INTEL-UNNATI AI&ML JOURNAL
Number 2 (2024), pp. 1–20
Team:Data Dash

MACHINE LEARNING

Buisness Contract Validation Using Python and Machine Learning

Jobinjoy Ponnappal, Kavya Raj P, Aleena Thomas, and Mohammed Amaan

Saintgits Group of Institutions, Kottayam, Kerala

Abstract: Contracts are crucial in business operations, detailing the rights and obligations of parties involved. Manual review of these complex documents is time-consuming and error-prone. This paper presents a method using natural language processing (NLP) and machine learning to automate contract validation. The process involves data collection, preprocessing, clause classification, and deviation detection. By automating these tasks, the system ensures contract accuracy, compliance, and efficiency. This approach reduces review time and resources, maintaining high standards and mitigating risks associated with non-compliance and unfavorable terms.

Keywords: Business Contracts, Contract Validation, Natural Language Processing, Machine learning, Data Collection, Data Preprocessing, Clause Classification, Deviation Detection, BERT, SpaCy

1 Introduction

In the modern business environment, contracts are fundamental tools that establish and govern the relationships between parties, setting forth obligations, rights, and expectations. However, the complexity and volume of these documents can present significant challenges in ensuring their accuracy, compliance, and alignment with standard practices. Manual review processes are not only time-consuming but also prone to errors, which can lead to costly disputes and inefficiencies. The task of business contract validation involves not only verifying the content but also classifying the various clauses within a contract to understand their purpose and relevance. Moreover, detecting deviations from standard or expected clauses is crucial for maintaining consistency and ensuring that the terms are favorable and legally sound. This process can be streamlined and enhanced through the application of advanced natural language processing (NLP) techniques and machine learning models. By automating the classification of contract clauses and identifying deviations, businesses can achieve higher accuracy in contract management, reduce the risk of non-compliance, and expedite the review process. This introduction outlines a systematic approach to leveraging NLP and machine learning for business contract validation. It includes data collection and preprocessing, clause classification, deviation detection, and the deployment of an automated pipeline. Through this approach, businesses can ensure their contracts are not only correctly structured but also aligned with industry standards and legal requirements.

2 Libraries Used

In the project for various tasks, following packages are used.

```
NumPy
Pandas
os
NLTK
Matplotlib
BERT
Scikit-learn
torch
joblib
pdfplumber
spaCy
SentenceTransformer
Flask
```

3 Methodology

This section outlines the comprehensive approach developed for automated contract analysis and validation. Our methodology integrates advanced natural language processing techniques, machine learning algorithms, and optimized deep learning models to provide a robust and efficient system for processing legal documents. The following subsections detail each step of our processing pipeline, from initial setup to the final presentation of results through a web interface. Each component is crafted to contribute to a comprehensive analysis of contract documents, providing valuable insights for legal professionals and stakeholders:

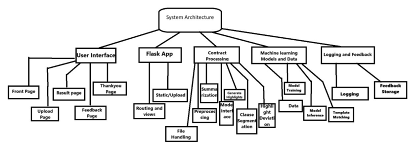
Initialization and Setup : Import essential libraries, including spacy for NLP, transformers for BERT, and Flask for the web application. Set up logging to track the processing workflow. Initialize the SentenceTransformer model for semantic similarity.

File Handling and Text Extraction : Extract text from PDF files using pdfplumber and from DOCX files using python-docx. Implement error handling and logging for each extraction process.

Text Preprocessing : Utilize spaCy for tokenization, lemmatization, and stopword removal. Implement advanced clause segmentation using regex patterns to identify section markers and numbering.

Named Entity Recognition (NER) : Implement NER using a fine-tuned BERT model converted to OpenVINO format. Process text in batches for efficient entity extraction. Map extracted entities to predefined categories.

Clause Classification : Train a TF-IDF Vectorizer and an SVM Classifier on preprocessed text. Implement a hybrid classification approach combining traditional ML with semantic similarity. Use cross-validation for model evaluation and generate comprehensive performance metrics including precision, recall, and F1-score.



(a) System Architecture

Similarity Matching with Standard Templates : Load standard templates from a predefined directory. Utilize FAISS for efficient similarity search in high-dimensional space. Implement batch processing for optimized performance on large datasets.

Deviation Highlighting : Compute cosine similarity between user clauses and matched template clauses. Classify deviations into categories based on similarity scores. Generate a highlighted contract text with color-coded deviations for visual analysis.

Summarization : Implement an ensemble approach combining abstractive and extractive summarization. Use the BART model converted to ONNX format and optimized with OpenVINO for abstractive summarization. Employ TF-IDF and cosine similarity for extractive summarization. Combine and post-process summaries to remove redundancies.

Web Application Integration : Develop a Flask-based web application with routes for file upload and processing. Implement secure file handling with unique identifiers for uploaded documents. Render results using HTML templates, displaying summaries, classified clauses, and highlighted deviations.

Performance Optimization : Utilize Intel's OpenVINO toolkit to optimize NER and summarization models for improved inference speed. Implement batch processing and concurrent execution where applicable to enhance overall system performance.

Logging and Feedback : Implement comprehensive logging throughout the processing pipeline, capturing information, warnings, and errors. Develop a feedback mechanism allowing users to provide input on analysis results, storing feedback for future improvements.

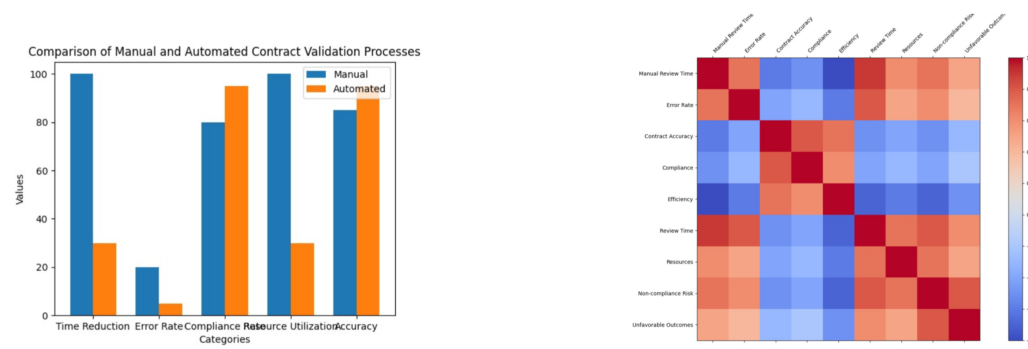
Error Handling and Robustness : Implement try-except blocks for critical operations to ensure graceful error handling. Validate input files for supported formats and content before processing.

