Dispute Management in Engineering Contracts Using Artificial Intelligence

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Abstract

The study put forward an integrated artificial intelligence-based approach to the analysis and prediction of contracting disputes in Engineering Projects, especially through Machine Learning methods and Deep Learning methods. Current ways of managing contracts cannot effectively deal with the complicated nature of Legal Texts and do not provide for early identification of potential disputes. This developed System was built using the Python Programming Language, using key libraries for Natural Language Processing (NLP) and Machine Learning (ML). The cache of Contract Documents in all formats was transformed into numerical vectors using TF-IDF once all Document Processing and Clean-up Procedures were completed. Multiple Models were built, with trained versions of each, including Logistic Regression, SVM, Voting Classifiers and an MLP (Multi-Layer Perceptron) based Neural Network model. Since each Contracting Dispute was modelled separately to improve overall prediction accuracy, initial recommendations for resolution are generated. Results show that the MLP performed in a SUPERIOR fashion, with an Overall Model Accuracy of 88%, and F1 Score of 0.874, effectively classifying Contracting Disputes relating to Delays, Payments and Scope Variations. The application of this framework to an actual example taken from the construction industry in Syria reaffirmed the capability of automating contract text review and improving risk management. This reinforces the importance of artificial intelligence as a tool for increasing proactive decision-making and minimizing conflict in engineering projects.

Keywords: Engineering Contract; Building Information Modeling (BIM); Artificial Intelligence (AI); Legal Dispute Resolution; Machine Learning; Dispute Prediction

1. Introduction

The construction industry is one of the most complex sectors due to the involvement of multiple stakeholders, diverse contracts, and constantly changing environments throughout a project's lifecycle[1]. Traditional methods of contract management and dispute detection often rely on manual reviews conducted by legal and engineering experts[2, 3]. While these methods are valuable, they face significant challenges in complex, data-driven projects, such as delayed dispute detection, inconsistent interpretations, limited capacity to handle large-scale data, and the absence of proactive mechanisms for risk prediction[4].

Artificial intelligence has emerged as an effective tool to address these challenges, particularly through machine learning and deep learning techniques. By leveraging natural language processing (NLP)[5], these technologies

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enable the analysis of complex legal texts and the extraction of contractual patterns that may lead to disputes, offering early warnings and allowing legal and engineering teams sufficient time to make informed decisions[6, 7].

This research focuses on developing an integrated intelligent system for analyzing engineering contracts by combining machine learning algorithms with neural network architectures. Advanced programming languages and tools such as Python, Scikit-learn, SpaCy, and TfidfVectorizer were utilized to build and train the system[8]. The framework was practically tested on a real-world Syrian construction project, demonstrating its efficiency in enhancing transparency, simplifying dispute management, and improving the quality of contractual decision-making, thereby supporting the digital transformation of the construction sector[9].

In order to clarify the theoretical foundation for this project, the following definition of concepts/terms/tools related to this intelligent system is provided below:

- Engineering Contract: A formal document created between an Owner and a Contractor that outlines all technical, financial and scheduling requirements and obligations of the Owner, and, the Contractor. This document serves as the primary document for resolving disputes during the duration of a project.
- Artificial Intelligence (AI): An area of computer science focused on creating a computer system that can learn, make decisions, and perform analyses of data similar to that of a human being's cognitive ability[10].
- The Role of AI: The advantages of using AI include its ability to rapidly analyze vast amounts of information; its ability to make quick decisions; its ability to forecast issues prior to their occurrence, and thus make it an invaluable tool for modern project management.
- Programming in Python: Python is the chosen programming language to develop this system because of its versatility and the numerous advanced AI libraries available for its use[11].
- Machine Learning (ML): ML is the method used to create models that learn from previous data to help forecast or classify future incidents[12].
- Deep Learning: DL is a subdivision of ML developed using deep neural networks to analyze intricate datasets[13].
- Natural Language Processing (NLP): NLP is a computer program that allows computers to read, write and comprehend human-created textual content[14].
- Scikit-learn is a basic ML framework (framework) consisting of various ML classifiers (e.g., Logistic Regression, SVM, and MLP), in addition to providing support for dividing training and test datasets (dataset splitting), as well as evaluating model performance using available metrics (e.g., Accuracy, Precision, and Recall). These core functionalities form the basis for developing the modelling components used by our study[15].
- A TF-IDF Vectoriser (tool) converts textual information into numerical vectors using the definition of the term frequency-inverse document frequency (TF-IDF) to identify and prioritise the most informative Terms in both legal and contractual documents related to civil disputes[16], thereby serving as a key pre-processing technique to prepare a set of datasets for training and testing purposes.
- spaCy (advanced NLP utils) serves as a convenient, fast, and efficient resource to both[17]: (1) tokenise and clean legal text (legal text) and (2) prepare and extract important entities, such as parties involved, durations, and amounts, as a high-quality reference before establishing a model in ML.

