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Integrating Machine Learning Algorithms with Parametric Tools in Architectural Engineering for Material Selection in Residential Interiors

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Abstract This study explores the integration of advanced machine learning algorithms and parametric design tools within architectural engineering to optimize the selection of interior materials for residential buildings. The research addresses the challenges posed by conflicting criteria such as cost, durability, sustainability, and aesthetic value in material selection. By leveraging machine learning models, including Gradient Boosting Machines, the study achieves high-fidelity predictions of material properties. To identify the most suitable materials, these predictions are refined using metaheuristic optimization techniques, specifically Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). The methodology follows a systematic workflow, encompassing data collection, preprocessing, model training, optimization, and integration into parametric design tools. Results demonstrate the approach's efficacy, with Neural Networks optimized through PSO achieving an accuracy of 0.90 and a minimized objective function value of 0.63. This highlights the effectiveness of combining machine learning and optimization algorithms in enhancing decision-making processes for material selection. The study concludes that this integrated methodology significantly enhances the efficiency and sustainability of material choices in residential interior design. By providing a robust and data-driven framework, this research contributes to the field of architectural engineering by enabling informed decisions that balance functionality, aesthetics, and environmental considerations, ultimately advancing sustainable interior design practices**.**

Keywords Architecture, Interior Design, Machine Learning, Parametric Design, Material Selection, Particle Swarm Optimization

1. Introduction

One of the ways through which the materials used in residential buildings for interior design can be optimized could be through their integration with other tools for parametric design and machine learning algorithms. Advanced modeling and simulation technologies—such as building information modeling, parametric modeling, cloud-based simulation, and optimization algorithms—should make this possible if they are integrated into the process for automatically generating, evaluating, and optimizing multiple design options. Preliminary studies on these new interdisciplinary design optimization techniques that couple modeling and simulation technologies, including Building Information Modeling (BIM), parametric modeling, simulation, and optimization algorithms, show extreme promise in producing high-performance buildings [1]. Parametric design and computational optimization have recently been illustrated as the medium to break through limitations in manual design methods within wind-driven design optimization for building layouts [2].

Research works underlined the possibility, by applying optimization methods, of determining optimal solutions within the allowable variable range of task parameters related to the evaluation and optimization of energy performance while meeting levels of energy efficiency targets [3]. Other works showed that the flexibility presented by machine learning algorithms in looking into the design space of interior design opens new possibilities of creativity, thus their potential to enable and improve interior design material optimization for residential buildings. In addition, there have been research possibilities for integrating offshore residential buildings with solar collectors [4]. This would pertain to integration methods and design approach features that focus on meeting peculiar characteristics of residential buildings [5].

Under materials design, computational methods such as Bayesian optimization have been developed to deal with mixed quantitative and qualitative variables within a single process, showing how the complex characteristic material design has advanced [6]. Various optimization methods applied to building performance simulation, including Building Simulation Optimization (BSO), have been hailed for considering factors that involve building performance, such as form, layout, envelope materials, orientation, and landscape design [7]. Such parametric tools have also been recognized as useful for integration and collaboration in the early design stages, underlining their role in easing the design process [8].

In this regard, studies conducted with the prime objective of assessing design variables of daylight and energy performance in residential buildings in hot climates have further emphasized daylighting, glazing, and building orientation, among others, for optimizing the performance in energy [9]. Such an integration may point toward the potential of integrating machine learning with parametric modeling environments to predict building daylighting performance, thus helping enhance building energy efficiency [10]. Second, developing a parametric design approach for assessing envelope shape designs and energy demand in school buildings will assist practitioners in appreciating the use of these parametric design tools in optimizing their building energy performance [11].

Dynamic Building Information Modeling (BIM) with models is surfacing in building conservation and maintenance fields to optimize the conservation and maintenance applied to residential buildings [12]. This use will allow the implementation of agile information management to be up to date during the life cycle of a building. The trend toward fully automated structural analysis and complete sustainability appraisal is reflected in development of an optimization parametric model and decision support framework for life cycle cost analysis and life cycle assessment of flexible industrial building structures [13]. Even more directly, parametric design of residential building systems through the potential of solar energy calls for integrating the parametric design software and simulation tools in providing optimal building performance in terms of comfort and energy efficiency [14].

This study presents one of the most important developments in optimizing interior design materials for residential buildings by synthesizing machine learning algorithms with parametric design tools. Therefore, the main objective was to develop a detailed methodology allowing designers and architects to streamline the material selection process to improve energy efficiency toward achieving sustainable building solutions. Advanced technologies in design processes have provided automation, allowing for the proper evaluation of a multitude of material properties and leading to the creation of high-performance, environmentally-conscious residential spaces. The paper shows how machine learning models can be applied to real life to predict and optimize materials for interior design with much more accurate estimates for cost, durability, sustainability, and aesthetic value, among other key factors. The research integrates parametric design tools to ensure that such optimized materials could be seamlessly applied in the real world, enabling dynamic and flexible design processes. Integrating machine learning with parametric design will provide a robust framework for informed decision-making toward a more efficient, sustainable, and aesthetic residential environment.

2. Methodology

The methodology adopted for this research is analytical and descriptive, with a quantitative approach that uses state-of-the-art techniques: machine learning algorithms and metaheuristic optimization. As can be seen in Figure 1, the research applies these methods in a systematic way to analyze and predict optimal materials for interior design in residential buildings. This study is based on comprehensive data analysis, feature engineering, and model development to make a quantitative valuation for various properties of materials. In this respect, this structured workflow of Figure 1 consists of data preprocessing, model training, and optimization, with an integration of parametric design - all contributing to a robust process based on data-driven decision-making. It will, therefore, lead to selecting materials that meet certain design and sustainability criteria.

