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Ensemble Learning Models for Energy Efficiency Prediction in Smart Sustainable Systems

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Abstract

The growing demand for energy-efficient buildings requires accurate predictive models to support sustainable development. However, conventional prediction approaches often struggle to capture the complex nonlinear relationships between building design characteristics and energy consumption, limiting prediction accuracy for practical building energy management. Therefore, developing more reliable predictive models has become an important challenge in supporting data-driven energy management. This study implemented and evaluated machine learning models, specifically ensemble learning methods, to predict building energy efficiency based on building design parameters. The study aimed to compare the predictive performance of conventional regression and ensemble learning models for estimating heating and cooling loads while identifying the most influential building design parameters affecting energy efficiency. The proposed methodology consisted of data preprocessing, model development using Linear Regression, Random Forest, and Gradient Boosting, followed by performance evaluation using Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2). The results indicate that the ensemble learning models substantially outperform Linear Regression in predicting both heating and cooling loads. Random Forest achieved the best performance for heating load prediction, while Gradient Boosting performed best for cooling load prediction. Feature importance analysis showed that geometric parameters, including relative compactness, overall height, and surface area, had the greatest influence on energy efficiency. These findings demonstrate that ensemble learning not only improves prediction accuracy but also enhances model interpretability through feature importance analysis, providing valuable support for data-driven decision-making in smart and sustainable building systems.

Keywords: *Ensemble Learning, Energy Efficiency, Machine Learning, Building Design, Prediction*

1. Introduction

The increasing demand for energy-efficient buildings has become an important issue in the development of sustainable systems. The building sector contributes a significant portion of global energy consumption; therefore, optimizing energy efficiency is a strategic step in supporting sustainable development and reducing carbon emissions [1,2]. Consequently, innovative approaches based on artificial intelligence and data analytics are increasingly required to improve energy efficiency in buildings. In addition to reducing operational costs, improving building energy efficiency has become a strategic priority in achieving global sustainability targets, including the Sustainable Development Goals (SDGs) and international commitments to carbon emission reduction. Buildings account for a substantial proportion of worldwide electricity consumption and greenhouse gas emissions; therefore, optimizing energy performance during the design stage can generate long-term environmental, economic, and social benefits. As digital technologies continue to evolve, integrating artificial intelligence into building design has become an increasingly promising approach for supporting intelligent and sustainable energy management.

The advancement of Artificial Intelligence (AI) and Machine Learning (ML) has made significant contributions to predictive modeling in energy systems. Machine learning techniques are capable of identifying complex patterns from data and generating accurate predictions of building energy consumption based on design parameters [3], [4]. Previous studies have applied regression methods and single machine learning algorithms to predict heating load and cooling load [5]. However, these approaches still have limitations in handling non-linear relationships and have not yet achieved optimal levels of accuracy [6,7].

As a solution, ensemble learning methods such as Random Forest and Gradient Boosting have been widely used to improve prediction performance through the combination of multiple models [8,9]. Recent studies have shown that ensemble learning approaches can produce more accurate and robust predictions compared to single models in the context of building energy prediction [10-12]. In addition, data-driven approaches are increasingly important in supporting efficient energy management in smart building systems [13,14].

Although previous studies have reported promising predictive performance using machine learning algorithms, several important challenges remain. Many studies primarily emphasize prediction accuracy while providing limited discussion regarding model interpretability and practical applicability in supporting building design decisions. In addition, comparative evaluations are often restricted to a small number of algorithms or focus exclusively on predictive performance without identifying which building design parameters contribute most significantly to energy efficiency. As a result, further investigation is required to improve the interpretability and practical applicability of machine learning models for building energy prediction.

Nevertheless, most previous studies have primarily focused on improving model accuracy without directly linking it to implementation within sustainable systems. Comparative studies generally emphasize model performance without exploring their contributions to data-driven decision-making [15,16]. Furthermore, the integration between predictive models and decision support systems in the context of energy efficiency remains insufficiently explored [17]. Recent research also indicates that the development of intelligent energy systems requires the integration of predictive models, data analytics, and digital technologies to support more effective and sustainable decision-making [18,19]. Therefore, an approach is needed that not only focuses on prediction accuracy but also on the relevance and applicability of models in supporting data-driven intelligent systems.

Addressing these research gaps, this study proposes a comprehensive evaluation of ensemble learning models for predicting building energy efficiency within the context of smart sustainable systems. This approach integrates multiple ensemble learning models to generate more robust predictions while providing a foundation for data-driven decision-making in the design of energy-efficient buildings. Thus, this study contributes not only through a comparative evaluation of ensemble learning models but also by providing practical insights for the development of intelligent sustainable systems.

Specifically, unlike previous studies that primarily compare prediction accuracy, this study extends previous work by integrating predictive performance evaluation with feature importance analysis to improve model interpretability. This integrated approach enables not only accurate estimation of heating and cooling loads but also a better understanding of how individual building design parameters influence energy efficiency. Consequently, the proposed framework provides practical insights that can support architects, engineers, and policymakers in making more informed and evidence-based decisions during the early stages of sustainable building design and energy planning.

Based on the identified research gaps, this study aims to implement and evaluate ensemble learning models for predicting building energy efficiency using building design parameters. The predictive performance of Linear Regression, Random Forest, and Gradient Boosting is compared using a benchmark energy efficiency dataset. Model performance is evaluated through MAE, MSE, and R^2 metrics, while feature importance analysis is conducted to improve model interpretability and identify the most influential design parameters affecting heating and cooling loads. The findings are expected to provide practical recommendations for researchers, architects, and engineers in developing intelligent decision-support systems for sustainable building design.

2. Research Methods

This study employs a machine learning-based approach to predict building energy efficiency, specifically heating load and cooling load, based on building design parameters. The research framework is carried out systematically through five main stages, as illustrated in Figure 1: dataset acquisition, data preprocessing, model development, model evaluation, and feature importance analysis. This sequential workflow ensures systematic implementation and objective comparison of the evaluated machine learning models.

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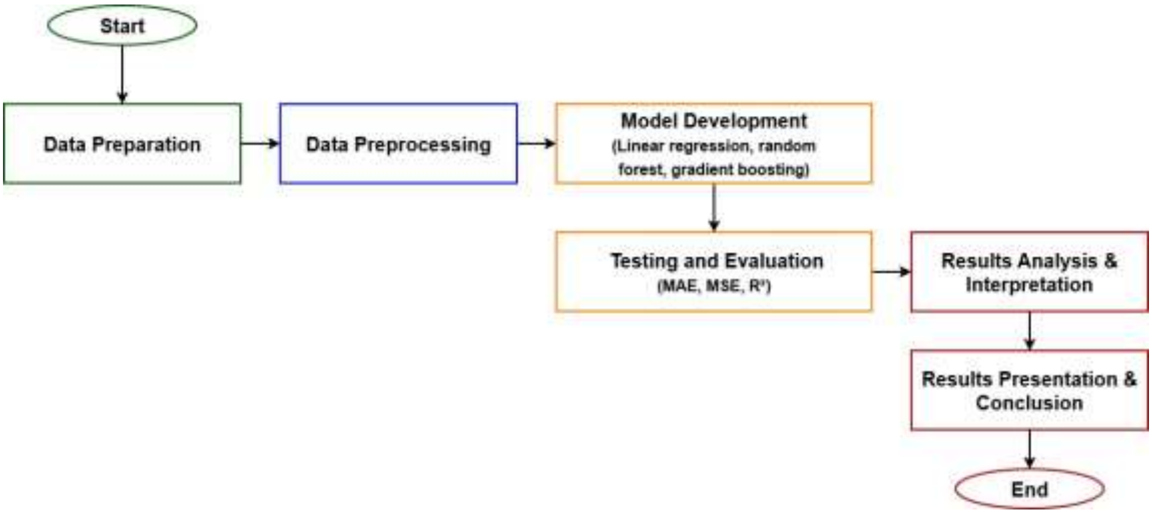

Figure 1. Research Workflow

The dataset used in this study was obtained from the Kaggle platform, namely the Energy Efficiency Dataset developed by Ahiale Darlington. This dataset consists of 768 samples with 10 variables, including eight input features and two target variables. The input variables represent building design characteristics such as relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution. Meanwhile, the target variables, heating load and cooling load, are used as indicators of building energy efficiency. The selection of these variables is based on previous studies indicating that building design parameters have a significant impact on energy consumption [5,10]. The selected dataset has been widely used as a benchmark for evaluating machine learning algorithms in building energy prediction studies, enabling fair comparisons with previous studies.

In the data preprocessing stage, the dataset is examined to identify any missing values or inconsistencies. The results show that there are no missing values, allowing the dataset to be directly used for modeling. The data is then separated into input features and target variables, followed by splitting into training and testing datasets with a ratio of 80:20. To improve model performance, feature scaling using StandardScaler is applied specifically to the Linear Regression model, while tree-based models such as Random Forest and Gradient Boosting do not require scaling.

In this study, three regression models are employed: Linear Regression as the baseline model, and two ensemble learning models, namely Random Forest and Gradient Boosting. Linear Regression was selected as a baseline model due to its simplicity and widespread use in regression problems. Random Forest was chosen because of its robustness against overfitting and its capability to capture nonlinear relationships through a bagging approach [8], while Gradient Boosting was included owing to its ability to iteratively minimize prediction errors through a boosting mechanism [9] and achieve high predictive performance in complex datasets. The Random Forest model is configured with 100 decision trees (n_estimators = 100), while the Gradient Boosting model is configured with n_estimators = 100 estimators and max_depth = 3. The selection of these models aims to compare the performance between linear and ensemble models in handling nonlinear relationships in the data. Each model is trained using the training dataset and evaluated using unseen testing data. The modeling process is conducted separately for heating load and cooling load predictions to obtain more accurate evaluation results for each target.

Model performance is evaluated using three complementary metrics, namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2), to provide a comprehensive assessment of predictive performance. MAE measures the average magnitude of prediction errors, MSE emphasizes larger errors through squared differences, and R^2 evaluates the proportion of variance explained by the model. These metrics are widely used in energy prediction studies to measure prediction errors and the model's ability to explain data variance [12,13]. The Mean Absolute Error is defined as shown in equation (1).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (1)$$

The Mean Squared Error is defined as shown in equation (2).

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

Meanwhile, the coefficient of determination is formulated as shown in equation (3).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (3)$$

where y_i represents the actual value, $\hat{y}_i$ represents the predicted value, $\bar{y}$ denotes the mean of the actual values, and n is the number of testing samples. The model exhibiting the lowest prediction error and the highest coefficient of determination is considered the best-performing model.

To enhance result interpretation, visualization techniques are applied, including bar charts comparing R^2 values across models and scatter plots showing the relationship between actual and predicted values. Feature importance analysis is performed using the Random Forest and Gradient Boosting models to identify the most influential building design parameters affecting heating load and cooling load prediction. This analysis enhances model interpretability by explaining the contribution of each feature beyond predictive accuracy and provides practical insights for building design optimization.

All experiments were implemented in the Python programming language using the Scikit-learn library. Data preprocessing and analysis were performed with the Pandas and NumPy libraries, whereas data visualization was carried out using Matplotlib.

Through this methodology, the proposed framework enables a comprehensive evaluation of prediction performance while providing insights into the contribution of individual building design features, thereby supporting data-driven decision-making in smart and sustainable building systems.

3. Results and Discussions

The performance evaluation of the proposed models was conducted by comparing three regression algorithms, namely Linear Regression, Random Forest Regressor, and Gradient Boosting Regressor. The evaluation was carried out using Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2) as described in the methodology. The results of model evaluation for both heating load and cooling load predictions are presented in Table 1.

Table 1. Model Performance Evaluation Results

Model	Target	MAE	MSE	R^2
Linear Regression	Heating Load	2.182047	9.153188	0.912184
Random Forest	Heating Load	0.354648	0.240882	0.997689
Gradient Boosting	Heating Load	0.386159	0.265312	0.997455
Linear Regression	Cooling Load	2.195295	9.893428	0.893226
Random Forest	Cooling Load	1.060435	2.934096	0.968334
Gradient Boosting	Cooling Load	1.055409	2.289829	0.975287

As shown in Table 1, the prediction performance varies considerably across the evaluated models. Overall, the ensemble learning models outperform the conventional Linear Regression model in predicting both heating load and cooling load. Specifically, the Linear Regression model consistently produces higher error values and lower R^2 scores compared to the ensemble learning models. These results indicate that the relationship between building design parameters and energy efficiency is inherently nonlinear. Consequently, ensemble learning methods are better suited for capturing complex interactions among building design variables than conventional linear regression models. This finding supports previous studies reporting the superior capability of ensemble learning techniques for building energy prediction [10-12].

In contrast, ensemble learning models demonstrate significantly better performance. The Random Forest model achieves lower error values and higher R^2 scores than Linear Regression, indicating its ability to model nonlinear relationships and interactions among features through a bagging-based approach. This finding aligns with previous studies highlighting the effectiveness of tree-based ensemble methods in handling complex datasets and improving prediction accuracy for building energy prediction [9,12].

Among all models, the best performance varies depending on the prediction target. For heating load prediction, the Random Forest model achieves the best performance, as indicated by the lowest MAE and MSE values and the highest R^2 score. This suggests that the bagging mechanism in Random Forest is highly effective in capturing complex relationships within the dataset.

For cooling load prediction, the Gradient Boosting Regressor demonstrates the best performance, producing the lowest MAE and MSE values along with the highest R^2 score. This indicates that the boosting approach is more effective in minimizing prediction errors for this target variable. The different performance observed between heating load and cooling load prediction suggests that each target variable exhibits distinct data characteristics. Random Forest appears more effective in capturing stable nonlinear relationships associated with heating load, whereas Gradient Boosting provides greater flexibility in minimizing residual errors for cooling load prediction through its sequential boosting strategy.

The superior performance of Gradient Boosting in cooling load prediction may be attributed to its iterative learning mechanism, where each subsequent model corrects the errors of the previous one. This boosting process enables the model to progressively improve prediction accuracy, making it highly suitable for datasets with nonlinear relationships such as building energy efficiency data.

To further analyze model performance, comparisons between the actual and predicted values generated by the best-performing models are presented in Figures 2 and 3. Figure 2 illustrates the Random Forest model for heating load prediction, whereas Figure 3 presents the Gradient Boosting model for cooling load prediction.

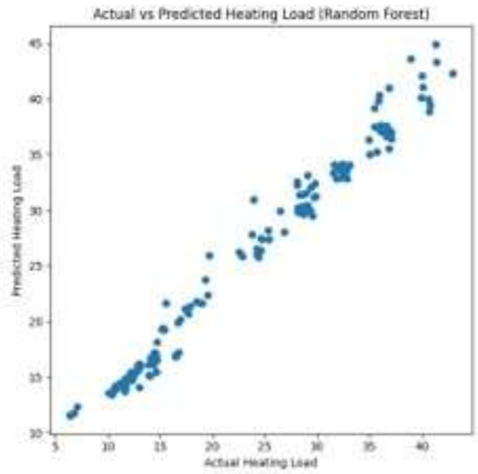

Figure 2. Actual vs Predicted Values for Heating Load using the Random Forest Model

Figure 2 compares the actual and predicted heating load values generated by the Random Forest model. Most prediction points are closely distributed along the diagonal line, indicating strong agreement between the predicted and actual values. This result demonstrates that the Random Forest model effectively captures the nonlinear relationship between building design parameters and heating load. Although slight deviations are observed at higher heating load values, the prediction errors remain relatively small, confirming the robustness and reliability of the model.

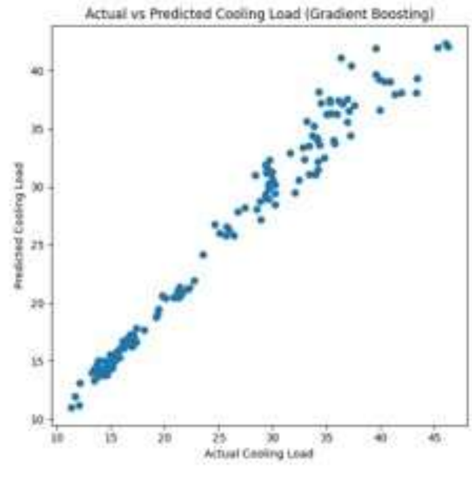

Figure 3. Actual vs Predicted Values for Cooling Load using the Gradient Boosting Model

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Figure 3 presents the comparison between the actual and predicted cooling load values obtained from the Gradient Boosting model. Similar to the heating load prediction, the predicted values closely follow the diagonal trend, indicating high prediction accuracy and good generalization capability. Minor deviations are visible for several extreme observations; however, the overall prediction performance remains highly consistent, confirming the effectiveness of the Gradient Boosting model in estimating cooling load.

Overall, the scatter plots demonstrate that both ensemble learning models generate predictions that closely match the observed values, confirming their strong predictive capability and generalization performance. The Random Forest model exhibits superior performance for heating load prediction, whereas Gradient Boosting provides the highest accuracy for cooling load prediction. These visual observations are consistent with the quantitative evaluation presented in Table 1 and further confirm the capability of ensemble learning methods to effectively model the nonlinear relationships between building design parameters and building energy efficiency.

In addition to prediction accuracy, feature importance analysis was conducted using the Random Forest and Gradient Boosting models to identify the most influential variables affecting building energy efficiency. The results are presented in Figure 4.

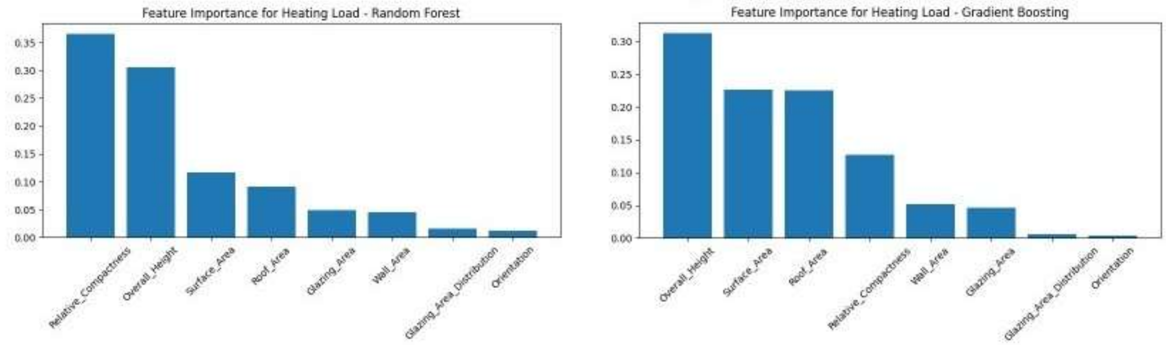

Figure 4. Feature Importance for Heating Load Prediction

Figure 4 illustrates the feature importance for heating load prediction obtained from the Random Forest and Gradient Boosting models. Although the feature rankings differ slightly between the two ensemble models, both consistently identify building geometry as the primary determinant of heating load prediction. In the Random Forest model, relative compactness is the most influential feature, followed by overall height, surface area, and roof area. In contrast, the Gradient Boosting model assigns the highest importance to overall height, followed by surface area, roof area, and relative compactness. Meanwhile, glazing area distribution and orientation contribute relatively little to the prediction performance.

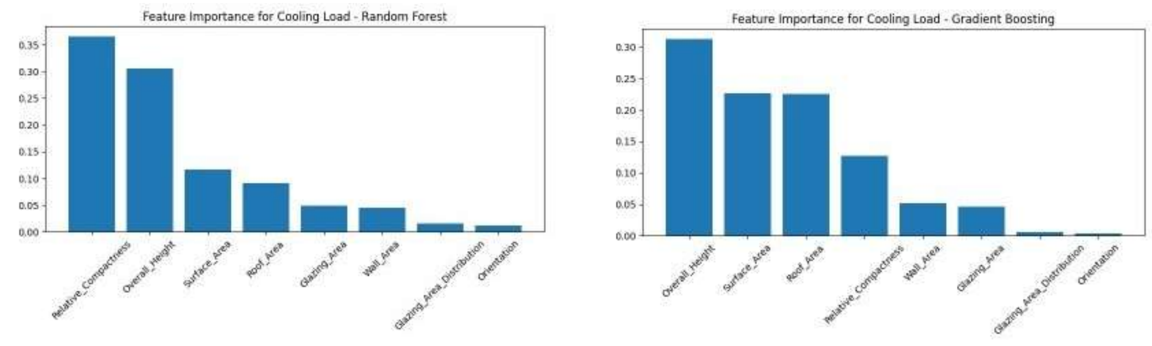

Figure 5. Feature Importance for Cooling Load Prediction

Figure 5 presents the feature importance for cooling load prediction obtained from the Random Forest and Gradient Boosting models. Consistent with the heating load results, both models identify building geometry as the dominant factor affecting cooling load prediction. Relative compactness is the most influential feature in the Random Forest model, whereas overall height has the highest importance in the Gradient Boosting model. Surface area and roof area also make substantial contributions, while glazing area distribution and orientation remain the least influential variables.

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Although the feature importance rankings vary across the evaluated ensemble learning models, both Random Forest and Gradient Boosting consistently emphasize the importance of building geometry in predicting energy efficiency. These differences indicate that each ensemble learning approach captures feature interactions differently while producing consistent conclusions regarding the dominant influence of structural building characteristics.

Surface area and roof area also contribute significantly, as they directly influence heat transfer and thermal exposure of the building. These findings highlight the importance of structural and geometric characteristics in energy performance prediction and are consistent with previous studies reporting that building geometry is one of the primary determinants of building thermal performance and energy consumption [5,12].

In contrast, glazing area, glazing area distribution, and orientation exhibit relatively low importance values in both prediction tasks. Although these variables influence building energy performance, their contributions are considerably smaller than those of the primary geometric characteristics.

Overall, the results demonstrate that building energy efficiency is primarily influenced by a combination of geometric and structural characteristics. Feature importance analysis provides valuable insights into the contribution of individual design parameters beyond prediction accuracy, thereby enhancing model interpretability and supporting more reliable energy prediction.

From a broader perspective, the findings suggest that ensemble learning approaches, particularly Random Forest and Gradient Boosting, are more effective than conventional linear regression models for predicting building energy efficiency. This observation supports the argument presented in the Introduction that nonlinear relationships within building energy systems require more advanced machine learning techniques.

From a practical perspective, the proposed ensemble learning framework can assist architects, engineers, and building designers in evaluating potential building energy performance during the early design stage. By accurately predicting heating and cooling loads while identifying the most influential design parameters, decision-makers can optimize building geometry before construction, thereby reducing future energy consumption and supporting sustainable building development.

These findings address the research gaps identified in the Introduction by demonstrating that ensemble learning models not only improve prediction accuracy but also enhance model interpretability through feature importance analysis. Consequently, the proposed framework provides practical support for data-driven decision-making in smart sustainable building systems.

Overall, integrating ensemble learning with feature importance analysis provides an accurate, interpretable, and practical framework for predicting building energy efficiency. Beyond improving predictive performance, the proposed framework enhances model interpretability and supports intelligent decision-making for the development of smart and sustainable building systems.

4. Conclusion

This study successfully implemented and evaluated machine learning models to predict building energy efficiency, specifically heating load and cooling load, using building design parameters. The results show that ensemble learning models, namely Random Forest and Gradient Boosting, significantly outperform Linear Regression, confirming their ability to capture nonlinear relationships in the data. The best-performing model varies depending on the prediction target, with Random Forest providing the highest accuracy for heating load prediction and Gradient Boosting achieving superior performance for cooling load prediction. Feature importance analysis further reveals that building geometry parameters, particularly relative compactness, overall height, and surface area, play a dominant role in determining energy efficiency. These findings highlight the effectiveness of ensemble learning not only in improving prediction accuracy but also in providing interpretable insights that support data-driven decision-making in smart sustainable building systems. From a scientific perspective, this study contributes to the growing body of research on explainable artificial intelligence for building energy prediction by demonstrating that ensemble learning can simultaneously achieve high predictive accuracy and meaningful model interpretability. Beyond achieving high predictive performance, this study demonstrates the practical potential of integrating explainable ensemble learning models into smart sustainable systems. By combining accurate prediction with interpretable feature importance analysis, the proposed framework enables architects, engineers, and decision-makers to identify the building design parameters that most significantly influence energy efficiency during the early design stage. This capability supports more informed planning strategies, contributes to reducing future energy consumption, and promotes the development of intelligent and sustainable building management systems. Despite these promising results, this study is limited to a benchmark building energy efficiency dataset. Future

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research may evaluate the proposed framework using real-world building datasets, incorporate additional environmental and operational variables, and investigate advanced explainable artificial intelligence techniques to further enhance model robustness and practical applicability in smart sustainable building systems.

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