

Düzce University
Journal of Science & Technology

https://dergipark.org.tr/tr/pub/dubited

Research paper

Analysis of Design-Build Contracts Utilising Machine Learning on the Axis of Time, Cost and Quality

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Article information:
Received: 24/03/2025, Revision: 23/05/2025, Accepted: 04/06/2025
DOI: 10.29130/dubited.1664225

ABSTRACT

In construction projects, contract management processes necessitate achieving a delicate equilibrium among time, cost, and quality. This work aims to analyse Design-Build standard construction contract texts by the application of machine learning (ML) methodologies to attain a more effective equilibrium among these three essential factors, hence enhancing the decision support process in contract management. The suggested model offers comprehensive predictions regarding time, cost, and quality in the management and risk assessment of construction projects where conventional methods are inadequate. A classification model employing text mining and ML algorithms is proposed in the study. The standard contract clauses of the FIDIC Conditions of Contract for Design, Build and Operate, as well as the JCT Design and Build Contract, have been analysed. In the realm of text mining, natural language processing (NLP) methodologies, including Term Frequency-Inverse Document Frequency (TF-IDF), Word2Vec (Continous Bag-of-Words (CBOW) and Skip-Gram), and Bag-of-Words (BoW), have been employed. Various ML algorithms, including Support Vector Machines (SVM), Decision Trees (DT), and Ensemble Learning (EL) techniques (XGBoost), have been employed to evaluate the efficacy of various text representation techniques. The models' performance was evaluated using 70%-30% and 80%-20% training-test data splits. The study concluded that the integration of the Skip-Gram approach with the XGBoost model yielded the highest accuracy (Acc) and F1 scores. In the 80%-20% train-test split, the F1 score was recorded at 0.8858 and the Acc at 0.8779, highlighting the significance of capturing contextual information. The primary constraint of the study is the inability to make a precise separation in the dataset, since the time and cost aspects in contract texts frequently overlap. This circumstance has led the model to erroneously categorise certain words into both the cost and time classifications, hence diminishing accuracy rates. The variety of legal and technical terminology in contracts has hindered the model's ability to appropriately evaluate some expressions. The results demonstrate that ML provides a novel approach to analysing construction contracts and has the capacity to enhance decision-making in contract management and negotiations. The model presented in this paper provides a framework for the more efficient management of time, cost, and quality factors.

Keywords: *Standard Construction Contracts, Natural Language Processing, Machine Learning, Ensemble Learning, Text Mining*

I. INTRODUCTION

Construction contracts are the basis for any significant construction project. They encompass a legally binding document between two or more parties which define the rules of engagement within the project scope for a stipulated period of time. However, the rife competition and business model do not stress the

Cite as: Demircan, A. & Uğur, L.O. (2025). Analysis of design-build contracts utilising machine learning on the axis of time, cost and quality. *Düzce University Journal of Science and Technology*, *13*(4), 1455-1475.

contractual build sufficiently. Due to a lack of understanding or uneven playing field in contractual knowledge, parties may be penalized unjustly or take projects under exploitative terms. As construction is a conservative industry, contracts based on old terms or practices may not adequately safeguard the involved parties or the structure or situation of the project. As such, there is great interest in determining how time, cost, and quality distributions are modified in reiterations of the same standard contract years apart (Sanni-Anibire et al., 2021). Other research may also delve into work aspect deviations in the same light, for comprehensive understanding. To meet these goals, analyzed contracts use ML techniques built on a toolkit of Python, Excel and GDPR-safe datasets, recently being the most preferred due to interpretability.

Construction contracts can be straightforward or highly complex, depending on project size and parties involved. Over time, evolving interests have made these contracts progressively more elaborate. Gap analysis has traditionally been employed for exploring discrepancies in construction contracts. In the context of contracts, a gap can be considered any detail not discussed in one quote but covered by another. This may be analysed on paper, for instance, by comparing contracts line-by-line. Alternatively, one could opt to have a lawyer familiar with the industry examine proposed contracts. Most of these inadequately adress a comprehensive assessment of time, cost and quality.

Contract strategy is an essential contributor to the execution of projects in the construction industry. Contractors and project professionals should know the differences and characteristics of the main contracts to be able to choose from various types of contracts with quantifiable costs, time, or even with management approach. A construction contract is an agreement between the employer and the contractor about the work required in terms of design and procurement, the conditions under which the work is to be executed, and the terms of payment (Du Plessis & Oosthuizen, 2018). The construction contract also dedicates the rights and obligations of all parties that have a vested interest in the project. An appreciation of the type of construction contract is fundamental, in terms of execution and contractual responsibility.

The standard contracts describe the nature of the agreement between two or multiple parties, outlining the conditions and terms under which the project should be conducted. Furthermore, the professional duties of all stakeholders in the agreement are also covered in the contract.

In recent years, ML methodologies have garnered attention for their capacity to provide predicted insights across diverse sectors and evaluate complex data. Utilising ML models to examine construction contracts enables the facilitation of decision-making processes, prediction of outcomes and identification of trends (Garcia et al., 2022). Nonetheless, the implementation of these strategies in construction contracts, especially regarding time, cost, and quality control, remains inadequately explored.

This study examines the standard Design-Build construction contracts through the application of three significant text representation methodologies—TF-IDF, BoW and Word2Vec (CBOW and Skip-Gram)—in conjunction with ML techniques including SVM, DT, and the EL method XGBoost. The objective is to establish a standardised methodology for assessing contracts and forecasting outcomes related to time, cost, and quality through these methodologies. This research's findings can enhance decision-making processes and project management efficiency by optimising contract analysis in the construction industry.

ML has been effectively applied to various fields including cost estimation, project planning and risk management (Nguyen, 2021). This research seeks to expand the utilisation of these methods in a relatively underexplored yet very potential field, specifically contract analysis. The primary aim of the study is to evaluate the efficacy of various ML models in analysing contract data and forecasting critical outcomes, while also offering a practical resource for construction professionals.

The study's contributions to the literature are outlined below;

A. Application of Text Mining and Machine Learning on Standard Construction Contracts

First of all, the literature reveals that scholars mostly focus on the diverse textual documents generated during a construction project, rather than the construction contract itself. Previous research has concentrated exclusively on construction contracts, which are agreements established between authorities and contractors. There is a paucity of research regarding standard form construction contracts. A new dataset has been developed in this study for the literature. In the research, the use of standard form

construction contract texts was preffered due to its universal applicability and significance across all phases of projects and disciplines. On the other hand, these contract forms are essential for defining the responsibilities of the parties involved in construction projects.

Additionally, construction contracts contain intricate and extensive textual data, rendering manual evaluations challenging. The literature reveals a limited application of modern data analysis methodologies, including text mining and ML in the examination of standard construction contracts. Contract texts have frequently been analysed exclusively from a legal perspective; nevertheless, this study demonstrates that a comprehensive examination concerning project components (time, cost, quality) addresses the existing gap in this field.

The research illustrates the application of ML techniques in analysing construction contracts and the utilisation of text mining methods to reveal the correlation between contract terms and critical project characteristics, including time, cost and quality. This approach results in an innovation that enhances industrial efficiency.

B. The Interrralation of Parameters and Standardisation of Contractual Texts

The majority of construction contracts are generally established within the framework of a particular organisation or project and are tailored to meet specific project requirements. This circumstance complicates comparisons and generic analysis. The literature lacks substantial research on comparability and analyzability of standard construction contract texts across projects utilising a standardised model approach.