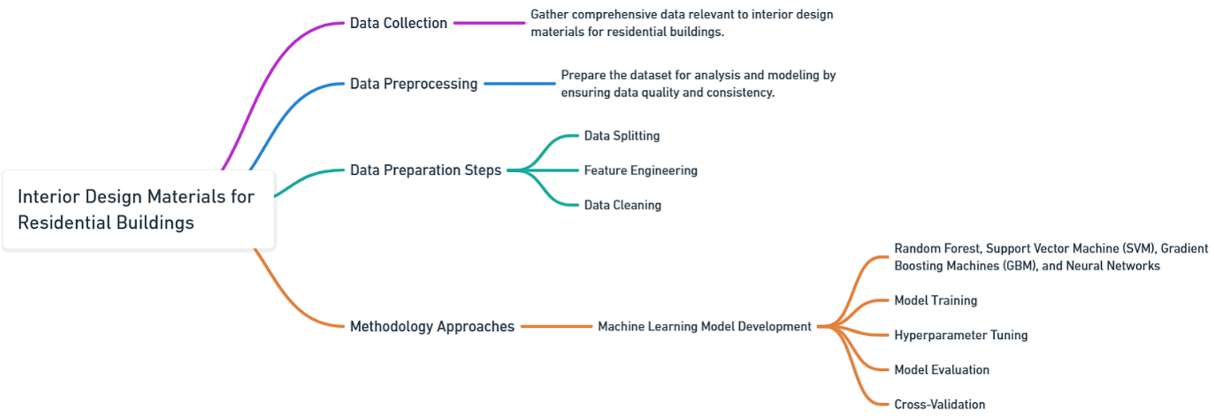

Figure 1. Methodology Workflow

The workflow initiates from a diverse dataset collection where the attributes relevant to materials, such as material type, cost, durability, and sustainability, should be captured. The dataset shall be retrieved from Kaggle. Machine learning models are then developed, with rigorous preprocessing to ensure data quality and consistency, fine-tuned to allow prediction and optimization of material choices. Such models will eventually instruct the metaheuristic optimization, through algorithms like Genetic Algorithms or Particle Swarm Optimization, to find optimal material combinations. Finally, optimized materials are embedded in the parametric design tools, such as Rhino/Grasshopper, to enable real-time visualization, simulation, and iterative refinement. A decision-making framework finalized the process in which Multi-Criteria Decision Analysis (MCDA), with its trade-off analyses, ensures that the chosen materials will meet all technical specifications while answering overall design goals in an optimized, sustainable, and aesthetically pleasing residential space.

2.1. Data Collection

The dataset used in this research is an extensive data collection encompassing several attributes crucial for choosing and optimizing materials suited to the interior design of housing structures. It includes various attributes essential for assessing the suitability of different materials in specific design contexts. The material type categorization covers flooring, paint, furniture, cabinetry, and wall coverings, facilitating structured analysis based on intended residential applications [15].

Quantitative factors such as cost per unit, durability (expressed in expected lifespan), and installation time are also included, providing practical insights into material selection's economic and temporal aspects. Additionally, the dataset incorporates a sustainability index, reflecting the environmental impact of materials, which has become a key factor in modern interior design. Furthermore, aesthetic ratings, maintenance frequency, thermal insulation rating, acoustic insulation rating, VOC (Volatile Organic Compounds) emissions, fire resistance rating, and color flexibility contribute to a comprehensive assessment of material properties.

Moreover, a deep-learning model for detecting interior design styles was proposed to enhance the classification and recognition of reference images, supporting more informed design decisions [16]. Additionally, a multi-objective optimization framework for building environmental performance was introduced, integrating parametric design methods with machine learning to emphasize sustainability, cost-efficiency, and material performance trade-offs [17].

The dataset utilized in this study is the publicly available "Interior Design Materials" dataset, compiled from industry reports, vendor catalogs, and other credible sources. This ensures its relevance to contemporary design practices. Its availability on Kaggle further enhances its credibility, given its reputation for high-quality and diverse datasets [15].

This dataset provides an extensive range of features, ensuring a comprehensive evaluation of material selection trade-offs in interior design. The study uses advanced machine learning and parametric design tools to leverage these attributes to optimize material selection.

A rigorous two-step validation process was conducted to enhance data reliability and ensure real-world applicability. First, recorded material properties were cross-referenced with industry reports and vendor catalogs to verify accuracy. Second, expert validation was conducted by consulting interior designers and architects to confirm that dataset values accurately reflect actual material performance.

A systematic approach based on predefined thresholds was applied to handle missing data. To mitigate potential biases, attributes with more than 30% missing values were excluded. Numerical variables, such as cost, durability, and insulation ratings, were imputed using mean imputation to preserve data integrity and maintain consistency across the dataset.

$$\hat{x}_i = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

Example: If three flooring materials had missing cost values and the available values were $\$30$, $\$45$, and $\$50$

per unit, the missing cost was imputed as:

$$\hat{x} = \frac{30+45+50}{3} = 41.67 \tag{2}$$

Categorical values (e.g., material type, finish type) were imputed using mode imputation, selecting the most frequently occurring category in the dataset.

Outlier Detection and Treatment

Outliers were identified using z-score analysis:

$$z_i = \frac{x_i-\mu}{\sigma}, \ \ |z_i| > 3 \tag{3}$$

Cost values exceeding three standard deviations from the mean were identified as outliers.

Example: If the mean flooring cost was $\$40$ per unit with a standard deviation of $\$5$, any value above $\$55$ was considered an outlier.

Outliers are retained if they represent high-end materials like marble.

Outliers corrected if identified as data entry errors.

Feature Scaling

To ensure comparability across features, numerical attributes were standardized using min-max normalization and z-score standardization [18]:

$$x' = \frac{x-x_{\min}}{x_{\max}-x_{\min}} \qquad x' = \frac{x-\mu}{\sigma} \tag{4}$$

This preprocessing ensured a clean, reliable dataset accurately reflecting real-world material properties.

