Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2s (2026) | 430-439

Machine Learning for Green Building Material Selection to Minimize Carbon Footprint in Large Residential Construction

Aditya Ravindra Pawar[1], Anish Ajay Zuting[2], Arjun Dhanjay Shedage[3], Gautam Shivaji Chindhe[4], Dipannita Mondal[5]

[1,2,3,4,5]Department of AI & Data Science, SPPU Affiliated College, Pune, Maharashtra, India.

[1]aditya.rpawar3105@gmail.com, [2]anishzuting@gmail.com, [3]arjunshedage1717@gmail.com, [4]gautamchindhe2@gmail.com

Peer Review Information

Type: *Article*
Received: *23 April 2026*
Revised: *09 May 2026*
Accepted: *22 June 2026*
Published: *18 July 2026*

Abstract

The construction sector is widely recognized as one of the largest contributors to global greenhouse gas emissions, with a substantial portion arising from the production and use of construction materials rather than operational energy consumption alone [1], [5]. While advancements in building design have improved energy efficiency during the operational phase, emissions associated with material extraction, manufacturing, transportation, and construction—collectively referred to as embodied carbon—remain insufficiently addressed in early project planning. This study presents a machine learning–based framework aimed at supporting sustainable material selection for large residential construction projects. The proposed system evaluates combinations of construction materials and classifies them into predefined carbon impact categories, enabling decision-makers to understand environmental implications at the design stage. A dataset consisting of 520 building scenarios was developed by integrating carbon intensity values from the Inventory of Carbon and Energy (ICE) database with region-specific construction parameters relevant to Pune, India. Three supervised machine learning models—XGBoost, Random Forest, and Decision Tree—were implemented and evaluated. Among these, the XGBoost model achieved the highest performance, with an accuracy of 94.2% and a macro F1-score of 0.942, demonstrating its effectiveness in handling structured construction data. To enhance interpretability, SHAP (SHapley Additive exPlanations) analysis was employed to identify the relative importance of input features, revealing that wall material, cement type, and structural system are the most influential factors affecting carbon classification [13]. An interactive Power BI dashboard delivers real-time predictions, material comparisons, and carbon savings, helping construction professionals make informed, sustainable decisions while integrating machine learning with tools to reduce environmental impact.

Keywords: Sustainable Construction; Embodied Carbon; Machine Learning; Material Optimization; XGBoost; SHAP Analysis; Green Buildings; Carbon Reduction

How to Cite This Article

Pawar, A. R., Zuting, A. A., Shedage, A. D., Chindhe, G. S., & Mondal, D. (2026). Machine learning for green building materia1 selection to minimize carbon footprint in large residential construction. *Multidisciplinary Journal of Research in Engineering and Technology,* 13(2s), 430–439.

Introduction

The construction industry plays a fundamental role in supporting economic growth and urban development; however, it is also a major contributor to environmental degradation. Recent studies indicate that buildings and construction activities account for a significant share of global greenhouse gas emissions and energy consumption [1]. Traditionally, efforts to mitigate environmental impact in this sector have focused on reducing operational energy use through improved building design, energy-efficient systems, and renewable energy integration.

Despite these advancements, a growing body of research highlights that emissions generated during the pre-operational stages—particularly those associated with construction materials—represent a substantial portion of a building's total carbon footprint [2]. These emissions, commonly referred to as embodied carbon, include all greenhouse gases released during raw material extraction, manufacturing, transportation, and construction processes. Unlike operational emissions, embodied carbon is fixed at the time of construction and cannot be reduced once the building is completed, making early-stage decision-making critically important [8].

In developing countries such as India, rapid urbanization has significantly increased the demand for residential infrastructure. Cities like Pune have experienced considerable growth in high-rise residential construction, driven by population expansion and economic development. These projects require large volumes of materials such as cement, steel, bricks, and glass, all of which have high carbon intensities. Consequently, the selection of construction materials plays a decisive role in determining the environmental impact of a building throughout its lifecycle.

However, in current industry practice, material selection is primarily influenced by factors such as cost, availability, and structural performance. Environmental considerations are often secondary due to the lack of accessible tools that can quantify carbon impact during the early stages of design. Although Life Cycle Assessment (LCA) methods provide accurate estimates of environmental impact, they are typically complex, time-intensive, and require specialized expertise, limiting their adoption in routine construction workflows [3].