This study introduces a notable novelty to the industry by examining standard construction contracts on a sentence-by-sentence basis in relation to time, cost, and quality metrics. This methodology facilitates a more objective and efficient analysis of language in construction contracts. Simultaneously, it facilitates the prompt identification of uncertainties and risks inherent in contractual texts.

C. Development of an Integrated Model on the Axis of Time, Cost and Quality

Analyses of the interrelationships among cost, time and quality are generally conducted separately. A gap exists in the research about a model that clarifies the relationship between these three criteria and contract texts, analysing them in a combined manner. Most previous research treat time, cost, and quality as distinct categories; however, it is less usual to examine their linked dynamics.

This paper introduces a methodology that analyses the interaction of characteristics including time, cost, and quality within a unified model. This model introduces a substantial advancement in the literature by illustrating how these three components, which influence the overall performance of construction projects, can be more effectively handled. Specifically, it enhances decision-making by illustrating the application of ML approaches for predicting key aspects.

D. Advancement of Data-Driven Decision Support System

In the construction industry, decision support systems generally depend on empirical knowledge and past experiences. This research facilitates the creation of data-driven decision support systems for construction projects through the analysis of contract texts utilising text mining and ML methodologies. It establishes the basis for a system that will assist project managers in making more precise and swifter judgements. This innovation enhances overall efficiency in the sector, facilitating analytical and better informed decision-making.

E. Establishing the Correlations Between Project Outcomes and Contractual Provisions

The correlation between construction contracts and project success is typically indirect and has not been extensively researched. The terminology in contract provisions and its connection to performance metrics such as time, cost, and quality in projects is sometimes neglected.

This study illustrates how the language in contract provisions may be analysed in a manner that directly influences project performance. Evaluating contract documents with greater objectivity and transperancy can provide more precise forecasts of project results and mitigate risks in construction projects.

II. CONTRACT STANDARDIZATION AND DESIGN-BUILD CONTRACTS

Standard agreements, or standard construction contracts, represent a widely recognized method of specifying and formalizing mutual agreements in construction. Although the construction sector is the focus of this survey, the broad overview and many of the classifications and discussions may apply well to other domains. Major components commonly exist in standard construction contract documents, both in text and within tables or forms embedded in text. At a high level, contract documents begin with a preamble or title page. Key parties associated with the professional liabilities are explicitly defined within contract articles. Project-oriented facts, conditions, and specifications are included, forming the basis for all structured descriptions and properties delineating the project and respective obligations. Commercially related elements such as project costs and settlements are also crucial for understanding the business aspects of the projects. Likewise, the contract documents define payment-related milestones for contractors who must deliver completed work, including accomplished schedule activities or other works to qualify and receive payments. Therefore, schedule and payment components in a construction contract are tightly related (Son & Lee, 2019). Because contracts are legal documents, such documents also define statutes, laws, and interpretations to facilitate understanding and prevent disputes.

Standard contracts have long been praised as a valuable asset in both the economic and legal domain. A study has pinpointed a widespread acceptance of standard form construction contracts as a positive innovation (Mewomo et al., 2018). The construction sector is typically fraught with continuous discrepancies and disputes, a high level of risk, and a litigious environment. The underlying structure and the robust legal framework of standard contracts have been cited as the core advantages with respect to consistency, foreseeable obligation, and equity. Standard contracts are constructed in a manner that should fairly distribute risk between the different stakeholders. One of the acknowledged benefits of using standard contracts is their tried-and-tested nature, built over time and adopted on a wide-reaching scale. Widely recognized forms of contract are also beneficial due to reduced ambiguities and interpretations disputes. While the presence of standard form agreements can improve the efficiency and consistency of contract arrangements, questions abound on whether this standardization hinders innovation and risk sharing compellingly. Numerous studies have highlighted the inherent complexity and risks linked to construction contracts, particularly regarding time, cost, and quality management (Sanni-Anibire et al., 2021; Du Plessis & Oosthuizen, 2018). Risk management in construction contracts has been thoroughly examined, emphasising the difficulties in balancing cost, time, and quality. Research demonstrates that ambiguity in contract provisions and inadequate risk distribution frequently lead to delays and disagreements (Ayhan et al., 2021; Jafari et al., 2021). Furthermore, despite their standardisation, these contracts may still result in inconsistencies owing to divergent interpretations by stakeholders, as indicated in recent studies (Zhou et al., 2023; Candaş & Tokdemir, 2022). The utilisation of machine learning (ML) for the analysis of construction contracts is more prevalent, as it facilitates the identification of potential risks and discrepancies, thereby enhancing contract management processes (Moon et al., 2022; Jiang et al., 2024).

Design-build is an alternative project delivery system in which one entity (design-builder) enters into a single contract with an owner to provide both design and construction services (Bogus et al., 2013). In design-bid-build projects, once the work begins, the number and cost of change orders are drastically and significantly higher, while the cost and size of claims are partly higher. Quality in design-bid-build project is defined as the work done right the first time, and is related to the number of claims but not the cost of schedule accelerations. This definition of quality is an analogy to that for manufacturing processes. In design-build projects the work is usually constructed right the first time, and less or no change orders and schedule accelerations are done.

III. SIGNIFICANCE OF THE ANALYSYS OF STANDARD CONSTRUCTION CONTRACTS UTILISING MACHINE LEARNING ON THE AXES OF TIME, COST, QUALITY

Every construction project requires a specific time frame for completion, specific resources are made available to contractors, and finishing on the due date is imperative for proper planning (Ola, 2018). A critical balance must be met between cost, quality, and time axes to achieve a satisfactory project work.

Addressing this subject in terms of time, cost and quality is crucial, as these three aspects are intricately interconnected and directly influence the success of construction projects. The effective management of these factors is essential for the successful completion of a project and each component influences distinct

aspects of project management. Our discussion clarifies the pivotal function of each component in construction projects and underscores the significance of our study in addressing them.

A. *Time Management*

In construction projects, time is a crucial aspect for project success. The inability to finalise a project timely frequently results in budgetary overruns, increased expenses and diminished quality. Effective time management guarantees project completion within budgetary constraints and aids in maintaining cost control. Effective time management is crucial for achieving defined goals and mitigating project risks. The effective utilisation of resources and time results in reduced expenses for projects that are executed more rapidly (Cantarelli et al., 2012).

B. Cost Management

Accurate cost control and estimation in construction projects are essential for guaranteeing successful project completion and reducing budget overruns. ML methodologies are progressively employed to analyse historical data, identify essential cost components and enhance the precision of cost estimations. For instance, the research conducted by Tayefeh Hashemi et al. (2020) comprehensively analysed ML techniques employed for cost estimation in construction projects, demonstrating their potential to improve prediction accuracy. Furthermore, effective management of cost-related provisions in construction contracts mitigates the potential for additional expenses that may occur throughout the project lifecycle. A recent study has highlighted the significance of including contract aspects into predictive models by suggesting a ML methodology that integrates contract parameters in cost estimation (Ben Talha et al., 2024).