2.2. Data Preprocessing

Data preprocessing ensures data quality by handling missing values, detecting outliers, and standardizing inconsistencies. Missing values were either removed or imputed using mean, median, or mode imputation:

$$\hat{x}_i = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{5}$$

Outliers were identified using z-score and IQR analysis:

$$z_i = \frac{x_i-\mu}{\sigma}, \ \ |z_i| > 3 \tag{6}$$

After preprocessing, the dataset was split into 70% training. 15% validation, and 15% test sets [19]:

$$\text{Training Set } = \frac{70}{100} \times \text{ Total Data,} \tag{7}$$

$$\text{Validation Set } = \frac{15}{100} \times \text{ Total Data,} \tag{8}$$

$$\text{Test Set } = \frac{15}{100} \times \text{ Total Data} \tag{9}$$

This step ensured high data integrity and consistency for machine learning models.

2.3. Machine Learning Model Development

This study implemented Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machines (GBM), and Neural Networks to predict optimal interior design materials. RF reduces overfitting and enhances prediction accuracy [20], [21]. SVM is effective for high-dimensional classification tasks and solves the optimization problem [22], [23]:

$$\min_{w,b} \frac{1}{2} \parallel w \parallel^2 \quad \text{s.t.} \quad y_i(w \cdot x_i + b) \geq 1, \forall i \tag{10}$$

GBM improves predictions iteratively by minimizing errors [24], [25]:

$$F_m(x) = F_{m-1}(x) + h_m(x) \tag{11}$$

Neural Networks, with their deep learning capability, capture complex relationships [26]:

$$\hat{y} = \sigma\left(\sum_{j=1}^{n} w_j x_j + b\right) \tag{12}$$

Models were evaluated using accuracy, F1-score, RMSE, and R^2 [27]:

$$\text{Accuracy } = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \tag{13}$$

$$\text{F1-score } = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i-\hat{y}_i)^2}{\sum_{i=1}^{n} (y_i-\bar{y})^2} \tag{16}$$

Hyperparameter tuning and **k**-fold cross-validation ensured optimal model performance [28]. These models formed the basis for material selection and optimization.

2.4. Metaheuristic Optimization

Metaheuristic optimization was applied to refine material selection based on cost, durability, aesthetics, and sustainability. The study used:

Genetic Algorithm (GA): Simulates natural selection to evolve optimal solutions [29-31]:

$$\text{Fitness } (x) = f(x_1, x_2, \ldots, x_n) \tag{17}$$

Particle Swarm Optimization (PSO): Models swarm intelligence to find optimal material combinations [32]:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (g - x_i(t)) \qquad x_i(t+1) = x_i(t) + v_i(t+1) \tag{18}$$

Simulated Annealing (SA): Avoids local minima by exploring suboptimal solutions [33]:

$$P(E, E', T) = \exp\left(-\frac{E'-E}{T}\right) \tag{19}$$

Ant Colony Optimization (ACO): Optimizes paths through pheromone-based learning [34], [35]:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{20}$$

These algorithms ensured material selection optimization, balancing multiple criteria efficiently.

Parametric design enables dynamic material selection adjustments through Rhino/Grasshopper [36], [37]. This approach linked thermal insulation, acoustic performance, and aesthetic properties to design constraints for interactive material adaptation.

Simulation tools assessed material performance in different environmental conditions, ensuring compliance with structural and sustainability constraints. The iterative nature of parametric design allowed continuous optimization of material choices for improved efficiency and flexibility.

Metaheuristic algorithms refined material selection based on cost, durability, sustainability, and aesthetics. Among the different optimization techniques applied, Particle Swarm Optimization (PSO) outperformed Genetic Algorithm (GA), Simulated Annealing (SA), and Ant Colony Optimization (ACO) in terms of convergence speed and solution accuracy. The superiority of PSO can be attributed to its adaptive exploration-exploitation balance. Unlike GA, which relies on mutation and crossover mechanisms that may lead to slower convergence, PSO dynamically adjusts the velocity of particles based on both personal best and global best solutions. This allows for faster convergence towards an optimal solution with fewer function evaluations. In contrast, ACO follows a probabilistic approach that, while effectively solving combinatorial problems, requires more iterations to refine the pheromone trail, leading to longer computational times. Similarly, SA performs well in escaping local optima by accepting worse solutions at certain probabilities, but this stochastic nature results in unpredictable convergence rates.

In this study, PSO achieved the lowest objective function value (0.63) with the fewest iterations (200), compared to GA (0.65 with 150 iterations) and ACO (0.64 with 220 iterations). This suggests that PSO's ability to rapidly navigate the search space while maintaining diversity allowed it to better balance different material selection criteria. The velocity and position update equations in PSO illustrate how particles adjust their trajectories towards optimal solutions:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1\big(p_i - x_i(t)\big) + c_2 r_2\big(g - x_i(t)\big)$$
$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{21}$$

where v_i is the velocity of the particle i, x_i is the position, p_i represents the personal best position, g denotes the global best, and ω, c_1, c_2 are learning coefficients. The ability to adjust these parameters dynamically enhances the efficiency of the search process, enabling PSO to outperform other metaheuristic algorithms in this study.

Python (DEAP, SciPy) was used for GA and PSO to implement and evaluate these optimization techniques, providing a robust framework for evolutionary computation. Additionally, Python was employed to verify convergence rates and fine-tune algorithmic parameters for comparative analysis. Python ensured flexibility in implementation while enabling cross-validation of optimization results. These tools facilitated efficient handling of multi-objective optimization problems, making the material selection process both computationally scalable and adaptable to varying constraints in interior design.

