Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250430
Published: December 20, 2025

Predicting Construction Cost Using Simple Machine Learning Techniques: A Case-Based Approach

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Abstract

Accurate construction cost estimation is essential for efficient project planning, particularly in developing countries like Bangladesh, where cost overruns are common. This study applies two simple machine learning algorithms, Decision Tree Regressor and K-Nearest Neighbors (KNN), to predict final construction costs of residential buildings using a dataset of 50 completed projects from various regions and seasons in Bangladesh. Key features include floor area, number of floors, construction duration, soil and foundation types, roof type, and cost components. The data were collected through structured field surveys and contractor records and preprocessed using standardization and one-hot encoding. Model performance was evaluated using MAE, RMSE, and R^2 score. The KNN model outperformed the Decision Tree, achieving an MAE of 0.276 million BDT, RMSE of 0.370 million BDT, and R^2 of 0.60. In contrast, the Decision Tree model yielded an MAE of 0.341 million BDT, RMSE of 0.442 million BDT, and R^2 of 0.44. An R^2 of 0.60 indicates a moderate but reliable level of predictive power that avoids overfitting, especially valuable in small, real-world datasets. Feature importance analysis from the Decision Tree revealed that material cost (62.1%), location (21.3%), and labor cost (12.5%) were the most significant predictors. The findings suggest that

interpretable and lightweight models can support cost forecasting even in data-scarce environments, aiding better budgeting and resource allocation in residential construction.
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Keywords
Construction cost estimation, K-Nearest Neighbors (KNN), Decision Tree Regressor; Feature importance; Residential projects

1. Introduction
Machine learning (ML) has emerged as a powerful alternative. ML models can detect complex patterns in historical data and outperform rule-based systems in predictive accuracy. Globally, many studies have applied ML to cost prediction in construction. Elmousalami (2019) compared 20 AI methods, including ANN, CBR, and XGBoost, finding ensemble models most effective. Similarly, Yamusa et al. (2025) showed Random Forest and XGBoost outperformed linear models in renovation cost estimation. Macroeconomic and technological shifts, such as the falling cost of solar PV highlighted by Roy et al. (2025), illustrate how innovation influences project cost dynamics. Advanced simulation-based material studies further highlight the relevance of data-driven engineering analysis (Galib et al., 2024). However, in Bangladesh, where large datasets are scarce, simpler models are more practical.

Recent studies support ML's applicability in data-scarce contexts. Sha et al. (2024) demonstrated that ML models can maintain reasonable accuracy even with limited data, making them ideal for settings like Bangladesh, where data collection often depends on field surveys or project archives. Accordingly, this study builds a model using data from 50 residential projects across districts and seasons, capturing variations in soil conditions, labor availability, seasonal material prices, and local practices. Key cost-influencing features in residential construction include total floor area, number of floors, duration, roof type, soil and foundation type, labor and material costs, and location. Das et al. (2024), using NGBoost and SHAP, found material cost, floor count, and location as dominant drivers. Similarly, Ramujee and Praseeda (2025) confirmed NGBoost's superiority over linear models using real project data.

Simple models like KNN and decision trees also perform well. De Guzman et al. (2024) showed Ridge regression achieving an R^2 of 0.81 and a MAPE of just over 7% in small datasets. Shamim et al. (2025) emphasized the increasing adoption of lightweight ML models for project management in small-to-medium construction firms.

In rural and semi-urban Bangladeshi contexts, features like roof type (RCC, tin, CI sheet), foundation type (caissons, raft, pile), and soil type (clayey, sandy, loamy) further impact costs. Han et al. (2025) showed how BIM-integrated ML models can handle qualitative features. While such methods may be inaccessible for small projects, simpler models can incorporate these variables via encoding, as shown by Chen et al. (2025) and Hassoon et al. (2025). Given this, the present study applies interpretable ML models, decision trees and KNN, for predicting residential construction costs. These models suit the Bangladeshi context, offering a practical balance between accuracy and interpretability. Using field-collected data and focusing on relevant features, this study aims to show how basic ML tools can aid in managing costs and minimizing overruns in residential construction.

1.1 Objectives
- Identifying key factors affecting residential construction costs in Bangladesh.
- Developing decision tree and KNN models for cost prediction.
- Evaluating model accuracy for reducing cost overruns.

2. Methodology
This study was conducted in a structured framework as shown in Figure 1. Detailed of each step are as following:

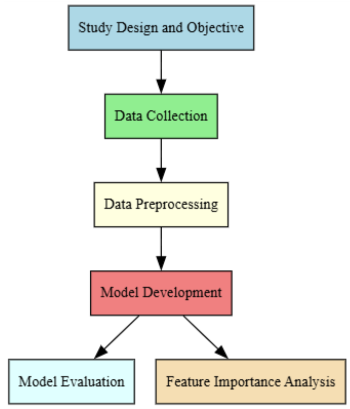

Figure 1. Methodological framework of the study

2.1 Data collection

This study adopts a practical and field-based approach to data collection, focusing exclusively on residential building projects within Bangladesh. Recognizing the scarcity of centralized digital construction data in the region, the dataset is envisioned to be developed through structured surveys of 50 recently completed residential construction projects. These projects are selected to reflect geographical, seasonal, and economic diversity by covering multiple districts across both urban and rural areas and accounting for construction activities completed in different seasons (summer, monsoon, and winter).

The data are collected using a standardized questionnaire administered through direct interviews with site engineers, project supervisors, or homeowners. Additional sources, such as contractor records and project cost sheets, are used where available to ensure accuracy and completeness. The questionnaire is designed to capture both quantitative and qualitative variables relevant to construction cost estimation.

The collected key variables include:

- Project characteristics: total floor area (sq.ft.), number of floors, and construction duration (in months)
- Site-specific attributes: location (urban, semi-urban, rural), soil type (clayey, sandy, loamy), and foundation type (shallow, raft, pile)
- Structural features: roof type (RCC, tin, CI sheet) and contractor type (individual or company)
- Cost variables: final construction cost (actual), material cost, and labor cost (in BDT)

Categorical variables such as soil type, foundation type, roof type, and location are recorded using predefined categories to facilitate later encoding during data preprocessing. Cost values are recorded in Bangladeshi Taka (BDT) and later normalized as necessary for modeling.

This field-oriented data collection method is expected to provide a realistic and context-sensitive dataset that captures variations in construction practices, labor availability, and material prices across different regions and time periods in Bangladesh. By grounding the dataset in actual project outcomes, the study aims to enhance the applicability and reliability of the machine learning models developed for construction cost prediction. A sample of the dataset can be found in Table 1. Here, costs are presented in 'lac BDT' where 1 lac BDT= 0.1 million BDT.

Table 1. A portion of the gathered dataset

Project Size	No of Floors	Project Duration	Location	Roof Type	Soil Type	Foundation Type	Material Cost	Labor Cost	Contractor Type	Final Cost
900	1	12	Semi-Urban	Tin	Clayey	Caissons	11.87	7.7	Individual	24.23
900	3	9	Urban	RCC	Sandy	Caissons	9.03	2.94	Individual	15.27
800	3	6	Rural	CI Sheet	Clayey	Pile	14.81	6.25	Company	26.35
800	1	12	Semi-Urban	RCC	Loamy	Caissons	17.82	3.27	Individual	22.36
1300	1	6	Semi-Urban	RCC	Loamy	Raft	10.96	5.15	Company	18.38
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2.2 Data preprocessing

To ensure data quality and readiness for machine learning, the dataset underwent several preprocessing steps. Missing numerical values were imputed using medians, and categorical ones with the most frequent category. Records with excessive missing data were removed. Categorical variables (e.g., roof type, soil type) were one-hot encoded to preserve their non-ordinal nature. Numerical features (e.g., project size, costs) were standardized using z-score normalization to support algorithms like KNN, though not essential for tree-based models. Finally, the dataset was split into training and testing sets (80:20). All steps were implemented using standard Python ML libraries for consistency and reproducibility.

2.3 Model development

This study employs two supervised machine learning algorithms, Decision Tree Regressor and KNN Regressor, to predict the final construction cost of residential building projects. Both models were selected for their simplicity, interpretability, and suitability for small to medium-sized datasets, making them particularly appropriate for real-world applications in the Bangladeshi construction sector.

The Decision Tree Regressor is a non-parametric model that partitions the feature space into rectangular regions by recursively splitting the data based on feature values that minimize the error in prediction. The model learns a hierarchy of decision rules in the form of a tree, where each internal node represents a decision on a feature, and each leaf node represents a predicted output. For regression tasks, the objective at each split is to minimize the Mean Squared Error (MSE), which is given by Equation 1.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \qquad (1)$$

Where, y_i is the actual value and $\widehat{y_i}$ is the predicted value. The tree grows by selecting the feature and threshold that result in the greatest reduction in MSE. To avoid overfitting, hyperparameters such as maximum tree depth, minimum samples per leaf, and the minimum number of samples required to split a node were tuned using grid search and cross-validation. The implementation was carried out using `DecisionTreeRegressor` from the `scikit-learn` library. A code snippet for Decision Tree Regressor can be found in Figure 2.

```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor(max_depth=5, min_samples_leaf=3, random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

Figure 2. A code snippet for the Decision Tree Regressor model development

The KNN Regressor is a non-parametric, instance-based learning algorithm that makes predictions based on the average output values of the k nearest data points in the training set. It does not make any assumptions about the underlying data distribution and is sensitive to the scale of input features, which necessitates standardization during preprocessing. Given a new observation x, the predicted output $\widehat{y_x}$ in KNN regression is computed as Equation 2.

$$\hat{y}(x) = \frac{1}{k} \sum_{i \in N_k(x)} y_i \quad (2)$$

Where, $N_k(x)$ denotes the set of the k closest neighbors to x, typically determined using Euclidean distance. The choice of k significantly affects model performance; small values of k may lead to high variance, while large values may over smooth the predictions. In this study, the optimal value of k was identified empirically through cross-validation. The model was implemented using the `KNeighborsRegressor` class in `scikit-learn`. A code snippet for KNN can be found in Figure 3.

```
from sklearn.neighbors import KNeighborsRegressor
model = KNeighborsRegressor(n_neighbors=5)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

Figure 3. A code snippet for KNN Regressor model development

Both models were trained on the preprocessed dataset described in the previous section. Hyperparameter tuning for both algorithms were conducted using grid search with 5-fold cross-validation to identify the parameter combinations that minimized the Root Mean Squared Error (RMSE). To ensure consistency in performance evaluation, the same training and test sets were used across both models. This comparative modeling approach allows for evaluating the effectiveness of rule-based versus instance-based learning in the context of residential construction cost forecasting.

2.4 Model evaluation and features importance analysis

To evaluate model performance, three regression metrics were used: MAE, RMSE, and R^2 score. MAE measures average prediction error, RMSE emphasizes larger errors, and R^2 reflects the proportion of variance explained by the model. Decision Tree and K-Nearest Neighbors models were trained on 80% of the data and tested on the remaining 20%, with 5-fold cross-validation applied during hyperparameter tuning. Performance metrics were calculated using the best model from cross-validation. Feature importance from the Decision Tree was analyzed based on reductions in mean squared error, highlighting key cost-driving factors such as material cost and project size. These insights support practical decision-making and are further discussed in the Results section.

3. Results and Discussion

3.1 Model performance comparison

To evaluate the predictive performance of the applied machine learning models, three standard regression metrics were used: MAE, RMSE, and R^2 Score. These metrics respectively measure the average magnitude of errors, penalize larger errors more significantly, and assess the proportion of variance in the target variable explained by the model (see Table 2). Following the methodology outlined earlier, both Decision Tree Regressor and KNN Regressor models were trained using an 80:20 train-test split. Hyperparameter tuning was conducted through grid search with 5-fold cross-validation to identify the optimal model configurations that minimize RMSE on the training data. Final performance metrics were calculated using the best model from cross-validation, evaluated on the unseen test set.

Table 2. Model evaluation results

Model	MAE	RMSE	R^2 Score
Decision Tree	0.341	0.442	0.44
KNN	0.276	0.370	0.60

The comparative analysis of model performance reveals that the KNN algorithm achieved superior predictive accuracy over the Decision Tree Regressor. KNN recorded a lower MAE of 0.276 million BDT and RMSE of 0.370 million

BDT, along with a higher R^2 score of 0.60, indicating its stronger ability to explain variance in the final construction cost. In contrast, the Decision Tree model yielded an MAE of 0.341 million BDT, RMSE of 0.442 million BDT, and an R^2 of 0.44. While Decision Trees offer interpretability, the better performance of KNN suggests that local pattern-based prediction is more effective for this dataset. Notably, the R^2 value of 0.60 reflects a balanced model that generalizes well without overfitting, particularly important given the small dataset size and variability in construction parameters.

3.2 Error pattern interpretation

The predicted versus actual cost plot (in million BDT) illustrates distinct error characteristics for the two models (see Fig. 4). The KNN model exhibits a tighter concentration of points near the reference line, indicating a strong alignment with actual costs. Numerically, KNN achieved a lower MAE of 0.276 million BDT and an RMSE of 0.370 million BDT, with an R^2 score of 0.60. Most of its predictions deviated by less than ±0.5 million BDT from actual values, reflecting consistent accuracy across the cost range. In contrast, the Decision Tree model shows more dispersed predictions, particularly for projects exceeding 3 million BDT, where underestimation is more common. It recorded an MAE of 0.341 million BDT, RMSE of 0.442 million BDT, and R^2 of 0.44, indicating weaker explanatory power. Some predictions deviated by over 0.6 million BDT, reflecting higher error variability. These visual and numerical patterns confirm that the KNN model offers more stable and reliable predictions for residential construction cost estimation in this context (Figure 4).

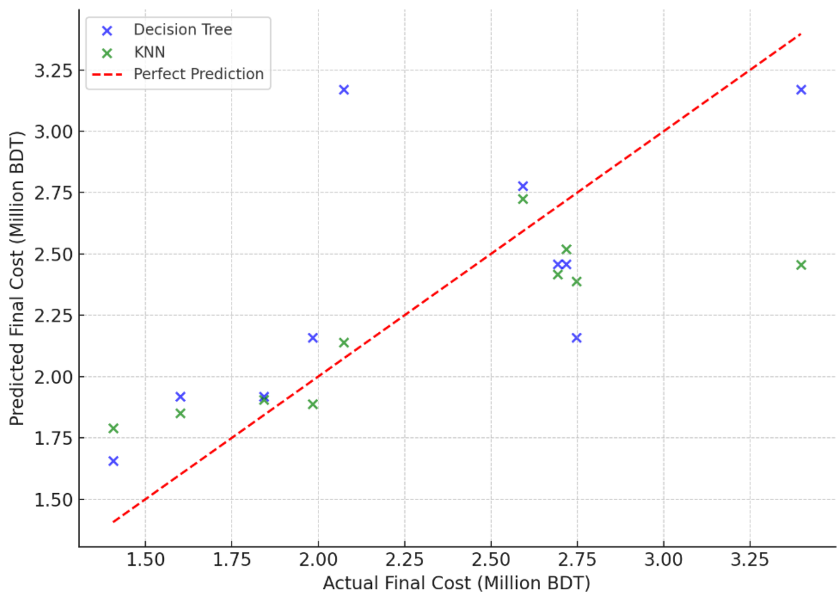

Figure 4. Predicted vs actual final cost

3.3 Feature influence and insights

To gain interpretability and practical understanding of the model's predictions, feature importance was derived from the Decision Tree Regressor, which is well-suited for such analysis due to its transparent rule-based structure. Among all features, material cost was found to be the most influential, contributing 62.1% to the model's predictive power. This dominance is consistent with real-world scenarios where construction materials such as cement, steel, and finishes represent the largest share of project expenses, and their costs fluctuate significantly based on design requirements, supplier choices, and market conditions.

The second most important variable was project location, specifically urban areas, with an importance score of 21.3%. Projects in urban locations generally incur higher costs due to elevated land prices, increased labor wages, complex logistics, and stricter regulatory requirements. Labor cost ranked third with an importance of 12.5%, which reflects the labor-intensive nature of residential construction in Bangladesh, where wage rates, skill levels, and availability vary across regions and influence overall expenditure. Roof type, particularly the use of reinforced cement concrete (RCC), contributed 2.7% to the prediction, highlighting that structural choices indicative of higher durability and quality are also associated with higher costs. Project duration had a smaller but notable influence (1.5%), as longer timelines can increase cumulative labor charges, administrative overhead, and exposure to material price escalation. Together, these top five features emphasize that a combination of direct cost components and contextual variables drives construction cost variability, and that decision tree-based feature analysis offers practical insights for informed decision-making in project planning and estimation (Table 3).

Table 3. Top 5 feature importance from decision tree regressor

Feature	**Importance**
Material_Cost	0.621
Location_Urban	0.213
Labor_Cost	0.125
Roof_Type_RCC	0.027
Project_Duration	0.015

4. Conclusion

This study examined the effectiveness of two simple machine learning techniques, Decision Tree Regressor and KNN, in predicting residential construction costs within the context of Bangladesh. Based on field-collected data from 50 completed residential projects, both models were developed and evaluated using standard performance metrics. The KNN model outperformed the Decision Tree, achieving an R^2 score of 0.60, MAE of 0.276 million BDT, and RMSE of 0.370 million BDT, demonstrating a relatively strong predictive capability despite the small sample size. In comparison, the Decision Tree model recorded an R^2 of 0.44, MAE of 0.341 million BDT, and RMSE of 0.442 million BDT. Feature importance analysis using the Decision Tree identified material cost, location, and labor cost as the most influential predictors, which aligns well with practical cost determinants in the local construction industry. These findings suggest that simple, interpretable models, particularly KNN in this case, can offer reliable and scalable solutions for cost forecasting in data-constrained environments, especially in small to medium-scale construction projects in developing countries. By leveraging real project data and incorporating contextual variables, the models generate actionable insights that can enhance planning accuracy and resource optimization. Nonetheless, the study has some limitations. The relatively small dataset (n = 50) limits generalizability, and the analysis was restricted to only two algorithms, reducing comparative depth. Moreover, the use of one-hot encoding for categorical variables may oversimplify the role of certain qualitative features. Future research should consider larger and more diverse datasets, integrate advanced ensemble methods such as Random Forest or XGBoost, and explore the use of time-series data to account for price dynamics. Additionally, combining machine learning with tools like Building Information Modeling (BIM) or GIS could further improve model applicability and stakeholder usability.

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Md Asiful Islam completed his bachelor's degree in Mechanical Engineering from the Bangladesh University of Engineering and Technology (BUET), one of the premier engineering institutions in South Asia. He is currently serving as a Project Engineer at INTERTEK PSI, USA, where he is engaged in project evaluation, materials testing, quality assurance, and construction compliance assessment across diverse infrastructure projects. Over the years, he has developed strong expertise in engineering analysis, system optimization, and multidisciplinary project coordination. His research interests encompass a broad range of contemporary engineering domains, including energy systems, sustainability transitions, process optimization, machine learning, artificial intelligence, and operations management. He is particularly interested in the use of data-driven tools to improve industrial efficiency, support engineering decision-making, and promote environmentally responsible practices.

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Md Tanvir Siraj earned his bachelor's degree in Mechanical Engineering from the Bangladesh University of Engineering and Technology (BUET). His multidisciplinary academic and professional work spans mechanical engineering, applied statistics, industrial systems, and sustainability studies. He has experience in conducting research across diverse engineering fields, including construction engineering, renewable energy systems, and decision-support modeling. His research interests include applied statistics, machine learning, sustainability assessment, industrial system analysis, and multi-criteria decision-making frameworks. He is particularly interested in the development of data-driven models for improving engineering efficiency, forecasting performance, and supporting strategic planning in construction and industrial sectors.

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