C. Quality Management

Ensuring quality in construction projects is crucial, since it directly influences the safety and durability of the completed structures. Inadequate workmanship frequently necessitates rework on projects, resulting in project delays and increased expenses. Establishing and regulating quality proactively not only improves project outcomes but also encourages sustainability. The incorporation of ML methodologies in this area presents significant potential. ML algorithms that examine historical Project data can forecast prospective quality concerns proactively, enabling the implementation of strategies to mitigate risks. A thorough analysis by Nguyen Van & Nguyen Quoc (2021) highlights that ML applications in construction management are crucial for evaluating and mitigating risks, consequently decreasing project error rates through the optimisation of quality management systems.

D. The Interaction of Three Axes

The interaction of time, cost and quality in construction projects necessitates a sophisticated equilibrium in project management. The three criteria mutually influence one another; for instance, reducing the project duration may elevate costs or diminish quality. Enhancing quality may necessitate additional effort and expenditure. Consequently, the balanced management of these three components is essential for the project's success. ML methodologies can evaluate data derived from previous projects, more precisely simulate the trade-offs among cost, time, and quality, and facilitate more informed decision-making in project management. For instance, the research conducted by Jiang et al. (2023) aims to optimize resource allocation in construction projects by deep reinforcement learning, therefore improving the balance of cost, time, and quality.

E. Data-Driven Improvement and Risk Management

The integration of ML methodologies into construction project management improves the precision of time, cost and quality estimations. ML algorithms that examine extensive datasets facilitate more accurate predictions by uncovering patterns and correlations that conventional approaches may neglect. For instance, Nguyen (2021) utilised the K-Nearest Neighbours (KNN) algorithm to predict the construction price index based on socio-economic variables in Vietnam, revealing that the KNN regression method yielded a reduced error rate relative to conventional methods. Additionally, Jiang et al. (2023) developed a methodology utilising deep reinforcement learning to enhance workflow and cash flow in construction projects. This method has exhibited superior performance compared to conventional empirical techniques and genetic algorithms, highlighting the capacity of ML to improve project efficiency.

Examining this study through the axes of time, cost, and quality is essential for optimising project management in the construction industry. Efficient management of each component will enhance the probability of successful project completion while simultaneously shortening durations, reducing costs and improving quality. This study can enhance decision-making in the construction business by illustrating how ML approaches can optimise the equilibrium among these three parameters.

IV. TEXT MINING AND MACHINE LEARNING APPLICATIONS IN CONSTRUCTION CONTRACT MANAGEMENT

Dikmen et al. (2025) employed NLP and ML to automate the assessment of risk and responsibility in construction contracts. They trained models using 2,268 sentences derived from FIDIC templates and evaluated them on a project contract consisting of 1,217 sentences. Sentences were categorised into Title, Definition, Obligation, Risk, Right, ,as well as the pertinent parties: Contractor, Employer, Shared. Employing diverse NLP vectorisation methods (e.g., Bag of Words, TF-IDF, Word Embeddings) alongside ML algorithms (e.g., Logistic Regression (LR), SVM, DTs, Recurrent Neural Networks (RNNs)), the optimal model attained 89% accuracy in classification of phrase kinds and 83% in identifying pertinent parties. These findings enhance the efficiency of proposal preparation and mitigate potential disagreements by facilitating more effective risk assessment in the management of time, cost, and quality in construction projects.

The research by Zhong et al. (2024) enhances project management by categorizing and analyzing disputes in construction contracts with deep learning-based text mining. Nine multi-label classification models—five shallow and four deep learning—were assessed with optimisations. The best performance was achieved by a Convolutional Neural Network (CNN) model with 256 filters and filter sizes [1,2,3,4]. Evaluation using Precision (P@k) and Normalized Discounted Cumulative Gain (NDCG@k) metrics showed satisfactory accuracy: P@1 = 65.99%, P@3 = 54.60%, P@5 = 44.32%, NDCG@1 = 65.99%, NDCG@3 = 62.41%, NDCG@5 = 65.09%. The research illustrates that employing ML and text mining methodologies in construction contract agreements can greatly enhance construction schedule management, especially by facilitating the early identification and examination of disputes. The decline in model performance for larger predictions underscores the necessity for enhancements in multi-label categorisation.

Debero & Sinesilassi (2024) assessed ML models in predicting the duration of construction project. The research contrasted Bromilow's and Love et al.'s time-cost models with ML algorithms. The Bromilow model (R^2 = 0.205) showed weak explanatory ability, while the Love model elucidated the impact of the number of floors on construction duration more effectively, achieving a R^2 value of 0.765. ML models outperformed traditional ones, with Random Forest (RF) (R^2 = 0.875) and XGBoost (R^2 = 0.860) achieving the highest Acc, followed by DT (R^2 = 0.820), KNN (R^2 = 0.800), and Polynomial Regression (R^2 = 0.750). The findings highlight ML's potential in mitigatingthe risk of delays, forecasting of construction duration and improving efficiency in project management.

Zhou et al. (2023) presents a deep learning and NLP-based methodology for detecting missing clauses in construction contracts, surpassing conventional manual review approaches. Contract texts were transformed into a digital vector format suitable for analysis by AI and a multi-label classification model was created. The MatchPyramid model and BERT-based similarity algorithms identified missing information, evaluated on 1,322 contracts. The classification model achieved 93% Acc, whilst the similarity matching technique reached 83%, with recall and F1 scores surpassing 0.7. The research significantly aids in averting disputes and financial losses in construction projects by automatically identifying missing contract terms.

Candaş & Tokdemir (2022) highlight the impact of ambiguous terminology in construction contracts on project success. They developed an NLP and ML-based system to detect such terms automatically. FIDIC contract texts were processed using lexical and morphological analysis, then classified by supervised ML methods. The unigram approach was employed for text representation, and model demonstrating optimal performance was, SVM, achieved 64.90% Acc, 95.2% precision, 81.2% recall, and an 82.7% F1 score. This study could enhance contract management processes and avert potential legal problems by facilitating the automatic examination of ambiguous terms in construction contracts.

Moon et al. (2022) developed an NLP and ML-based system for automated analysis of construction contracts and technical specifications. Conventional review methods are laborious and susceptible to inaccuracies, prompting automation to detect inconsistencies in project management. The study compared

SVM, Logistic Regression, and Deep Neural Networks, using TF-IDF and word embeddings. SVM achieved the best performance with 89.3% precision, 87.8% recall, an F1 score of 88.5%, and 92.4% Acc. Extensive text evaluations have revealed that deep learning models yield superior accuracy, albeit at a significant computational expense. This study enhances quality control and efficiency in contract analysis, mitigating the risk of cost overruns.

Jiang et al. (2024) developed deep learning algorithms for classifying complex technical papers in construction. The study incorporated NLP and targeted feature processing to manage unstructured large-scale text data. TF-IDF enhanced classification accuracy by detecting critical terms. The BERT-based model attained the maximum performance, achieving 91.5% Acc, with precision, recall, and F1 scores of 88.3%, 89.7%, and 89.0%. The model's effectiveness in large-scale technical texts suggests its potential to improve information management and documentation in construction projects.

Deza et al. (2022) employed ML and text mining to autonomously categorise Bills of Quantities (BoQ) in construction projects according to the International Construction Measurement Standard (ICMS). The study assessed linguistic representation strategies utilising 50,000 item descriptions from 24 UK infrastructure projects. Among ML models, CNN and RNN were employed, with the Temporal Convolutional Network (TCN) identified as the most effective. The models attained an average F1 score of 90% across 32 ICMS categories, with TCN often outperforming RNNs. The research illustrates that ML and text mining methodologies can be proficiently employed for the automatic categorisation of construction cost documents, hence enhancing cost management in construction projects and yielding time and financial efficiencies.