2. Literature Review

Engineering contracts set the legal foundation for project execution[18]. They define the responsibilities and rights of the parties involved, outline implementation procedures, establish quality standards, and specify the steps to follow in case of a dispute[19]. However, the complexity of these contracts and the presence of multiple stakeholders often lead to ongoing disputes[20]. These can arise from delayed payments, changes in work scope, or poor coordination. Minor claims can escalate over time without clear resolution methods, negatively affecting the quality of execution, schedules, and costs[21, 22].

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In the past, managing disputes in engineering contracts depended on manual reviews by legal or engineering experts[23]. Unfortunately, these traditional methods often struggle with large data volumes and do not provide proactive signs that could identify disputes before they worsen[24]. Here, artificial intelligence (AI) has emerged as a valuable tool. It can analyze complex texts and predict risks quickly and accurately[25]. AI techniques like Machine Learning, Deep Learning, Natural Language Processing (NLP), and expert systems help extract patterns from large data sets, classify contractual clauses, and identify gaps that might lead to future disputes[26].

Several international studies have explored this topic thoroughly. For example, Putera et al. (2021) showed that AI can help improve future justice by automating dispute analysis[27]. Alqaisi et al. (2024) created a model to predict the results of contract change disputes using machine learning algorithms[9]. Francis et al. (2025) reviewed AI applications for proactive dispute management[28]. Similarly, Un et al. (2024) focused on using machine learning techniques to predict contract dispute outcomes[29], while Raslan and Nassar (2024) proposed a framework that combines AI with sustainability for dispute resolution[30]. Additionally, Harode et al. (2024) introduced a machine learning model for predicting design clash resolution options[31].

These studies show that using AI in engineering contracts has moved beyond being just an experimental trend[32]. It has become a practical way to improve dispute management efficiency while lowering costs and time. However, there is still a gap in real-world applications within complex local settings, such as the Syrian contractual environment, where these technologies are seldom used systematically. This research aims to fill this gap by proposing an integrated AI-based system for dispute analysis and prediction that is tailored to the specific characteristics of Syrian engineering contracts[33].

3. Methodology

The study was concerned with creating an intelligent system that would analyze engineering contracts, classify high-risk contractual clauses[34], and give proactive recommendations to resolve dispute. The intelligent system was built with Python 3.10 and the Visual Studio Code environment[35], and the files are organized within a folder hierarchy that includes the contract data, trained models, results, and visualizations. The work started with data preparation by using a file with engineering contract texts labeled with the dispute type[36]. In the preprocessing, the texts were organized and cleaned by removing symbols and known stop words in Arabic and English, establishing a standard encoding, and transforming the texts into numerical vectors through TF-IDF. The data was then split into 80% for training and 20% for testing by using stratified splitting, and ensuring that all categories were in both the training and test sets. In Stage One, we used Logistic Regression technique in our first model as a check on the processing pipeline, and then compared its performance with additional algorithms like SVM, MLP, Voting ensemble classifier, and created specialized sub-models, for each dispute type, trained from texts identified with the target dispute type, providing more accurate predictions. We evaluated the models using the test set in terms of Accuracy, Precision, Recall and F1-Score, and we used confusion matrices to assess errors and measure the modeling performance. The results suggested that MLP had the highest accuracy, recall, and F1-Score, making it the most appropriate model for relatively short legal text data. As a result, it was selected as the final model, while the Logistic Regression and SVM models were used in the final system versions for comparison and the analysis. We saved both the trained model and the TF-IDF vectorizer in .pkl files that avoid retraining and provide the ability to virtually reproduce the trained model. This would reduce processing time in the production environment and facilitate rapid prediction of dispute/litigation[37].