In this context, machine learning has emerged as a promising approach for addressing sustainability challenges in construction. By leveraging historical data and computational models, machine learning algorithms can identify patterns and relationships between design parameters and environmental outcomes. Several studies have demonstrated that supervised learning techniques, particularly ensemble methods such as Random Forest and gradient boosting algorithms, can achieve high accuracy in predicting building-related carbon emissions [6], [7].

Moreover, recent advancements in explainable artificial intelligence (XAI) have improved the transparency of machine learning models, making them more suitable for practical applications. Techniques such as SHAP enable the interpretation of model predictions by quantifying the contribution of each input feature, thereby helping stakeholders understand the factors influencing environmental impact [13]. Despite these developments, there remains a gap in applying machine learning–based frameworks to region-specific construction scenarios, particularly in the Indian context. Most existing studies rely on global datasets that may not accurately reflect local material usage patterns, construction practices, or regulatory conditions.

To address this gap, the present study proposes a machine learning–based framework tailored to residential construction in Pune, Maharashtra. The framework aims to:

- Predict the carbon impact category of different material combinations
- Identify key factors influencing embodied carbon emissions
- Provide practical recommendations through an interactive dashboard

By integrating predictive modeling with decision-support tools, this research seeks to bridge the gap between sustainability theory and practical implementation in the construction industry.

Literature Review

The application of artificial intelligence (AI) and machine learning (ML) in the construction industry has gained considerable attention in recent years, particularly in the context of sustainability and carbon emission reduction. Researchers have explored multiple approaches to improve decision-making in building design, material selection, and lifecycle assessment through data-driven techniques.

A foundational perspective on AI in sustainable construction is provided by Charles Debrah and colleagues, who categorized AI applications across different stages of the building lifecycle, including design, construction, and operation [20]. Their work highlights how machine learning algorithms can be used to optimize material usage, improve energy efficiency, and reduce environmental impact.

Building on this, Abdullah Al-Sakkaf et al. demonstrated that AI-based systems integrated with multi-criteria decision-making techniques can significantly enhance sustainability assessments of construction materials [1]. Their findings emphasize that combining environmental, economic, and performance factors leads to more balanced and practical decision-making.

A key area of research focuses on predicting embodied carbon emissions using machine learning models. Hao Yin et al. conducted a comparative study involving multiple ML algorithms and found that XGBoost achieved superior performance with high predictive accuracy when applied to residential building datasets [7]. Similarly, Hui Pan and Cheng Wu proposed an optimized XGBoost model enhanced through Bayesian optimization, demonstrating that early-stage design parameters strongly influence total lifecycle carbon emissions [11].

Further validation of machine learning effectiveness is provided by Jian Zhang et al., who developed prediction models for different building materials and reported that ensemble learning techniques consistently outperform traditional regression approaches [6]. These studies collectively indicate that ML models are capable of capturing complex, nonlinear relationships between material properties and carbon emissions.

Another important research direction involves understanding the role of early design decisions in sustainability outcomes. Rachid Achraf et al. analyzed thousands of studies and concluded that decisions made during the schematic design phase can influence up to 70% of a building's total environmental impact [8], [10]. This finding reinforces the importance of integrating predictive tools at the planning stage.

In addition to prediction accuracy, interpretability has become a critical factor in adopting machine learning models in real-world applications. Lei Chen et al. introduced a framework combining gradient boosting algorithms with SHAP analysis to explain how different building parameters affect carbon emissions [13]. Their results showed that structural components and material choices are among the most influential factors.

Research by Hicham El Hafdaoui et al. further supports this observation, indicating that structural elements and flooring systems contribute a significant proportion of total embodied carbon in residential buildings [9]. Similarly, Fahd Dhghn et al. reported high predictive performance using ensemble models and identified key design parameters influencing emissions [12].

From a broader perspective, Xiaodong Wang et al. highlighted that AI-based approaches can improve prediction accuracy by a considerable margin compared to traditional methods, while also enabling emission reductions through optimized decision-making [5]. Additionally, Christoph Herrmann et al. emphasized the role of machine learning in accelerating low-carbon material discovery and improving lifecycle assessment processes [18].