Moon et al. (2021) facilitated an NLP and ML-based extraction model for automated evaluation of construction specification documents, particularly in tender processes. The study developed a Named Entity Recognition (NER) model utilising a Bi-LSTM network, trained on 4,659 phrases from 56 construction specifications and evaluated with 30 datasets. Texts were vectorised using Word2Vec before Bi-LSTM analysis. The model achieved 91.9% precision, 91.4% recall, and a 91.7% F1 score, excelling in reference information (94.6 F1) and organisation names (94.5 F1). The study presents a technology that autonomously identifies contractual requirements to enhance time, cost, and quality management procedures in construction contracts so that, error rates diminished, the contract analysis processes have been expedited and more effective decision-making in project management has been facilitated.

Ayhan et al. (2021) investigated ML techniques to forecast the occurance of disputes in construction projects. A conceptual model was developed based on literature analysis, followed by expert surveys and chi-square tests to identify key dispute factors. Various classification strategies were evaluated, with the SVM model achieving 90.46% Acc and ensemble models 91.11%. Chi-square analysis indicated project changes, unexpected circumstances, communication abilities, and response times as key factors in the emergence of disagreements. The research indicates that ML methodologies can serve as an efficient instrument for the early identification of disputes in construction contracts, enabling the implementation of proactive strategies to mitigate any adverse effects on construction timelines, expenses, and quality.

Jafari et al. (2021) employed NLP, ML, and Monte Carlo simulation to autonomously extract reporting requirements from construction contracts and forecast their impact on time, cost, and quality management. Manual reporting is time-consuming and error-prone, encouraging the development of an automated framework. Reporting needs were derived by NLP and ML, while Monte Carlo simulation estimated report production time and costs. Among ML models, XGBoost attained the greatest Acc (98.4%), with an F1 score of 92%, recall of 89%, and precision of 96%. The simulation found an average reporting duration of 5083 work hours and a total cost of 304,939 CAD, with 31% of the burden on project managers, 25% on engineers, and the remaining on field teams. These findings establish an essential basis for enhancing time, cost, and quality management in construction projects, facilitating expedited contract analysis, diminishing reporting obligations, and enabling more precise budget forecasting.

Hassan & Le (2021) developed an NLP and ML-based system to automate requirement extraction and subcontractor agreement formulation in Design-Build (DB) contracts. Manual contract analysis is time-consuming and error-prone, leading to the use of text mining for classification. Various ML and deep learning models (NB, SVM, LR, DT, KNN, CNN, RNN) were compared, along with feature selection methods (RFE, TF-IDF, MI). Training on 3000+ contract clauses, SVM achieved the highest performance (F1 = 92.67%), with an RFE-refined SVM reaching 93.20% precision, 93.08% recall, and 92.98% F1 score. The

Weighted Majority Voting technique further improved accuracy and generalisation. The study introduces a method that enhances the management of time, cost, and quality in DB projects, facilitating a rapid, precise, and error-free interpretation of contract requirements. The proposed methodology has been shown to provide a more efficient and reliable contract management tool than manual review techniques.

Hassan & Le (2020) established an NLP and ML-based framework for automating contract requirement identification in construction projects. Manual methods are labor-intensive and error-prone, leading to the development of an automated text categorisation model that facilitates improved management of contract scope in construction projects. ML techniques (NB, SVM, LR, Feedforward Neural Network (FNN)) were evaluated, with SVM achieving the highest Acc (98.51%) and recall (95%). The model's efficacy was evaluated in an experimental study involving human participants, demonstrating substantial time savings relative to manual techniques. The program discerns the requirements within a 9-page contract in merely 1.88 seconds, whereas human participants require between 15 and 30 minutes for the same task. This study emphasises the capability of ML and text mining methodologies to enhance time, cost, and quality management in construction contracts, providing a more effective strategy for project scope management.

V. MATERIAL AND METHOD

The construction industry is fundamental to global economic advancement, and project completion frequently relies on proficient contract management. Standard construction contracts, including the Design-Build project delivery technique, are essential instruments that define the scope, timeframes, and costs of projects. These contracts are crucial for risk management, quality assurance, and the maintenance of project budgets and timelines. Nonetheless, the substantial volume of textual data and the variety in contract clauses render the analysis and optimisation of these contracts a highly complex process. This study investigates the application of ML methodologies in the analysis of Design-Build standard contract texts prevalent in the construction industry.

A. Dataset

This section clarifies the dataset employed in the study, the ML and EL methodologies, and the performance metrics utilised for developing classification models with these approaches.

A dataset was proposed to be created from sentences derived from two standard contract texts: the FIDIC Conditions of Contract for Design, Build and Operate and the JCT Design and Build Contract.

The analysis of the sentences in the contract texts was intended to be conducted by categorising them from the perspective of cost, time and quality.

From the sections of the two standard contract texts, sentences that can be included in the Cost, Time and Quality categories have been extracted by manually analyzing the entire texts (while extracting and categorizing sentences from the texts with the point of view thought in the beginning, support has also been obtained from ChatGPT (GPT-4) for verification purposes).

The perspective employed during the extraction of these sentences was as follows:

A.1. Cost

The selection of statements related to cost emphasised the aspects influencing the expenses of a construction project. The factors generally encompass:

A.1.1. Cost Fluctuation

Any alteration or modification that can directly influence the project expenditure. For instance, expenses related to materials, labour wages, alterations in the schedule, and the incorporation of these modifications into the contractual price.

A.1.2. Timelines and Deadlines

Details regarding delays, project completion failures and their financial impacts.

A.1.3. Terminology Pertaining Subcontractors and Suppliers

Factors associated with the supply of materials and services and their influence on expenses.

A.1.4. Warranties and Insurance

Expenses and the scope of insurance coverage for project risks and their management.

A.1.5. Administrative and Legal Regulations

Permissions, licences, legal obligations and their influence on expenses.

A.1.6. Payments and Cost Calculations

Information pertaining to payment conditions, advance/ interim payments and their schedules, final payment and cost calculations.

A.2. Time

The selection of sentences pertaining to the construction project's timeframe concentrated on statements that could influence the project's schedule, delivery deadlines, payment timelines, or any timings associated with legal proceedings.. Specific emphasis has been given on the following points:

A.2.1. Payment Terms

Sentences detailing the timing of payments, procedures for addressing delayed payments or penalties for late payments.

A.2.2. Project and Contract Management

Statements specifying the commencement and completion dates of the duties encompassed by the contract, together with the stipulations on the suspension or continuation of the work.

A.2.3. Termination and Penalty Clauses

Explanatory statements regarding the timelines associated with contract termination, work stopage, or the execution of penalty clauses.

A.2.4. Legal Disputes and Resolutions

Sentences pertaining to the commencement of legal proceedings, including mediation and arbitration, established for the resolution of conflicts and the scheduling of these processes.

A.3. Quality

While identifying sentences that may impact quality in the construction project, the following criteria and logic were considered:

A.3.1. Points Directly Pertinent to Quality Standards

Sentences incorporating terminology such as quality assurance, quality control procedures, material quality, and workmanship standards.

A.3.2. Considerations of Design, Material and Workmanship

Aspects pertaining to the standards of materials employed, the calibre of workmanship, design specifications, and the methods of their regulation.