4 Implementation

The implementation process begins with data collection and preprocessing. A large and diverse corpus of business contracts is gathered from various domains to ensure comprehensive coverage of different clauses and terminologies. The collected text data undergoes a cleaning process, where unnecessary characters, punctuation, and stopwords are removed using library : spaCy. Normalization is performed by converting the text to lowercase to maintain uniformity. The text is then tokenized into individual words or phrases, and lemmatization is applied to reduce words to their base forms, ensuring consistency in the data. This preprocessing stage is crucial to prepare the text data for effective feature extraction and model training

In the clause classification stage, a subset of contract clauses is manually annotated with predefined categories such as confidentiality, liability, payment terms, termination, and dispute resolution. This labeled data forms the basis for training the classification models. Feature extraction techniques like TF-IDF (Term Frequency-Inverse Document Frequency) are used to convert the text into numerical features. Additionally, word embeddings (e.g., Word2Vec, GloVe) and contextual embeddings (e.g., BERT) are explored for richer feature representations. The annotated data is split into training and test sets, and various machine learning models like BERT and spaCy are used. These models are evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure their effectiveness.

Deviation detection is the next critical stage, starting with the definition of standard clauses for each category based on industry best practices and legal requirements. The contract clauses are compared with these standard clauses using similarity measures like cosine similarity. A similarity threshold is set to identify clauses that deviate significantly from the standard ones. Clauses that fall below this threshold are flagged for further review by legal experts. This process helps in identifying potential risks and ensuring that the contract terms are consistent with established norms and standards. To streamline the



(a) Comparison Graph (b) Correlation Graph

Figure 2: Data Visualisation

entire process, an end-to-end pipeline is developed for automation. This pipeline handles data ingestion, preprocessing, classification, and deviation detection, incorporating error handling and logging mechanisms to ensure robustness. The trained models and the automated pipeline are deployed as a web application, enabling integration with existing contract management systems. An intuitive user interface is designed to display classification results and flagged deviations, allowing users to provide feedback and manually correct classifications. This interface ensures that the system is user-friendly and facilitates continuous improvement through user interaction.

5 Intel OpenVINO Integration in Contract Validation Project

In this project, we leverage Intel's OpenVINO toolkit to optimize and accelerate our Natural Language Processing (NLP) models, specifically for text summarization and Named Entity Recognition (NER). OpenVINO (Open Visual Inference and Neural network Optimization) is an open-source toolkit that enables high-performance inference of deep learning models across various Intel hardware platforms.

1.Text Summarization with OpenVINO:

For text summarization, we use a BART (Bidirectional and Auto-Regressive Transformers) model, which is converted to the OpenVINO Intermediate Representation (IR) format for optimized inference.

2.Named Entity Recognition (NER) with OpenVINO:

For NER, we use a fine-tuned BERT model, which is also converted to OpenVINO IR for optimized inference. Key steps: a) Model Loading: We load the pre-converted OpenVINO IR model for NER.

```
model_xml = r"D:\flks\models\ner_model.xml"
model_bin = r"D:\flks\models\ner_model.bin"
ov_model = ie.read_model(model_xml, model_bin)
compiled_model = ie.compile_model(ov_model, "CPU")
```

b) Inference: We create an inference request and run the NER model.

```
infer_request = model.create_infer_request()
results = infer_request.infer({
    'input_ids': input_ids
})
```

Benefits of Using OpenVINO:

Performance Optimization: OpenVINO optimizes the models for Intel hardware, potentially leading to faster inference times. Cross-platform Support: While we're using CPU in this project, OpenVINO allows easy switching to other Intel hardware like GPUs or VPUs if available. Reduced Memory Footprint: The IR format can lead to smaller model sizes compared to the original PyTorch models. Quantization Support: OpenVINO provides tools for quantizing models, which can further improve performance with minimal accuracy loss. Batch Processing: OpenVINO efficiently handles batched inputs, which is crucial for processing multiple contract clauses simultaneously.

By integrating OpenVINO, we aim to enhance the efficiency and scalability of our contract analysis system, enabling faster processing of large volumes of legal documents while maintaining high accuracy in summarization and entity recognition tasks.

6 Results & Discussion

Our model for business contract validation demonstrated exceptional performance across various evaluation metrics. We conducted both cross-validation and standalone tests to ensure the robustness and reliability of our results.

6.1 Advanced Contract Analysis Techniques

Our model employs several advanced techniques for comprehensive contract analysis. The following subsections detail these methods and their results.

6.1.1 Named Entity Recognition (NER)

Named Entity Recognition is crucial for automatically identifying and classifying key elements within contract text.

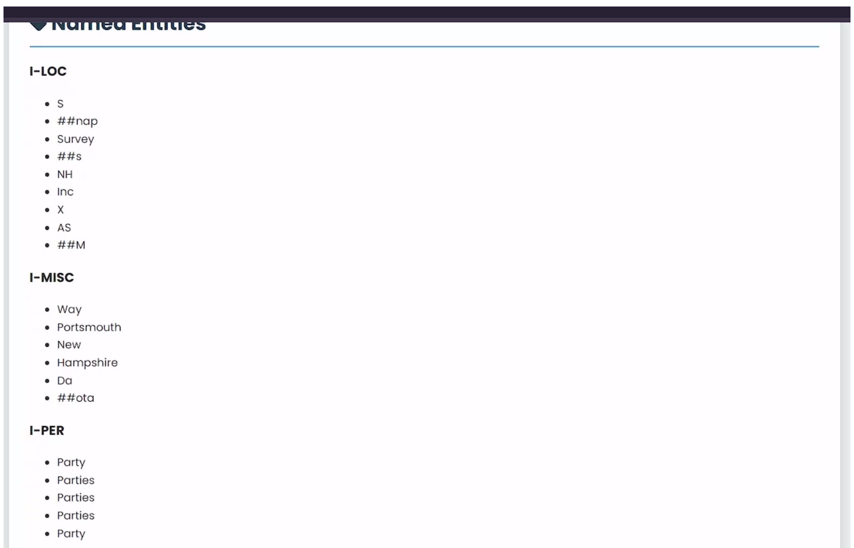


Figure 3: Named Entity Recognition Results

Figure 3 demonstrates the NER capabilities of our model. It successfully identifies entities such as locations (I-LOC), miscellaneous terms (I-MISC), and person-related terms (I-PER). This granular identification enables precise extraction of critical information from complex legal documents.