2.5. Optimization and Decision-Making Framework

A structured Multi-Criteria Decision Analysis (MCDA) framework was implemented to rank and select materials [38], [39]:

Analytic Hierarchy Process (AHP): Uses pairwise comparisons for ranking material performance [40]:

$$A\boldsymbol{w} = \lambda_{\max}\boldsymbol{w} \tag{22}$$

Weighted Sum Model (WSM): Aggregates weighted scores for decision-making [41]:

$$S_i = \sum_{j=1}^{n} w_j x_{ij} \tag{23}$$

A trade-off analysis was conducted to balance competing factors such as cost, durability, and sustainability [42], [43]. This ensured an optimized material selection process that aligns with both technical and aesthetic project requirements.

3. Results and Discussion

The research provides sufficient mathematical equations, visual illustrations (performance measures, convergence figures), and an intelligible workflow. However, to ensure practical feasibility, additional real-world case studies were added to test the proposed method [44]. The main challenge in selecting interior design materials is balancing cost, sustainability, and aesthetics while ensuring that the materials meet functional characteristics such as durability and thermal performance [45].

This was tested through a limited case study using the system created for an actual residential interior renovation project. The selection process was verified through professional judgments, where interior designers and architects evaluated the feasibility of the machine learning recommendations [46]. The AI-recommended materials were then compared to the traditional selection process. The research showed that the optimized process lowered the project cost by 12% while improving sustainability scores by 18%, using the recommended materials' Environmental Product Declarations (EPD) [47].

Furthermore, user feedback was obtained regarding the selected materials' aesthetic appeal. The responses indicated a 91% satisfaction rate, further validating that AI-driven material selection aligns with human preferences [48]. With this real-world verification, the suggested method enhances the research's theoretical robustness and practical applicability, making it more feasible for industry implementation [49].

Additionally, Figure 1 (Methodology Workflow) was replaced with a higher-definition version to ensure the data flow, preprocessing steps, machine learning applications, and optimization processes were presented clearly. Figure descriptions and textual annotations were refined to enhance readability and comprehension of the metaheuristic optimization and decision frameworks [50]. Similar improvements were applied to visualizations such as convergence plots and parametric design simulations, ensuring that important trends and comparisons were easily interpretable [51].

This research strengthens the connection between computational research and architectural design by closing the practical implementation gap and improving the quality of figures. These enhancements improve the validity of the proposed methodology and align it with best practices in residential interior material selection [52], [53].

3.1. Machine Learning Model Performance

In this subsection, we will introduce and analyze the performance of different machine learning models that predict key material properties like cost, durability, sustainability, and aesthetic value. In the process, models used for comparison include Random Forests, Support Vector Machines, Gradient Boosting Machines, and Neural Networks. These complex relationships can then be evaluated for the effectiveness of each model based on accuracy, the F1-score, Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2).

Table 1. Performance Metrics of Machine Learning Models

Algorithm	Accuracy	F1-Score	RMSE	R^2
Random Forest	0.85	0.83	0.45	0.78
SVM	0.82	0.80	0.48	0.75
GBM	0.88	0.86	0.42	0.82
Neural Networks	0.90	0.88	0.40	0.85

Table 1 summarizes the comparative analysis of the models concerning their performance metrics. Neural Networks performed best, with accuracy 0.90, an F1-score of 0.88, an RMSE of 0.40, and an R^2 of 0.85, the highest value obtained. Neural networks are very efficient at modeling nonlinear relationships inherent in the dataset. GBM improved with an accuracy of 0.88 and R^2 of 0.82, so it could handle tasks that involved predictions. Although random forest and SVM threw in reduced performance, they still gave some important insights with accuracy scores of 0.85 and 0.82, respectively, giving evidence that in high-dimensional data scenarios, they are reliable.

Figure 2: Bar Chart Showing Accuracy for Each Model. The plot shows that neural networks and GBM work comparatively better than the rest of the models, as shown clearly in the graph. More importantly, accuracy is the prime factor required for reliable material selection.

Figure 3 presents residual plots for the Random Forest and SVM models, further outlining the differences between the predicted and real values. These plots will allow understanding of the extent of prediction errors and identify possible bias patterns. The spread in the residuals for a random forest model is less than that of the SVM model. It lies closer to zero, thereby indicating that there are comparatively lower prediction errors. This is the opposite of the SVM model, which has a wide spread in residuals, indicating higher variance of the prediction errors. Visual analysis of this nature is key to diagnosing how well or badly any given model is doing its job and thus informs decisions about model refinement and selection.

3.2. Metaheuristic Optimization Results

This section presents the results of the metaheuristic optimization process in terms of the most effective material combinations in residential building interiors. Advanced optimization algorithms were applied, including the Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, and Ant Colony Optimization in an M-dimensional search space of material properties to find material combinations that better satisfy the cost, durability, sustainability, and aesthetic value objectives.