A.3.3. Conditions for Inspection, Testing, and Compliance

Statements pertaining to the inspection, testing and certification procedures to be executed within the project's scope.

A.3.4. Rectification of Deficiencies, Errors and Unsuitable Work

Clauses pertaining to the correction of errors that may occur during or subsequent to construction, together with the penalties imposed for unsuitable work.

A.3.5. Occupational Health, Safety and Environmental Impacts

Statements addressing occupational safety, sustanability concerns, employee health conditions, environmental restrictions.

A.3.6. The Relationship Among Performance, Time Management ,Job Delivery and Quality

Factors influencing the impact of scheduling and the timely completion on Quality.

A.3.7. Amendments and Adherence to the Contract

Provisions that assess the effects of modifications on project quality.

A sample dataset of 827 sentences has been established: 268 sentences in the "cost" category (100 sentences from FIDIC, 168 sentences from JCT), 227 sentences in the "time" category (114 sentences from FIDIC, 113 sentences from JCT), and 332 sentences in the "quality" category (195 sentences from FIDIC, 137 sentences from JCT).

B. Machine Learning

ML is a primary technique employed to categorise construction contract texts based on time, cost and quality (Etli et al., 2024). The study analysed the DT, SVM, and XGBoost algorithms. The models were evaluated using several text representation approaches (TF-IDF, BoW, Word2Vec) to identify significant patterns in contract texts and evaluate their classification efficacy.

B.1. Decision Tree

DTs are supervised ML algorithms that formulate decision rules in a hierarchical framework derived from the dataset's attributes. This model has been employed to classify construction contract documents into categories of time, cost, and quality (Öztürk et al., 2022).

DTs possess a straightforward and comprehensible framework. The model's decision-making process is distinctly observable. It can execute feature selection and discern the most critical decision points within the data. Nonetheless, it poses the risk of overfitting. It may overfit the training data leading to suboptimal performance on novel data. The generalisation capability of decision trees is constrained, and their efficacy may diminish while handling complex textual material.

B.2. Support Vector Machine

SVM is a robust ML technique employed for classification and regression tasks. This approach executes classification by identifying the hyperplane that optimally divides the data points. It functions efficiently with high-dimensional data sets, particularly producing favourable outcomes with high-dimensional text representations such as TF-IDF and BoW. Due to regularisation processes, it exhibits resistance to overfitting. It fails to adequately capture contextual relationships, particularly demonstrating limited performance with word embedding techniques such as Word2Vec (Üstebay et al., 2023).

B.3. Extreme Gradinet Boosting

XGBoost is an ensemble learning technique derived from the gradient boosting algorithm. It sequentially trains weak learners to rectify the model's inaccuracies and generates robust predictions. Among tree-based algorithms, it has superior performance and operates efficiently with extensive datasets. It includes regularisation approaches that mitigate overfitting. It more effectively encapsulates contextual relationships. The model is intricate and necessitates hyperparameter optimisation. The training duration is extended relative to DTs and SVMs (Başarslan & Kayaalp, 2024).

C. Text Representation

Construction contract data has been preprocessed before classification. This involved removing punctuation marks and symbols from the comments, converting characters to lowercase, and normalizing them to root words. These operations were carried out using the Python NLTK (Natural Language ToolKit) library.

Word representations are extracted to provide improved representations of words within a document. The objective is to extract semantic and syntactic information from documents into a dataset.

Feature selection entails the identification of key features within the dataset. The dataset obtained after preprocessing is in the form of words or terms. As ML algorithms cannot directly recognise text data, it is essential to transform these terms into feature vectors (Liu et al., 2007).

Text representation techniques facilitate the numerical processing of contract texts by ML models (Bafna et al., 2016). The study employed TF-IDF, BoW, and Word2Vec (CBoW and Skip-Gram) methodologies.

C.1. Term Frequency - Inverse Document Frequency (TF-IDF)

TF-IDF is a weighting method employed to ascertain the significance of a word within a document (Parmar & Tiwari, 2024).

C.1.1. TF

Indicates the frequency of the word's occurrence inside the document.

C.1.2. IDF

Assesses the significance of a word within the complete corpus of documents.

TF-IDF emphasises significant keywords by filtering out frequently occurring words. Nonetheless, it exhibits deficiencies in assessing the contextual relationships between words. The study demonstrated effective results with SVM and DT, but exhibited average performance with XGBoost.

C.2. Bag of Words

BoW is a straightforward yet effective text mining methodology that represents text based on word frequencies (Başarslan & Kayaalp, 2023).

It relies on word frequency while disregarding the order of the words.

Due to its reliance on word frequency, it may induce the high dimensionality issue in extensive datasets.

C.3. Word2Vec

Word2Vec is a text embedding technique that transforms words into dense vectors while considering contextual relationships (Çaki & Başarslan, 2024).

C.3.1. CBOW (Continuous Bag of Words)

It generates predictions by utilizing the words in the context of the word.

C.3.2. Skip-Gram

Predicts the words in the context of a given Word.

Word2Vec maintains the semantic integrity of words by capturing contextual relationships.

VI. EXPERIMENTAL SETTINGS

Experimental studies were executed in the Google Colab environment, and hyperparameter optimisation was accomplished utilising the scikit-learn library to attain optimal model performance.

Two distinct train-test splits have been utilised in the model training;
70% train and 30% test
80% train and 20% test

These various distinctions have been employed to evaluate the models' generalisation ability and accuracy rates. Throughout the training, the knowledge acquired from the training set was validated against the test set, and the model's efficacy on real-world data was assessed.

The GridSearchCV method was employed for hyperparameter optimisation, utilising the parameters listed in Table 1.

Table 1. Hyperparameter details.

Model	**Parameter**	**values**
DT	max_depth,	3, **5**, 10, None
	criterion,	**'gini'**, 'entropy', 'log_loss'
	min_samples_split	2, **5**, 10, 20
SVM	C	[0.1, **1**, 10, 100]
	Kernel	'linear', 'poly', **'rbf'**, 'sigmoid'
	Gamma	'scale', 'auto', 0.001, 0.01, **0.1,** 1
XgBoost	n_estimators	50, **100**, 200, 300
	max_depth	3, **6**, 9, 12
	learning_rate	0.01, 0.05, 0.1**, 0.3**
	Subsample	0.5, 0.7, **1.0**

*the selected parameters are marked in bold.

Each model was evaluated using 5-fold cross-validation, and the final models were trained by selecting optimal hyperparameters. The findings were examined to compare the performance of models derived from various train-test splits.

Performance evaluation metrics, including Acc, precision, recall, and F1 score, are employed to assess models developed for classification tasks. These methods are derived from the confusion matrix. The model's Acc is defined as the ratio of correctly classified samples to the overall sample size. High acc signifies the model's strong predictive capability, whilst low acc suggests the necessity for enhancements in the model's performance. The Acc value is calculated as per Equation (1) [32]

$$Accuracy = \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \quad (1)$$

The Acc performance metric is calculated as in Equation (1).

Precision denotes the ratio of samples that the model identifies as positive to the actual true positives. A high precision indicates a low rate of false positive predictions, with the majority of samples categorised as positive are actually positive. Precision is calculated as outlined in Equation (2) [32].

$$Precision \ = \frac{T_P}{T_P + F_P} \tag{2}$$

Recall is a metric utilised in categorisation tasks. It denotes the proportion of actual positive examples accurately identified as positive. Sensitivity is a crucial metric for decreasing false negatives and minimising the omission of true positive examples. Recall is computed as delineated in Equation (3) [32]

$$Recall = \frac{T_P}{T_P + F_N} \tag{3}$$

The F1 score is a metric frequently employed in classification applications, including information retrieval and ML . It offers a metric for assessing model performance, considering both precision and recall. F1 is mathematically defined as the harmonic mean of precision and recall. The F1 is presented in Equation (4) [32].