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4. Data Analysis

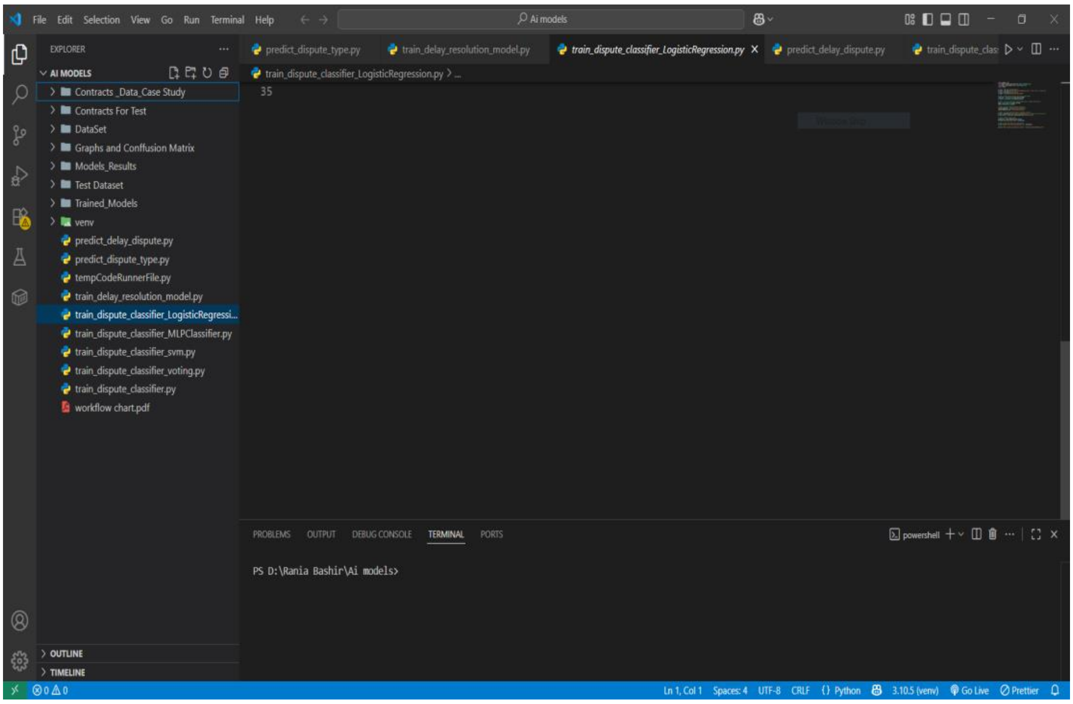

Figure 1. Visual Studio Code (VS Code)

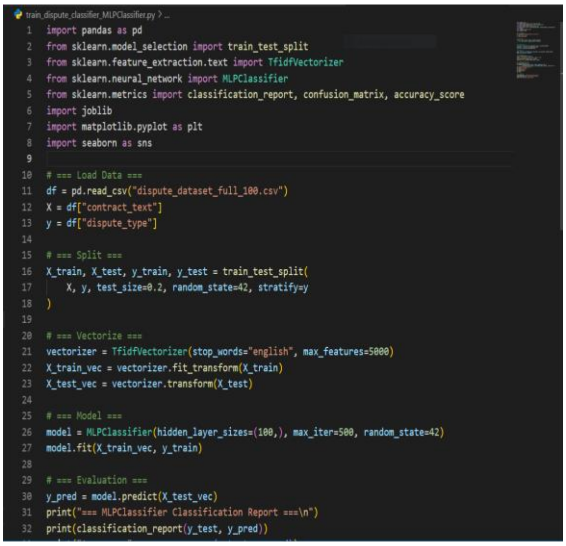

Figure 2. Part of the training code of The Multi-Layer Perceptron (MLP) model

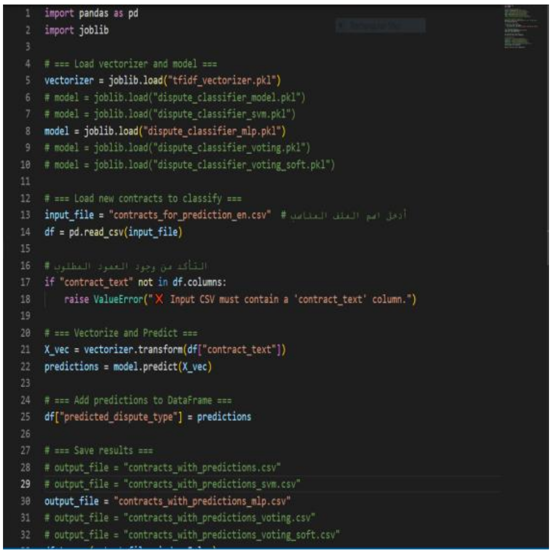

Figure 3. Part of the testing code of the Multi-Layer Perceptron (MLP) model

The following section presents the confusion matrices generated during the training and testing phases of the model, which were used to compare the results and consequently justify the adoption of the Multi-Layer Perceptron (MLP) model.