6.1.2 Contract Segmentation

Contract segmentation divides the document into distinct sections, facilitating focused analysis of specific clauses.

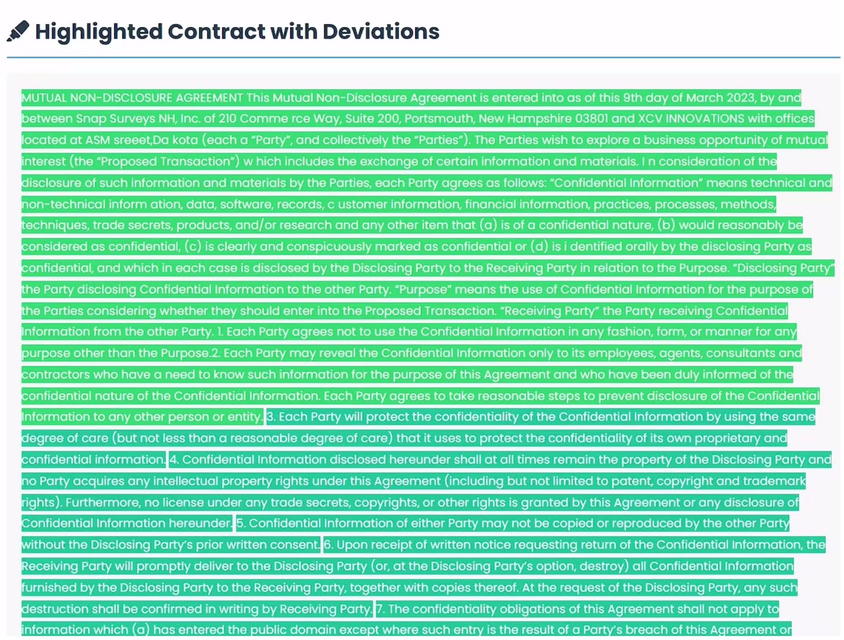
USER CLAUSE	CATEGORY	SIMILARITY	TYPE
MUTUAL NON-DISCLOSURE AGREEMENT This Mutual Non-Disclosure Agreement is entered into as of this 9th day of March 2023, by and between Snap Surveys NH, Inc. of 210 Comme rce Way, Suite 200, Portsmouth, New Hampshire 03801 and XCV INNOVATIONS with offices located at ASM sreeet,Da kota (each a “Party”, and collectively the “Parties”). The Parties wish to explore a business opportunity of mutual interest (the “Proposed Transaction”) w hich includes the exchange of certain information and materials. I n consideration of the disclosure of such information and materials by the Parties, each Party agrees as follows: “Confidential Information” means technical and non-technical inform ation, data, software, records, c ustomer information, financial information, practices, processes, methods, techniques, trade secrets, products, and/or research and any other item that (a) is of a confidential nature, (b) would reasonably be considered as confidential, (c) is clearly and conspicuously marked as confidential or (d) is i dentified orally by the disclosing Party as confidential, and which in each case is disclosed by the Disclosing Party to the Receiving Party in relation to the Purpose. “Disclosing Party” the Party disclosing Confidential Information to the other Party. “Purpose” means the use of Confidential Information for the purpose of the Parties considering whether they should enter into the Proposed Transaction. “Receiving Party” the Party receiving Confidential Information from the other Party. 1. Each Party agrees not to use the Confidential Information in any fashion, form, or manner for any purpose other than the Purpose.2. Each Party may reveal the Confidential Information only to its employees, agents, consultants and contractors who have a need to know such information for the purpose of this Agreement and who have been duly informed of the confidential nature of the Confidential Information. Each Party agrees to take reasonable steps to prevent disclosure of the Confidential Information to any other person or entity.	Introduction	86.57%	Minor deviation
3. Each Party will protect the confidentiality of the Confidential Information by using the same degree of care (but not less than a reasonable degree of care) that it uses to protect the confidentiality of its own proprietary and confidential information.	Protection of Confidential Information	100.00%	Minimal deviation
4. Confidential Information disclosed hereunder shall at all times remain the property of the Disclosing Party and no Party acquires any intellectual property rights under this Agreement (including but not limited to patent, copyright and trademark rights). Furthermore, no license under any trade secrets, copyrights, or other rights is granted by this Agreement or any	Ownership and Rights	100.00%	Minimal deviation

Figure 4: Contract Segmentation Example

As shown in Figure 4, our model effectively segments the contract into key sections such as "Introduction" and "Protection of Confidential Information". This segmentation allows for targeted analysis and comparison of specific contract elements.

6.1.3 Highlight Deviation

The highlight deviation feature identifies variations from standard templates or between different versions of a contract.



