Improving Lean Construction by Integrating ML for Contractor Performance Prediction

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***Abstract*—In this paper, we present a novel framework that integrates Machine Learning (ML) with Lean Construction practices to address construction industry challenges in quality management and waste reduction. While Lean Construction offers solutions, its effectiveness is often limited by manual processes such as data collection and processing. Our primary novelty is the application of ML-based methods to predict contractor performance using historical data, an approach not widely explored previously. We address this by developing a custom web application to automate the collection of audit data from a large-scale real-world oil refinery construction project spanning 586 hectares. This data was employed to train several ML models to predict contractor performance grades. Our results demonstrate the framework's effectiveness, with the models achieving high predictive accuracy of over 85%, showing their potential to provide reliable, data-driven insights.**

***Index Terms*—Lean Construction, Machine Learning, Predictive Analytics, Contractor Performance**

I. Introduction

Construction projects are inherently complex and often struggle with quality due to the dynamic interaction of tasks, disciplines, and stakeholders. With typical cost overruns between 15% and 28% due to poor planning and inefficient management, the industry increasingly turns to tools that emphasize automation, digitization, and intelligent data processing. Within this shift, Lean Construction methodology stands out as a powerful framework for continuous improvement, offering formal performance metrics and the ability to eliminate waste, potentially resolving up to 90% of defects [1]. The integration of digital tools for construction data collection and processing further enhance Lean practices by improving safety compliance and enabling near real-time project quality monitoring [2]. These tools also facilitate the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) to create predictive models that support smarter data-driven planning from the earliest stages of a project.

As the construction sector embraces data-rich environments, ML emerges as a cornerstone of intelligent Lean practices. Its ability to process vast amounts of data collected at the construction site and detect hidden patterns allows project teams to anticipate issues before they escalate. Unlike traditional construction data processing approaches, which are largely descriptive, ML empowers Lean systems to become more adaptive, efficient, and responsive. The integration of ML techniques can improve operational efficiency and optimize resource allocation. The capability of ML models to analyze real-time site data can revolutionize construction planning and forecasting. Using historical data analytics, these models can generalize across different projects and provide predictive insights to improve projects' outcomes. This is critical, given that traditional construction methods often struggle to take full advantage of Lean methodology frameworks.

In this paper, we investigate the employment of ML-based methods to improve the Lean methodology and support its application in a real construction project. To facilitate the use of these ML-based methods, we develop an accessible web application that allows to automate the data collection and processing from the construction site, and integrates studied ML-based methods to grade the quality of work conducted by contractors and produce predictions on the future grades based on the historical data. To verify our approach, we present a case study of various ML-based methods with the data collected earlier in a real-world construction project. Results show promising performance, with predicted grades accuracy exceeding 80%. These findings contribute to the development of practical tools aimed at enhancing efficiency and quality in construction projects while reinforcing Lean principles through data-driven decision-making.

This paper makes three primary contributions: **(1)** we investigate and propose a novel application of ML-based methods to advance Lean construction by predicting contractor performance grades using historical data from a real-world project, addressing a gap in existing research; **(2)** to support this methodology, we designed and implemented a web application to digitize Lean workflows, which facilitates automated data acquisition, processing, and preparation for ML model input; **(3)** we conducted a case study to identify the most effective ML-based methods for predicting contractor grades and to demonstrate a practical use case where insights derived from historical data collected in a real construction project can support more informed contractor selection. The practical impact of this approach relies on objective, data-driven evidence rather than abstract qualitative assessments, with the potential to reduce project costs and enhance overall quality.

Our work strengthens the Lean Construction philosophy by inserting data-driven intelligence into continuous improvement cycles. ML models transform audit data into predictive insights, allowing a prompt identification of performance risks and