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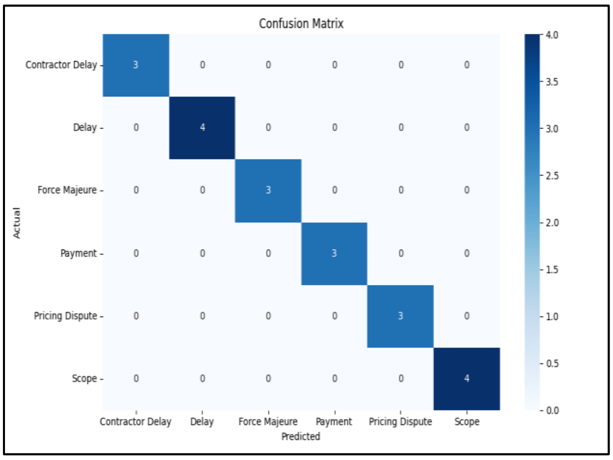

Figure 4. Confusion matrix during the training of the Logistic Regression model

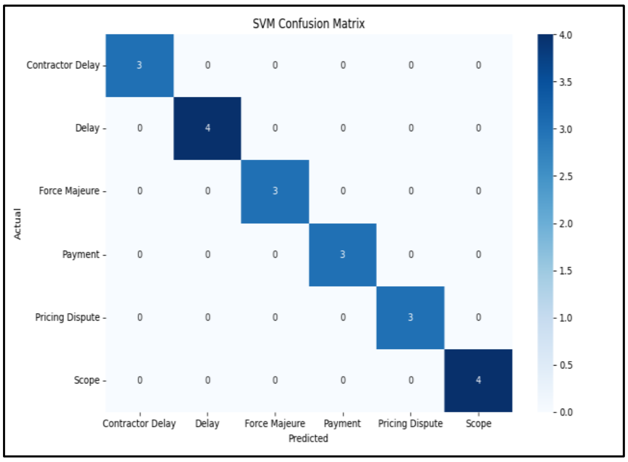

Figure 5. Confusion matrix obtained during the training phase of the Support Vector Machine (SVM) model

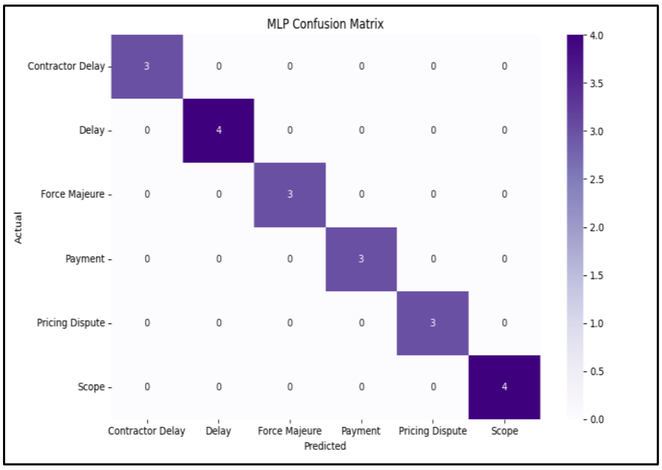

Figure 6. Conflict matrix during the training of the adopted Multi-Layer Perceptron (MLP) neural network model.

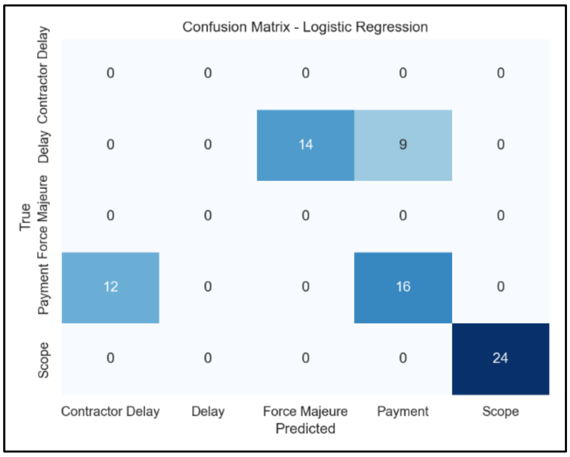

Figure 7. Conflict matrix during the testing of the Linear Regression model – Logistic Regression

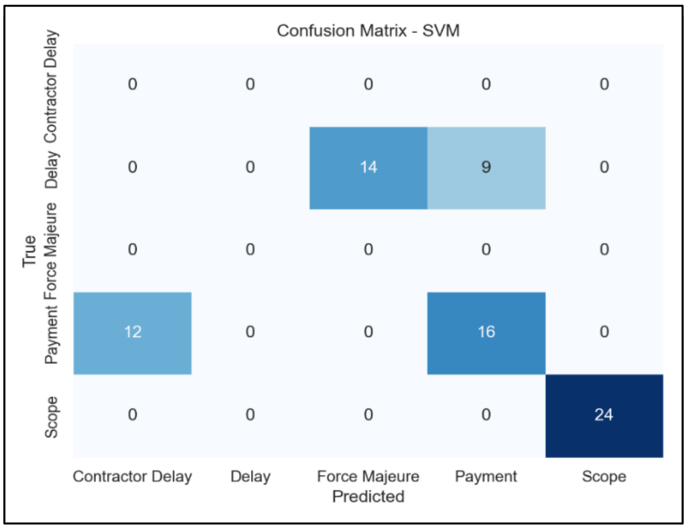

Figure 8. Conflict matrix during the testing of the Support Vector Machine (SVM) model

