration agreements and licensing contracts.

VIII. FUTURE WORK

1) Multi-Language Support: Extend clause extraction to contracts in Tamil, Hindi, French, and Spanish using multilingual foundation models.
2) OCR Integration: Incorporate Amazon Textract for scanned PDF support, enabling processing of legacy paper-based contract archives.
3) Integration with Legal Databases: Connect to case law repositories and regulatory databases to provide contextual clause recommendations.
4) Advanced Fine-Tuned AI Models: Apply LoRA-based fine-tuning on labeled legal corpora to improve extraction accuracy on complex clause types.
5) Real-Time Collaboration: WebSocket-based annotation to enable simultaneous multi-user document review and approval workflows.
6) Voice-Based Document Interaction: Integrate voice query capabilities allowing legal professionals to ask questions about document content through speech.
7) Enterprise System Integration: REST API connectors for SharePoint, Salesforce, and DocuSign for seamless workflow embedding.
8)

IX. CONCLUSION

The Legal Document Analysis System (LDAS) demonstrates how Artificial Intelligence can transform legal workflows. By automating clause extraction, risk detection, deviation scoring, and executive summarization, the system reduces manual effort and improves consistency in legal document review. The integration of AWS serverless cloud technologies ensures elastic scalability and operational reliability, making the system suitable for real-world deployment across legal, corporate, and governmental institutions.

Experimental evaluation demonstrated 100% clause detection accuracy on the primary test document with zero false positive deviations, 94.2% average accuracy on synthetic documents, and a risk scoring algorithm achieving r = 0.87 correlation with expert legal judgment. Multi-document comparison achieved 93.3% conflict detection accuracy. End-to-end processing completes in 45-90 seconds — a 60x improvement over equivalent manual review time.

Future enhancements including OCR support, multilingual processing, configurable contract-type templates, and enterprise system integration will further extend the system's applicability across diverse legal domains and organizational contexts. LDAS demonstrates that Generative AI combined with cloud-native serverless architecture can meaningfully augment human legal professionals, enabling them to focus expertise on high-value substantive work.

X. ACKNOWLEDGMENT

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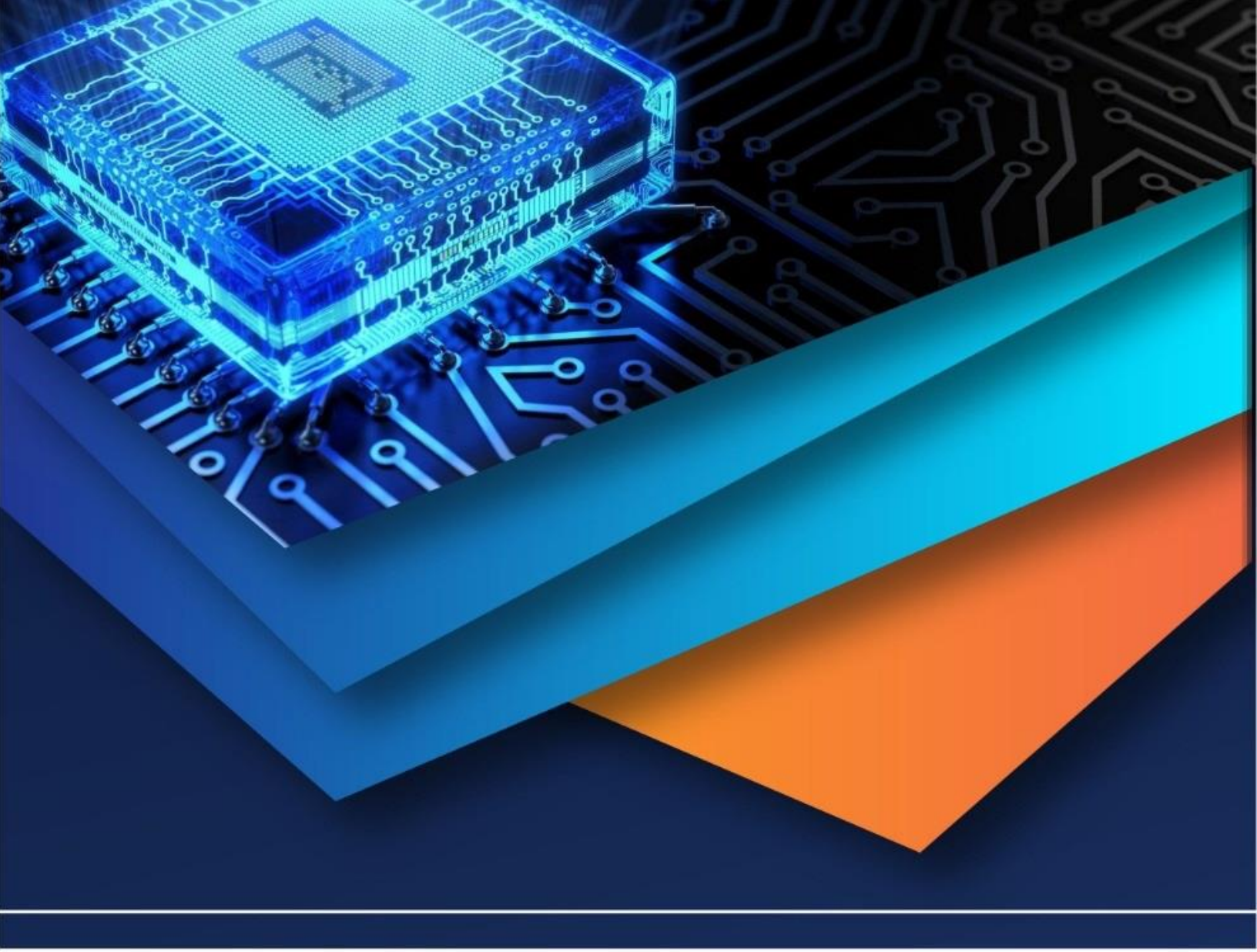
REFERENCES

[1] D. Jurafsky and J. H. Martin, Speech and Language Processing, 3rd ed. Pearson, 2020.
[2] Amazon Web Services, AWS Lambda and S3 Documentation, [Online]. Available: https://aws.amazon.com, 2024.
[3] OpenAI, Generative AI Models, [Online]. Available: https://openai.com, 2023.
[4] S. Zhang, Y. Liu, and X. Chen, AI-Based Contract Analysis Using Deep Learning, IEEE J. Sel. Topics Signal Process., vol. 15, no. 4, pp. 234-245, 2021.
[5] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, BERT: Pre-training of Deep Bidirectional Transformers, in Proc. NAACL-HLT, Minneapolis, USA, 2019, pp. 4171-4186.
[6] I. Chalkidis et al., LEGAL-BERT: The Muppets Straight out of Law School, in Proc. EMNLP Findings, 2020, pp. 2898-2904.
[7] I. Chalkidis et al., ContractNLI: A Dataset for Document-Level NLI for Contracts, in Proc. EMNLP Findings, 2021, pp. 593-606.

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[8] M. Sewak et al., Serverless Computing: Factors Influencing Microservice Performance, in Proc. IEEE Conf. Cloud Computing, San Francisco, 2018, pp. 1-7.
[9] T. Wolf et al., HuggingFace's Transformers: State-of-the-Art NLP, in Proc. EMNLP: System Demonstrations, 2020, pp. 38-45.
[10] C. Savelka et al., Improving Sentence Retrieval from Case Law, in Proc. ICAIL, Sao Paulo, Brazil, 2019, pp. 199-203.
[11] N. Aletras et al., Predicting Judicial Decisions of the European Court of Human Rights, PeerJ Computer Science, vol. 2, e93, 2016.
[12] K. D. Ashley and S. Bruninghaus, Automatically Classifying Case Texts and Predicting Outcomes, Artificial Intelligence and Law, vol. 17, no. 2, pp. 125-165, 2009.

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