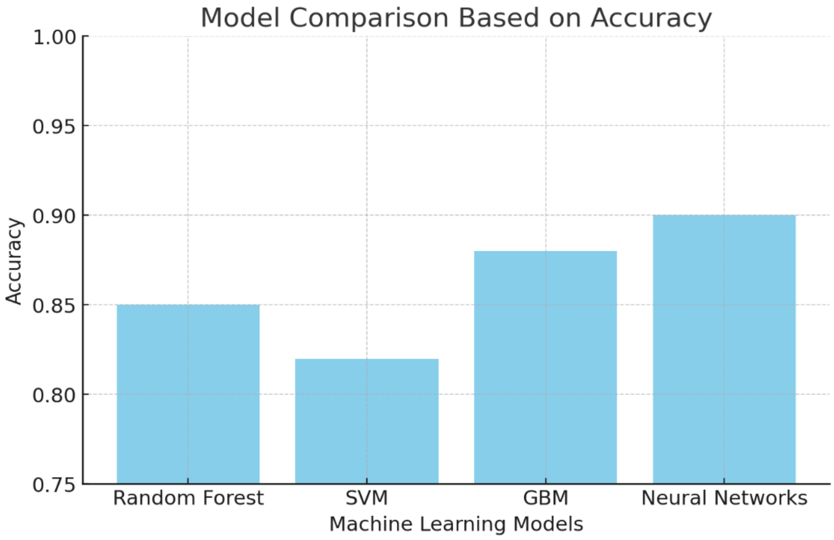

Figure 2. Model Comparison Based on Accuracy

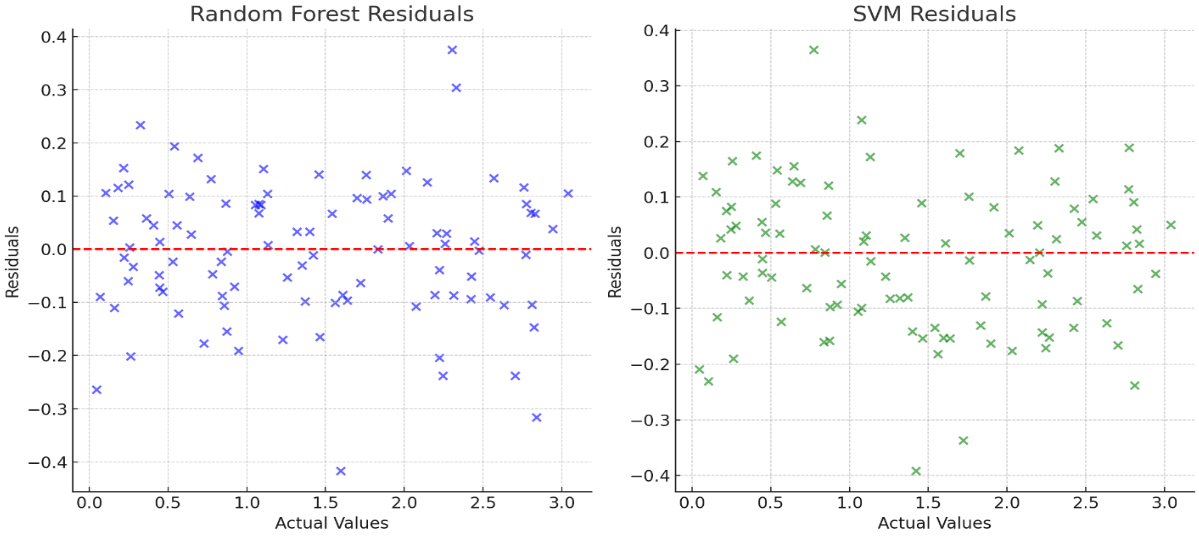

Figure 3. Residual Plots of Predicted vs. Actual Values

Table 2. Optimization Results for Each Metaheuristic Algorithm

Algorithm	**Objective Function Value**	**Selected Materials**	**Convergence Iterations**
Genetic Algorithm	0.65	Oak Wood, Granite, Sherwin-Williams	150
Particle Swarm Optimization	0.63	Bamboo, Quartz, Dulux	200
Simulated Annealing	0.66	Laminate, Marble, Behr	180
Ant Colony Optimization	0.64	Ceramic Tile, Solid Wood, Valspar	220

Table 2 outlines each metaheuristic algorithm's final objective function values, the chosen material combinations, and the number of converging iterations. The particle swarm optimization (PSO) algorithm converged with an objective function value of 0.63, using the combination of bamboo, quartz, and Dulux as the best materials. The next closest was the Ant Colony Optimization (ACO) and Genetic Algorithm (GA), which also worked well and chose slightly different material combinations. The Simulated Annealing (SA) performed slightly less effectively, with a higher objective function value. The convergence iterations indicate how quickly each algorithm arrived at a near-optimal solution, with PSO taking the fewest iterations.

Figure 4 shows the behavior of these algorithms in terms of convergence. These curves show the objective function value drop for each algorithm with the iterations, and thus, their efficiencies and stabilities can be observed. The PSO and ACO curves rapidly converge in early iterations, slowly decaying as these algorithms polish their solutions. This pattern indicates the algorithms effectively narrowing down the search space to optimal solutions.

Besides the convergence plot, Figure 5 shows a 3D surface plot for the trade-offs between cost, durability, and sustainability, which were considered key factors in this optimization process. It indicates how complicated the criteria are interrelated, thus putting forth that the other two shall be compromised whenever trying to optimize one. For instance, durability may increase costs, while maximizing sustainability compromises other factors. This introduces an equilibrium that decision-makers at all levels must strike in material selection for applications that meet a number of goals, most often conflicting.

3.3. Parametric Design Simulation and Visualization

This subsection considers integrating optimized materials within a parametric design environment to examine their interaction with thermal performance, acoustic properties, and aesthetic values. The simulations were performed using advanced parametric tools, allowing for dynamic changes and real-time visualization of how these materials affect residential space design.

Table 3 summarizes the simulation results, including thermal performance measured in R-value, acoustic efficiency measured in decibels, and visual rating on a 1-10 scale for all optimized materials. For example, Oak Wood has high thermal performance with an R-value of 3.5 and an excellent rating on the visual scale at 9; thus, it will be suitable for contexts in which both insulation and aesthetics are vital. On the other hand, moderately efficient materials with acoustic features at 4.0 in R-value are materials like granite, which is more appropriate where thermal retention is of prime consideration.