TABLE I. COMPARISON OF STUDIES INTEGRATING ML INTO CONSTRUCTION SETTINGS

Studies\Criteria	**Used ML Method**	**Integration with Lean Construction Frameworks**	**Performance Prediction Using Historical Data**	**Providing Digital Tools for Data Collection/Processing**
Hu et al. (2020) [3]	Data Analysis Decision Support Tool	Lean waste reduction framework	No	No
Velezmoro Abanto et al. (2021) [4]	Artificial Neural Networks	Lean scheduling models	No	No
Rahaman et al. (2022) [5]	Big Data Analysis	No direct Lean integration	No	No
Harichandran et al. (2020) [6]	Support Vector Machine	No direct Lean integration	No	No
Liu et al. (2019) [7]	Bayesian inference–based method	No direct Lean integration	No	No
Florez et al. (2020) [8]	K-nearest neighbor, Deep Neural Network	Productivity improvement (Lean methodology)	Yes, for task productivity	No
Mostofi et al. (2021) [9]	Node2vec-based recommendation system	No direct Lean integration	Yes, contractor recommendation based on historical performance data	Yes, digital contractor records
Sholeh et al. (2022) [10]	Particle Swarm Optimization	No direct Lean integration	No	No
Lam et al. (2020) [11]	Support Vector Machine, Artificial Neural Networks	No direct Lean integration	No	No
This Study (2025)	Random Forest, XGBoost, SVR, LightGBM	Lean quality auditing	Yes, prediction of contractor performance grades	Yes, digital platform for audit data collection

preventing rework. This are two key aspects of waste reduction – a major goal of Lean practices. Moreover, by providing standardized, objective assessments of contractor performance, our tools advance Lean´s goal of fostering transparency and learning across projects, representing a high impact contribution toward the digital transformation of Lean practices.

II. RELATED WORK

The integration of Lean methodologies with digital tools and ML is redefining how construction projects are managed. Studies confirm that Lean principles significantly improve project performance by increasing efficiency and reducing costs, while ML helps align project goals with these principles for more successful outcomes. The synergy between Lean and data analysis enables smarter resource planning and execution, as emphasized by Hu *et al.* [3] and Velezmoro-Abanto *et al.* [4]. Specific data-driven applications further illustrate this trend; for example, Rahaman *et al.* [5] used Big Data analytics to enhance operational efficiency, while others have applied Support Vector Machines (SVM) to infer construction activities in real-time [6] or developed decision-support systems to optimize equipment management [7].

Another critical application of ML in construction is predicting and mitigating project risks. Researchers have developed frameworks to anticipate project delays by analyzing historical data, reflecting Lean's emphasis on data-driven decisions [12], [13]. Beyond delays, ML-powered predictive analytics can forecast trends in costs and labor productivity [14], and other work demonstrates how ML enhances the adaptability and performance of Lean strategies [8]. These approaches often feed into larger Lean learning frameworks that integrate data streams throughout the project lifecycle to support continuous improvement and proactive decision-making [15]. This focus on performance extends to contractor analysis, where ML also plays a growing role. Recent work in this area includes performance-driven contractor recommendation systems [9], AI-based methods using Particle Swarm Optimization to find optimal contractor combinations [10], and the use of unsupervised learning to uncover hidden performance patterns for improved risk management [16]. In related studies, ML algorithms have been used to forecast labor needs for better resource allocation [17], and SVM models have been applied to classify contractors, enhancing transparency in the prequalification process [11].

Table I summarizes the prior studies, presented in this section, that have made significant progress in improving Lean frameworks with the use of ML techniques. To the best of our knowledge, predicting grades for the contractors based on Lean Construction practices driven by the available historical data has not been fully explored. The innovation of this research lies in the integration of ML-based methods to enhance the contractor selection process in order to improve the overall quality of the project. This study contributes to the development of intelligent tools that enable the practical application of Lean Construction methodologies.

III. IMPROVING LEAN CONSTRUCTION WITH DATA COLLECTION TOOLS IN REAL PROJECT

A. *Dos Bocas Oil Refinery Construction*

The Dos Bocas Oil Refinery is a large-scale construction project located in the southern Mexican state of Tabasco. The project spans approximately 586 hectares and represents one of the most ambitious infrastructure initiatives in the country. Construction was organized into six *packages*. These packages were further subdivided into forty-seven construction fronts, referred to in the project as Work Breakdown Structures (WBS) This hierarchical structure is common in large-scale construction projects For the purposes of this research, we investigated the data collected in the construction stages of Integration Services, Buildings, and Internal Urbanization.

B. Lean Methodology for Work Quality Evaluation

The project's Lean methodology, adapted from Gonzalez and Solis [18], evaluates quality, productivity, and safety through randomized audits. These audits use technical rubrics with specific criteria to assess compliance with standards, generating Key Performance Indicators (KPIs) across five classes: *Equipment, Materials, Processes, Project Documents, and Safety*. Performance its assessed grading several criteria for each KPI. For each criteria a three-point grading scale is used: (*"40 – Does not meet the criteria"*, *"70 – Meets the criteria"*, and *"100 – Exceeds the criteria"*). As an example, the rubric for the *Processes* class activity KPI *Concrete Casting* evaluates multiple criteria such as: the *"Speed of the concrete truck barrel"*, *"Concrete casting height, "* and *"Concrete vibration time"*, among others; which directly influences the overall quality of the work.