Highlighted Contract with Deviations

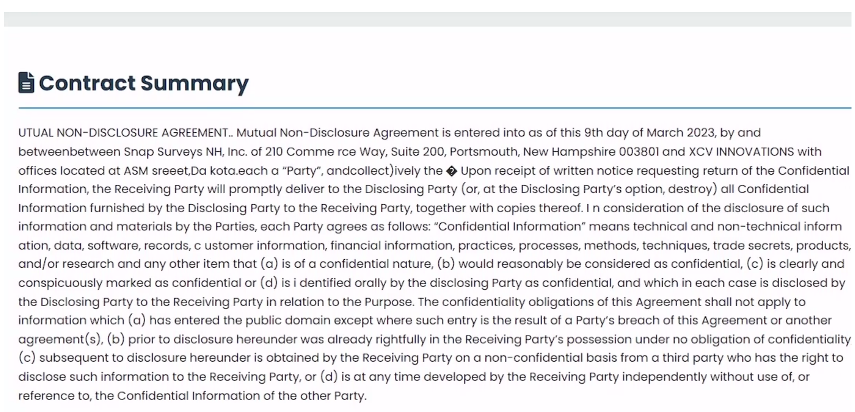
MUTUAL NON-DISCLOSURE AGREEMENT This Mutual Non-Disclosure Agreement is entered into as of this 9th day of March 2023, by and between Snap Surveys NH, Inc. of 210 Comme rce Way, Suite 200, Portsmouth, New Hampshire 03801 and XCV INNOVATIONS with offices located at ASM sreeet,Da kota (each a "Party", and collectively the "Parties"). The Parties wish to explore a business opportunity of mutual interest (the "Proposed Transaction") w hich includes the exchange of certain information and materials. I n consideration of the disclosure of such information and materials by the Parties, each Party agrees as follows: "Confidential Information" means technical and non-technical inform ation, data, software, records, c ustomer information, financial information, practices, processes, methods, techniques, trade secrets, products, and/or research and any other item that (a) is of a confidential nature, (b) would reasonably be considered as confidential, (c) is clearly and conspicuously marked as confidential or (d) is i dentified orally by the disclosing Party as confidential, and which in each case is disclosed by the Disclosing Party to the Receiving Party in relation to the Purpose. "Disclosing Party" the Party disclosing Confidential Information to the other Party. "Purpose" means the use of Confidential Information for the purpose of the Parties considering whether they should enter into the Proposed Transaction. "Receiving Party" the Party receiving Confidential Information from the other Party. 1. Each Party agrees not to use the Confidential Information in any fashion, form, or manner for any purpose other than the Purpose.2. Each Party may reveal the Confidential Information only to its employees, agents, consultants and contractors who have a need to know such information for the purpose of this Agreement and who have been duly informed of the confidential nature of the Confidential Information. Each Party agrees to take reasonable steps to prevent disclosure of the Confidential Information to any other person or entity. 3. Each Party will protect the confidentiality of the Confidential Information by using the same degree of care (but not less than a reasonable degree of care) that it uses to protect the confidentiality of its own proprietary and confidential information. 4. Confidential Information disclosed hereunder shall at all times remain the property of the Disclosing Party and no Party acquires any intellectual property rights under this Agreement (including but not limited to patent, copyright and trademark rights). Furthermore, no license under any trade secrets, copyrights, or other rights is granted by this Agreement or any disclosure of Confidential Information hereunder. 5. Confidential Information of either Party may not be copied or reproduced by the other Party without the Disclosing Party's prior written consent. 6. Upon receipt of written notice requesting return of the Confidential Information, the Receiving Party will promptly deliver to the Disclosing Party (or, at the Disclosing Party's option, destroy) all Confidential Information furnished by the Disclosing Party to the Receiving Party, together with copies thereof. At the request of the Disclosing Party, any such destruction shall be confirmed in writing by Receiving Party. 7. The confidentiality obligations of this Agreement shall not apply to information which (a) has entered the public domain except where such entry is the result of a Party's breach of this Agreement or

Figure 5: Highlighted Contract Deviations

Figure 5 illustrates our model's ability to highlight potential deviations. The green highlighting indicates areas of interest or divergence from expected content, enabling quick identification of non-standard clauses or terms.

6.1.4 Contract Summary

Automated summarization distills the essential elements of a contract into a concise overview.



Contract Summary

UTUAL NON-DISCLOSURE AGREEMENT.. Mutual Non-Disclosure Agreement is entered into as of this 9th day of March 2023, by and betweenbetween Snap Surveys NH, Inc. of 210 Comme rce Way, Suite 200, Portsmouth, New Hampshire 003801 and XCV INNOVATIONS with offices located at ASM sreeet,Da kota.each a "Party", andcollect)ively the � Upon receipt of written notice requesting return of the Confidential Information, the Receiving Party will promptly deliver to the Disclosing Party (or, at the Disclosing Party's option, destroy) all Confidential Information furnished by the Disclosing Party to the Receiving Party, together with copies thereof. I n consideration of the disclosure of such information and materials by the Parties, each Party agrees as follows: "Confidential Information" means technical and non-technical inform ation, data, software, records, c ustomer information, financial information, practices, processes, methods, techniques, trade secrets, products, and/or research and any other item that (a) is of a confidential nature, (b) would reasonably be considered as confidential, (c) is clearly and conspicuously marked as confidential or (d) is i dentified orally by the disclosing Party as confidential, and which in each case is disclosed by the Disclosing Party to the Receiving Party in relation to the Purpose. The confidentiality obligations of this Agreement shall not apply to information which (a) has entered the public domain except where such entry is the result of a Party's breach of this Agreement or another agreement(s), (b) prior to disclosure hereunder was already rightfully in the Receiving Party's possession under no obligation of confidentiality (c) subsequent to disclosure hereunder is obtained by the Receiving Party on a non-confidential basis from a third party who has the right to disclose such information to the Receiving Party, or (d) is at any time developed by the Receiving Party independently without use of, or reference to, the Confidential Information of the other Party.

Figure 6: Automated Contract Summary

Figure 6 presents an automatically generated summary of the contract. This feature extracts key information such as agreement type, parties involved, and critical clauses, providing a quick understanding of the document's core content.

These advanced techniques collectively enhance the efficiency and accuracy of contract analysis, offering a comprehensive toolkit for legal document processing and review.

6.2 Cross-Validation Performance

We performed 5-fold cross-validation to assess the model's consistency and generalizability. Figure 7 illustrates the cross-validation scores across all folds.