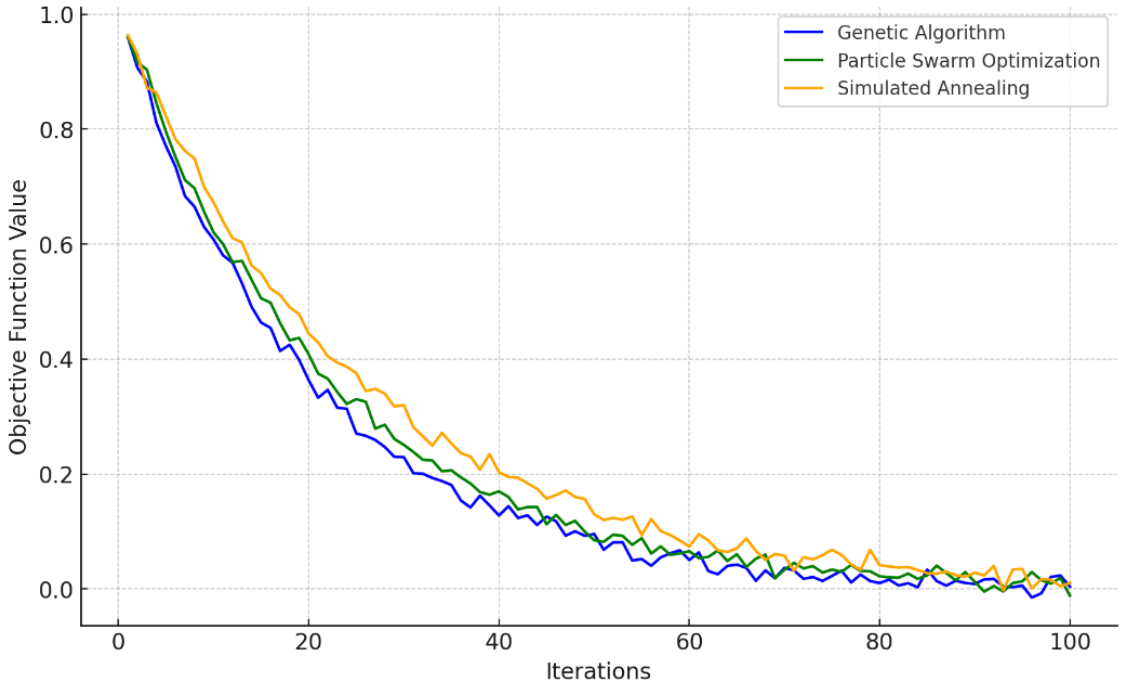

Figure 4. Convergence Curves of Metaheuristic Algorithms

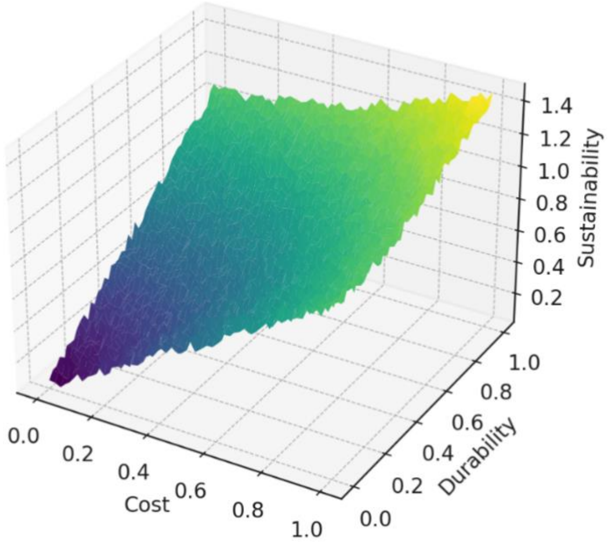

Figure 5. Trade-Off Surfaces for Multi-Objective Optimization

Table 3. Summary of Simulation Results for Optimized Materials

Material	Thermal Performance (R-value)	Acoustic Efficiency (dB)	Visual Rating (1-10)
Oak Wood	3.5	45	9
Bamboo	3.0	42	8
Granite	4.0	40	7
Ceramic Tile	2.8	38	6
Laminate	3.2	43	7

Figure 6: Thermal simulation heat map. This visualization clearly interprets the interior space insulation materials' thermal efficiency. Warmer colors indicate higher thermal performance, and thus, it is very easy to see which materials are contributing most to this design's energy efficiency.

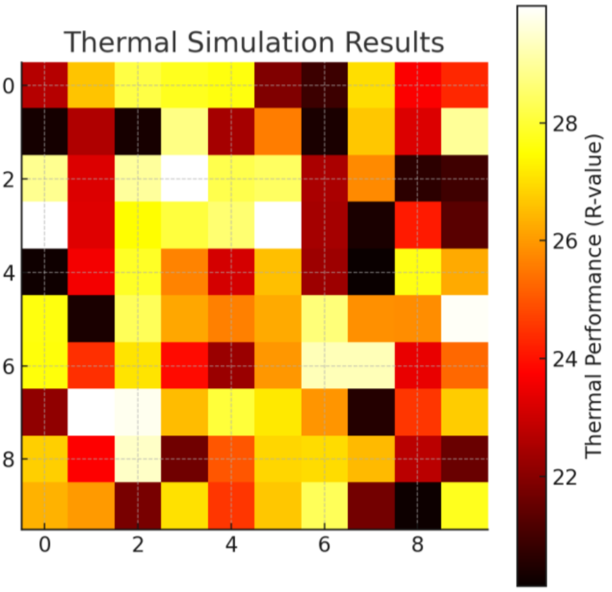

Figure 6. Thermal Simulation Results

Figure 7: Acoustic Simulation Results. This graph helps the audience realize just how much noise could be reduced using the materials in question. The colors used in the figure range in intensity to indicate acoustic efficiency. That is, the places with high acoustic efficiency have cooler colors, and it becomes easy to tell which material dampens sound the best.