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

Precision quantifies the ratio of true positive predictions relative to the total number of predicted positives. It seeks to measure the accuracy of positive forecasts. Precision, alternatively referred to as sensitivity or true positive rate. It quantifies the ratio of correct positive predictions relative to the total number of true positives. It demonstrates the model's efficacy in identifying all positive samples [32].

The F1 balances these two metrics, considering precision and sensitivity, and provides a single value. It is particularly beneficial when the class distribution is unbalanced or when false positives and false negatives lead to different results. The F1 is especially significant when both precision and sensitivity are important for assessing tasks such as information retrieval systems [32].

VII. EXPERIMENTAL RESULTS

This section will describe the results of the models developed using XgBoost, DTs and SVMs following the text representation approaches for two distinct train-test splits (80%-20% and 70%-30%). Table 2 presents the findings of the 70%-30% train-test split, whereas Table 3 displays the results of the 80%-20% train-test split.

Table 2. Text representation and classifier model results after 70%-30% train-test split.

Model	**Text representation**	**Precision**	**Recall**	**F1**	**Acc**
XGBoost	CBow	0.7737	0.7506	0.7891	0.8159
DT		0.7639	0.7643	0.7636	0.7547
SVM		0.7544	0.7541	0.7398	0.7542

Table 2 (cont). Text representation and classifier model results after 70%-30% train-test split.

XGBoost	Skip-Gram	**0.8477**	**0.8645**	**0.8600**	**0.8524**
DT		0.7558	0.7533	0.7506	0.7619
SVM		0.7305	0.7309	0.7381	0.7667
XGBoost	TF-IDF	0.7638	0.72261	0.7485	0.7952
DT		0.7412	0.7450	0.7401	0.7571
SVM		0.7267	0.7553	0.7271	0.7333
XGBoost	BoW	0.7353	0.7356	0.7353	0.7364
DT		0.7301	0.7303	0.7305	0.7314
SVM		0.7298	0.7299	0.7296	0.7317

Table 2 indicates that XGBoost is the most successful model, demonstrating superior performance, particularly in conjunction with Skip-gram (F1: 0.8600, Acc: 0.8524). The results indicate that the Skip-gram model, proficient in capturing contextual information, achieves high accuracy when integrated with XGBoost, a decision tree-based algorithm. CBoW also yielded robust results, however slightly lower to those of Skip-gram. Conventional text representation techniques such as TF-IDF and BoW typically exhibit lower performance due to their inability to capture contextual information. The BoW model, as a frequency-based approach, disregards the order and relationships of words, resulting in diminished performance, particularly in tasks where semantic relationships are significant. TF-IDF, although proficient in determining term weights, has become inferior to Word2Vec-based methodologies due to its disregard for the contextual relationships among words.

Upon model evaluation, the DT demonstrated consistent performance across all text representation approaches; nevertheless, it lagged behind XGBoost due to the potential for overfitting. Conversely, SVM has demonstrated the least success among all approaches, particularly in its inability to capture contextual interactions. This issue may arise due to SVM's inability to work effectively with high-dimensional word vectors.

Table 3. Text representation and classifier model results after 80%-20% train-test split.

Model	**Text representation**	**Precision**	**Recall**	**F1**	**Acc**
XGBoost	CBoW	0.7969	0.7732	0.8127	0.8403
DT		0.7868	0.7872	0.7865	0.7773
SVM		0.7770	0.7767	0.7619	0.7768
XGBoost	Skip-Gram	**0.8731**	**0.8904**	**0.8858**	**0.8779**
DT		0.7784	0.7758	0.7731	0.7847
SVM		0.7524	0.7528	0.7602	0.7890

Table 3 (cont). Text representation and classifier model results after 80%-20% train-test split.

XGBoost	TF-IDF	0.7867	0.7442	0.7709	0.8190
DT		0.7634	0.7673	0.7623	0.7798
SVM		0.7485	0.7779	0.7489	0.7552
XGBoost	BoW	0.7573	0.7576	0.7573	0.7584
DT		0.7520	0.7522	0.7524	0.7533
SVM		0.7516	0.7517	0.7514	0.7536

The table presents the updated findings for the 80%-20% train-test division. A slight increase in model performance has been noted due to the expanded training set. XGBoost consistently demonstrates superior performance, particularly in conjunction with Skip-gram. CBOW has yielded robust results; nonetheless, TF-IDF and BoW methods have lagged behind other text representation techniques due to their inability to effectively capture contextual information. DTs have demonstrated reliable performance; nonetheless, their restricted generalisation capacity has resulted in its inferiority to XGBoost. The SVM model has demonstrated the least success owing to its inadequacy in effectively capturing contextual meaning. The results demonstrate that model performance generally enhances with increased training data; nonetheless, contextual text representation methods are the key to the success.

Figures 1 and 2 provide the confusion matrix visualisations depicting the classification performances of various ML models, including XGBoost, DTS, and SVMs, utilising text representations such as CBoW, Skip-Gram, TF-IDF, and BoW, following the 80%-20 and 70%-30 train-test splits.