C. Web Application for Construction Data Collection and Processing

One of the major challenges in implementing Lean Construction practices is the reliance on data collection and the lack of standardized processes. To address these issues, a web application was developed to support real-time data acquisition from the construction site. The primary objective of the application is to enable auditors to perform assessments on-site and submit data directly, thereby streamlining both the evaluation and data analysis workflows. The application digitizes Lean rubrics into standardized electronic forms. Each form clearly outlines the audit criteria and allows users to assign grades from a predefined drop-down menu. All collected data is automatically processed to generate audit scores, contractor grades, class-level grades, and overall project performance indicators. The web application was deployed at the Dos Bocas Oil Refinery site for nearly three years, from 2021 to 2023. During this period 83 contractors were evaluated, generating 5,818 audit reports.

IV. Improving Lean Construction with ML Prediction Based on Historical Data

One of the key advantages of digitizing the Lean methodology through a web application is the capacity to collect and analyze large volumes of structured, high-quality data. In this study, the data gathered from the Dos Bocas project was leveraged to train ML models aimed at predicting contractor performance in future construction activities. Specifically, the objective was to forecast which contractors are most likely to achieve high performance scores across defined KPIs. These predictive insights can inform smarter contractor selection and more strategic task assignment in upcoming projects, thereby contributing to an intelligent, data-driven contractor selection.

A. Description of Collected Construction Data

The data used for our case study consists of individual audit records, each capturing the evaluation outcome of a contractor's performance on a specific task. Each record includes a

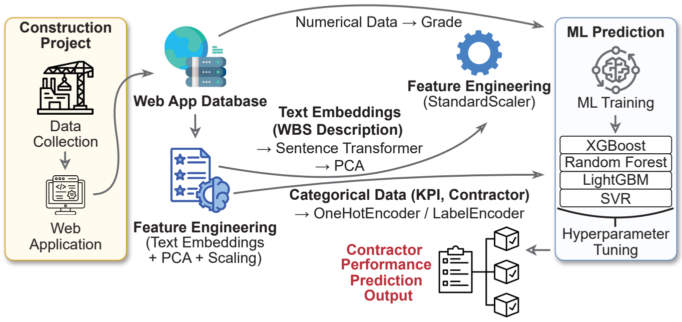


Fig. 1. Illustration of how the developed web application digitizes the Lean Construction methodology. On-site construction data is collected, processed, and fed into ML-based methods to generate contractor performance predictions

numeric grade assigned based on predefined audit rubrics, the corresponding KPI, the contractor, and the WBS description. For instance, a KPI field could be *"Welding on steel pipe"*, while a WBS description might be *"Fire extinguisher network: A set of components designed to provide water for firefighting. This network includes water sources, pumping equipment, ..."*. For the overall project,a total of 5849 audits were collected, each one comprehend an observation in the data set.

A data sanity check was performed to ensure reliability and consistency of the data. The following statistics values were calculated for all numerical variables to identify potential anomalies or outliers. For contractor performance scores exhibited a mean of 67.06, with a standard deviation of 4.88, and ranges between 45 and 84. The quartile values (25% = 65, 50% = 67, 75% = 70) shows that the data is well distributed with no extreme deviations. These results confirm that the dataset is well balanced and suitable for ML applications. A sample of the dataset is shown in Table II.

B. Integration of ML-Based Methods

To develop predictive models capable of estimating contractor performance, we implement an ML pipeline that includes data preprocessing, model training, and evaluation of results. The primary objective is to predict the grade obtained by a contractor for a specific KPI, based on features derived from the audit records. A flowchart of the process can be seen in Fig.1.