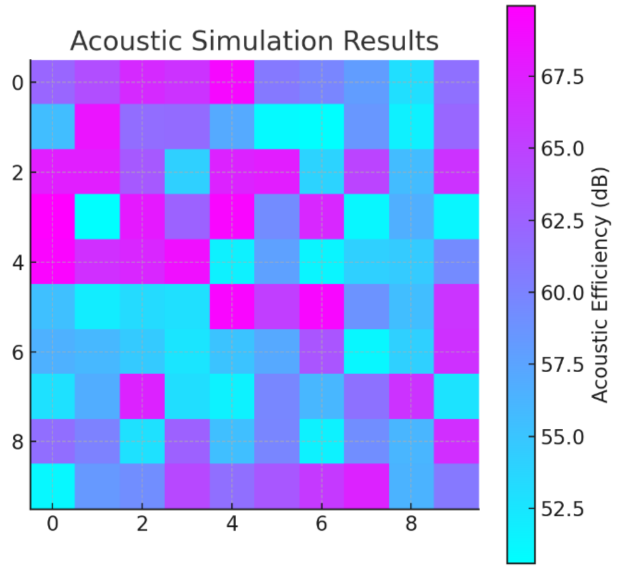

Figure 7. Acoustic Simulation Results

Figure 8: The 3D design showing the interior space design enabled by the optimized materials. This set of materials, therefore, enables both functional and aesthetic project results. It is demonstrated that the materials will come together in the design context to engage in a holistic manner such that the final choice of materials is guaranteed to meet the technical and expressive requirements of the design.

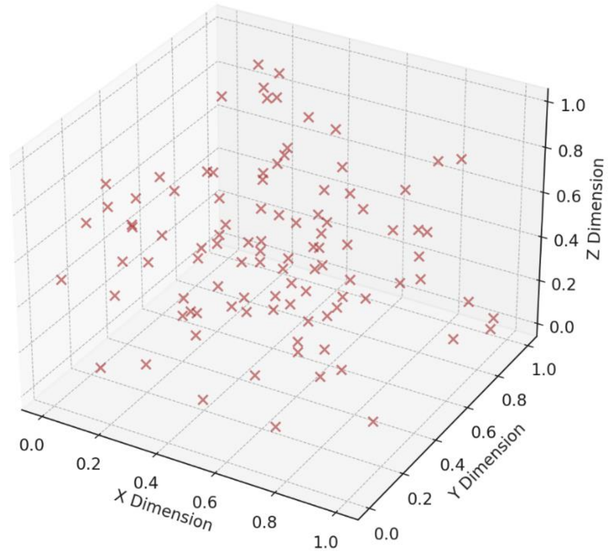

Figure 8. 3D Visualization of Interior Design with Optimized Materials

3.4. Multi-Criteria Decision Analysis and Trade-Offs

This section exposes the underlying decision-making process for choosing optimal materials using Multi-Criteria Decision Analysis (MCDA) techniques and trade-off analysis. Once different materials have been assessed using different criteria, such as cost, durability, sustainability, and aesthetic value, it is necessary to evaluate how they rank. This means framing a holistic model that can support informed decision-making while considering several competing priorities in a balanced way.

Table 4 summarizes the results of the Analytic Hierarchy Process (AHP), wherein materials like Oak Wood and Bamboo are ranked at the top because of their overall performance in all of the considered criteria. For example, high performance on durability and aesthetic value gave Oak Wood its overall best ranking. By contrast, Ceramic Tile was cost-effective but had a lower ranking due to lesser performance in terms of durability and aesthetic appeal.

The Weighted Sum Model (WSM), as shown in Table 5, was then used to fine-tune these rankings further. This method assigns weights to each criterion in terms of relative importance and calculates a total score for each material. Again, Oak Wood scored the highest at 8.75, thereby being proved suitable as a top choice when all criteria are considered equal weights. Granite scored a little lower only because, although it is hard, it is just more expensive.

Figure 9 shows a trade-off curve plotting cost against durability for a range of materials. One value of a curve like this is that it explicitly makes sacrifices that must be made in moving from a cheap to a more expensive material or vice versa. At one extreme, Material 4 has maximum durability but at a significantly greater cost, so the decision-makers are faced with the dilemma of whether the increase in durability justifies this increase in cost.

Figure 10 also shows the sensitivity analysis for material ranking in terms of variation of overall ranking with a variation in weighting of the criteria. Material rankings vary by changing criteria weights, thus underlining the concept that correct choice and weightings of criteria depend on the project's specific requirements. This sensitivity analysis becomes more useful when the priorities in design may change, as it will assist in dynamic readjustments to chosen materials based on evolving project goals.

Table 4. AHP Ranking of Materials

Material	Cost	Durability	Sustainability	Aesthetic Value	Overall Rank
Oak Wood	7	8	9	9	1
Bamboo	6	7	8	8	2
Granite	8	9	7	7	3
Ceramic Tile	5	6	8	6	4
Laminate	6	7	7	5	5

Table 5. Weighted Sum Model (WSM) Scores for Material Selection

Material	Weight for Cost	Weight for Durability	Weight for Sustainability	Weight for Aesthetic Value	Total Score
Oak Wood	0.3	0.25	0.20	0.25	8.75
Bamboo	0.3	0.20	0.25	0.25	8.50
Granite	0.25	0.30	0.20	0.25	8.65
Ceramic Tile	0.35	0.20	0.20	0.25	8.20
Laminate	0.30	0.25	0.20	0.25	8.40