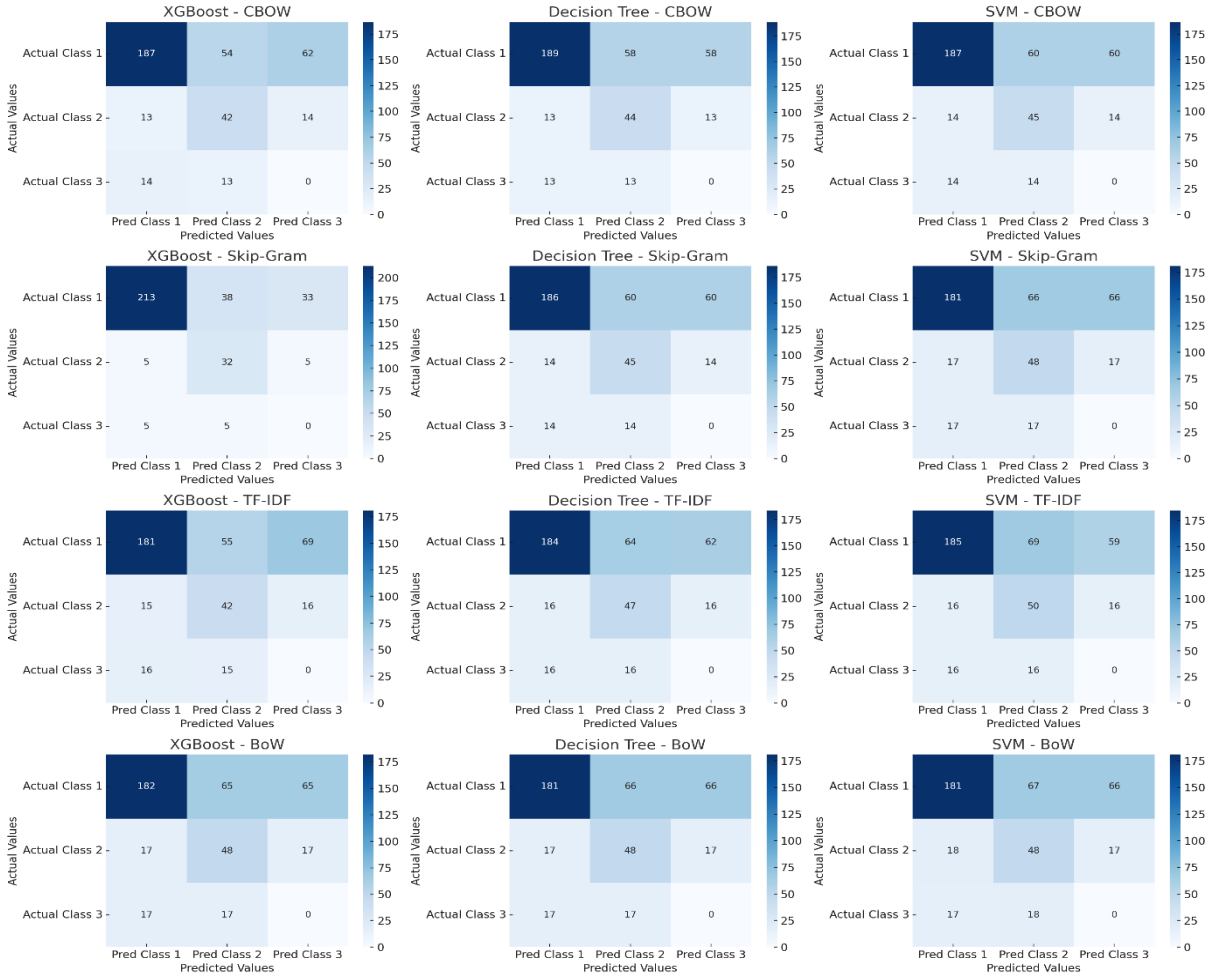


Figure 1. %80-20 train-test confusion matrix results.

Figure 1 illustrates that the XGBoost model, especially when utilising the Skip-Gram technique, had the most superior performance. The combination of XGBoost and Skip-Gram has attained the highest Acc rates by reducing misclassifications. This approach effectively distinguishes between class 2 (cost-related texts) and class 3 (time-related texts). Minimal false positive (FP) and false negative (FN) rates signify that the model commits fewer errors between these classifications.

The CBoW approach has shown robust efficacy in gathering contextual information; yet, it has not quite realised the benefits offered by Skip-Gram. Utilising XGBoost with CBoW, class 1 (quality-related texts) was successfully classified; nevertheless, there were increased errors in the cost and time classes. The elevated misclassifications for Class 2 and Class 3 indicate that the model encounters difficulties in differentiating these texts effectively.

DT and SVM models have resulted in increased misclassifications, especially while employing TF-IDF and BoW. This results from the approaches' failure to effectively capture the contextual relationships among words. TF-IDF and BoW particularly disregard the sequence of words in texts, as they are predicated on word frequency. This results in a significant classification error in construction contracts where time and cost-related statements are intertwined.

The SVM model has exhibited the least success. The elevated misclassification rates for class 2 (cost) and class 3 (time) suggest that the model has difficulty differentiating between these categories and struggles to make a clear distinction. Class 3 (texts pertaining to time) has been misclassified, particularly when employing approaches devoid of contextual significance, such as TF-IDF and BoW.

In general, contextual word embedding techniques (Skip-Gram and CBOW) produce superior outcomes relative to conventional text mining approaches (TF-IDF and BoW). The XGBoost model has produced

optimal outcomes in capturing contextual information and class differentiation, particularly when utilised with Skip-Gram, resulting in a significant decrease in the model's error rates.

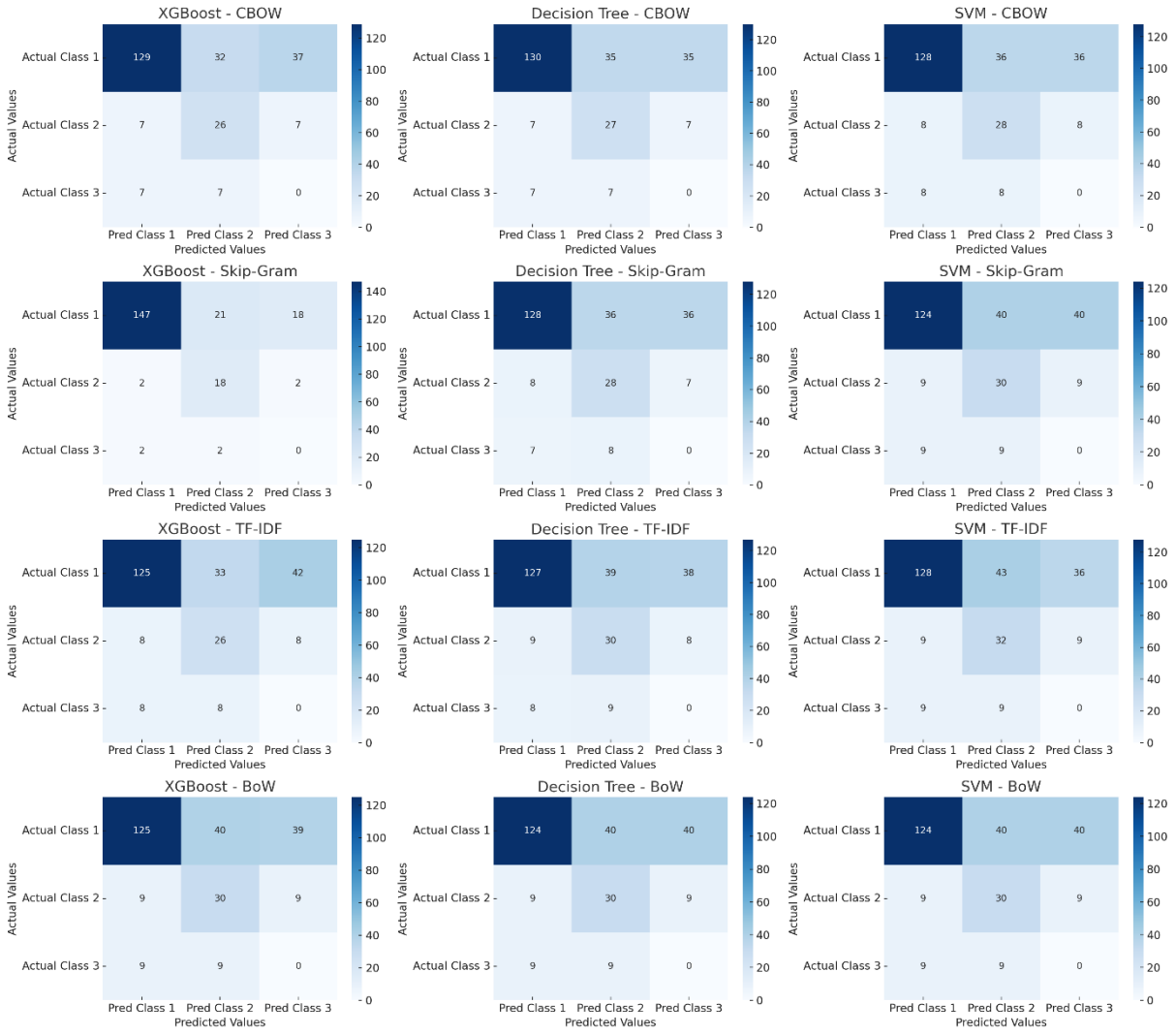


Figure 2. %70-30 train-test confusion matrix results.