1) Data Preparation: to prepare the raw data for model training, several preprocessing steps are necessary to handle the mix of categorical and textual data. The dataset consists of four main fields: the audit grade (target variable), the KPI (rubric), the contractor name, and the WBS description. First, for Text Embedding, the free-text *WBS Description* field is converted into numerical representations using the `SentenceTransformer` library with the `all-MiniLM-L6-v2` pre-trained model to generate dense vector embeddings that capture semantic meaning. Next, for categorical encoding, the *Contractor* and *Rubric (KPI)* fields are transformed into a binary vector format using `OneHotEncoder`, allowing the models to distinguish between different categories. The resulting dataset, which combines the encoded categorical features and WBS embeddings, undergoes

TABLE II. EXAMPLE OF AUDIT DATA USED FOR ML EXPERIMENTATION

Grade	Rubric (KPI)	Contractor	WBS Description
63	Welding machine	Contractor 1 Name	Fire extinguisher network: A set of components designed to provide water for firefighting. This network includes water sources, pumping equipment, and the piping network that distributes water to hydrants and other extinguishing devices.
65	Safety excavation	Contractor 2 Name	Water supply and return system. Water is extracted from a source and used in the building. The water is then treated, and the system returns the water to the source. It includes pipes, pumps, and a water treatment plant.
70	Scissor lift	Contractor 3 Name	Construction of structural elements to support the rails and keep the railway track in place. These include cleats, which will be used to secure the rails to the sleepers.
68	On-site Security	Contractor 4 Name	Piping interconnection is the process of connecting different pipes and services to create an integrated system. This process allows the flow of liquids, gases, or solids between different sections of the building.

TABLE III. GRID OF HYPERPARAMETERS TUNED FOR EACH MODEL

Model	Tuned Hyperparameters
RF	`n_estimators`: {100, 200} `max_depth`: {None, 10, 20} `min_samples_split`: {2, 5}
XGBoost	`n_estimators`: {100, 200} `max_depth`: {3, 6, 10} `learning_rate`: {0.01, 0.1}
SVR	`kernel`: {'rbf', 'linear'} `C`: {1, 10} `epsilon`: {0.1, 0.2}
LightGBM	`num_leaves`: {31, 50} `learning_rate`: {0.01, 0.1} `n_estimators`: {100, 200}

feature scaling using `StandardScaler` to normalize the feature space and prevent bias from variables with larger ranges. For the experiment, the data is split into 80% for training and 20% for testing.

2) Model Training: In our case study, we investigate four regression models that demonstrated commendable performance in previous construction-related studies [19], [5], [11]: Random Forest Regressor (RF); Extreme Gradient Boosting Regressor (XGBoost); Support Vector Regressor (SVR); and Light Gradient Boosting Machine Regressor (LightGBM). The models are trained using *ski-learn* Python package. The hardware used is a machine running on an Intel® Core™ i5-13450HX, with a NVIDIA® GeForce RTX™ 3050 GPU card. Hyperparameter tuning is conducted for each model using grid search and cross-validation. Table III summarizes the hyperparameters employed for each model in the experiments.

3) Performance Evaluation: after training, each model's performance was evaluated on a held-out test set using several metrics. To quantify the average prediction error and the variance captured, we used standard metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). Additionally, to reflect the practical precision needed in contractor evaluation, we defined a custom metric called Tolerance Accuracy. This measures the proportion of predictions falling within a ±5 point range of the actual grade, which is particularly useful in contexts where slight deviations are acceptable. Tolerance Accuracy (TA) is defined as:

$$TA_\tau = \frac{1}{n}\sum_{i=1}^{n} 1\left(|y_i - \hat{y}_i| \leq \tau\right),$$

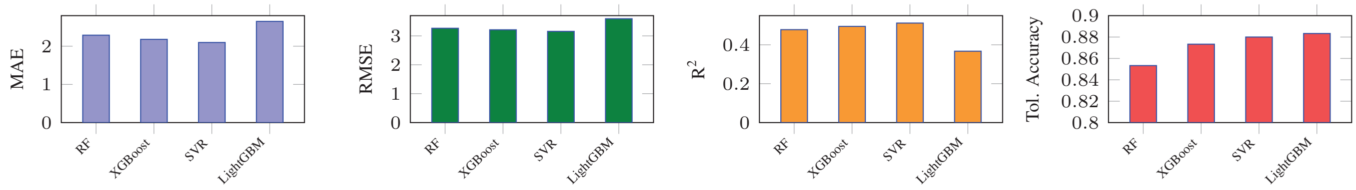
where y_i is the true grade; $\hat{y}_i$ is the predicted grade; τ is the tolerance threshold (5 points in this case); $1(\cdot)$ is the indicator function that returns 1 if the condition is true, and 0 otherwise; and n is the total number of samples.