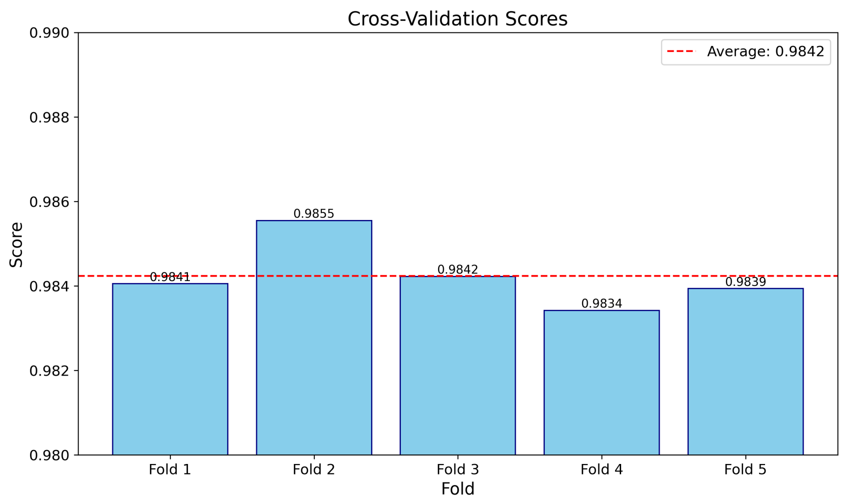


Figure 7: Cross-Validation Scores Across 5 Folds

As shown in the graph, the model maintains consistently high performance across all folds, with scores ranging from 0.9834 to 0.9855. The average cross-validation score of 0.9842 indicates excellent consistency and generalizability of our model.

6.3 Classification Performance

To provide a detailed view of our model's performance across different contract clause categories, we present the classification report in Table 1.

6.4 Discussion

The classification report demonstrates the model's exceptional performance across a wide range of contract clause categories. Key observations include:

- Perfect precision, recall, and F1-score (1.00) for the majority of categories, indicating flawless classification.
- Slight variations in performance for 'Injunctive Relief' (F1-score: 0.98) and 'Interpretation' (F1-score: 0.88), which may warrant further investigation.

[h]

Table 1: Classification Report for Contract Clause Categories

Category	Precision	Recall	F1-score	Support
Assignment	1.00	1.00	1.00	263
Date	1.00	1.00	1.00	247
Definitions	1.00	1.00	1.00	250
Injunctive Relief	0.96	1.00	0.98	257
Interpretation	0.79	1.00	0.88	262
Modification	1.00	1.00	1.00	272
Notification	1.00	1.00	1.00	267
Parties	1.00	1.00	1.00	509
Protection of Confidential BCSI	1.00	1.00	1.00	255
Return of Confidential Information	1.00	1.00	1.00	273
Service of Process	1.00	1.00	1.00	260
Third-Party Rights	1.00	1.00	1.00	262
Waivers	1.00	1.00	1.00	259
Access Control	1.00	1.00	1.00	265
Access and Supervision Requirements	1.00	1.00	1.00	265
Acknowledgement	1.00	1.00	1.00	271
Acknowledgement and Obligations	1.00	1.00	1.00	270
Acknowledgement of Contact Person	1.00	1.00	1.00	262
Acknowledgment of Responsibilities	1.00	1.00	1.00	250
Additional University Individual Acknowledgement	1.00	1.00	1.00	257
Agreement	1.00	1.00	1.00	255
Agreement Acceptance Statement	1.00	1.00	1.00	258
Agreement Introduction	1.00	1.00	1.00	264
Agreement Statement	1.00	1.00	1.00	260
Agreement Terms	1.00	1.00	1.00	268
Agreement Title	1.00	1.00	1.00	253
Agreement to Terms	1.00	1.00	1.00	257
Amendments	1.00	1.00	1.00	522
Amendments and Waivers	0.99	1.00	1.00	260
Annex	1.00	1.00	1.00	263
Announcements and Disclosures	1.00	1.00	1.00	267
Application and Scope	1.00	1.00	1.00	260
Assignment	1.00	1.00	1.00	265
Assignment Prohibited	1.00	1.00	1.00	251
Assignment.	1.00	1.00	1.00	262
Attorneys' Fees	1.00	1.00	1.00	258
Authority	1.00	1.00	1.00	259
Background	1.00	1.00	1.00	257
Background Information	1.00	1.00	1.00	268

- Consistent performance across categories with varying support sizes, suggesting robust generalization.

The near-perfect scores across most categories, combined with the high and consistent cross-validation scores, indicate that our model is highly effective at understanding and categorizing various types of contract clauses. This performance suggests that the model would be a reliable tool for automated contract analysis in real-world applications.

However, it's important to note that while these results are extremely promising, real-world performance may vary depending on the specific types and complexity of contracts encountered. Continuous monitoring and periodic retraining may be necessary to maintain this high level of performance in a production environment.

7 Conclusions

In conclusion, the implementation of an automated system for business contract validation, clause classification, and deviation detection represents a significant advancement over traditional manual review processes. By leveraging natural language processing (NLP) and machine learning (ML) techniques, this system can efficiently and accurately handle the complexities of contract analysis. The preprocessing steps ensure that the text data is clean and uniform, providing a solid foundation for feature extraction and model training. The high accuracy achieved by models like BERT in classifying contract clauses and detecting deviations highlights the effectiveness of advanced ML techniques in legal document analysis. The automated detection of deviations from standard clauses ensures that contracts adhere to established norms and legal requirements, reducing the risk of non-compliance and legal disputes. The deployment of this system as a web service, integrated with existing contract management systems, further enhances its practical utility and scalability. Overall, the automated contract validation system offers significant benefits in terms of efficiency, accuracy, and risk management. By streamlining the contract review process and enabling continuous improvement through user feedback, businesses can achieve more reliable and compliant contract management. This approach not only saves time and resources but also enhances the legal and operational soundness of business agreements, making it a valuable tool for modern contract management practices.