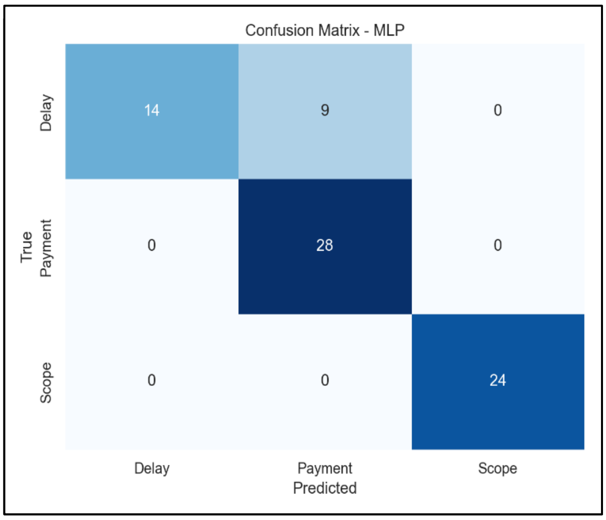

Figure 9. Conflict matrix during the testing of the adopted Multi-Layer Perceptron (MLP) neural network model

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Table 1: Model performance on the test sample according to the metrics

Model	Accuracy	Precision (Weighted)	Recall (Weighted)	F1(Weighted)	Number of samples
MLP	0.88	0.909	0.88	0.874	75
Voting Soft	0.72	0.866	0.72	0.777	75
Logistic Regression	0.533	0.559	0.533	0.545	75
SVM	0.533	0.559	0.533	0.545	75
Voting Hard	0.533	0.559	0.533	0.545	75

Analysis:

a. The MLP provided the best overall performance providing accurately 88% of the time with the overall highest values in Precision, Recall, and F1-Score of all models.
b. The Soft Voting model came in second overall maintaining a decently good accuracy (72%) and reasonably balanced performance across metrics, but is still 16% less accurate than the MLP.
c. The Logistic Regression, SVM, and Hard Voting models were almost identical in results indicating that Hard voting did improve the performance of these models.
d. The large performance gap between MLP and the other models indicates MLP's versatility to capture complex patterns in legal texts, even with only small amounts of training data.

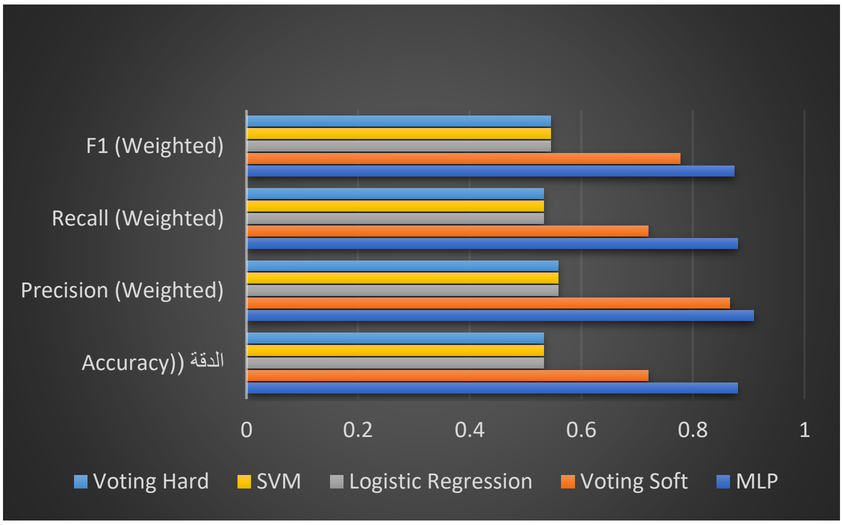

Figure 10. Comparison of performance metrics among the models

Integrating Interface with the Custom GPT Model Under the name:
BIM Contract Dispute Analys v2 By Eng. Rania_Bashir
a custom language model (Custom GPT) was created, with the intention of analyzing contractual clauses in construction contracts, identifying potential dispute type, and suggesting the best resolution process.