Figure 2 illustrates that the XGBoost model, especially utilising the Skip-Gram technique, had optimal performance in the 70%-30% division. The XGBoost and Skip-Gram combination has attained the maximum Acc and the lowest error rates by reducing misclassifications. The CBoW representation has demonstrated remarkable performance; yet, it has somewhat underperformed due to the contextual information capture superiority of Skip-Gram.

DT and SVM models have resulted in increased misclassifications, particularly when employing TF-IDF and BoW methodologies. This situation arises from these methodologies' inability to effectively capture the contextual links between words and the complexities associated with the interrelation of variables such as time, cost, and quality in construction contracts. The SVM model has consistently demonstrated the least efficacy and has encountered difficulties in class differentiation, particularly when employing TF-IDF and BoW methodologies.

Overall, contextual word embedding techniques (Skip-Gram and CBoW) produce superior outcomes relative to conventional text mining approaches (TF-IDF and BoW).

VIII. DISCUSSION

This study aims to analyse standard Design-Build construction contract texts categorised by time, cost, and quality via NLP approaches. The primary goal was to develop an automated model capable of classifying contract clauses based on these critical parameters. The study involved performance comparisons utilising various text representation approaches (CBOW, Skip-gram, TF-IDF, BoW) and ML models (XGBoost, DT and SVM). XGBoost, particularly when utilised with Word2Vec techniques (CBOW and Skip-gram) that incorporate contextual data, has produced optimal outcomes. The classifications executed using Skip-gram yielded the greatest F1 score (88,58% for the 80-20 train-test split, 86,00% for the 70-30 train-test split) and the Acc (87,79% for the 80-20 train-test split, 85,24% for the 70-30 train-test split). Conventional text representation techniques like TF-IDF and BoW exhibit inferior performance relative to Word2Vec representations due to their inability to capture contextual relationships.These results align with existing research (e.g., [19] and [21]) which emphasise the effectiveness of embedding-based models in capturing semantic nuances in technical documents.

The primary constraint of the study is that the distinction in the dataset has not been fully achieved. The frequent intertwining of time and cost components in construction contract texts has complicated the ability to draw a clear difference. An escalation in project costs can be directly correlated with alterations in duration. This circumstance has prompted the algorithm to assess specific terms within both cost and time classifications, resulting in elevated error rates. The wide range of legal and technical terminology present in the contract content has hindered the model's ability to interpret these specialised expressions.

Although this phenomena explicitly discussed in prior ML studies on contracts, it indicates a necessity for improved domain-specific annotation and possibly hybrid labelling approaches that facilitate multi-label categorisation.

Furthermore, conventioanl classifiers such as SVM and DT exhibited relatively diminished performance, especially when employed with non-contextual representation methods. The findings suggest that NLP techniques may be successful for the automated analysis of contract texts utilised in construction projects, categorised by time, cost, and quality labels. To achieve more precise distinction, the dataset needs to be meticulously labelled, and various feature engineering techniques should be employed. Future research may include more sophisticated contextual analyses utilising BERT or Transformer-based deep learning models. This may enhance contextual comprehension, thereby increasing model accuracy. Moreover, preprocessing methods which in accordance with legal terminology and specialized lexical databases can be developed to more effectively elucidate the complex relationships between cost and time.

The study also supports a growing shift towards data-driven instruments in contract analysis. Automating the categorisation of contract clauses can substantially reduce human error, expedite legal review processes, and improve decision-making in construction project management. Compared to prior studies, the results underscore the superiority of contextual text representation approaches like Skip-Gram over conventional methods such as TF-IDF and BoW. This study's dynamic approach, incorporating contextual embeddings, provides a more robust framework for comprehending contractual nuances, in contrast to previous research that primarily concentrated on static text analysis.

Consistent with the research conducted by [25] and [26], the application of NLP and ML in standard construction contract review presents significant potential in enhancing both legal clarity and operational efficiency.

The discussion affirms that although machine learning presents a powerful toolset for construction contract analysis, meticulous consideration is required regarding the inherent ambiguities of legal language and the design of training datasets that accurately reflect the nuanced interdependencies among contractual components.

IX. CONCLUSION

This study set out to examine the application of machine learning techniques in the analysis of Design-Build standard construction contracts, concentrating on time, cost and quality. The research objectives were threefold: (1) to classify contractual clauses utilising NLP techniques, (2) to evaluate the efficacy of

diverse ML algorithms and text representation methods, and (3) to develop a foundational model for improved contract analysis and decision-making in construction management.

The findings reveal that contextual text representation techniques such as Skip-Gram, when employed with advanced ML models like XGBoost, yield high accuracy and robust classification performance. This confirms the capability of NLP and ML tools to enhance the analysis of legal construction documents. The study contributes through the methodological integration of these tools and their practical implications, facilitating more efficient and objective analysis of standard contract clauses.

One notable benefit of the proposed model is its ability to process intricate textual material efficiently, minimizing manual labor and reducing the likelihood of human error. The study provides a significant basis for analysing documents related to construction projects through NLP techniques. However, the study also faced limitations, primarily related to the inherent overlap between time and cost factors in construction contracts. This overlap complicated the classification process, leading to occasional misclassifications. Additionally, the diversity in legal and technical terminology across contracts posed challenges in achieving consistent text representation. The utilisation of larger and more balanced datasets in the development of NLP models can enhance the understanding of the cost-time relationship, yielding substantial advantages for construction management and risk assessment.

In practical terms, the outcomes of this research have significant implications for construction managers and legal practitioners involved in contract analysis. Automating the classification of contract clauses accelerates the evaluation process and facilitates a more systematic approach for identifying risks and controlling contract performance. The proposed model, therefore, signifies a meaningful advancement in integrating machine learning into the domain of construction contract analysis. Utilising modern machine learning models can enhance the consistency, transparency, and efficiency of contract evaluation, hence resulting in superior project outcomes.

DECLARATIONS

Acknowledgements: The authors do not wish to acknowledge any individual or institution.

Author Contributions: Conceptualization, A.D.; Methodology, A.D. and L.O.U. ; Validation, A.D. and L.O.U. ; Investigation, A.D. and L.O.U..; Resources, A.D.; Data Curation, A.D.; Writing—Original Draft, A.D.; Writing—Review & Editing, L.O.U. ; Supervision, L.O.U.

Conflict of Interest Disclosure: The author/authors declare no conflict of interest.

Copyright Statement: The author(s) retain the copyright of their work published in the journal, which is licensed under the CC BY-NC 4.0 license, allowing others to share and adapt the work for non-commercial purposes with appropriate attribution.

Funding/Supporting Organizations: This research received no external funding.

Ethical Approval and Participant Consent: This study does not involve human or animal participants. All procedures followed scientific and ethical principles, and all referenced studies are appropriately cited.

Plagiarism Statement: This article has been evaluated for plagiarism and no instances of plagiarism were detected.

Availability of Data and Materials: Data could be shared if desired.

Use of AI Tools: OpenAI ChatGPT-4 has been used in the language and readability adjustments of this study. The authors also declare that while extracting and categorizing sentences from Standard Construction Contract texts with the point of view thought in the beginning, support has also been obtained from OpenAI ChatGPT-4 for verification purposes.

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