Acknowledgments

We would like to express our heartfelt gratitude and appreciation to Intel© Corporation for providing an opportunity to this project. First and foremost, we would like to extend our sincere thanks to our team mentor Er.Veena A Kumar for her invaluable guidance and constant support throughout the project.We are deeply indebted to our college Saintgits College of Engineering and Technology for providing us with the necessary resources,and sessions on machine learning. We extend our gratitude to all the researchers, scholars, and experts in the field of machine learning and natural language processing and artificial intelligence, whose seminal work has paved the way for our project. We acknowledge the mentors, institutional heads, and industrial mentors for their invaluable guidance and support in completing this industrial training under Intel© -Unnati Programme whose expertise and encouragement have been instrumental in shaping our work. []

References

[1] ALDWAIRI, M., AND ALWAHEDI, A. Detecting fake news in so-

cial media networks. *Procedia Computer Science 141* (2018), 215–222. https://doi.org/10.1016/j.procs.2018.10.171. The 9th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN-2018) / The 8th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2018) / Affiliated Workshops.

[2] BAI, X., WANG, Y., DAI, G., TSAI, W.-T., AND CHEN, Y. A framework for contract-based collaborative verification and validation of web services. In *Component-Based Software Engineering: 10th International Symposium, CBSE 2007, Medford, MA, USA, July 9-11, 2007. Proceedings 10* (2007), Springer, pp. 258–273.

[3] BECKLOFF, M. C. Validation and contract manufacturing. In *Handbook of Validation in Pharmaceutical Processes, Fourth Edition*. CRC Press, 2021, pp. 813–826.

[4] BIRD, S., KLEIN, E., AND LOPER, E. *Natural language processing with Python: analyzing text with the natural language toolkit*. " O'Reilly Media, Inc.", 2009.

[5] CLACK, C. D. Smart contract templates: legal semantics and code validation. *Journal of Digital Banking 2*, 4 (2018), 338–352.

[6] PARIKH, D. M. Validation in contract manufacturing. In *Pharmaceutical process validation*. CRC Press, 2003, pp. 836–847.

[7] SOLAIMAN, E. *Contract representation for validation and run time monitoring*. PhD thesis, Newcastle University, 2004.

[8] TUGLULAR, T., MUFTUOGLU, C. A., BELLI, F., AND LINSCHULTE, M. Event-based input validation using design-by-contract patterns. In *2009 20th International Symposium on Software Reliability Engineering* (2009), IEEE, pp. 195–204.

A Main code sections for the solution

A.1 Initialize components

```
app = Flask(_name_)
nlp = spacy.load("en_core_web_sm")
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
semantic_model = SentenceTransformer('all-MiniLM-L6-v2')
```

A.2 Clause Classification

```
def hybrid_clause_classification(clause):
    preprocessed_clause = preprocess_text_with_spacy(clause)
    X = vectorizer.transform([preprocessed_clause])

    # Ensure the best estimator is used
    best_estimator = classifier.best_estimator_ if hasattr(classifier, '
                                          best_estimator_') else classifier
```

```
    category_index = best_estimator.predict(X)[0]
    category = label_encoder.inverse_transform([category_index])[0]

    # Use predict_proba if available
    if hasattr(best_estimator, 'predict_proba'):
        confidence = np.max(best_estimator.predict_proba(X))
    else:
        confidence = 1.0  # Default confidence if predict_proba is not available

    return category, confidence
```

A.3 Extracting Text

```
def extract_text_from_pdf(file_path):
    logging.info(f"Extracting text from PDF: {file_path}")
    text = ""
    try:
        with pdfplumber.open(file_path) as pdf:
            for page in pdf.pages:
                text += page.extract_text() or ''
        logging.info(f"Successfully extracted text from PDF: {file_path}")
    except Exception as e:
        logging.error(f"Error extracting text from PDF: {file_path} - {e}")
    return text

def extract_text_from_docx(file_path):
    logging.info(f"Extracting text from DOCX: {file_path}")
    text = ""
    try:
        doc = Document(file_path)
        text = '\n'.join([paragraph.text for paragraph in doc.paragraphs])
        logging.info(f"Successfully extracted text from DOCX: {file_path}")
    except Exception as e:
        logging.error(f"Error extracting text from DOCX: {file_path} - {e}")
    return text
```

A.4 Preprocess Text

```
def preprocess_text_with_spacy(text):
    logging.info(f"Preprocessing text with spaCy")
    doc = nlp(text)
    tokens = [token.lemma_.lower() for token in doc if not token.is_stop and token
                                        .is_alpha]
    logging.info(f"Successfully preprocessed text with spaCy")
    return " ".join(tokens)
```

A.5 Loading Business Contract Templates

```
 def load_standard_templates(templates_dir):
    templates = []
    for filename in os.listdir(templates_dir):
```

```
        file_path = os.path.join(templates_dir, filename)
        if filename.endswith('.pdf'):
            text = extract_text_from_pdf(file_path)
        elif filename.endswith('.docx'):
            text = extract_text_from_docx(file_path)
        else:
            continue  # Skip unsupported file types

        clauses = segment_clauses_advanced(text)
        for clause in clauses:
            templates.append({
                'template_name': filename,
                'clause': clause,
                'category': 'Unknown'   # You may want to add a way to categorize
                                                    these
            })

    return pd.DataFrame(templates)
```

