MPBA G519 – NLP FOR BUSINESS PROJECT REPORT

MBA BUSINESS ANALYTICS SECOND SEMESTER 2024-25



TOPIC - CONTRACT REVIEW AND LEGAL DOCUMENT ANALYSIS USING NLP

SUPERVISOR: PROF. SATANIK MITRA

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SUBMITTED BY-

- 1. KARTIK VIJAY BADKAS 2024H1540809P
- 2. SATHEESH M K 2024H1540810P
- 3. SARVESH KULKARNI 2024H1540820P
- 4. GUZZU ADITYA 2024H1540827P
- 5. SAKET PITALE 2024H1540836P

Table of Content:

Sr No.	Topic	Page No.
1	Abstract	2
2	Introduction	2
3	Problem Statement	2
4	Objective	3
5	Literature Review / Base Paper Summary	3
6	Methodology	3
7	Technologies Used	3
8	Implementation	3
9	Results	5
10	Sample Output Screenshots	6
11	Conclusion	8
12	Future Scope	8
13	References	8

Abstract:

Legal contract review is a time-consuming and error-prone process that demands deep legal knowledge and meticulous attention to detail. LegalDocNLP is a Natural Language Processing (NLP) based system developed to automate and simplify the review process of legal contracts. The application extracts standard contractual clauses, classifies them with Legal-BERT, flags risky clauses, and generates concise summaries using T5. Built using Python and Flask, the system also supports keyword context analysis, enabling faster, more accurate, and scalable contract analysis.

1. Introduction:

Contracts form the foundation of most business agreements. Manual review of legal documents is labor-intensive, subjective, and prone to oversight. The advent of NLP provides an opportunity to leverage machine learning models trained on legal text to automate much of this process. This project implements a contract analyzer that reads a PDF file, extracts key clauses, classifies them using Legal-BERT, summarizes them using LegalT5, and displays the results in a structured, user-friendly web interface.

2. Problem Statement:

Manual contract review involves:

- Identifying risky clauses
- Understanding obligations
- Locating key parties and dates
- Analyzing terminations, indemnities, liabilities, etc.

All of the above are resource-heavy and inconsistent. The challenge is to build a system that:

- Automates clause classification
- Flags risky content
- Summarizes clauses
- Allows legal professionals to work faster and with fewer errors

3. Objective:

- Automate legal clause identification using Legal-BERT
- Summarize clauses using LegalT5
- Classify clauses by type (e.g., Termination, Indemnity, Confidentiality)
- Display extracted content via a user-friendly Flask interface
- Allow keyword-based clause context extraction

4. Literature Review / Base Paper Summary:

The project is built upon foundations laid in the CUAD (Contract Understanding Atticus Dataset) and research papers involving Legal-BERT and LegalT5. CUAD is a curated dataset of legal contracts annotated for clause types. Legal-BERT, built upon the BERT architecture, is pre-trained on legal documents and is ideal for classification tasks in the legal domain. LegalT5 is an adaptation of the T5 transformer model, trained to generate clause summaries.

5. Methodology:

The methodology includes the following components:

- Step 1: PDF Extraction (using PyMuPDF/fitz)
- Step 2: Clause Segmentation (sentence tokenization)
- Step 3: Clause Classification using Legal-BERT
- Step 4: Labelling using keyword mapping
- Step 5: Summarization using LegalT5
- Step 6: Keyword Context Analysis
- Step 7: Render through Flask web app

6. Technologies Used:

- Programming Language: Python 3.10+
- Libraries:
 - o transformers (HuggingFace)
 - o nltk
 - o Flask
 - o PyMuPDF (fitz)
 - o json/os/re/torch

7. Implementation:

This section outlines the implementation.

a) Clause Classification-

Using Legal-BERT, each sentence is passed through a pre-trained model:

```
# Load models and tokenizers
summarizer_tokenizer = T5Tokenizer.from_pretrained( pretrained_model_name_or_path: "SEBIS/legal_t5_small_summ_en", use_fast=False)
summarizer_model = T5ForConditionalGeneration.from_pretrained("SEBIS/legal_t5_small_summ_en")
bert_tokenizer = BertTokenizer.from_pretrained("nlpaueb/legal-bert-base-uncased")
bert_model = BertForSequenceClassification.from_pretrained( pretrained_model_name_or_path: "nlpaueb/legal-bert-base-uncased", num_labels=2)
```