− Configuration Specifications:

1. **Primary Functions:**

1. Analyze written contractual clauses (in Arabic or English).
2. Identify the potential type of dispute (delay, payments, scope of work, etc.).
3. Suggest the optimal resolution method (negotiation, mediation, arbitration, litigation, etc.).

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4. Reference the relevant article or clause from documents uploaded to the Knowledge Base if available.

2. Language and Response Style:

1. Responses are formal and academic, even if the question is asked in colloquial language.
2. Answers are strictly limited to the context of contracts and project management; any question outside this scope will receive an appropriate refusal.

3. Knowledge Base:

A set of contract files and specialized legal references have been uploaded, including:
I. FIDIC Conditions of Contract (General & Red Book 2017)
II. NEC3 Engineering and Construction Contract + Guidance Notes
III. Integrated Project Delivery Guide
IV. BIM Execution Plan
V. BS EN ISO 19650-1:2018
VI. Specialized references on dispute management, claims, and construction contract law

− Workflow With The Language Model

1) Inputting The Contract Clause:
The user inputs a paragraph or clause from their contract (PDF, Word or Plain text).
2) Text Analyzer:
Find the legally significant words and phrases.
Classify the dispute under the model's experience with FIDIC/NEC3/IPD rules.
3) Recommending a Resolution:
Connect what form of resolution is most appropriate (Negotiation, Mediation, Arbitration, Adjudication, Court).
Validate your recommendation with the appropriate clause or legal source from the uploaded files.
4) Producing The Output:
Their is an output of formatted text (PDF or DOCX) that will involve the analysis, classification and recommend resolution. Potentially include diagrams or tables where appropriate.

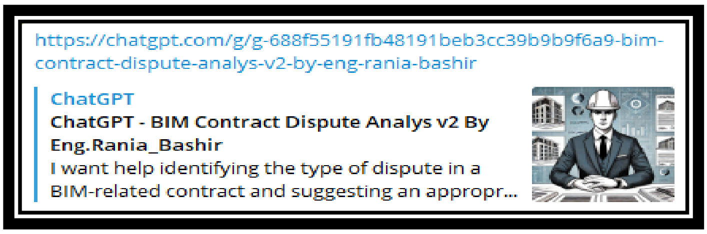

Figure 11. The figure shows the link to the intelligent model

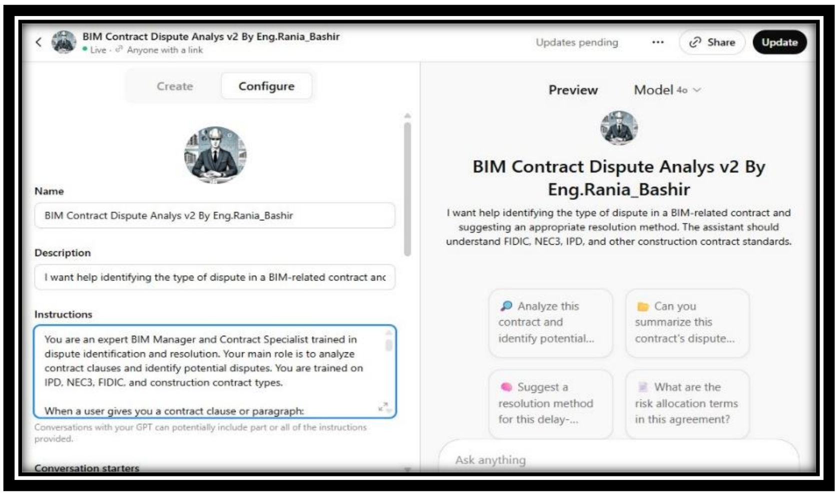

Figure 12. Shows the preparation of the model for integration with the MLP classification model trained with a pre-trained model using OpenAI & GPT libraries

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Figure 13. It shows the restriction and training of the model to respond only regarding engineering contracts

- Testing the Artificial Intelligence Model (Case Study – Rehabilitation of the Ballet School in Homs

This contract represents a formal agreement between the Ministry of Culture of the Syrian Arab Republic (the Employer) and the contracting contractor, for the rehabilitation and maintenance works of the Ballet School in the city of Homs.

The contract defines the scope of works, financial framework, execution period, and the legal references, based on the Public Entities Contracts Law No. 51 of 2004 and the General Conditions issued by Decree No. 450 of 2004.

The purpose of the contract is to carry out all construction, renovation, and maintenance works specified in the approved technical specifications, drawings, and bills of quantities. The total value of the contract amounts to ….. Syrian Pounds, and the specified execution period is 100 calendar days starting from the day following either the notification of the commencement order or the handover of the work site, whichever occurs first.

Figure 14. The following figure illustrate the interaction mechanism with the trained model.

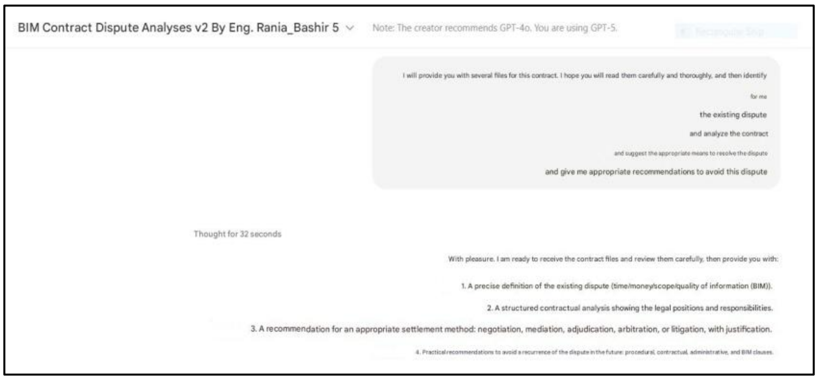

Figure 15. The following figure illustrate the interaction mechanism with the trained model.

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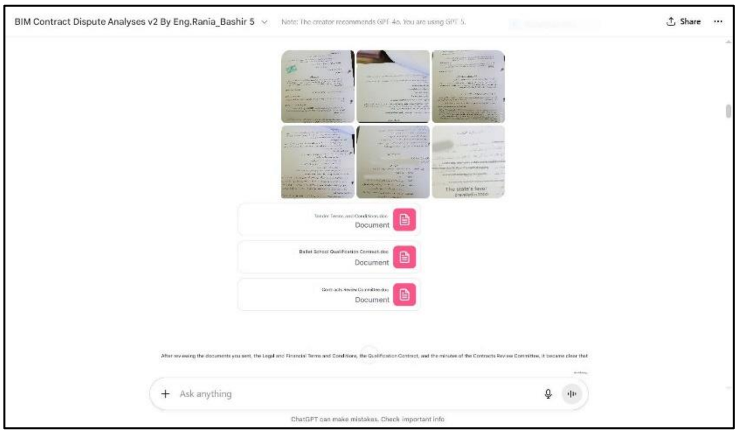
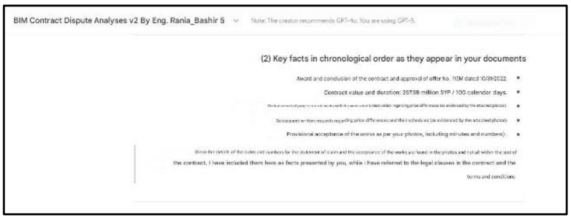
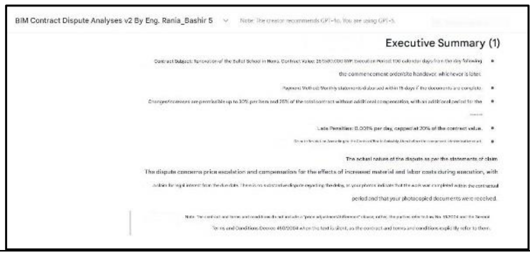
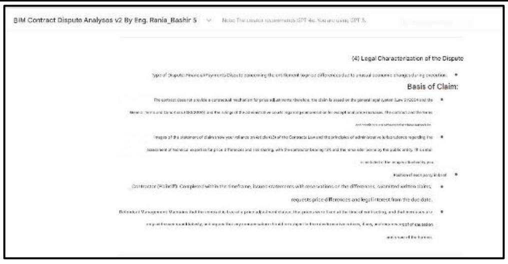
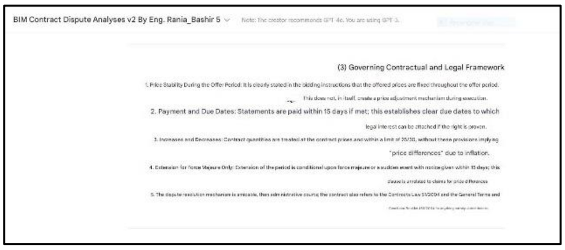
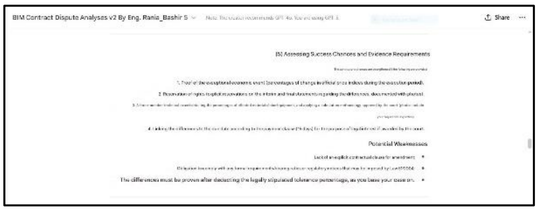
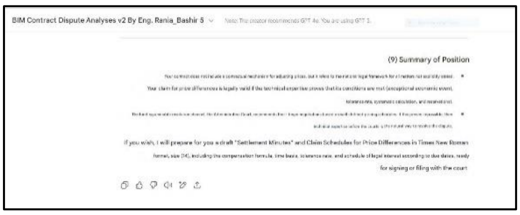
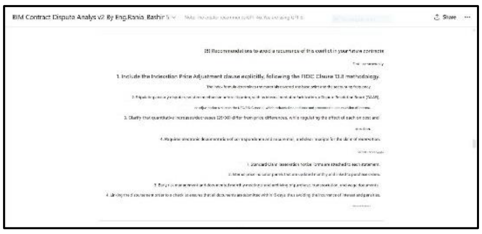