C. Case Study Results

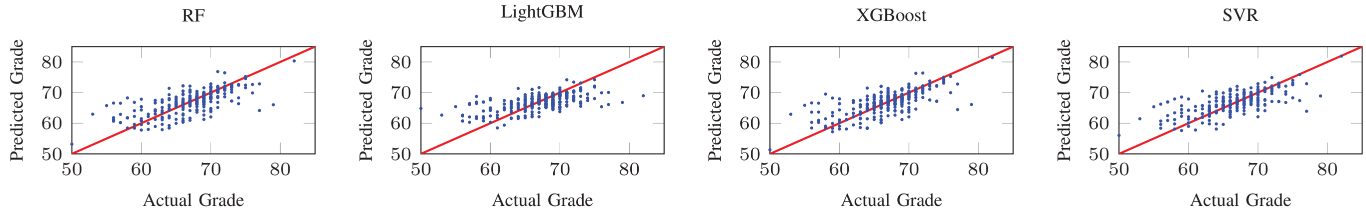
The performance of the considered ML models is summarized across the visualizations in Fig.2. A direct comparison of key performance metrics for each model is presented in Fig.2a. The SVR demonstrated the strongest overall performance, achieving the lowest MAE of 2.10 and RMSE of 3.16, along with the highest R^2 score of 0.51. The XGBoost model followed closely with an MAE of 2.18 and an R^2 of 0.49. While the LightGBM model had the highest error rates (MAE of 2.65), it achieved the highest Tolerance Accuracy (0.883), indicating its effectiveness when a ±5 point error margin is acceptable. These results highlight the relative strengths of each algorithm in capturing contractor grading patterns and demonstrate the suitability of SVR for this regression task.

The quality of the predictions was further assessed by plotting each model's predicted grades against the actual grades (Fig. 2b). A reference line indicating perfect prediction ($y = x$) allows for a visual assessment of accuracy, where closer alignment of points to this line indicates stronger predictive performance. To analyze error distribution, scatter plots of the residuals (the difference between predicted and actual grades) were represented (Fig.2c). The plots show that for all models, the residuals are randomly scattered around the zero line, indicating no systematic bias in the predictions and a relatively constant variance across the predicted grades.

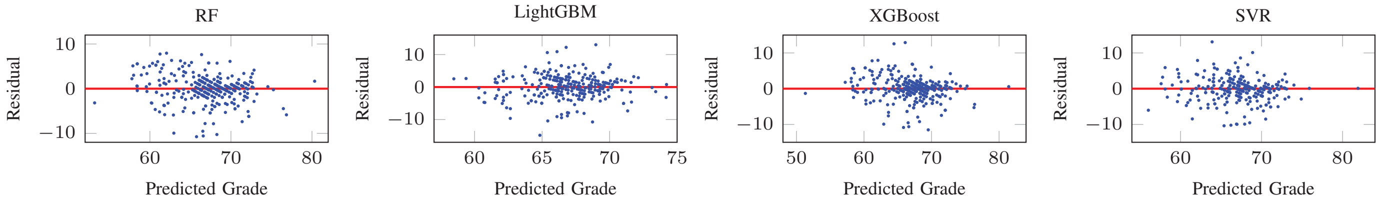
To examine the spread and consistency of model errors, boxplots of the absolute prediction errors were created (Fig. 2d). The boxplot reveals that while all models have comparable MAE, LightGBM exhibits slightly more variability and a greater number of high-error outliers. Conversely, XGBoost and SVR demonstrate tighter interquartile ranges, indicating more consistent predictions.



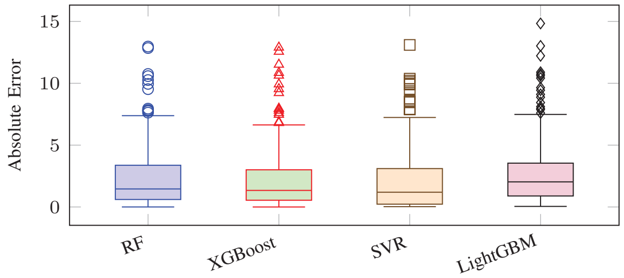
(a) Performance metrics for each model



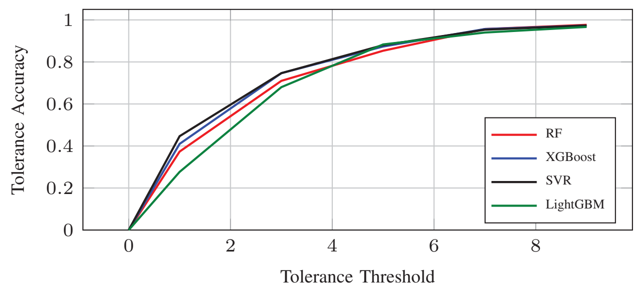
(b) Predicted vs. Actual grades for each model



(c) Residual plots for each model



(d) Boxplot of absolute errors



(e) Tolerance accuracy curve

Fig. 2. Visualization of model performance metrics, error analysis, and prediction accuracy

Fig.2e illustrates the relationship between tolerance thresholds and prediction accuracy. This graph demonstrates how model performance improves as prediction flexibility increases. A tolerance of 5 was selected as a suitable threshold because it provides a high accuracy of over 85% for most models while maintaining a practical error margin. As seen in the plot, the accuracy gains begin to diminish after this point, making it a suitable balance for construction management contexts where exact precision is less critical than acceptable performance.

D. Contractor Performance Prediction Illustrative Use Case

In the context of the considered large-scale *Dos Bocas Oil Refinery* construction project, an analysis of the data gathered during performance audits revealed that the contractor named *HIDROTIC* consistently exhibited a pattern of underperformance. A specific and illustrative example of this trend can be observed in audit #6390 from the project database. In this instance, the contractor received a low score of 63 for the KPI *Welding on steel pipe*, a grade that falls below acceptable quality thresholds. For this specific case, the predictions generated by a suite of employed ML models were remarkably close to the actual outcome: RF predicted a score of 66.86, XGBoost predicted 66.00, SVR predicted 64.01, and LightGBM predicted 64.93. This demonstrates that if the management team had been equipped with an ML-driven decision support tool, it would have been possible to leverage historical data to proactively flag this contractor as a potential performance risk. This capability would have enabled the project team to make a more informed, data-driven selection, thereby mitigating risks before they materialized on-site.

The conclusive results from this case study compellingly demonstrate that integrating ML-based methods with detailed data sourced from Lean Construction practices enables the generation of highly accurate predictions of contractor performances. This synergy represents a significant advancement for the practical application of the Lean methodology, enhancing it with powerful predictive capabilities. By empowering a fundamental shift from a reactive to a predictive management stance, construction managers can effectively anticipate which contractors are likely to underperform on specific tasks before work commences. This foresight supports a more strategic and objective, data-driven contractor selection process, which can directly lead to substantial benefits such as reduced operational costs by minimizing rework and a tangible improvement in the overall quality of the final project. Our findings underscore the transformative value of data-driven decision-making and strongly support the integration of predictive analytics into traditional construction workflows. Such an integration is crucial for modernizing the construction industry that has often been traditionally slow to fully utilize the benefits of digitization and the integration with AI. To foster reproducibility and facilitate practical deployment of our approach, the complete database, source code, and all experiments for this study are made publicly available in the following GitHub repository: *Click to Repository*.

V. Limitations

While this research makes a valuable contribution to the practical integration of ML within Lean Construction methodologies, limitations must be acknowledged. The primary limitation is the single-project scope of the case study. All data used in this study were collected from a single construction project. Although the project was significantly larger than the industry average, expanding the dataset to include multiple projects would enhance the generalizability of the findings and increase their practical relevance. Another limitation is the limited diversity of input features used for model training. At present, the models rely solely on task type and activity description. However, additional variables, such as resource availability, cost, scheduling restrictions, and regulatory compliance, can significantly impact contractor performance and should be incorporated into future work.

VI. Conclusion

In this paper, we presented a novel approach that successfully integrates ML with Lean Construction principles to address challenges critical for the construction industry, such as project quality control and cost management. Our work yields three primary results with significant implications for construction practitioners: **(1)** we demonstrated that by leveraging historical audit data, it is possible to predict contractor performance grades with high accuracy; **(2)** we developed a novel web application to facilitate data collection and digitize construction processes, overcoming the common barrier of inconsistent data collection. This makes the application of advanced analytics like ML more accessible and scalable for construction projects; and **(3)** employing the data collected in a real construction project, we assessed the performance of multiple ML models and showed how historically poor-performing contractors could be flagged. The results of our research directly benefit project stakeholders by reducing human bias in contractor selection, which in turn can lead to significant cost savings and enhanced project quality.

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