b) Clause Labeling-

Keyword-based tagging is applied for labels like "Indemnity", "Confidentiality", etc.

```
# Define your clause labels
LABELS = [
    "Confidentiality",
    "Indemnity",
    "Termination",
    "Payment Terms",
    "Governing Law",
    "Intellectual Property",
    "Arbitration",
    "Exclusivity",
    "Non-compete",
    "Other"
]

lusage
def classify_clause(clause_text):
    inputs = tokenizer(clause_text, return_tensors="pt", truncation=True, padding=True)
    with torch.no_grad():
        outputs = model(**inputs)
        logits = outputs.logits
        predicted_class_id = logits.argmax().item()
        return LABELS[predicted_class_id]
```

c) Clause Summarization-

Using T5 model trained on legal text:

```
from transformers import T5Tokenizer, T5ForConditionalGeneration
from transformers import BertTokenizer, BertForSequenceClassification
import torch
import nltk
import fitz # PyMuPDF

nltk.download('punkt')

# Load models and tokenizers
summarizer_tokenizer = T5Tokenizer.from_pretrained( pretrained_model_name_or_path: "SEBIS/legal_t5_small_summ_en", use_fast=False)
summarizer_model = T5ForConditionalGeneration.from_pretrained("SEBIS/legal_t5_small_summ_en")
```

d) Flask Integration-

A front-end is provided to:

- Upload contracts
- View clause-wise labels and summaries

e) Keyword Context Extraction-Important keywords are highlighted with context from surrounding clauses.

```
def extract_keywords_contexts(pdf_path, top_n=5, window=40):
   doc = fitz.open(pdf_path)
   keyword_counts = Counter()
   keyword_contexts = defaultdict(list)
   for page_num, page in enumerate(doc, start=1):
       text = page.get_text()
       words = re.findall( pattern: r'\b\w+\b', text.lower())
       keyword_counts.update(words)
   stopwords = set([
       'on', 'at', 'by', 'an', 'be', 'this', 'are', 'from', 'or', 'it', 'was',
       'which', 'we', 'not', 'can', 'has', 'have', 'will', 'may', 'shall'
   1)
   for word in list(keyword_counts):
        if word in stopwords or len(word) < 3:</pre>
           del keyword_counts[word]
   top_keywords = keyword_counts.most_common(top_n)
   for keyword, _ in top_keywords:
        for page_num, page in enumerate(doc, start=1):
           text = page.get_text().lower()
           matches = [m.start() for m in re.finditer(r'\b{}\b'.format(re.escape(keyword)), text)]
           for match in matches:
                start = max(0, match - window)
                end = min(len(text), match + window)
                context = text[start:end]
```

8. Results:

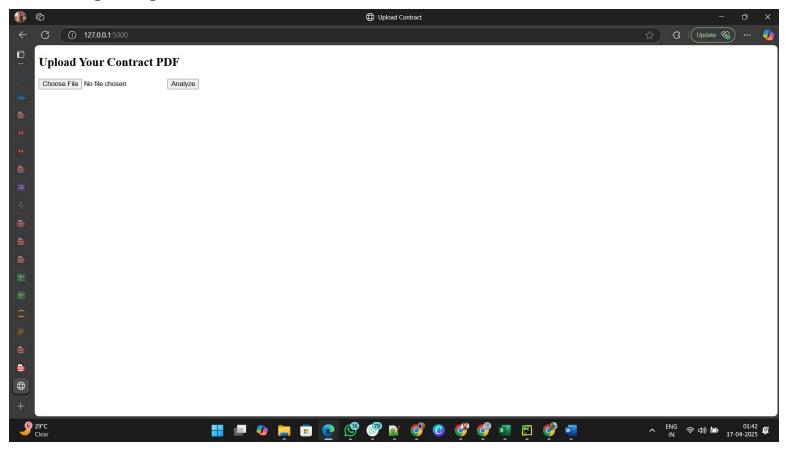
Results are presented in a structured HTML interface. Each clause is displayed with:

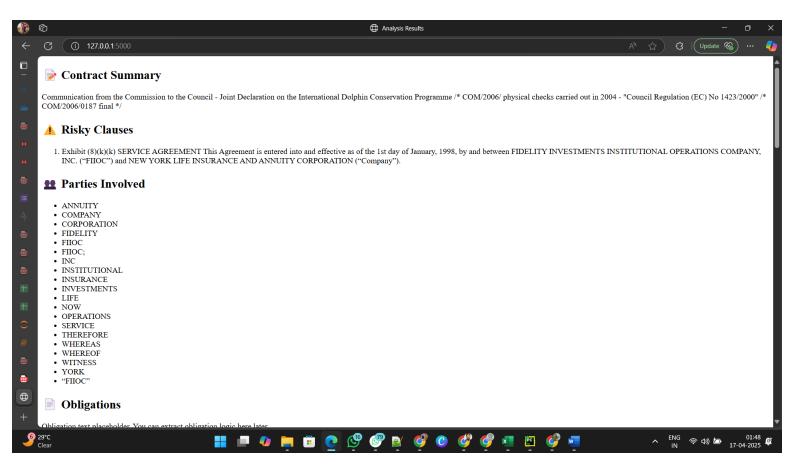
- Clause Label (e.g., Termination)
- Full Text
- Abstractive Summary

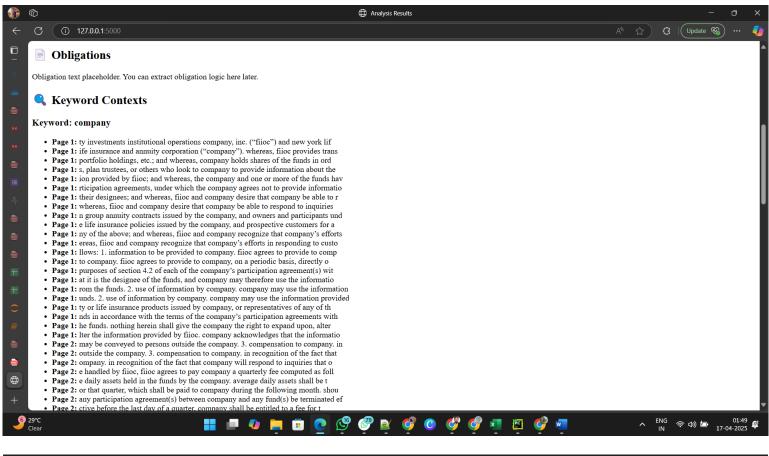
Additionally:

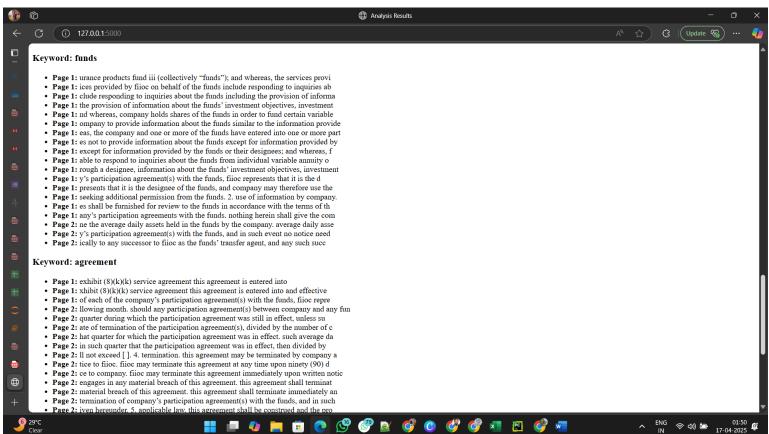
- All parties are extracted
- Obligations are listed
- Top keywords are shown with contextual usage

9. Sample Output Screenshots









10. Conclusion:

This project demonstrates how domain-specific NLP models can enhance the speed and accuracy of legal contract analysis. Using Legal-BERT and LegalT5, we successfully:

- Identified and labeled clauses
- Summarized legal language
- Highlighted risky content
- Delivered outputs in a clean, structured format
- The tool provides meaningful assistance to legal teams, saving time and effort.

11. Future Scope:

- Add OCR for scanned contracts
- Support multi-language contracts
- Train on user-provided templates
- Integrate with enterprise CMS (e.g., SharePoint, Salesforce)
- Add clause editing and clause comparison features

12. References

- https://huggingface.co/nlpaueb/legal-bert-base-uncased
- https://huggingface.co/SEBIS/legal_t5_small_summ_en
- CUAD Dataset: https://huggingface.co/datasets/cuad
- PyMuPDF: https://pymupdf.readthedocs.io/
- T5 paper: "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer"