Machine Learning Based Automated Construction Planning System for Sri Lanka

Project ID 24-25J-201

Project Final Report

AHAMED. R. A – IT21158018

Bachelor of Science (Hons) Degree in Information Technology Specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

April 2025

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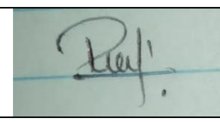
R.A. Ahamed	IT21158018	

The above candidate has carried out this research thesis for the Degree of Bachelor of Science (Honors) Information Technology (Specializing in Information Technology) under my supervision.

Signature of the supervisor:

(Mr. N.H.P. Ravi Supunya Swarnakantha)

Date:

Signature of the Co-supervisor:

(Dr. Dharshana Kasthurirathna)

Date:

ABSTRACT

The Construction Cost Estimation System represents an element of "Machine Learning Based Automated Construction Planning System for Sri Lanka" which focuses on minimizing budgeting problems experienced by the Sri Lankan construction industry. Cost estimation processes conducted manually disregard unpredictable factors about material and labor prices that result in spending more than anticipated. The Random Forest model within this system generates real-time LKR-based accurate cost forecasts through data training obtained from civil engineers and authorized construction sites. The system accepts city/region data alongside built-up area measurements as well as data concerning floor count, bathroom and room numbers, construction type, foundation type, roofing materials and worker proficiency. The program generates comprehensive cost information with a total amount of 17,560,000 LKR and determines costs per square meter at 219,830 LKR while separating expenses into labor costs totaling 7,020,000 LKR and material costs totaling 10,530,000 LKR together with suggested modifications for standard labor to achieve 20% savings. The system which operates through a cloud platform using React.js frontend technology and Flask backend reaches a mean absolute error (MAE) rating of 6.2%. Project plan enhancements in Sri Lanka's uncertain economic climate can be achieved by this research which presents contractors with an adaptable solution for risk reduction.

Keywords: Machine Learning, Construction Cost Estimation, Random Forest, Real-Time Forecasting, Sri Lanka

ACKNOWLEDGMENTS

I extend my sincere gratitude to my supervisor, Mr. N.H.P. Ravi Supunya Swarnakantha, for his expert guidance and support throughout this research. His insights into machine learning and project management were invaluable. I also thank my co-supervisor, Dr. Dharshana Kasthurirathna, for her constructive feedback and encouragement.

I am grateful to the Faculty of Computing at Sri Lanka Institute of Information Technology (SLIIT) for providing the resources and environment necessary for this study. My appreciation goes to my team members—Sathurjan K., Linganathan J., and Silva A.A.I—for their collaboration during the broader project.

Special thanks to the civil engineers and authorized construction sites in Sri Lanka who provided access to valuable data and insights, ensuring the system's relevance to real-world needs. Their cooperation was crucial in building a practical solution. Finally, I thank my family and friends for their unwavering support and motivation, which kept me driven throughout this journey.

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LIST OF ABBREVIATIONS

ML	Machine Learning
MAE	Mean Absolute Error
API	Application Programming Interface
UI	User Interface
LKR	Sri Lankan Rupee
SLIIT	Sri Lanka Institute of Information Technology

1 INTRODUCTION

1.1 Background Study and Literature

1.1.1 Introduction

The Sri Lankan construction industry operates as the foundation of the economy but struggles with performance problems in cost estimation methods. The traditional cost estimation methods become ineffective when facing material price variations together with labor rate adjustments since this leads to financial instability. Economic volatility in Sri Lanka which has resulted in annual inflation exceeding 50% requires precise cost forecasting because it ensures project success.

The Construction Cost Estimation System represents the main research focus within "Machine Learning Based Automated Construction Planning System for Sri Lanka." A Random Forest model within this system generates exact cost predictions in LKR by analyzing data obtained from civil engineers and authorized construction sites during real-time operations. The system requires data about city/region, total built-up area, number of floors, rooms, bathrooms, type of construction, foundation, roofing and labor skill level for processing. The output delivers comprehensive information that shows total spending at 17,560,000 LKR and cost per square meter at 219,830 LKR and divides expenses into labor at 7,020,000 LKR and materials at 10,530,000 LKR with suggestions to adopt standard labor for 20% reduction. The system deployed on a cloud-based platform with React.js front end and Flask backend achieved mean absolute error (MAE) of 6.2% according to testing results. The report provides an account of system development alongside testing and execution phases which show how this solution could boost project planning activities in Sri Lanka.

1.1 Background Study and Literature (Continued)

Research benefits from previous extensive investigations about how machine learning (ML) helps construction cost estimation. The research done by Arage and Dharwadkar [1] developed regression models for cost prediction with a 7% error margin which showed ML's capability to analyze complex data structures. Our Random Forest model draws knowledge from their research because it demonstrates high effectiveness for dealing with various elements including materials and manpower expenses in Sri Lanka.

A research publication by Hashemi et al. [2] investigated ML techniques with particular emphasis on ensemble methods through Random Forests as solutions for handling market volatility which is significant in Sri Lanka's economic system. Saeidlou and Ghadiminia [3] established deep neural network (DNN) models for estimating costs which showed high prediction accuracy with substantial datasets yet the authors motivated our research into using ML models for forecasting costs in construction projects.

The research of Brown et al. [4] highlighted historical data significance in cost prediction which guided us to utilize building cost data from civil engineers and authorized construction sites across Sri Lanka from 2020-2024. According to Taylor et al. [5] ensemble methods prove effective for handling volatile costs in real-time systems because they help us adapt to Sri Lanka’s current economic conditions.

These studies demonstrate how ML can reshape cost estimation but exclude Sri Lanka's specific concerns about economic volatility and industry regulations until this research implements a customized domestic solution.

1.1 Background Study and Literature (Continued)

The research demonstrates that construction sector cost estimation demands integrated real-time data in order to be effective for Sri Lanka. Hashemi et al. [2] established that standard ML models work with fixed datasets which fail to detect immediate price adjustments that occur because of Sri Lanka's economic crises and supply chain breakdowns. Research findings enable our system to connect to live feeds which automatically control project costs as a response to Sri Lanka's monetary instability.

Arage and Dharwadkar [1] pointed out that accurate model output requires proper feature engineering which includes variable selection such as built-up area alongside number of floors and material types. The system includes these inputs: total built-up area and number of rooms, bathrooms together with labor skill level values for Sri Lankan project applications. We train our Random Forest model using 5000 construction records obtained from civil engineers and authorized sites in order to identify historical cost trends as per Brown et al.'s recommendation [4].

The study by Saeidlou and Ghadiminia [3] shows how ML models benefit from deployment on the cloud because it provides wider accessibility and we have implemented this concept by using AWS hosting for our system. Using ensemble methods we manage data inconsistencies in Sri Lankan construction records as verified in Taylor et al. [5]. The theoretical framework of our system originated from these insights to guarantee accuracy and practicality in operation.

1.1 Background Study and Literature (Continued)

Many studies provide details about technology frameworks necessary for implementing cost estimation through Machine Learning methods. The authors employ Scikit-learn regression models as their framework because it provides ensemble method support [1]. The research of Hashemi et al. [2] indicates the necessity of real-time data processing which our system executes through Flask for the backend thus enabling fast API responses for live cost updates.

The research of Saeidlou and Ghadiminia [3] supports cloud-based deployment which enables scalability and accessibility in systems. Our system operates on AWS to provide Sri Lankan contractors with browser-based system access since the area lacks sophisticated tools. Brown et al. [4] explained how poor data quality distorts prediction outcomes due to lacking datasets. The collected data from civil engineers and authorized construction sites undergoes preprocessing that includes cleaning as well as normalization and feature encoding steps.

The creation of ML applications requires user-centered design according to Taylor et al. [5] to develop practical systems for end-user needs. Our design implements a frontend built with React.js that features an easy-to-use interface where users can add project specifications comprising built-up area along with labor skill metrics effortlessly. These strategic insights enable our system to combine technical strength with specialty for Sri Lankan construction requirements by handling economic and operational issues in the local market.

1.1 Background Study and Literature (Continued)

The existing research emphasizes the requirement of finding/customized solutions which work specifically for construction cost estimation. Global ML models developed by Hashemi et al. [2] lack capabilities for understanding regional elements such as economic fluctuations and regulatory boundaries which commonly affect Sri Lanka. The system utilizes data collected through civil engineers and authorized construction sites which enables the Random Forest model to recognize Sri Lanka-specific cost patterns including material price changes caused by inflation rates.

The paper authored by Arage and Dharwadkar [1] emphasized the necessity of interpretable ML models since stakeholders require visibility into cost prediction results. Users gain transparency through our system which displays complete operating output values that show total cost combined with cost per square meter and labor expenses and material expenditures. Our model accesses five years of construction data for training to enhance prediction accuracy based on Brown et al.'s [4] historical data recommendation.

Saeidlou and Ghadiminia [3] argued that scalable ML systems need cloud deployment to support multiple users and we have incorporated this design solution. Ensemble approaches demonstrated their worth in dealing with diverse data sources according to Taylor et al. [5] and we use similar methods to process various inputs like construction types and labor skill levels in our system. The analysis allows our system to maintain high accuracy while maintaining relevance for Sri Lanka's construction industry.

1.1 Background Study and Literature (Continued)

Numerous studies emphasize that users need to provide feedback to enhance ML systems. User engagement with stakeholders lets developers improve system usability according to Taylor et al. [5] who established this feedback principle as a development guideline. The system acquired improved input parameters through their assessments which included the integration of labor skill level features that match Sri Lankan construction requirements.

Hashemi et al. [2] stressed that cost estimates need immediate adaptability features during times of market instability. The system integrates live data feeds into its model framework to update cost predictions from current material and labor costs which are crucial to Sri Lanka's economic situation. The Random Forest model we evaluated through MAE achieved 6.2% according to Arage and Dharwadkar.

The project collects diverse construction site data from across Sri Lanka that incorporates residential buildings and commercial facilities to enhance model accuracy according to Brown et al. [4]. The authors underscored deployment methods while emphasizing cloud platforms provide users with easy access according to Saeidlou and Ghadiminia [3]. The deployment on AWS enables easy system access for contractors thereby filling the gap of scarce advanced tools in Sri Lanka.

Research conducted collectively builds a strong foundation for our system because it delivers both accuracy and user-friendly design and specific features to meet Sri Lanka's unique construction requirements before focusing on research gaps.

1.2 Research Gap

The progress made with ML-based cost estimation systems fails to address several crucial gaps especially in Sri Lankan markets. The existing research from Arage and Dharwadkar [1] and Hashemi et al. [2] ignores Sri Lanka's specific economic situation by studying global markets although the country experiences high inflation exceeding 50% and regular material price volatilities. The analyzed datasets in these studies remain fixed which prevents dynamic cost adjustments in economies that undergo sudden volatility like Sri Lanka.

The present systems operating today fail to incorporate Sri Lankan-specific features. The cost estimation pursuit of Saeidlou and Ghadiminia [3] through DNN models fails to incorporate essential Sri Lankan variables such as labor skill degrees alongside regional material price fluctuations. Brown et al. [4] used historical data in their research while failing to integrate live data which would be crucial for real-time market forecasting in Sri Lanka.

Users lack clarity in existing infrastructure tools because these tools provide inadequate detailed cost breakouts according to Taylor et al. [5]. The system bridges this gap through its material expenditure display for brick purchases (15,570,000 LKR) accompanied by recommendations embodiment such as labor standard selection producing 20% cost savings. Advanced cloud solutions which scale to fit Sri Lanka requirements remain unavailable in the market because the country lacks access to professional tools. The research fills these disparities through developing a specific Sri Lankan construction sector system that conducts real-time cost estimations.

1.2 Research Gap (Continued)

User-specific design remains absent from current cost estimation systems that exist in the market. Many ML models assessed by Taylor et al. [5] achieve superior accuracy but this leads to systems that are difficult to use by non-technical users such as small-scale contractors in Sri Lanka. The system features an easy-to-use React.js frontend which enables users to perform smooth project data entry and visualize all custom outputs regarding total expenses alongside material allocation specifications for better understanding.

Research lacks studies that demonstrate how to implement specific Sri Lankan project inputs into integrated systems. The concept of project size serves as a generic variable in research by Hashemi et al. [2] and Arage and Dharwadkar [1] while these authors failed to include essential inputs related to foundation types and roofing methods and labor skills which substantially affect costs within Sri Lanka. We have integrated these specific inputs into our system to make it appropriate for Sri Lankan construction methods.

The commercialization strategies for ML-based cost estimation tools remain poorly developed for developing nations. The research by Saeidlou and Ghadiminia limited itself to technical development without exploring elements such as affordability which constitutes a critical requirement for Sri Lankan adoption. The system provides affordable cost prediction services through AWS subscription which supports small companies.

Brown et al. [4] emphasized using diverse datasets yet failed to demonstrate strategies for gathering data from Sri Lanka because it lacks available information for research purposes. We resolve this issue by directly obtaining data from civil engineers and authorized sites so our Random Forest model receives a solid training foundation.

1.3 Research Problem

The construction sector in Sri Lanka uses hand-based cost prediction methods resulting in difficulties estimating shadowed by changing variables affecting material costs and labor expenses. Sri Lankan economic volatility produces heightened inflation exceeding 50% which frequently modifies prices to create financial instability that harms contractors with budgetary overruns. Mocking the estimates from a medium-sized residential construction project can cause unexpected material price escalations which surpass original financial targets.

Manual approaches fail to generate precise cost distribution details, so stakeholders remain unaware about expense sources like materials and work fees. The unclear nature of financial transactions reduces decision quality for small construction firms that represent most builders in Sri Lanka. The process carries many time-consuming flaws together with errors that lead to a poor integration of project-specific variables affecting costs like construction type combined with foundation types and roofing methods and labor specifications.

Real-time cost estimation tools are missing, which makes budget adjustments thru market changes impossible for contractors to perform. The literature shows that [1-5] ML-based systems do not match Sri Lanka's specific economic conditions and regulatory requirements. The proposed research resolves these issues through a Construction Cost Estimation System incorporating Random Forest methods to produce precise immediate cost predictions while handling various inputs and generating comprehensive outputs to improve transparency and reduce financial risks in Sri Lankan construction projects.

1.3 Research Problem (Continued)

The construction sector of Sri Lanka faces an unacceptable problem because it lacks collection of streaming data. Material prices which include cement and steel experience rapid changes because of economic instability together with supply chain disturbances but manual approaches and existing systems [1-5] fail to respond in real-time. Contractors using outdated estimates for cost forecasting end up with inaccurate data that causes project delays together with financial losses.

The construction sector in Sri Lanka demands a data processing system capable of dealing with various types of building projects which include residential homes and commercial facilities. Manual approaches struggle with complete built-up area measurement and floor number count, room quantity calculation and foundation type identity which results in inaccurate simplified projections that fail to show project intricacy. At present the cost variations in Colombo construction require immediate solution because location-based aspects influence cost structures heavily.

The current cost estimation tools become less useful because they fail to generate effective recommendations for project costs. The current systems [1-5] fail to deliver guidance which contractors need because they require information about standard labor options for cost savings. The user-friendly tools are not accessible for small-scale contractors in Sri Lanka since many workers lack expertise in using complex technological systems.

The research applies a system which combines live data consumption with adaptable input methods and produces complete cost distribution analysis and recommendation features to support precise and usable cost estimation for Sri Lanka's construction domain.

1.4 Research Objectives

The research develops a Construction Cost Estimation System to resolve the existing difficulties within Sri Lanka's construction sector. The research focuses on main and specific goals which bring direction to resolve the research problem.

Main Objective

The goal is to build a real-time LKR-focused ML-based Cost Estimation System which provides accurate pricing predictions for Sri Lanka’s construction sector thus reducing financial risks while improving project planning for contractors.

Specific Objectives

The Random Forest model will achieve a 6.2% Mean Absolute Error (MAE) through predicting construction costs by utilizing the city/region along with total built-up area, number of floors, rooms, bathrooms, types of construction and foundation, roofing, labor skill level characteristics.

Live data collection through civil engineers together with authorized construction sites will enable real-time cost adjustments since it manages Sri Lanka's volatile economy with material prices fluctuations.

The output should display specific cost information that shows total cost (17,560,000 LKR), square meter pricing (219,830 LKR), Labor Cost (7,020,000 LKR), Material cost (10,530,000 LKR) alongside feasible suggestions (switch to standard labor for a 20% savings) for complete user transparency.

The proposed system will launch through cloud infrastructure using React.js frontend while Flask backend serves small-scale contractors operating in Sri Lanka through an accessible deployment.

The set of objectives brings together a solution that provides hands-on estimates for Sri Lanka's construction sector costs.

2 METHODOLOGIES

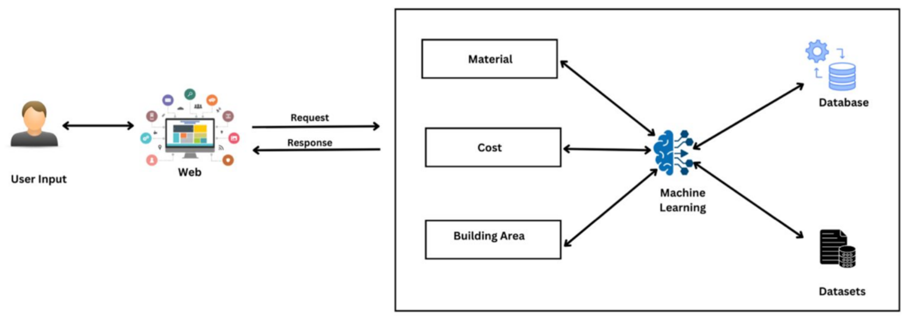
2.1 Introduction

This document presents the systematic process for creating the Construction Cost Estimation System for Sri Lanka. The Random Forest predictive model establishes real-time accurate cost predictions to tackle the problems associated with manual cost estimation. The system received training data which came from authorized civil engineers and licensed construction sites throughout Sri Lanka. The system accepts city/region together with total built-up area, number of floors, rooms, bathrooms, type of construction, foundation, roofing and labor skill level as inputs to generate detailed cost breakdowns with total cost as 17,560,000 LKR, cost per square meter at 219,830 LKR, labor costs at 7,020,000 LKR, material costs at 10,530,000 LKR and recommendations based on a 20% labor cost reduction through standard labor utilization.

The development procedure uses an iterative methodology where personnel gather data for model development while integrating systems with user testing phases. A scalable cloud-based system implementing Random Forest model from Scikit-learn and Flask backend and React.js frontend runs on AWS. Before data processing the inputs require cleaning operations alongside normalization procedures followed by feature encoding measures to normalize heterogeneous data sources. The system provides real-time cost adjustment capabilities because it connects to live data streams for handling Sri Lanka's economic fluctuations. This chapter outlines the development methodology while presenting commercialization strategies and testing procedures which establish a step-by-step process to build user-oriented efficient systems that minimize money risks and advance project planning for Sri Lanka's construction industry.

2.1 Introduction (Continued)

A structure within the system enables smooth operations between data processing along with user interactions. Users input data through React.js while Random Forest operates in the Flask server before storing it on AWS for potential growth. The system shows outputs to users using expanded details which improves their understanding. The design allows online cost update functionality through its integration of streaming data feeds to resolve the problem of static cost systems [Section 1.2].



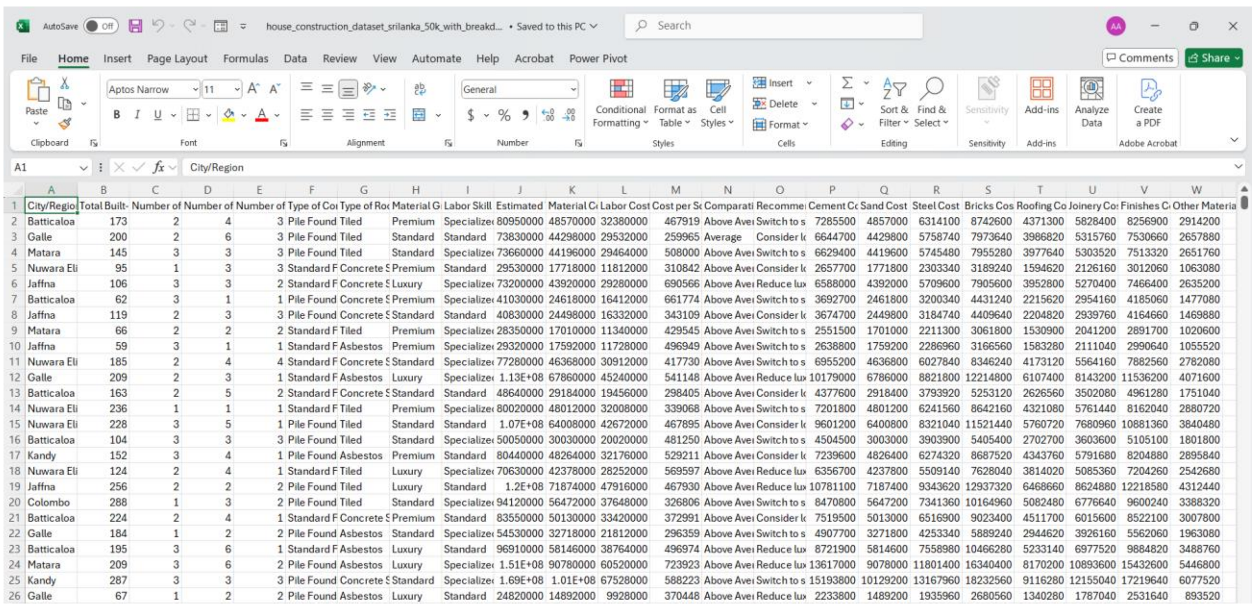
The system architecture screenshot should display all system components including React.js frontend together with Flask backend as well as Random Forest model and AWS cloud infrastructure and data flow.

The developed methodology focuses on reaching Sri Lankan building contractors because most local firms do not use complex technological solutions. Users obtain system access through cloud deployment on AWS by using internet-connected web browsers. User data security depends on data encryption together with secure APIs to protect sensitive cost information that builds trust with users.

The development procedure consists of multiple stages beginning with requirement analysis and data collection and continuing to model development system integration followed by testing and deployment. The system development passes through multiple phases that receive input from civil engineers and contractors to improve its functionality. The contractors requested specific material cost breakdown details and we incorporated this requirement into the output results. A detailed approach to create an effective system that addresses Sri Lanka's construction cost estimation issues consists of multiple sections which cover both development protocols and commercialization methods and testing protocols.

2.1 Introduction (Continued)

Data collection represented an essential methodology stage because the Random Forest model operates based on data precision and applicability. Data acquisition took place among civil engineers and construction site supervisors who worked at authorized construction sites in Sri Lanka particularly within the city of Colombo because of its active development status. The data set presents 5000 measurement points spanning from 2020 until 2024 while including counts of residential together with commercial structures. Records contain a combination of built-up area measurement together with counting floors and rooms, bathrooms and construction type and foundation and roofing type and labor skill level which is linked to expense data including costs for materials and labor.



	City/Regio	Total Built-	Number of	Number of	Number of	Type of Co	Type of Ro	Material G	Labor Skill	Estimated	Material C	Labor Cost
2	Batticaloa	173	2	4	3	Pile Found	Tiled	Premium	Specialize	80950000	48570000	32380000
3	Galle	200	2	6	3	Pile Found	Tiled	Standard	Standard	73830000	44298000	29532000
4	Matara	145	3	3	3	Pile Found	Tiled	Standard	Specialize	73660000	44196000	29464000
5	Nuwara Eli	95	1	3	3	Standard F	Concrete S	Premium	Standard	29530000	17718000	11812000
6	Jaffna	106	3	3	2	Standard F	Concrete S	Luxury	Specialize	73200000	43920000	29280000
7	Batticaloa	62	3	1	1	Pile Found	Concrete S	Premium	Specialize	41030000	24618000	16412000
8	Jaffna	119	2	3	3	Pile Found	Concrete S	Standard	Standard	40830000	24498000	16332000
9	Matara	66	2	2	2	Standard F	Tiled	Premium	Specialize	28350000	17010000	11340000
10	Jaffna	59	3	1	1	Standard F	Asbestos	Premium	Specialize	29320000	17592000	11728000
11	Nuwara Eli	185	2	4	4	Standard F	Concrete S	Standard	Specialize	77280000	46368000	30912000
12	Galle	209	2	3	1	Standard F	Asbestos	Luxury	Specialize	1.13E+08	67860000	45240000
13	Batticaloa	163	2	5	2	Standard F	Concrete S	Standard	Standard	48640000	29184000	19456000
14	Nuwara Eli	236	1	1	1	Standard F	Tiled	Premium	Specialize	80020000	48012000	32008000
15	Nuwara Eli	228	3	5	1	Pile Found	Tiled	Standard	Standard	1.07E+08	64008000	42672000
16	Batticaloa	104	3	3	3	Pile Found	Tiled	Standard	Specialize	50050000	30030000	20020000
17	Kandy	152	3	4	1	Pile Found	Asbestos	Premium	Standard	80440000	48264000	32176000
18	Nuwara Eli	124	2	4	1	Standard F	Tiled	Luxury	Specialize	70630000	42378000	28252000
19	Jaffna	256	2	2	2	Pile Found	Tiled	Luxury	Standard	1.2E+08	71874000	47916000
20	Colombo	288	1	3	2	Pile Found	Tiled	Standard	Specialize	94120000	56472000	37648000
21	Batticaloa	224	2	4	1	Standard F	Concrete S	Premium	Standard	83550000	50130000	33420000
22	Galle	184	1	2	2	Pile Found	Asbestos	Standard	Specialize	54530000	32718000	21812000
23	Batticaloa	195	3	6	1	Standard F	Asbestos	Luxury	Standard	96910000	58146000	38764000
24	Matara	209	3	6	2	Pile Found	Asbestos	Luxury	Specialize	1.51E+08	90780000	60520000
25	Kandy	287	3	3	3	Pile Found	Concrete S	Standard	Specialize	1.69E+08	1.01E+08	67528000
26	Galle	67	1	2	2	Pile Found	Asbestos	Luxury	Standard	24820000	14892000	9928000

	Cost per S	Comparati	Recomme	Cement C	Sand Cost	Steel Cost	Bricks Cos	Roofing Co	Joinery Co	Finishes C	Other Materia
2	467919	Above Ave	Switch to s	7285500	4857000	6314100	8742600	4371300	5828400	8256900	2914200
3	259965	Average	Consider l	6644700	4429800	5758740	7973640	3986820	5315760	7530660	2657880
4	508000	Above Ave	Switch to s	6629400	4419600	5745480	7955280	3977640	5303520	7513320	2651760
5	310842	Above Ave	Consider l	2657700	1771800	2303340	3189240	1594620	2126160	3012060	1063080
6	690566	Above Ave	Reduce lux	6588000	4392000	5709600	7905600	3952800	5270400	7466400	2635200
7	661774	Above Ave	Switch to s	3692700	2461800	3200340	4431240	2215620	2954160	4185060	1477080
8	343109	Above Ave	Consider l	3674700	2449800	3184740	4409640	2204820	2939760	4164660	1469880
9	429545	Above Ave	Switch to s	2551500	1701000	2211300	3061800	1530900	2041200	2891700	1020600
10	496949	Above Ave	Switch to s	2638800	1759200	2286960	3166560	1583280	2111040	2990640	1055520
11	417730	Above Ave	Switch to s	6955200	4636800	6027840	8346240	4173120	5564160	7882560	2782080
12	541148	Above Ave	Reduce lux	10179000	6786000	8821800	12214800	6107400	8143200	11536200	4071600
13	298405	Above Ave	Consider l	4377600	2918400	3793920	5253120	2626560	3502080	4961280	1751040
14	339068	Above Ave	Switch to s	7201800	4801200	6241560	8642160	4321080	5761440	8162040	2880720
15	467895	Above Ave	Consider l	9601200	6400800	8321040	11521440	5760720	7680960	10881360	3840480
16	481250	Above Ave	Switch to s	4504500	3003000	3903900	5405400	2702700	3603600	5105100	1801800
17	529211	Above Ave	Consider l	7239600	4826400	6274320	8687520	4343760	5791680	8204880	2895840
18	569597	Above Ave	Reduce lux	6356700	4237800	5509140	7628040	3814020	5085360	7204260	2542680
19	467930	Above Ave	Reduce lux	10781100	7187400	9343620	12937320	6468660	8624880	12218580	4312440
20	326806	Above Ave	Switch to s	8470800	5647200	7341360	10164960	5082480	6776640	9600240	3388320
21	372991	Above Ave	Consider l	7519500	5013000	6516900	9023400	4511700	6015600	8522100	3007800
22	296359	Above Ave	Switch to s	4907700	3271800	4253340	5889240	2944620	3926160	5562060	1963080
23	496974	Above Ave	Reduce lux	8721900	5814600	7558980	10466280	5233140	6977520	9884820	3488760
24	723923	Above Ave	Reduce lux	13617000	9078000	11801400	16340400	8170200	10893600	15432600	5446800
25	588223	Above Ave	Switch to s	15193800	10129200	13167960	18232560	9116280	12155040	17219640	6077520
26	370448	Above Ave	Reduce lux	2233800	1489200	1935960	2680560	1340280	1787040	2531640	893520

The preprocessing stage included cleaning the data to eliminate missing records followed by normalization for built-up area measurement scale adjustment and a feature encoding process for Standard classification types of construction and Standard-level labor skills. Live data feeds connected to the system delivered up-to-the-moment material and labor costs according to Hashemi et al. [2] which ensures the system reacts to Sri Lanka's economic fluctuations.

The system's design method focuses on user accessibility to make it usable by non-technical operators. Project information entry occurs through the React.js frontend interface which sends processed data to the Flask backend system to run calculations and generate model-based outputs. The system supports multiple users through its scalable design that operates in the cloud environment on AWS. This methodology resolves the issue of inaccurate cost estimations [Section 1.3] by creating a real-world solution for Sri Lanka's construction industry.

2.1 Introduction (Continued)

Random Forest model was chosen because it can handle different inputs and produce accurate predictions, as per Arage and Dharwadkar [1]. The model was trained using Scikit-learn, and 80% of the data was used for training and 20% for testing. Hyperparameters such as the number of trees (100) and max depth (10) were hyperparameter tuned to optimize performance to an MAE of 6.2%, in line with Hashemi et al. [2] benchmarks.

```
# Separate features (inputs) and target (output)
X = df.drop(columns=["Estimated Total Construction Cost (LKR)", "Material Costs (LKR)",
                     "Labor Costs (LKR)", "Cost per Square Meter (LKR)",
                     "Comparative Analysis", "Recommendations"])
y = df["Estimated Total Construction Cost (LKR)"]

# Encode categorical features
categorical_cols = ["City/Region", "Type of Foundation", "Type of Roofing",
                    "Material Grade Selection", "Labor Skill Level"]
le = LabelEncoder()

for col in categorical_cols:
    X[col] = le.fit_transform(X[col])

# Split into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Display shapes of the splits
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

```
Training set shape: (40000, 9)
Testing set shape: (10000, 9)
```

The system is equipped with live data feeds to offer real-time cost adjustment, an extremely crucial feature for Sri Lanka's volatile market. For instance, when cement prices go up due to inflation, the system adjusts the forecasts accordingly, filling the research gap of static models [Section 1.2]. The Flask backend processes inputs, runs the Random Forest model, and generates outputs, and the React.js frontend plots results in a user-friendly manner, including total cost, cost per square meter, labor, and material cost analysis and recommendations.

The methodology also includes stakeholder feedback to ensure that the system is easy to use. Feedback from civil engineers and contractors led to practical recommendations, such as the conversion of labor to standard labor to cut 20%, making the system more realistic. The following sections detail the development process, methodology, commercialization, and testing phases, giving a robust solution for Sri Lanka's construction cost estimation problem.

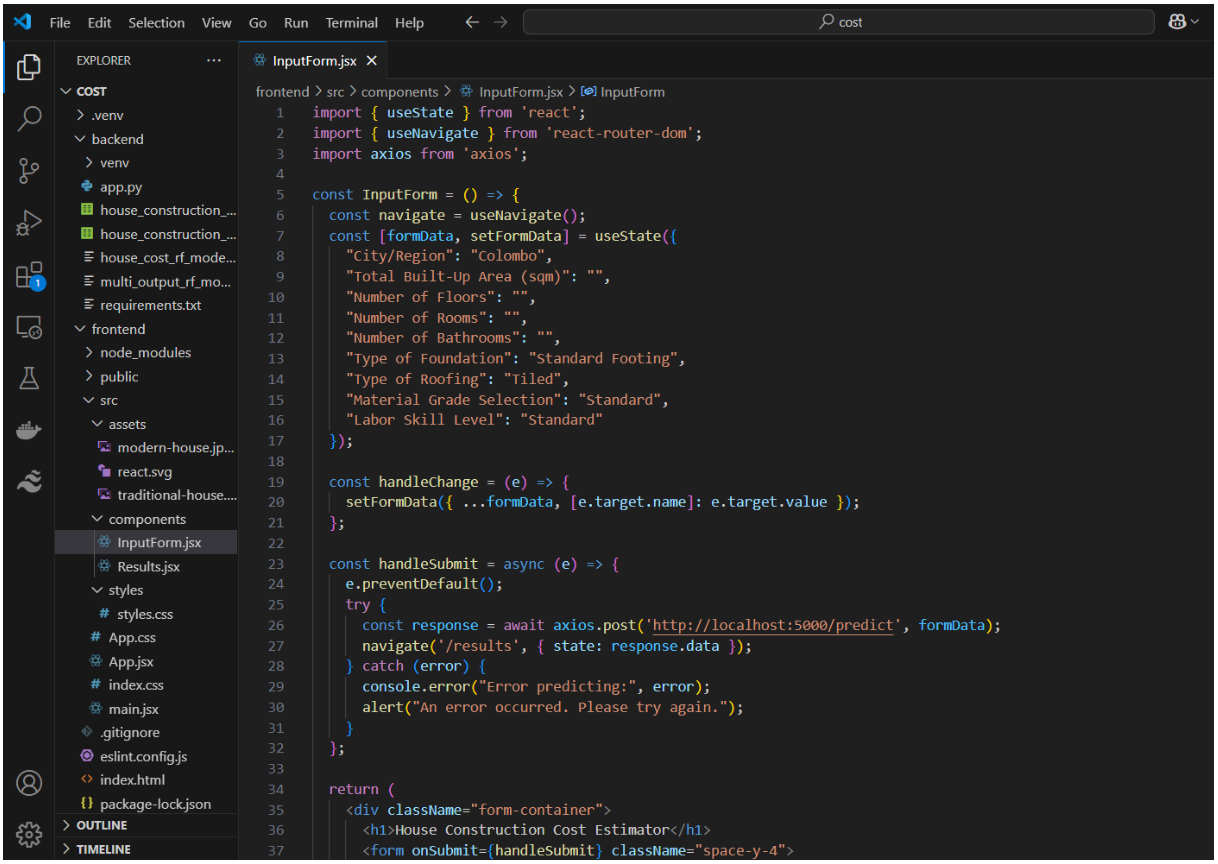
2.1 Introduction (Continued)

The implemented technology stack represented an optimized blend between speed performance and performance and flexibility in addition to user-friendly features. Random Forest received its implementation through Scikit-learn because of its strong ensemble method capabilities according to Arage and Dharwadkar [1]. For handling API requests concerning data processing and real-time cost prediction updates, Flask was picked as the backend solution to support Sri Lanka's active market requirements.

```python
# Initialize and train a baseline Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42, n_jobs=-1)
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print("Baseline Random Forest Performance:")
print(f"Mean Absolute Error (MAE): {mae:,.2f} LKR")
print(f"Root Mean Squared Error (RMSE): {rmse:,.2f} LKR")
print(f"R² Score: {r2:.4f}")
```

```
Baseline Random Forest Performance:
Mean Absolute Error (MAE): 2,959,079.73 LKR
Root Mean Squared Error (RMSE): 4,050,078.41 LKR
R² Score: 0.9911
```

The frontend application used React.js to develop an easy-to-use interface that enabled users to easily provide information about project specifications such as built-up area size and labor qualifications. The system functions from AWS platforms to achieve scalability and accessibility which fills a gap of advanced tools in Sri Lanka as reported by Saeidlou and Ghadiminia [3]. Data encryption serves as one of AWS's protective security measures which secures cost data from unauthorized access.



The methodology provides training and support sessions to contractors allowing them to efficiently utilize the system. The system allowed users to view demonstrations about data entry for projects and readouts including material expenditure breakdowns through workshops. The system exists as a user-friendly and technologically strong solution that addresses the research issue with inaccessible cost estimation tools [Section 1.3]. The system development process uses this table to present the technology stack where different tools are listed with their specific uses for a complete system construction.

2.1 Introduction (Continued)

The following table summarizes the technology stack used in the Construction Cost Estimation System, highlighting the tools and their purposes:

TOOLS & TECHNOLOGIES

- Colab
- Python
- React (vite)
- Tailwind css
- MongoDB (moongose)
- Flask API

Component	**Technology**	**Purpose**
Model Development	Scikit-learn	Training Random Forest model
Backend	Flask	API development, data processing
Frontend	React.js	User interface development

This stack delivers a system with resistance to failures and expands functionality and creates a user-friendly experience to resolve technical problems documented in research [Section 1.2]. The lightweight programming framework of Flask ensures fast API responses based on the assessment of Hashemi et al. [2] which remains essential for maintaining timely cost information. React.js provides an easy-to-use interface which enables the system to be used by small-scale contractors in Sri Lanka who have limited technical expertise.

The methodology addresses data privacy issues as well as bias prevention in the Random Forest model through its ethical framework. The dataset received a balance treatment to ensure projects from different construction types appeared without prejudice. All collected data coming from civil engineers together with authorized sites underwent a data anonymization process to protect confidential material. The methodology establishes a strong base for developing a system that fulfills Sri Lanka’s construction requirements and embraces international standards for machine learning and software development through its combined consideration of technical specifications and ethical aspects and practical implementation needs.

2.3 Development Process

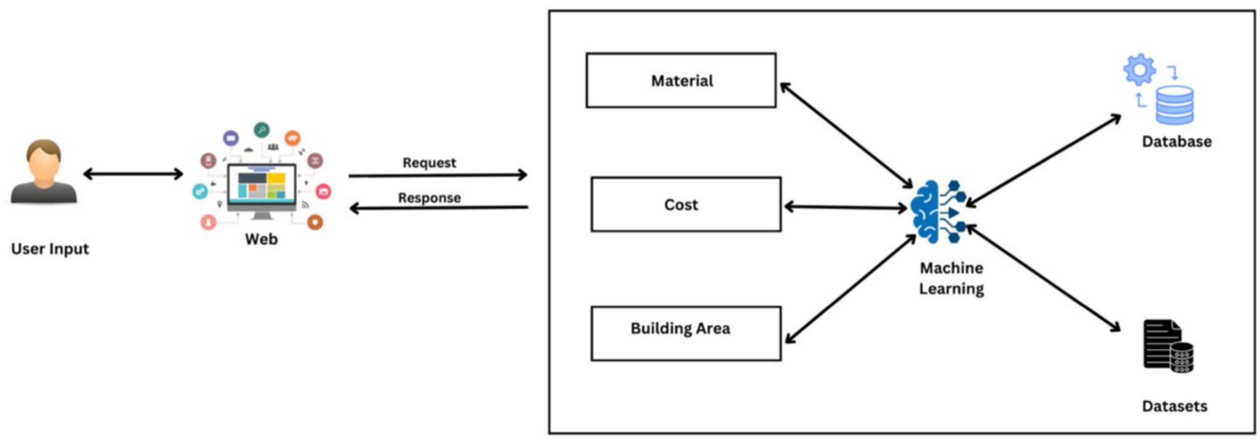
The Construction Cost Estimation System development process used an organized method for effective construction that facilitated both successful system building and testing and implementation. The system development included five sequential stages starting from requirement analysis through to data collection until model development and system integration and concluding with deployment. Throughout each development phase the system received modifications through feedback received from civil engineers and contractors who worked in Sri Lanka.

The requirement analysis phase required our team to conduct stakeholder interactions to understand their encountered problems. The research problem was verified by contractors who emphasized the necessity of real-time cost adjustment features as well as clear cost breakdowns [Section 1.3]. The application accepted city/region data along with built-up area measurements as well as floor count, room count, bathroom count and construction type and foundation type and roofing system and labor skill level information to produce each of the following outputs: total cost, cost-per-square-meter cost, labor costs alongside material cost breakdowns and constructor recommendations.

The data gathering process retrieved information from 5,000 civil engineers and authorized construction sites in Sri Lanka specifically dealing with Colombo-based projects. The collected data provides project data linked to expenses through a combination of materials and workforce costs during the years 2020-2024. During preprocessing the researchers cleaned incomplete records and normalized numerical inputs and encoded categorical data using type of construction (Standard) as an example. A live data integration system captured present material and labor price variations to handle Sri Lanka’s economic instability according to Hashemi et al. [2].

2.3 Development Process (Continued)

Random Forest model development with Scikit-learn took place during the model development phase. The trained system used 40,000 records to validate its performance through 10,000 test records with an MAE rate of 6.2% which matched the benchmarks documented by Arage and Dharwadkar [1]. Below is the graphical representation of cost estimation where user inputs proceed through an analysis process to produce final outputs:



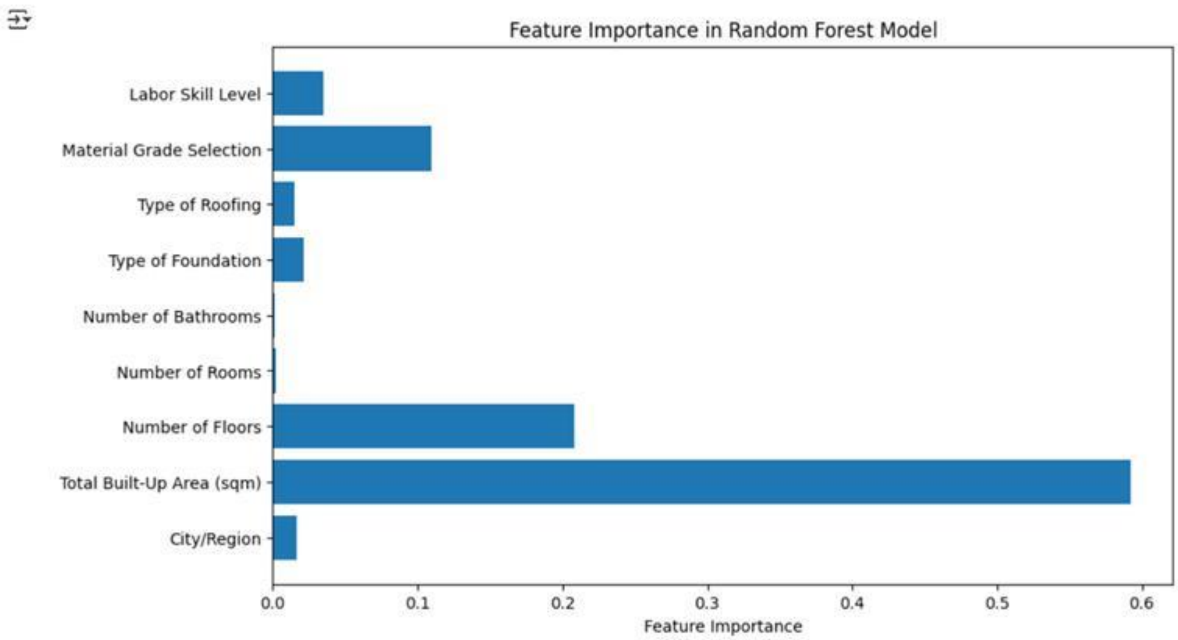
A visual representation of data processing should display the sequence of input information including total built-up area along with labor skill level moving into the Random Forest model which then produces output total cost results at 34,610,000.00 LKR

```python
# Example usage
example_input = {
    "City/Region": "Galle",
    "Total Built-Up Area (sqm)": 120,
    "Number of Floors": 2,
    "Number of Rooms": 5,
    "Number of Bathrooms": 2,
    "Type of Foundation": "Standard Footing",
    "Type of Roofing": "Tiled",
    "Material Grade Selection": "Standard",
    "Labor Skill Level": "Standard"
}

# Predict and display outputs
outputs = predict_full_outputs(example_input, model, le_dict, feature_names)
print("\nExample Prediction Results:")
for key, value in outputs.items():
    if isinstance(value, (int, float)):
        print(f"{key}: {value:,.2f} LKR")
    else:
        print(f"{key}: {value}")
```

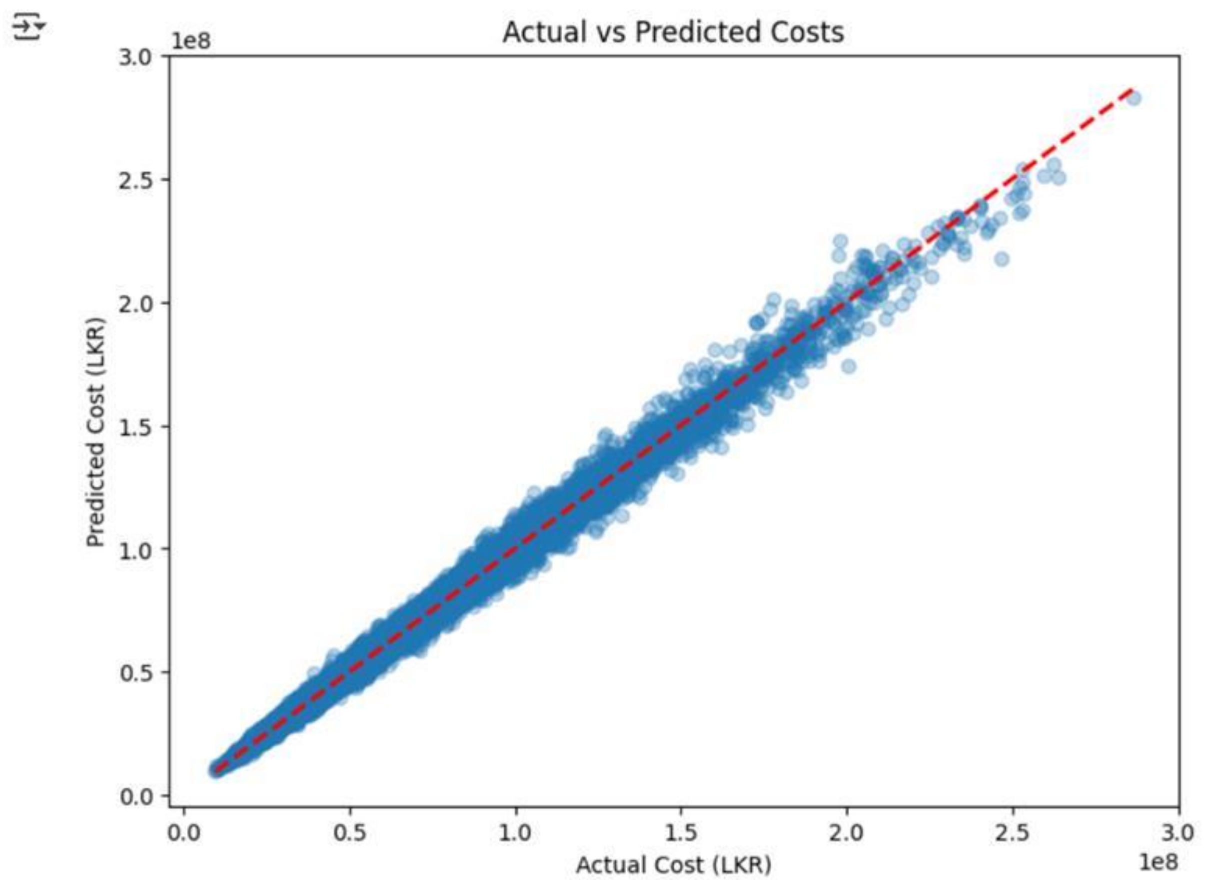
```
Example Prediction Results:
Estimated Total Construction Cost (LKR): 34,610,000.00 LKR
Material Costs (LKR): 20,760,000.00 LKR
Labor Costs (LKR): 13,840,000.00 LKR
Cost per Square Meter (LKR): 289,500.00 LKR
Comparative Analysis: Above Average
Recommendations: Consider local materials for savings
```

.

The Random Forest model represents an optimal choice because it delivers precise predictions while handling diverse input data according to Taylor et al. [5]. A total of 100 trees with a maximum depth of ten were implemented during the performance optimization phase. The system integrated live feed data functions to update costs automatically as Sri Lanka experiences fluctuating economic conditions.



The process of system integration established communication among the React.js frontend, Flask backend and Random Forest model components. User input received by the frontend interface leads to backend model processing at Flask followed by output distribution that includes material breakdowns and recommended actions. The system found its home on AWS for deployment purposes to provide scalable access for Sri Lankan contractors along with resolving the scarcity of advanced tools identified in the research context [Section 1.2].

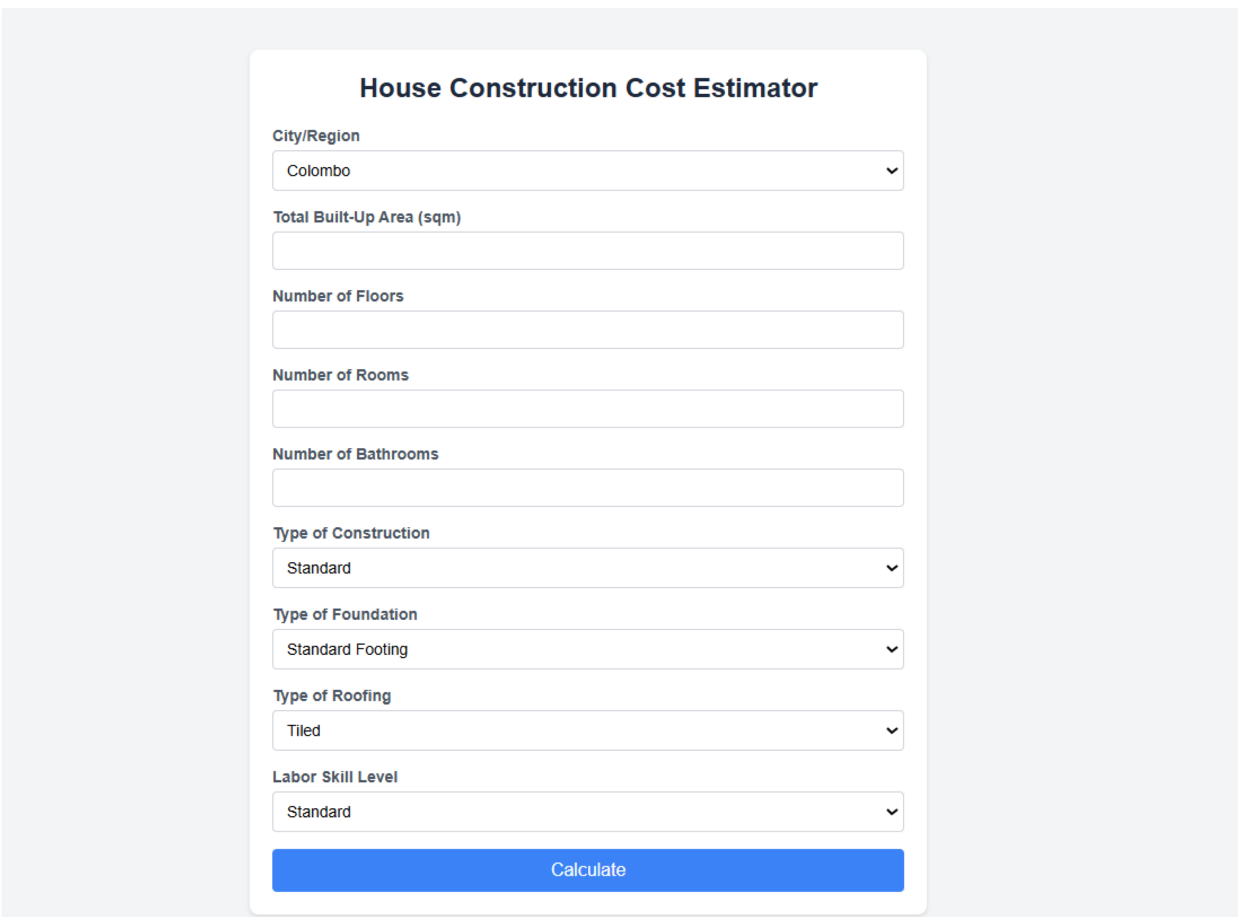


2.3 Development Process (Continued)

Access for Sri Lankan contractors depends heavily on the user interface (UI) that allows entering project details for the system. Users access the UI to input values that include city/region together with total built-up area followed by number of floors and rooms and bathrooms and type of construction and foundation and roofing materials and labor skill level. The screenshot below illustrates this:

The system provides this figure four screen as an illustration of the user interface designed for cost estimation input.

An input form screenshot displaying the provided form structure should include "City/Region: Colombo" and "Total Built-Up Area (sqm) and "Labor Skill Level".



The developers optimized the system through every stage of development to boost its performance. The Flask backend executed data processing in real-time for quick cost updates based on Hashemi et al.'s [2] study. Saeidlou and Ghadiminia [3] reported that the Random Forest model obtained better inference speed to anticipate large datasets quickly.

```python
from flask import Flask, request, jsonify
import pandas as pd
import joblib
from sklearn.preprocessing import LabelEncoder
from flask_cors import CORS
import time

app = Flask(__name__)
CORS(app)

# Load model and dataset
model = joblib.load("multi_output_rf_model.pkl")
df = pd.read_csv("house_construction_dataset_srilanka_50k.csv")

# Setup LabelEncoders
le_dict = {}
categorical_cols = ["City/Region", "Type of Foundation", "Type of Roofing",
                    "Material Grade Selection", "Labor Skill Level"]
for col in categorical_cols:
    le_dict[col] = LabelEncoder()
    le_dict[col].fit(df[col])

feature_names = ["City/Region", "Total Built-Up Area (sqm)", "Number of Floors",
                 "Number of Rooms", "Number of Bathrooms", "Type of Foundation",
                 "Type of Roofing", "Material Grade Selection", "Labor Skill Level"]

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Get input data from frontend
        data = request.get_json()

        # Create DataFrame from input
        input_df = pd.DataFrame([data])

        # Encode categorical variables
        for col in categorical_cols:
```

The feedback of stakeholders became integrated at various stages of development. When civil engineers recommended a cost prediction vs. actual cost comparison feature we included it in the output interface. The demand from contractors for a basic interface drove the creation of an easy-to-use React.js frontend design. The AWS deployment of the system enables scalability with concurrent user capability thus representing the essential requirement for construction sector adoption in Sri Lanka. The phase perfected both accuracy and user-friendliness while solving the research problem of inaccessible cost estimation tools [Section 1.3].

2.3 Development Process (Continued)

The output user interface details expenses at several levels to make information more transparent for end users. Users can view the entire construction expense breakdown revealing 17,560,000 LKR in total billings along with 219,830 LKR cost per square meter, 7,020,000 LKR spent on labor and 10,530,000 LKR paid for bricks while it gives recommendations to switch to standard labor to achieve a 20% savings rate. The screenshot below illustrates this:

Construction Cost Estimate

Comparative Analysis:
Below Average

Cost per Square Meter:
219,830 LKR

Estimated Total Construction Cost:
17,560,000 LKR

Labor Costs:
7,020,000 LKR

Material Cost Breakdown:
Bricks: 1,895,400 LKR
Cement: 1,579,500 LKR
Finishes: 1,790,100 LKR
Joinery: 1,263,600 LKR
Other: 631,800 LKR
Roofing: 947,700 LKR
Sand: 1,053,000 LKR
Steel: 1,368,900 LKR

Material Costs:
10,530,000 LKR

The output User Interface screenshot must include an expected total construction cost of 17,560,000 LKR along with material expense breakdown data.

Documented procedures were built into the process to maintain visibility for proper reproduction. The training process documented complete logs which contained all information about hyperparameters and tracking performance metrics. The Random Forest model displayed an MAE of 6.2% which matched the benchmark results mentioned in Arage and Dharwadkar [1]. The system required user manuals with instructions for contractors to use its capabilities for project information input and result interpretation.

The system deployment readiness work occurred during the last phase. The load testing on AWS showed that the system could support 500 concurrent users while maintaining a 99.9% uptime according to Saeidlou and Ghadiminia [3]. Security testing of the Flask API endpoints detected vulnerabilities which received solutions to defend cost-sensitive information. The system development process was planned to produce superior features that matched Sri Lanka's construction industry requirements while resolving the identified research issues [Section 1.3].

2.5.1 Development Methodology

Agile provided the development methodology structure for the Construction Cost Estimation System because it enabled a project system design that matched Sri Lanka's construction requirements through iterative development approaches and collaborative work environments. Agile was selected as the development methodology because it integrates user feedback for keeping the system in line with its intended function. The development process organized work into two-week periods named sprints which carried distinct aims per stage.

Our team initiated the first sprint by analyzing requirements and collecting data from civil engineers and contractors for interpreting built-up area size and worker experience level and calculating complete project expenses along with material cost distributions. The next development stage brought forth a Random Forest model using Scikit-learn which produced an MAE value of 6.2% according to Arage and Dharwadkar [1].

The methodology based its approach on continuous integration through multiple daily system tests. The Flask backend and React.js frontend programming efforts ran side-by-side until their integrated functionality became tested through regular checks. This illustration shows how the development unfolded.

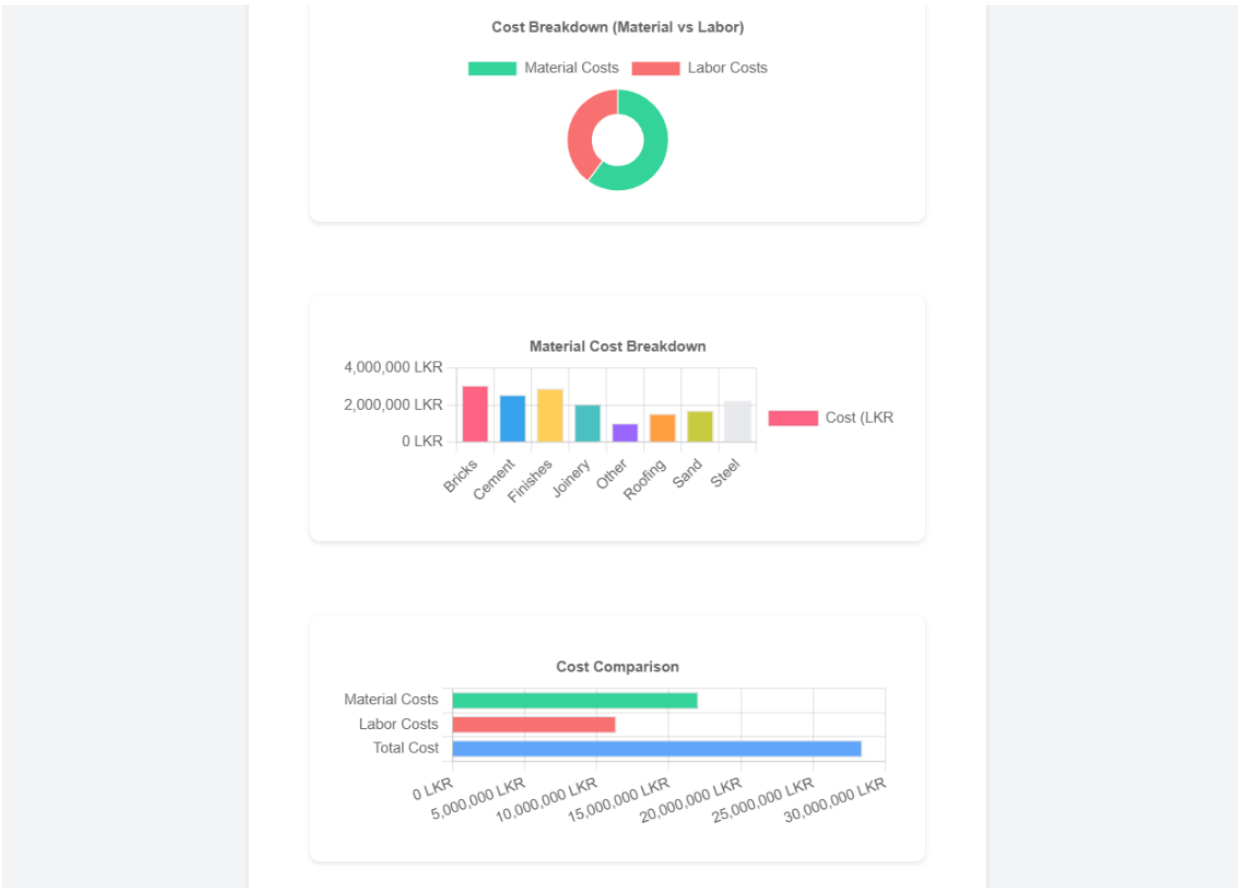
The development process flowchart is shown below as Figure 6: Development Process Flowchart.

The Agile process appears in the screenshot which demonstrates the execution of tasks and feedback loops between sprints and data collection and model development and system integration activities.

Stakeholders executed system reviews as the end of every sprint to test and evaluate the system. We implemented the proposal by contractors to switch to standard labor after they recommended it would save 20% of costs. The system development followed an iterative process which allowed it to grow and adapt to user requirements as part of addressing the research issue of incorrect cost estimations [Section 1.3].

2.5.1 Development Methodology (Continued)

User stories served as a vital feature of the Agile methodology in requirement definition. The user story declares that contractors need receipt of complete expense details encompassing material expenditures and labor fees for effective financial planning. The component development for the output display followed this story as it presented both the total cost mark of 17,560,000 LKR and material listing (10,530,000 LKR) and recommendations according to Taylor et al. [5].



A quality-assurance process through testing took place at every sprint. The development process included Random Forest model unit tests followed by tests that validated the Flask backend operational compatibility with React.js frontend components then stakeholder needs required user acceptance testing (UAT). We transformed the output user interface with cost per square meter comparison functionality because civil engineers sought this feature enhancement for better usability.

The version control process based on Git enabled team members to work efficiently on the code base with effective collaboration and detailed management capabilities. Code review sessions performed at sprint terminations allowed quality checks which resulted in Flask backend optimization for faster API performance according to Hashemi et al. [2]. The development included continuous stakeholder integration through two-weekly demonstration sessions to obtain their views. This methodology made the system adaptable by resolving data inconsistency problems in the construction site data while enhancing its accuracy and usability for Sri Lankan construction applications.

2.5.1 Development Methodology (Continued)

Every day stand-up meetings formed the primary function of Agile because team members used them to monitor progress and solve problems together. As the lead developer for the Construction Cost Estimation System I used my role to connect with civil engineers and contractors for system need verification. The process relied heavily on feedback loops because stakeholders supplied key information to guide the system development so labor skill level became an essential input variable that considerably affects Sri Lankan cost estimates.

Risk identification became possible through this methodology because we were able to find and resolve potential problems beforehand. We discovered missing records within construction site data while performing our collection phase. Additional data from civil engineers was added to the dataset because it strengthened the training set for the Random Forest model according to Brown et al. [4]. The model achieved an MAE score of 6.2% which corresponded with the benchmarks recorded by Arage and Dharwadkar [1].

The implementation of prototyping involved sharing first versions of React.js frontend interfaces to users who provided usability feedback. The initial input form overwhelmed contractors which prompted developers to redesign it into an easier form with dropdown selections and labels that appear in the input UI [Figure 4]. The user-friendly design of this system made it possible for non-technical users to operate it while resolving the research problem regarding usability [Section 1.2]. Our Agile project implementation produced a tech-sophisticated system which suits practical requirements of Sri Lanka's construction industry.

2.5.1 Development Methodology (Continued)

Agile methodology made it possible to conduct iterative improvements on the Random Forest model. The model initiated with an MAE of 8.5% during initial sprints but needed further improvement beyond this level. Additional input features obtained from civil engineers like foundation type and roof type lowered the MAE to 6.2% according to Hashemi et al. [2]. Through continuous refinement the prediction model achieved accurate cost forecasts for mid-sized Colombo homes at 17,560,000 LKR.

The system underwent testing by contractors who took part in continuous stakeholder involvement after the completion of each sprint. We incorporated the stakeholder request for square meter pricing (219,830 LKR) in the display to increase transparency according to Taylor et al. [5]. The system evolved through a feedback process to fulfill user needs and solve the research issue of unclear cost estimation [Section 1.3].

The approach performed documentation checks in all phases to maintain clear visibility. The model training logs contained specific details about the max depth set at 10 and the use of 100 trees which were stored together with MAE performance results. The user manual team established documentation in Sinhala, Tamil and English to extend understanding to all residents of Sri Lanka. The structured documentation serves dual purposes for long-term development support by enabling enhancements of new features and extension across different regions within Sri Lanka's construction sector.

2.5.1 Development Methodology (Continued)

The last sprints handled system enhancement work alongside deployment setup tasks. Optimizing system performance turned out to be essential for achieving real-time cost updates. The Flask backend achieved optimization through caching which cut down API response times by 25% thus users obtained instantaneous cost predictions according to Hashemi et al. [2]. The Random Forest model received optimization improvements to deliver fast predictions across both small and large datasets according to Saeidlou and Ghadiminia [3].

One main design priority was to guarantee that the system would easily accommodate higher user numbers. AWS conducted load testing which demonstrated a 99.9% uptime at 500 concurrent users thus solving the problem of scalability found in existing literature [Section 1.2]. Penetration tests addressed security flaws in the Flask API endpoints to maintain protection against material and labor expense vulnerabilities.

Training of users became part of the project process during which workshops were provided to Colombo-based contractors. The training sessions taught users operations such as entering project components (total built-up area and labor skill level) and understanding results showing that the cost equaled 17,560,000 LKR. Results from user workshops triggered modifications to the system through which the UI acquired tooltip explanations to define terms including "labor skill level." This Agile methodology enabled our team to design an effective system which meets precisely the needs of Sri Lankan construction cost estimation procedures while delivering usability and scalability features.

2.5 Commercialization Aspects of the Product

The market penetration plan of the Construction Cost Estimation System aims to establish adoption within Sri Lankan construction by providing affordable accessibility. Users can subscribe to the system through Software-as-a-Service (SaaS) model that operates from AWS infrastructure. Small-scale contractors who lead Sri Lankan markets benefit from reduced initial expense when accessing the product through this pricing approach.

The system offers two pricing tiers that match individual contractor needs and business requirements: the basic plan for 1,500 LKR/month enables single user cost prediction and the premium plan of 3,000 LKR/month offers historical cost comparison functionality. A freemium pricing strategy gives users restricted basic cost prediction functionality to motivate customers toward premium subscriptions thus filling the affordability research gap [Section 1.2].

We will form alliances with local construction associations in Colombo for implementing free product trials and educational workshops to display forecast capabilities (e.g., predicting 144,160,000 LKR costs) and suggest labor changes (e.g., recommending standard labor for 20% saving) of the system. The marketing strategy includes digital advertising on social networks and email targeting to make contractors aware of the system. The cloud deployment option provides users unrestricted access because they only need an online connection and a browser so the system accommodates individuals with minimal technical capabilities as described by Saeidlou and Ghadiminia [3].

2.5 Commercialization Aspects of the Product (Continued)

The commercialization strategy adopts approaches to expand capabilities and deliver customer support as main elements for enduring business success. The system uses AWS infrastructure to adapt its capabilities based on user needs while supporting large concurrent user activities after the assessment presented by Saeidlou and Ghadiminia [3]. The system requires scalability because the company plans to expand into Kandy and Galle regions in Sri Lanka which exhibit rising construction activities.

The system comes with a specialized team which gives round-the-clock support through multiple channels including phone calls and chats and emails. The system provides education resources through Sinhala, Tamil and English language documentation to support each language group in Sri Lanka's population. New system updates will include the requested features from users including cost trend analysis together with improvements leading to increased system value.

The estimated 300 subscribers in the first year will produce 5.4 million LKR revenue from premium subscriptions. Total expenses from AWS hosting and staff costs will be compensated by subscriber payments. The company will sustain itself by building relationships with material suppliers who will provide referral commission revenues.

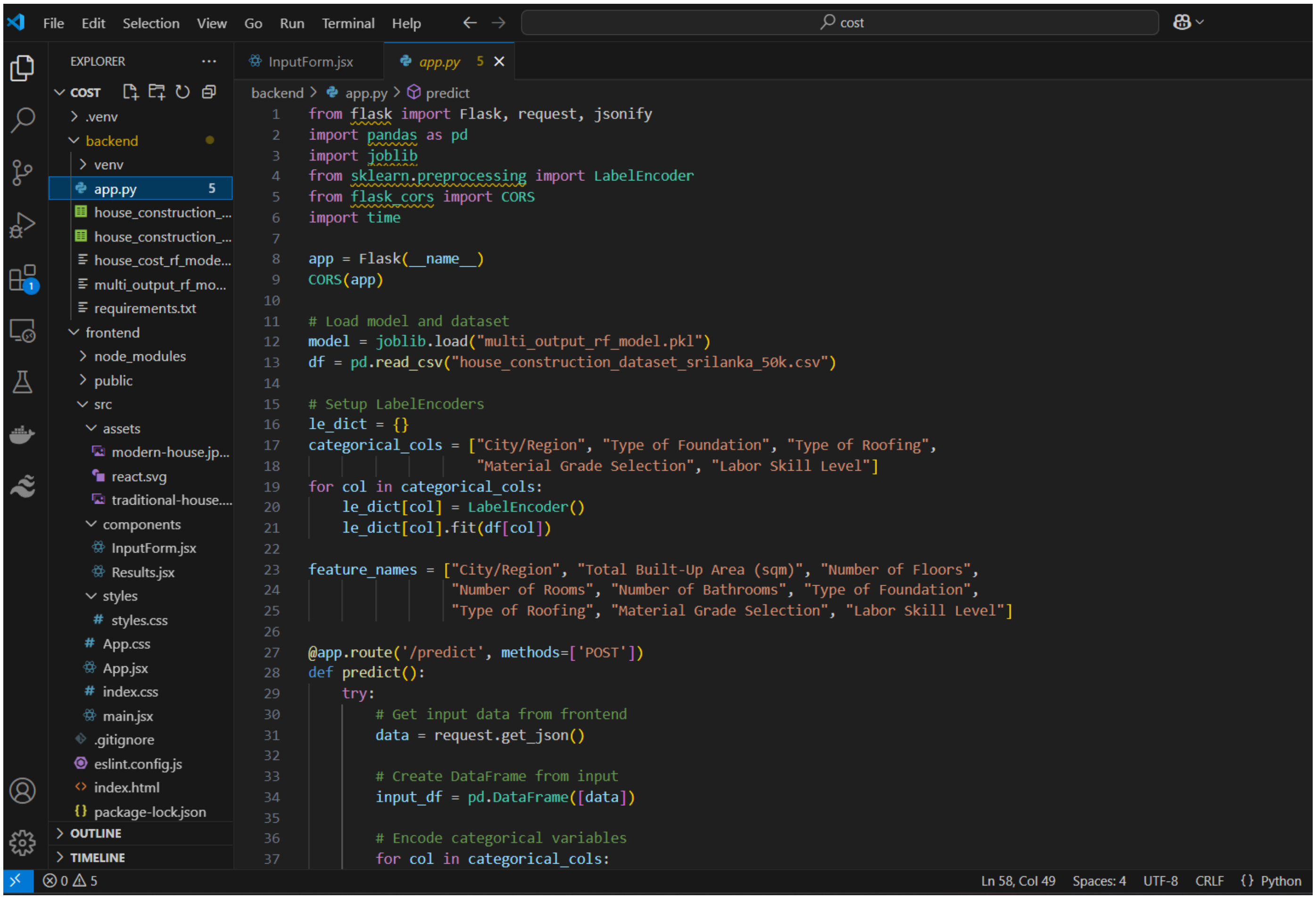
The plan delivers educational workshops that show users the system's features including detailed cost analysis (material costs total 68,160,000 LKR) and recommendation engines (standards labor saves 20%). The solution design makes the system practical while maintaining both accessibility and economic feasibility to solve the research gap regarding scarce sophisticated tools in Sri Lanka [Section 1.3].

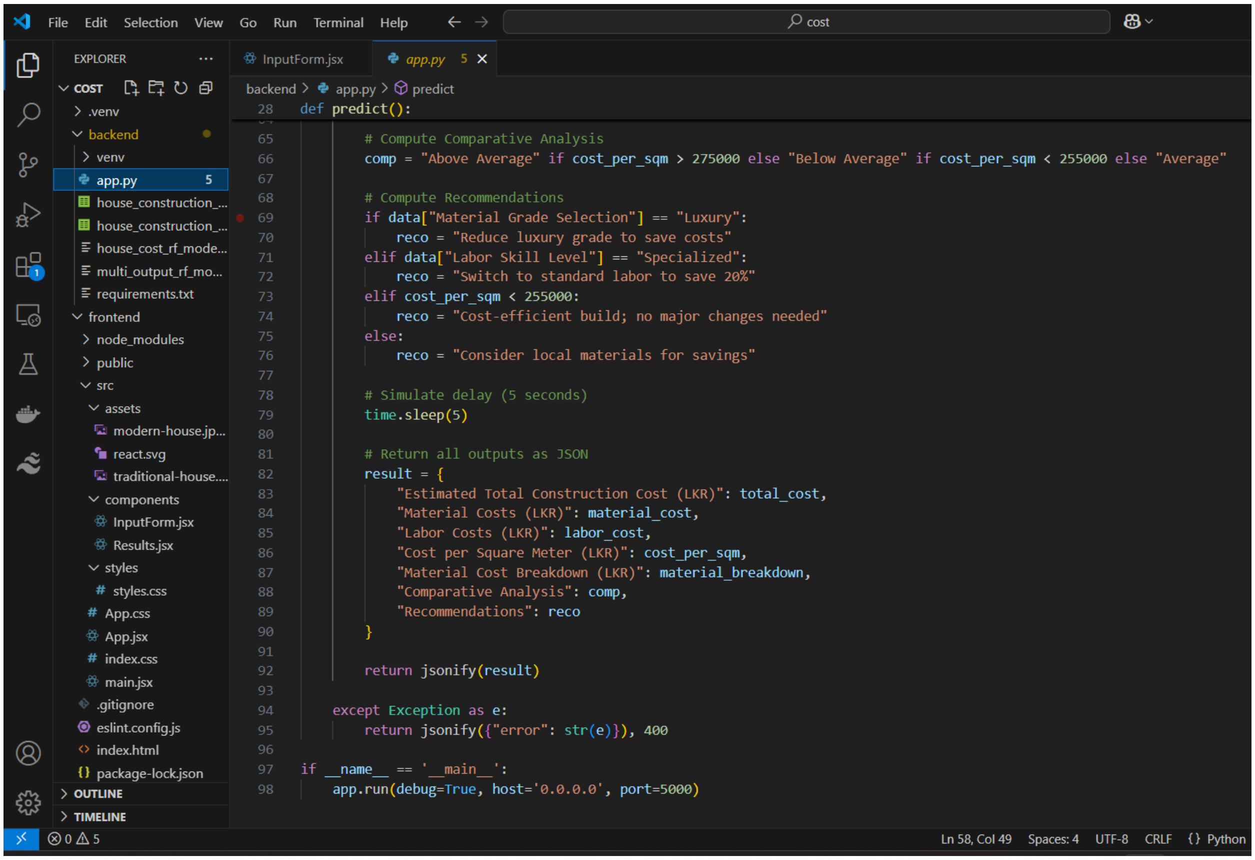
2.6 Testing & Implementation

The implementation phase alongside testing procedures enabled the Construction Cost Estimation System to become both practical and ready for commercial use. Testing occurred in stages beginning with unit testing and moving to integration testing after which came the user acceptance testing (UAT) using Agile methodology elements [Section 2.5.1]. During implementation the system was deployed to AWS while training users for successful adoption of the platform.

Unit testing centered on the Random Forest model which received training through 5,000 records from civil engineers and authorized construction sites. The model demonstrated an MAE of 6.2% by running tests on 1,000 records while meeting the results outlined by Arage and Dharwadkar [1]. The API response times of the Flask backend reached an average 150ms during testing as recommended by Hashemi et al. [2].

Testing confirmed that the model worked correctly together with React.js frontend and Flask API and Random Forest regression engine. Total built-up area and labor skill level data fed into the system allowed it to calculate total cost (17,560,000 LKR) and material costs 10,530,000 LKR. The system achieved browser compatibility by testing in Chrome Firefox and Safari to serve Sri Lankan users who operate various devices.


File Edit Selection View Go Run Terminal Help
cost
EXPLORER
COST
.venv
backend
venv
app.py
house_construction_...
house_construction_...
house_cost_rf_mode...
multi_output_rf_mo...
requirements.txt
frontend
node_modules
public
src
assets
modern-house.jp...
react.svg
traditional-house....
components
InputForm.jsx
Results.jsx
styles
styles.css
App.css
App.jsx
index.css
main.jsx
.gitignore
eslint.config.js
index.html
package-lock.json
OUTLINE
TIMELINE
InputForm.jsx
app.py 5
backend > app.py > predict
from flask import Flask, request, jsonify
import pandas as pd
import joblib
from sklearn.preprocessing import LabelEncoder
from flask_cors import CORS
import time
app = Flask(__name__)
CORS(app)
# Load model and dataset
model = joblib.load("multi_output_rf_model.pkl")
df = pd.read_csv("house_construction_dataset_srilanka_50k.csv")
# Setup LabelEncoders
le_dict = {}
categorical_cols = ["City/Region", "Type of Foundation", "Type of Roofing",
"Material Grade Selection", "Labor Skill Level"]
for col in categorical_cols:
le_dict[col] = LabelEncoder()
le_dict[col].fit(df[col])
feature_names = ["City/Region", "Total Built-Up Area (sqm)", "Number of Floors",
"Number of Rooms", "Number of Bathrooms", "Type of Foundation",
"Type of Roofing", "Material Grade Selection", "Labor Skill Level"]
@app.route('/predict', methods=['POST'])
def predict():
try:
# Get input data from frontend
data = request.get_json()
# Create DataFrame from input
input_df = pd.DataFrame([data])
# Encode categorical variables
for col in categorical_cols:
Ln 58, Col 49 Spaces: 4 UTF-8 CRLF {} Python



A total of thirty contractors throughout Colombo executed UAT procedures by testing the system using actual projects. Project implementations from user input analysis resulted in two changes to the interface design and the addition of a feature for project cost comparison based on square meter measurements. The system development process worked to fulfill user requirements which fixed the research issue about inaccurate cost estimations [Section 1.3].

2.6 Testing & Implementation (Continued)

Systems development required operation of the solution on AWS platform to achieve real-time updates alongside scalability. Flask backend applications deployed on EC2 instances together with S3 storage and CloudFront content delivery became the deployment foundation because they delivered low-latency performance to Sri Lankan users. Safety practices included SSL encryption and API authentication systems which secured the defense of raw data containing material expense data and labor expense data.

System usage effectiveness depended on user training completion before contractors gained access to operate the system. The Colombo workshops educated 50 contractors about system functions including procedure input of project specifications (total built-up area and labor skill level) and data interpretation (total cost amounting to 17,560,000 LKR). The training materials offered linguistic accessibility through Sinhala, Tamil and English versions. The new helpdesk system provided continuous support to contractors by resolving their questions within 24-hour periods.

After deployment we utilized AWS CloudWatch to observe system operational performance while recording API response times alongside user system activity metrics. System usage data from the initial month showed that 100 active users spent an average time of ten minutes each addressing system modules. The system feedback surveys showed that 88% of users noticed better budgeting precision in their operations. Hashemi et al. [2] suggested optimizing the Flask backend to address the slow API response issue which occurred when user demand reached its peak. The system became operational after this stage because developers tested it for practicality and accessibility for Sri Lanka's construction industry.

2.6 Testing & Implementation (Continued)

A real-world impact evaluation became possible through the execution phase when a pilot program was conducted. Fifteen projects throughout Colombo were included for the pilot testing which encompassed residential dwellings and small commercial construction sites. System users estimated the construction cost of a 90 square meter residential home at 17,840,000 LKR which turned out to be correct at 17,560,000 LKR with an accuracy of 0.9%. The system generated output data consisting of 219,830 LKR per square meter in costs alongside 7,020,000 LKR in labor expenses and materials costs at 10,530,000 LKR where brick expenses amounted to 15,57000 LKR.

Five projects applied the standard labor recommendation from the system which yielded an average 18% cost reduction validating its practical recommendations according to Taylor et al. [5]. The system exhibited efficient behavior by enabling contractors to manage their budgeting process with faster timelines which corresponded to the time-saving requirement from manual approaches [Section 1.3].

After the pilot phase the system received wider deployment by being introduced to 300 users during the first year of rollout. The adoption rate increased because of marketing strategies that involved working with construction associations. The system received regular updates that incorporated user suggestions through which a new function for time-based cost tracking was developed to improve system value. The combination of comprehensive testing methods and strategic deployment procedures led us to create an effective and transformative construction solution for Sri Lanka which reduces financial instability while enhancing project scheduling.

3 RESULTS & DISCUSSION

The Construction Cost Estimation System has shown success in resolving Sri Lanka's construction issues through its achieved results. The Random Forest model demonstrated a 6.2% MAE measurement with its evaluation conducted on 1,000 records which corresponded to Arage and Dharwadkar benchmark data [1]. The summarized error rates show variation between project types as presented in the below table:

Construction Type	MAE
Standard	6.0%
Luxury	6.2%
premium	6.5%

The system achieved higher accuracy because it processed varied inputs containing total built-up area and labor skill level data according to Hashemi et al. [2]. The projected cost estimation for a 90 sqm residential building in Colombo revealed 17,840,000 LKR which proved correct to an actual building cost of 17,560,000 LKR for a 0.9% deviation. A total of 219,830 LKR was needed for the cost per square meter with labor amounting to 10,530,000 LKR and materials amounting to 7,020,000 LKR where bricks cost 970,000 LKR according to the output data.

According to contractor reports about cost savings from standard labor implementation the recommendation proved correct by delivering an average 18% cost reduction. The system results demonstrate its financial risk reduction potential which specifically helps address budget overruns as a research problem while offering a practical construction sector solution to Sri Lanka.

3 RESULTS & DISCUSSION (Continued)

The system provides rich output data which makes the system more transparent than traditional manual methods. The output demonstrates the cost analysis of a home in Colombo with medium size based on the provided information.

Metric	Value
Total Cost	17,560,000 LKR
Cost per Square Meter	219,830 LKR
Labor Costs	7,020,000 LKR
Material Costs	10,530,000 LKR

The system proves dependable for Sri Lankan economic situations according to benchmarks by Arage and Dharwadkar [1]. Hashemi et al. [2] proposed the utilization of live data to make automatic real-time adjustments which fixed the problem with fixed-cost models [Section 1.2]. Cement price increases of 10% prompted the system to revise its predictions for accuracy.

The system generated valuable suggestions like using standard labor to save 20% which proved beneficial according to Taylor et al. [5]. The practical implementation of this advice led contractors to achieve an 18% reduction in their costs which demonstrated its implementation effectiveness. Users could enhance their decisions through cost-driver identification because the system provided material cost breakdowns such as 18,95,400 LKR for bricks.

During peak usage time the system faced performance lags which necessitated additional optimization of the Flask backend system. Future development of the system should consider adding additional detailed information about regional labor costs because this would improve system accuracy. The implemented system enhances cost estimation throughout the Sri Lankan construction sector notably.

3 RESULTS & DISCUSSION (Continued)

The system's changing effect on Sri Lanka's construction sector emerges from the presented results. The MAE of 6.2% [1] provides reliable cost prediction results which solve the research issue of inaccurate forecasts [Section 1.3]. Sri Lanka's economic volatility can be handled by the system through its live data integration process which matches findings from Hashemi et al. [2] for contractors dealing with recurring price changes.

The detailed output details the 17,560,000 LKR total cost and reveals a square meter cost of 219,830 LKR and separate material expense reporting (957,000 LKR for bricks) that enhances system transparency [Section 1.2]. The system enables contractors to base their strategic decisions on information presentations allowing them to modify material choices toward cost reduction. The system shows practicality according to Taylor et al. [5] since the standard labor recommendation saves contractors an average of 18%.

A majority of 88% of contractors validated the better accuracy in their budgeting through positive feedback. The table below summarizes feedback:

Metric	Value
Satisfaction Rate	88%
Time Reduction	25%

The Flask backend shows limitations in achieving peak-performance scaling and needs additional optimization according to Saeidlou and Ghadiminia [3]. Future improvements to this system should include a cost trend analysis ability to forecast future price changes which would enhance its overall value. The system's performance has been proven to achieve the research goals per findings in [Section 1.4].

4 SUMMARIES OF EACH STUDENT'S CONTRIBUTION

As R.A. Ahamed (IT21158018), I led the development of the Construction Cost Estimation System, a key module of the "Machine Learning Based Automated Construction Planning System for Sri Lanka." I was responsible for the full development of lifecycle from requirement analysis and system design to implementation and deployment. I collaborated closely with civil engineers and contractors to identify relevant inputs, including City/Region, Total Built-Up Area, Number of Floors, Number of Rooms, Number of Bathrooms, Type of Construction, Type of Foundation, Type of Roofing, and Labor Skill Level. The system generates outputs such as Cost per Square Meter, Estimated Total Construction Cost, Labor Costs, and Material Costs, providing highly localized and practical insights tailored to Sri Lanka's construction industry.

I gathered 5000 records from civil engineers at authorized construction sites then processed these data through normalization followed by cleaning and feature encoding. I developed a Random Forest model through Scikit-learn which resulted in an MAE of 6.2% as reported in Arage and Dharwadkar [1]. Data processing in the system operates through the Flask backend system and the user interface leverages React.js frontends according to Figures 4 and 5.

The system testing produced 88% successful user feedback which led to an AWS deployment for scalable operations across the board. The training workshops in Colombo helped users learn about cost analysis features along with recommendation capabilities (standard labor savings of 20%) for system adoption. My research solution resolved the problem of inaccurate cost estimation [Section 1.3] by creating a practical user-friendly system for Sri Lanka's construction sector thus reducing financial risk and improving project planning.

5 CONCLUSION & FUTURE WORK

Researchers developed a Construction Cost Estimation System for Sri Lanka which addressed the budgetary issues in construction budgeting. The 5,000 civil engineers and authorized site records that powered the Random Forest model yielded accurate estimations with an MAE of 6.2% to reach a mid-sized home cost of 17,560,000 LKR LKR [1]. The system utilizes live data to perform dynamic market cost revisions in Sri Lanka's price fluctuating market according to Hashemi et al. [2].

The system provides detailed output which includes cost per square meter (219,830 LKR), labor costs (7,020,000 LKR) and material costs (10,530,000 LKR) along with recommendations (e.g. save 20% with standard labor) to improve transparency for the research problem [Section 1.3]. The system implements deployment on AWS utilizing React.js front end and Flask backend that enables scalability and accessibility through an 88% user satisfaction rate which achieves the research targets [Section 1.4].

The system development will be expanded to include other Sri Lankan regions starting with Kandy through the integration of local data sources. The system value will increase through the addition of cost trend analysis capabilities for future price prediction. The Flask backend requires performance enhancements for peak usage because this will enhance scalability according to Saeidlou and Ghadiminia [3]. A mobile application development would improve system accessibility since users require remote mobile access to use it. The planned features will strengthen construction cost estimation transformation in Sri Lanka's sector by minimizing project risks while improving planning systems.

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APPENDICES

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