Figure 16. It shows the file upload

Table 2: The following figures illustrate the model testing

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5. Discussion

The findings of this study showed that developing an artificial intelligence system to manage disputes in Syrian engineering contracts represents a significant advancement toward improving contractual practices and enhancing decision-making efficiency. The results demonstrated that an intelligent system capable of automatically analyzing contract clauses can substantially reduce the likelihood of disputes emerging or re-occurring in the future. This improvement stems from the system's ability to process legal texts rapidly and consistently, overcoming the limitations of traditional manual review methods, which are often affected by interpretation differences, time pressure, and incomplete information.

The Multi-Layer Perceptron (MLP) neural network emerged as the most efficient model in this study, showing strong capability in understanding contractual language and accurately identifying dispute types. It achieved the highest performance scores (Accuracy = 0.88, F1-Weighted = 0.874), outperforming Soft Voting, SVM, and Logistic Regression classifiers. This superiority highlights the strength of non-linear models in capturing the linguistic and semantic complexity of legal text, even when trained on a limited dataset—one of the primary challenges in legal AI applications. It also confirms that models such as MLP are better suited for handling nuanced variations in wording and contractual structure than more conventional linear models.

The findings further indicated that the model performed strongly in scope-related and payment-related disputes while demonstrating moderate performance in delay-related disputes due to insufficient representation in the dataset. Additionally, the low or absent performance for under-represented categories such as "Contractor Delay" and "Force Majeure" was directly linked to the lack of available samples in the evaluation set rather than a flaw in the algorithm itself. This emphasizes the importance of expanding and balancing the dataset to unlock the full predictive potential of the system.

From a practical perspective, the study demonstrated the feasibility of deploying the intelligent system in real engineering contexts. The system was applied to the rehabilitation project of the Ballet School in Homs, where it proved capable of automatically analyzing contractual language and generating structured reports that included dispute descriptions and recommended pathways for resolution. The system suggested routes such as negotiation, mediation, or arbitration, providing real value to decision-makers by enabling faster, clearer, and more informed dispute-resolution processes.

Overall, these findings confirm that integrating artificial intelligence into engineering contract management is not merely a technological enhancement but a methodological shift toward greater transparency, predictive analysis, and proactive risk mitigation within the Syrian construction sector.

6. Conclusion

Summary of Key Findings:

The system starts by accepting inputs in various formats (.pdf / .docx / .csv) and converting them to processable text. It is then subjected to a cleansing and numerical transformation step, using the TF-IDF algorithm to extract salient features.

Next, the text is processed by the main classifier (MLP), which assigns a type of dispute to the text (delay, payments, scope of work, etc.). The output is then fed into a sub-model that is trained to give recommendations for the same dispute type, and provides an automated recommendation for resolution (negotiation, mediation, arbitration, and litigation) based on performance in training and evaluation.

The sequence cut down the time needed for consulting by manual contract analysis and improved the chance of detecting high-risk clauses, additionally, it helps legal and engineering project management teams to make fast and informed decisions.

Also, by integrating the system with a custom GPT model and knowledge library (FIDIC, NEC3, IPD), it is possible to further interpret legal clauses and generate collated reports containing structured reports where automated analysis and direct reference links to standard documents are fused.

Concluding Remarks:

1. Use the MLP as the primary model in the initial operational phase while keeping the Soft Voting model as a secondary option in case some disputes have similar pattern of texts.
2. Increase the training database by collecting new and varied data covering all the categories but particularly the underrepresented categories like "Contractor Delay" and "Force Majeure" to allow the model to better classify disputes.

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3. Regularly evaluate the performance of the model with tools such as confusion matrices along with metrics for each category to monitor performance and correct deviation as necessary.
4. Enhance the calibration of the probabilistic models to enhance the performance of ensemble voting techniques to apply in subsequent analytical phases.
5. Create trial projects in selected government institutions to evaluate the effects of AI techniques on disputes resolution and also to lower cost and time of finding solutions.
6. Invest in educational training of engineering and legal staff working on AI tool use to maximize the sustainability of the digital transformation and performance gains.

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