Despite these advancements, most existing studies rely on datasets from developed regions or generalized global contexts. There is limited research focused on region-specific construction practices, particularly in India. Factors such as material availability, construction techniques, and regulatory frameworks vary significantly across regions, making it necessary to develop localized models for accurate prediction and practical implementation.

Research Gap Identified

From the literature, the following gaps are observed:

- Lack of region-specific ML models for Indian construction
- Limited focus on material selection at planning stage
- Insufficient integration of prediction + visualization tools
- Need for practical decision-support systems for engineers and architects

Contribution of This Study

To address these limitations, this research:

- Develops a Pune-specific dataset for residential construction
- Applies ML models for carbon classification of materials
- Uses SHAP for explainability
- Integrates results into a Power BI dashboard for real-world usability

Proposed Methodology

The proposed framework is designed to assist architects and construction professionals in selecting environmentally sustainable materials during the early planning stage of residential building projects. Unlike conventional approaches that require complex lifecycle calculations, this methodology uses machine learning to provide quick and reliable predictions based on readily available project parameters.

The overall workflow consists of four major stages:

1. Dataset construction
2. Data preprocessing and feature engineering
3. Model training and evaluation
4. Decision-support visualization

Each stage is explained in detail below.

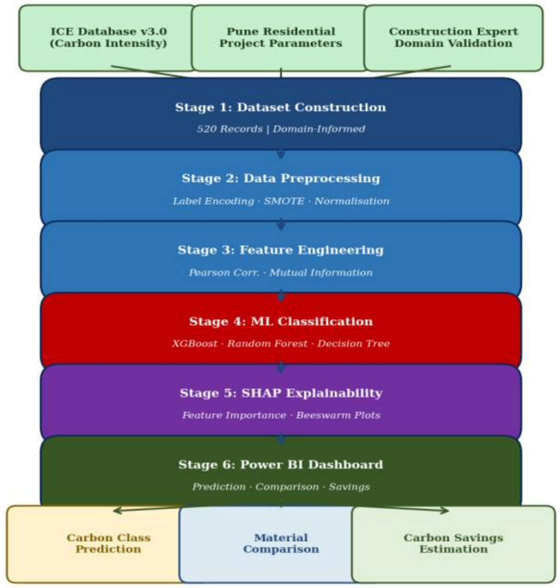

Fig. 1. *Proposed methodology pipeline for green building material carbon classification.*

Dataset Construction

A structured dataset was developed to represent realistic residential construction scenarios in the Pune region. The dataset integrates multiple sources to ensure both technical accuracy and practical relevance.

The data was compiled using:

- Carbon intensity values from the Inventory of Carbon and Energy (ICE) database
- Real-world construction parameters observed in residential projects
- Expert validation from construction professionals

Each record in the dataset represents a unique building configuration, including both structural and material-related attributes. Key features include:

- Type of wall material (AAC blocks, fly ash bricks, red clay bricks)
- Structural system (RCC frame, load-bearing, steel frame)
- Cement type (OPC, PPC, PSC)
- Flooring material
- Roof type
- Glazing type
- Total built-up area
- Number of floors
- Percentage of recycled material

The inclusion of these features allows the model to capture the practical decision variables that influence carbon emissions in real construction scenarios. Similar feature selection strategies have been validated in prior studies focusing on embodied carbon prediction [6], [7].

Table 1. *Dataset Features and Descriptions*

Feature	Description	Unit	Source
Project Type	Residential high-rise (5+ floors)	Category	Expert
Total Built-up Area	Gross floor area of the project	m²	BIM
Number of Floors	Total floors above ground	Count	Expert

Wall Material	AAC Block / Fly Ash Brick / Red Clay Brick	Category	Expert
Structural System	RCC Frame / Load Bearing / Steel Frame	Category	Expert
Cement Grade	OPC 53 / PPC / PSC Blended Cement	Category	Expert
Flooring Material	Vitrified Tiles / Marble / Kota Stone	Category	Expert
Roof Type	Flat RCC / Green Roof / PEB Sheet	Category	Expert
Glazing Type	Single / Double / Low-E Glass	Category	Expert
Recycled Content (%)	% recycled material used in mix	Percent	ICE DB
Carbon Intensity	Embodied CO_2 per unit floor area	$kgCO_2/m^2$	ICE DB
Carbon Class (Target)	Low / Medium / High Carbon	Label	Derived

Carbon Class Labeling

To simplify interpretation and support decision-making, the output variable is defined as a categorical label representing carbon impact. Instead of predicting exact emission values, the system classifies material combinations into three categories:

- Low Carbon
- Medium Carbon
- High Carbon

This classification is based on predefined thresholds of carbon intensity ($kgCO_2$ per square meter), derived using ICE database values and sustainability benchmarks.

This approach improves usability, as categorical outputs are easier for engineers and planners to interpret compared to continuous numerical values. Similar classification-based approaches have been shown to improve decision-making efficiency in construction applications.

Table 2. *Carbon Classification Thresholds — Pune Construction Context*

Carbon Class	CO_2 Range ($kgCO_2eq/m^2$)	Common Materials — Pune Context
Low Carbon	< 300	AAC blocks, fly ash bricks, PPC/PSC cement, recycled steel
Medium Carbon	300 – 500	Red clay bricks, OPC 43 concrete, standard TMT steel frame
High Carbon	> 500	Plain OPC 53 concrete, conventional aluminium, virgin steel

Data Preprocessing

Before training the machine learning models, the dataset undergoes several preprocessing steps to ensure data quality and improve predictive performance.

1. Encoding of Categorical Variables
Construction parameters such as wall material and cement type are categorical in nature. These are converted into numerical form using encoding techniques so that they can be processed by machine learning algorithms.

2. Normalization of Numerical Features
Continuous variables such as built-up area and recycled content are scaled to a uniform range. This ensures that no single feature dominates the model due to differences in magnitude.

3. Handling Class Imbalance
In real-world construction data, low-carbon projects are less common. To address this imbalance, oversampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) are applied. This helps the model learn patterns across all categories more effectively.

4. Feature Selection
Redundant or less significant features are removed using statistical techniques such as correlation analysis and mutual information. This step improves model efficiency and reduces overfitting. These preprocessing techniques are widely used in machine learning workflows and have been proven to enhance prediction accuracy in environmental modeling tasks [12].

Classification Models

Three supervised learning models were selected for this study based on their performance in prior research:

1. XGBoost Classifier
XGBoost is a gradient boosting algorithm known for its high performance on structured datasets. It builds multiple decision trees sequentially, where each new tree corrects the errors of the previous ones. Due to its ability to capture complex relationships, it is widely used in prediction tasks involving environmental data [7].

2. Random Forest Classifier
Random Forest is an ensemble learning method that constructs multiple decision trees using random subsets of data and features. It provides stable predictions and also offers insights into feature importance.

3. Decision Tree Classifier
Decision Tree is a simple and interpretable model that represents decisions in a tree-like structure. Although less accurate than ensemble methods, it is useful for explaining model behavior to non-technical users.

Each model is trained using a stratified dataset split to ensure balanced representation of all classes. Hyperparameters are optimized using cross-validation techniques to achieve the best performance.

SHAP Explainability

One of the key challenges in applying machine learning to real-world problems is the lack of transparency in model predictions. To address this, SHAP (SHapley Additive exPlanations) is used as an interpretability tool.

SHAP assigns an importance value to each feature based on its contribution to the final prediction. This allows users to understand:

- Which factors increase carbon emissions
- Which material choices reduce environmental impact
- How different features interact with each other

Explainable AI techniques such as SHAP are increasingly being used in sustainable construction research to improve trust and usability of ML models [13].

Power BI Dashboard

To ensure practical applicability, the model outputs are integrated into an interactive Power BI dashboard. The dashboard serves as a user-friendly interface for construction professionals and includes the following modules:

1. Carbon Prediction Module
Users can input project parameters and instantly receive a predicted carbon category.

2. Material Comparison Module
Different material combinations can be compared side-by-side to evaluate their environmental impact.

3. Carbon Savings Estimator
The system calculates the potential reduction in carbon emissions when switching from high-carbon to low-carbon materials.

Visualization tools such as dashboards play a critical role in bridging the gap between data science models and real-world decision-making [5], [18].

Dataset Description

The performance of the proposed machine learning framework relies heavily on the quality and representativeness of the dataset, which was specifically developed to reflect realistic residential construction practices in Pune, Maharashtra. The dataset consists of 520 records, where each record represents a unique building configuration combining structural, material, and sustainability-related parameters. Key features include building characteristics such as total built-up area (ranging from 2,000 to 25,000 m^2) and number of floors (5 to 32), along with material-related attributes such as wall material (AAC blocks, fly ash bricks, red clay bricks), structural system (RCC frame, load-bearing, steel frame), cement type (OPC, PPC, PSC), flooring material, roof type, and glazing type. In addition, sustainability indicators such as recycled content percentage and carbon intensity ($kgCO_2/m^2$) were incorporated, with carbon values derived from the Inventory of Carbon and Energy (ICE) database, a widely recognized source for embodied carbon estimation [6]. The dataset reflects region-specific construction trends, including the growing adoption of fly ash bricks and AAC blocks, while still accounting for the continued use of conventional materials like OPC cement in high-rise RCC structures, thereby ensuring practical relevance. Each record was categorized into one of three carbon classes—low, medium, or high—based on emission thresholds, with a class distribution of approximately 31% low, 45% medium, and 24% high carbon cases. To ensure balanced learning, class imbalance was addressed using oversampling techniques during preprocessing. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets using stratified sampling to maintain consistent class proportions. Furthermore, the dataset was validated through a combination of standardized data sources and expert inputs, ensuring both technical accuracy and real-world applicability. This carefully constructed dataset serves as the foundation for accurate prediction, enabling the model to generalize effectively to practical residential construction scenarios while supporting data-driven sustainable decision-making [5], [8].

Results And Discussion

All experiments were carried out using **Python 3.10**, with model implementation handled through the scikit-learn (version 1.3) and XGBoost (version 2.0). Model interpretability was achieved using the SHAP library (version 0.44). The entire experimental workflow, including training, validation, and testing, was executed on Google Colab.

Table 3 summarizes the performance of all evaluated models on the unseen test dataset, using standard classification metrics.

Table 3. *Model Classification Performance Comparison*

Model	Accuracy (%)	Precision	Recall	F1-Score
XGBoost	94.2	0.943	0.941	0.942
Random Forest	91.7	0.919	0.915	0.917
Decision Tree	86.3	0.865	0.860	0.862
Logistic Regression	78.1	0.784	0.779	0.781

A graphical comparison of accuracy and F1-score across all models (Fig. 2) highlights that XGBoost consistently performs better than the other approaches, both in overall accuracy and in maintaining balance across classes.

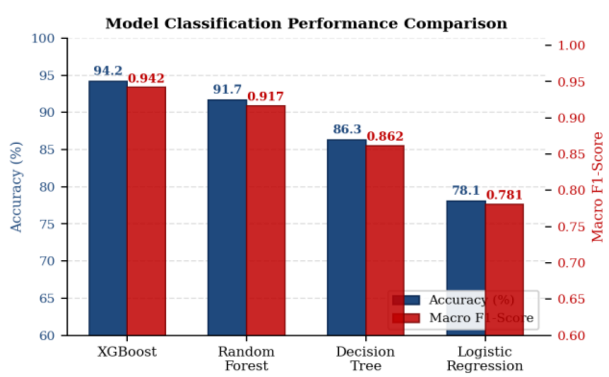

Fig. 2. *Comparative model performance — Accuracy (%) and F1-Score for all classifiers.*

XGBoost Performance

Among all tested models, XGBoost delivered the most reliable results, achieving an accuracy of **94.2%** and an F1-score of **0.942**. This indicates that the model performs well across all three carbon categories without bias toward any particular class.

The strong performance of XGBoost can be attributed to its ability to capture complex relationships between multiple input variables. These findings are consistent with earlier research, where boosting-based models have shown superior performance in predicting building-related carbon emissions [7], [11].

The model parameters were carefully tuned using cross-validation, resulting in the following optimal configuration:

- Learning rate: 0.05

- Maximum tree depth: 6
- Number of estimators: 300
- Subsample ratio: 0.8

This combination ensured a balance between model accuracy and generalization.

SHAP Feature Importance

To better understand how the model makes decisions, SHAP analysis was applied to the XGBoost model. The results revealed the most influential features contributing to carbon classification, as illustrated in Fig. 3.

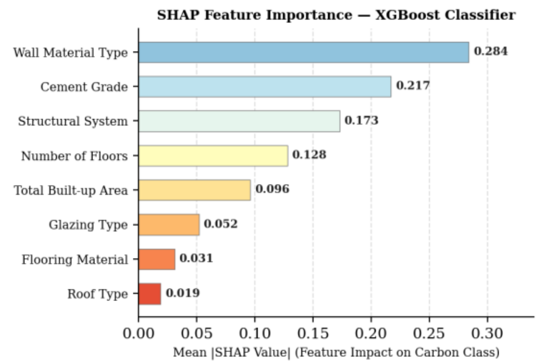

Fig. 3. *SHAP feature importance — Mean absolute SHAP values for XGBoost classifier*.

- Wall Material Type emerged as the most critical factor, contributing approximately 28.4% to the prediction outcome. This highlights the significant difference in emissions between materials such as AAC blocks, fly ash bricks, and traditional clay bricks.
- Cement Grade accounted for 21.7%, with OPC 53 strongly associated with higher carbon emissions.
- Structural System contributed 17.3%, where conventional RCC systems tend to produce higher emissions compared to alternatives with recycled components.
- Number of Floors and Total Built-up Area also influenced predictions, contributing 12.8% and 9.6%, respectively.

These findings confirm that both material selection and building scale play a key role in determining overall carbon impact, aligning with conclusions from previous studies [13], [9]

Baseline Comparison

Random Forest achieved 91.7% accuracy (F1 = 0.917). The Random Forest model achieved an accuracy of **91.7%**, demonstrating strong performance but slightly below XGBoost. The Decision Tree model achieved **86.3%**, offering better interpretability but lower predictive power.

Logistic Regression showed the weakest performance, with an accuracy of **78.1%**. This indicates that linear models are not well-suited for this problem, as the relationship between construction parameters and carbon emissions is inherently nonlinear.

These observations are consistent with prior research, which shows that ensemble models generally outperform simpler models in complex prediction tasks [14].

Dashboard Carbon Savings

The Power BI dashboard was used to evaluate the real-world impact of different material choices. For a typical residential building in Pune (10 floors and 8,000 m² area), the following improvements were observed:

- Replacing OPC 53 cement with PPC resulted in a reduction of approximately 18.3 tonnes of CO_2 emissions.
- Substituting red clay bricks with AAC blocks contributed an additional reduction of 24.7 tonnes.

Together, these changes resulted in a total reduction of around 43 tonnes of CO_2 per project. This is equivalent to the carbon absorption capacity of over 2,000 mature trees in one year, demonstrating the practical significance of sustainable material selection.

City-Scale Impact

When these improvements are scaled across the city, the environmental benefits become even more significant. Based on an estimated 340 large residential projects approved annually in Pune:

- Total potential reduction: approximately 14,620 tonnes of CO_2 per year

This highlights the potential of adopting data-driven approaches in construction to support broader sustainability goals. Such reductions contribute directly to regional environmental targets and align with India's long-term commitment to achieving carbon neutrality under international climate agreements.

Conclusion

This study presented a practical machine learning–based framework for guiding low-carbon material selection in large residential construction projects, with a specific focus on the Pune region. By combining predictive modeling with explainable AI techniques, the proposed system not only classifies material combinations based on their carbon impact but also provides clear insights into the key factors influencing these predictions. Among the evaluated models, XGBoost demonstrated the highest accuracy and balanced performance, while SHAP analysis highlighted the dominant role of wall materials, cement type, and structural systems in determining embodied carbon levels. The integration of results into an interactive Power BI dashboard further enhances usability, enabling architects, engineers, and project planners to make informed decisions during the early design stage. The findings also show that adopting alternative materials such as PPC cement and AAC blocks can significantly reduce carbon emissions at both project and city scales. Overall, this work bridges the gap between theoretical sustainability research and real-world construction practices by offering a data-driven, accessible solution. Future improvements can include expanding the dataset to cover different building types, incorporating transportation and lifecycle emissions, and integrating the framework with BIM tools for automated and real-time decision support.

References

1. Al-Sakkaf et al., "AI-assisted sustainability assessment of building materials and its application in green architectural design," J. Industrial Engineering and Applied Science, vol. 3, no. 4, 2025.
2. Anonymous, "Artificial intelligence for sustainable building materials," Int. J. Computer Science and Information Technology, 2025. [Online]. Available: https://wepub.org/index.php/IJCSIT/article/view/5364
3. M. Adamczyk et al., "The potential of using artificial intelligence to analyse the impact of construction industry on the carbon footprint," Mobile Networks and Applications, Springer, 2024. doi: 10.1007/s11036-024-02368-y
4. W. Liu et al., "How AI shapes the future landscape of sustainable building design with climate change challenges," PMC, 2026. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC12955912/
5. X. Wang et al., "Artificial intelligence for calculating and predicting building carbon emissions: a review," Environmental Chemistry Letters, Springer, 2025. doi: 10.1007/s10311-024-01799-z
6. J. Zhang et al., "Considering critical building materials for embodied carbon emissions in buildings: a machine learning-based prediction model and tool," Sustainable Production and Consumption, vol. 37, pp. 142-155, 2024.
7. H. Yin et al., "Predictive models of embodied carbon emissions in building design phases: machine learning approaches based on residential buildings in China," Building and Environment, 2024.
8. R. Achraf et al., "Progressive prediction of embodied carbon emissions across stages of schematic design with machine learning," J. Cleaner Production, vol. 517, Art. 145854, 2025.
9. H. El Hafdaoui, A. Khallaayoun, I. Bouarfa, and K. Ouazzani, "Machine learning for embodied carbon life cycle assessment of buildings," J. Umm Al-Qura University for Engineering and Architecture, vol. 14, pp. 188-200, 2023. doi: 10.1007/s43995-023-00028-y
10. R. Achraf et al., "Embodied greenhouse gas emissions of buildings: machine learning approach for early stage prediction," Building and Environment, 2024.
11. H. Pan and C. Wu, "Bayesian optimization + XGBoost based life cycle carbon emission prediction for residential buildings," Building Simulation, vol. 16, pp. 1451-1466, 2023. doi: 10.1007/s12273-023-1024-2
12. F. Dhghn et al., "Evaluating machine learning models for sustainable building design: energy, emissions, and comfort metrics," Building and Environment, 2025.
13. L. Chen et al., "An explainable machine learning framework for multi-objective carbon reduction targeting material operational seasonal emissions in building retrofits," Scientific Reports, 2025. doi: 10.1038/s41598-025-29418-z
14. S. Mahjoubi et al., "Review of AI-assisted design of low-carbon cost-effective concrete toward carbon neutrality," Artificial Intelligence Review, Springer, 2025. doi: 10.1007/s10462-025-11182-1
15. J. Orr et al., "Talking carbon: a lexical approach to predictive embodied carbon analysis via machine learning," Architectural Engineering and Design Management, 2026. doi: 10.1080/17452007.2026.2613773
16. M. Nur-E-Alam et al., "Integrating machine and deep learning technologies in green buildings for enhanced energy efficiency and environmental sustainability," Scientific Reports, 2024. doi: 10.1038/s41598-024-70519-y

17. A. Ullah et al., "Active learning-based machine learning approach for enhancing environmental sustainability in green building energy consumption," Scientific Reports, 2024. doi: 10.1038/s41598-024-70729-4
18. C. Herrmann et al., "Machine learning in life cycle assessment and low carbon material discovery: challenges and pathways forward for the construction industry," Resources, Conservation and Recycling, 2025.
19. R. Ahmed et al., "Machine learning applications for carbon emission estimation," Cleaner Environmental Systems, 2025.
20. Debrah, A. P. Chan, and A. Darko, "Artificial intelligence in green building," Automation in Construction, vol. 137, Art. 104192, 2022.