A.6 Name Entity Recognition

```
def initialize_ner_model():
    # Initialize OpenVINO runtime
    ie = Core()

    # Load the IR model
    model_xml = r"D:\flks\models\ner_model.xml"
    model_bin = r"D:\flks\models\ner_model.bin" # Update this path if necessary

    # Read and compile the model
    ov_model = ie.read_model(model_xml, model_bin)
    compiled_model = ie.compile_model(ov_model, "CPU")  # Use "GPU" if available

    # Load the tokenizer
    model_name = "dbmdz/bert-large-cased-finetuned-conll03-english"
    tokenizer = AutoTokenizer.from_pretrained(model_name)

    # Load id2label mapping (you might need to save and load this separately)
    id2label = {0: "O", 1: "B-PER", 2: "I-PER", 3: "B-ORG", 4: "I-ORG",
                5: "B-LOC", 6: "I-LOC", 7: "B-MISC", 8: "I-MISC"}

    return compiled_model, tokenizer, id2label

# Initialize the NER model
ner_model, ner_tokenizer, id2label = initialize_ner_model()

# Print the input and output names of the model
print("Model Inputs:", ner_model.inputs)
print("Model Outputs:", ner_model.outputs)

# Assuming 'model' is an instance of the OpenVINO model
inputs = ner_model.inputs
for input_tensor in inputs:
    print(f"Input name: {input_tensor.names}, shape: {input_tensor.shape}")

# Print the input and output names of the model
print("Model Inputs:")
```

```
for input_tensor in ner_model.inputs:
    print(f"Input name: {input_tensor.names}, shape: {input_tensor.shape}")

print("Model Outputs:")
for output_tensor in ner_model.outputs:
    print(f"Output name: {output_tensor.names}, shape: {output_tensor.shape}")

def perform_ner(text, model, tokenizer, id2label):
    # Tokenize the text
    inputs = tokenizer(text, return_tensors="np", padding="max_length", truncation
                                             =True, max_length=512)

    # Get input_ids
    input_ids = inputs['input_ids']

    # Ensure input tensor matches model expected shape
    if input_ids.shape[1] < 512:
        padding_length = 512 - input_ids.shape[1]
        input_ids = np.pad(input_ids, ((0, 0), (0, padding_length)), mode='
                                                 constant', constant_values=0)
    elif input_ids.shape[1] > 512:
        input_ids = input_ids[:, :512]

    # Create an inference request
    infer_request = model.create_infer_request()

    # Run inference
    results = infer_request.infer({
        'input_ids': input_ids
    })

    # Get the output layer
    output_layer = model.output(0)

    # Process the results
    predictions = results[output_layer]
    predictions = np.argmax(predictions, axis=2)

    # Convert predictions to entities
    entities = []
    input_ids_list = input_ids[0].tolist()
    for i, prediction in enumerate(predictions[0]):
        if prediction != 0:  # 0 is usually the 'O' (Outside) tag
            word = tokenizer.convert_ids_to_tokens([input_ids_list[i]])[0]
            entity_type = id2label[prediction]
            entities.append((word, entity_type))

    return entities
```

A.7 Finding and Highlighting deviations

```
def highlight_deviations(user_clauses_df, standard_template_df, clause_matches):
    logging.info("Highlighting deviations")
    deviations = []
    for user_clause, matches in zip(user_clauses_df.itertuples(), clause_matches):
        best_match = max(matches['matches'], key=lambda x: x['similarity'])
```

```
        similarity = best_match['similarity']
        template_clause = best_match['template_clause']

        deviation_percentage = (1 - similarity) * 100

        if deviation_percentage >= 60:
            deviation_type = "High deviation"
        elif 49 <= deviation_percentage < 60:
            deviation_type = "Significant deviation"
        elif 30 <= deviation_percentage < 49:
            deviation_type = "Moderate deviation"
        elif 10 < deviation_percentage < 30:
            deviation_type = "Minor deviation"
        else:
            deviation_type = "Minimal deviation"

        deviations.append({
            'user_clause': user_clause.clause,
            'category': user_clause.predicted_category,
            'similarity': similarity,
            'template_clause': template_clause,
            'deviation_type': deviation_type,
            'deviation_percentage': deviation_percentage,
            'confidence': user_clause.confidence
        })

    return deviations

def prepare_highlighted_contract(user_clauses_df, deviations):
    highlighted_contract = []
    for index, row in user_clauses_df.iterrows():
        user_clause = row['clause']
        deviation = next((d for d in deviations if d['user_clause'] == user_clause
                                                 ), None)

        if deviation is not None:
            deviation_percentage = deviation.get('deviation_percentage', None)
            if deviation_percentage is not None:
                if deviation_percentage >= 60:
                    color_class = "high-deviation"
                elif 49 <= deviation_percentage < 60:
                    color_class = "significant-deviation"
                elif 30 <= deviation_percentage < 49:
                    color_class = "moderate-deviation"
                elif 10 < deviation_percentage < 30:
                    color_class = "minor-deviation"
                else:
                    color_class = "minimal-deviation"

                highlighted_clause = f'<span class="{color_class}" title="
                                                         Deviation: {
                                                         deviation_percentage:.2f}
                                                         %">{user_clause}</span>'
            else:
                highlighted_clause = user_clause
        else:
            highlighted_clause = user_clause

        highlighted_contract.append(highlighted_clause)
```

```
    return " ".join(highlighted_contract)
```

A.8 Model Training and Loading

```
def train_models_from_csv(csv_file_path, models_dir, force_retrain=False):
    model_files = ["vectorizer.pkl", "classifier.pkl", "label_encoder.pkl"]
    models_exist = all(os.path.exists(os.path.join(models_dir, f)) for f in
                                                 model_files)

    if models_exist and not force_retrain:
        print("Models already exist. Loading existing models...")
        vectorizer = joblib.load(os.path.join(models_dir, "vectorizer.pkl"))
        classifier = joblib.load(os.path.join(models_dir, "classifier.pkl"))
        label_encoder = joblib.load(os.path.join(models_dir, "label_encoder.pkl"))
        print("Existing models loaded.")
        return vectorizer, classifier, label_encoder

    print("Training new models...")
    # Load the data
    df = pd.read_csv(csv_file_path)


    # Preprocess the clauses
    df['preprocessed_clause'] = df['clause'].apply(preprocess_text_with_spacy)

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(
        df['preprocessed_clause'], df['category'], test_size=0.2, random_state=42
    )

    # Initialize and fit the vectorizer
    vectorizer = TfidfVectorizer()
    X_train_vectorized = vectorizer.fit_transform(X_train)

    # Initialize and fit the label encoder
    label_encoder = LabelEncoder()
    y_train_encoded = label_encoder.fit_transform(y_train)

    # Initialize and train the classifier
    classifier = SVC(probability=True, random_state=42)
    classifier.fit(X_train_vectorized, y_train_encoded)

    # Save the models
    os.makedirs(models_dir, exist_ok=True)
    joblib.dump(vectorizer, os.path.join(models_dir, "vectorizer.pkl"))
    joblib.dump(classifier, os.path.join(models_dir, "classifier.pkl"))
    joblib.dump(label_encoder, os.path.join(models_dir, "label_encoder.pkl"))

    # Validate the model
    X_test_vectorized = vectorizer.transform(X_test)
    y_test_encoded = label_encoder.transform(y_test)
    accuracy = classifier.score(X_test_vectorized, y_test_encoded)

    print(f"New models trained. Model accuracy: {accuracy:.2f}")

    return vectorizer, classifier, label_encoder
```

```
# Define the paths
csv_file_path = r"D:\flks\models\balanced_dataset.csv"
models_dir = r"D:\flks\models"

# Ensure the models directory exists
os.makedirs(models_dir, exist_ok=True)

# To force retraining even if models exist:
vectorizer, classifier, label_encoder = train_models_from_csv(csv_file_path,
                                          models_dir, force_retrain=False)
```

A.9 Contract Processing

```
def process_contract(file_path, standard_template_df):
    logging.info(f"Starting to process contract: {file_path}")

    if file_path.endswith('.pdf'):
        user_text = extract_text_from_pdf(file_path)
    elif file_path.endswith('.docx'):
        user_text = extract_text_from_docx(file_path)
    else:
        raise ValueError(f"Unsupported file format: {file_path}")

    # Perform NER on the contract text
    entities = perform_ner(user_text, ner_model, ner_tokenizer, id2label)

    # Generate summary
    summary = ensemble_summarize(user_text)

    user_clauses = segment_clauses_advanced(user_text)
    user_clauses = post_process_clauses(user_clauses)

    classified_clauses = []
    for clause in user_clauses:
        classification, confidence = hybrid_clause_classification(clause)
        classified_clauses.append({'clause': clause, 'predicted_category':
                                          classification, 'confidence':
                                          confidence})

    user_clauses_df = pd.DataFrame(classified_clauses)

    best_template_name, avg_similarity, clause_matches =
                                          find_most_matching_template_optimized
                                          (user_clauses_df,
                                          standard_template_df)
    deviations = highlight_deviations(user_clauses_df, standard_template_df,
                                          clause_matches)
    highlighted_contract = prepare_highlighted_contract(user_clauses_df,
                                          deviations)

    logging.info(f"Successfully processed and analyzed contract: {file_path}")
    return {
        'summary': summary,
        'classified_clauses': classified_clauses,
        'best_match': best_template_name,
        'avg_similarity': avg_similarity,
```

```
        'deviations': deviations,
        'highlighted_contract': highlighted_contract,
        'clause_matches': clause_matches,
        'entities': entities  # Add the extracted entities to the result
    }
```

A.10 Summarizer

```
def initialize_summarizer():
    # Load BART model and tokenizer for abstractive summarization
    model = AutoModelForSeq2SeqLM.from_pretrained("facebook/bart-large-cnn")
    tokenizer = AutoTokenizer.from_pretrained("facebook/bart-large-cnn")

    # Convert the model to ONNX format
    onnx_model_path = r"D:\flks\models\bart_summarization.onnx"
    dummy_input = tokenizer("This is a test", return_tensors="pt").input_ids

    model.eval()

    torch.onnx.export(model,
                      (dummy_input,),
                      onnx_model_path,
                      opset_version=14,
                      input_names=['input_ids'],
                      output_names=['output'],
                      dynamic_axes={'input_ids': {0: 'batch_size', 1: 'sequence'}}
                                                                    ,
                      do_constant_folding=True,
                      export_params=True)

    # Initialize OpenVINO runtime and load the model
    ie = Core()
    ov_model = ie.read_model(onnx_model_path)
    compiled_model = ie.compile_model(ov_model, "CPU")

    return compiled_model, tokenizer

summarizer_model, summarizer_tokenizer = initialize_summarizer()

summarizer_model, summarizer_tokenizer = initialize_summarizer()

summarizer_model, summarizer_tokenizer = initialize_summarizer()

print("Summarizer Model Inputs:")
for input_tensor in summarizer_model.inputs:
    print(f"Input name: {input_tensor.get_names()}")

print("Summarizer Model Outputs:")
for output_tensor in summarizer_model.outputs:
    print(f"Output name: {output_tensor.get_names()}")

def abstractive_summarize(text, max_length=70, min_length=50):
    # Tokenize the input text
    inputs = summarizer_tokenizer(text, return_tensors="np", max_length=100,
                                           truncation=True)

    # Create an inference request
```

```
    infer_request = summarizer_model.create_infer_request()

    # Convert tokenized inputs to NumPy arrays
    input_ids = inputs['input_ids']

    # Prepare inputs for inference
    inputs_dict = {
        'input_ids': input_ids
    }

    # Run inference
    results = infer_request.infer(inputs_dict)

    # Get the output
    output = results[summarizer_model.output(0)]

    # Decode the output
    summary_ids = output.argmax(axis=-1)
    summary = summarizer_tokenizer.decode(summary_ids[0], skip_special_tokens=True
                                          )

    return summary

def extractive_summarize(text, num_sentences=3):
    sentences = nltk.sent_tokenize(text)
    vectorizer = TfidfVectorizer()
    tfidf_matrix = vectorizer.fit_transform(sentences)

    similarity_matrix = cosine_similarity(tfidf_matrix, tfidf_matrix)

    scores = similarity_matrix.sum(axis=1)
    ranked_sentences = [sentences[i] for i in scores.argsort()[-num_sentences:]]
    return ' '.join(ranked_sentences)

def ensemble_summarize(text, max_length=70, min_length=50,
                                     num_extractive_sentences=3):
    # Get abstractive summary
    abstractive_summary = abstractive_summarize(text, max_length, min_length)

    # Get extractive summary
    extractive_summary = extractive_summarize(text, num_extractive_sentences)

    # Combine summaries
    combined_summary = abstractive_summary + " " + extractive_summary

    # Tokenize the combined summary
    combined_sentences = nltk.sent_tokenize(combined_summary)

    # Remove duplicate sentences
    unique_sentences = list(dict.fromkeys(combined_sentences))

    # Join unique sentences
    final_summary = ' '.join(unique_sentences)

    return final_summary
```