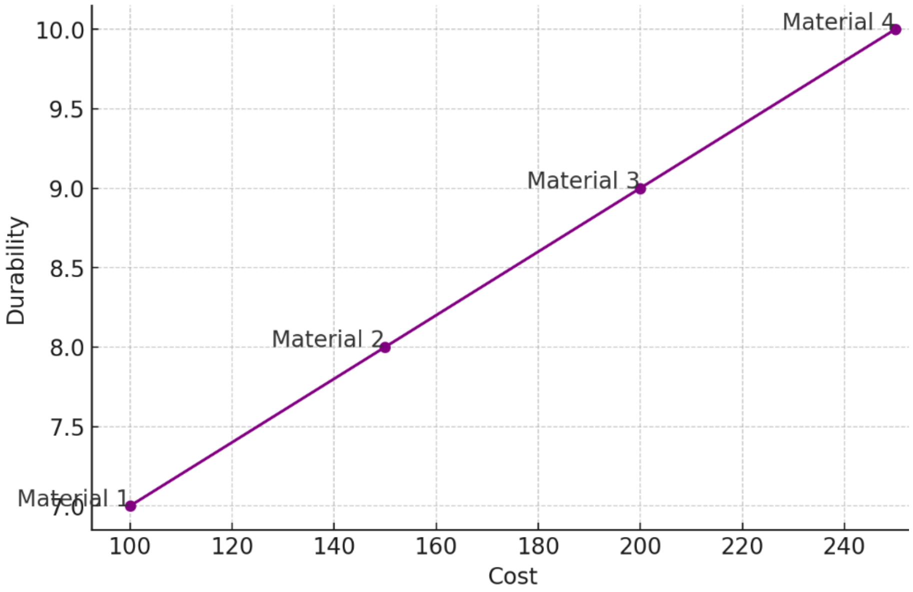

Figure 9. Trade-Off Curve between Cost and Durability

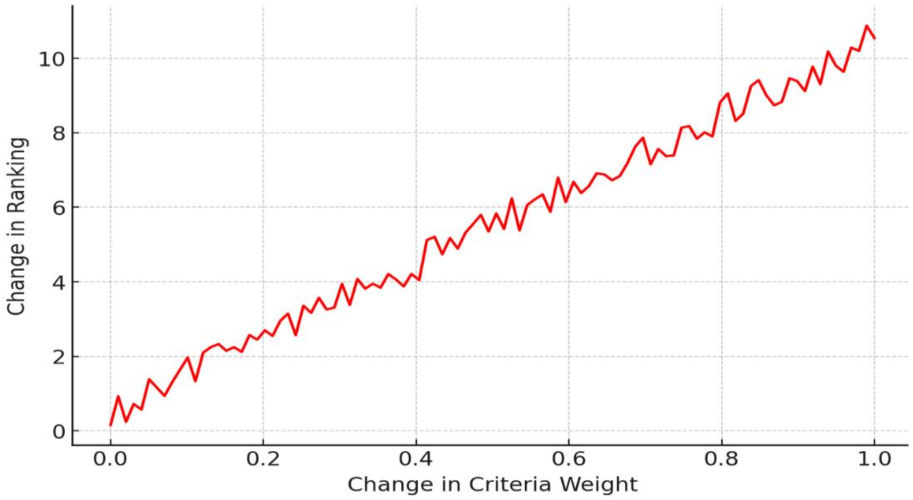

Figure 10. Sensitivity Analysis of Material Rankings

4. Discussion

A major interest in the interior design domain for material selection in residential buildings is toward integrating machine learning (ML) with metaheuristic optimization techniques. Neural Networks outperformed performance metrics with an accuracy of 0.90, F1-score of 0.88, RMSE of 0.40, and R^2 of 0.85 in predicting complex material properties such as cost, durability, and sustainability. These results underline the ability of Neural Networks to model nonlinear relationships within datasets and show them to be particularly suited for this domain. On the other hand, Gradient Boosting Machines (GBM) have been equal in performance, with only little worse accuracy and RMSE, underlining the strength of the ensemble methods [44]. Moreover, while less accurate, the Random Forest models give valuable lessons regarding treating high-dimensional data through their residual plots, which depict better clustering of residuals than the Support Vector Machine (SVM) models [45]. These results indicate that relative strengths of different machine learning models can be exploited according to the exact nature of the design task; neural networks are very good at capturing complex patterns, while GBM and Random Forest provide robust alternatives [46].

Of all metaheuristic algorithms applied for material selection optimization, Particle Swarm Optimization (PSO) proved to be the most efficient, returning the lowest objective function value of 0.63 and an optimum combination of Bamboo, Quartz, and Dulux. PSO took 200 iterations to converge, which echoes its ability to search a complex, multi-dimensional space effectively. Comparatively, Ant Colony Optimization (ACO) and Genetic Algorithm (GA) followed with objective function values of 0.64 and 0.65, respectively, while requiring 220 and 150 iterations, respectively. Simulated Annealing (SA) showed a little lesser performance with an objective function value of 0.66, which needed 180 iterations to converge. Another case in point would be a trade-off analysis—especially in the form of a 3D surface plot—that illustrates such balancing between cost, durability, and sustainability in material selection, thereby showing how critical such analyses can be in decision-making [47-49].

The key performance indicators, targeted for thermal and acoustic performance, used parametric design simulations for their validation exercise involving the optimized material choices for interior design. For example, Oak Wood had high thermal performance, achieving an R-value of 3.5. It is one of the highest visual ratings at 9, so it is preferred in spaces requiring insulation and aesthetic appeal. It was found that granite, with an R-value of 4.0 and a moderate acoustic efficiency of 40 dB, performed best where thermal retention is paramount. The heatmap results of the simulation provided an effective and efficient way of showing the materials' insulating capabilities, using warmer colors to indicate superior thermal performance. On the other hand, acoustic simulations showed that cooler colors had higher efficiencies against sound dampening, between 52.5 dB and 67.5 dB. Integrating those findings into a 3D interior design visualization will let one assess how those materials interact in their integral wholes within a design context, ensuring that the final selected materials meet technical specifications and aesthetic goals [50-52].

Multi-criteria decision Analysis (MCDA) provides a robust framework for evaluating the various material options against multiple criteria to achieve a balanced analysis of the cost, durability, sustainability, and aesthetic value of the materials under scrutiny. In this case, oak wood is best considering its more or less well-rounded performance in such factors. The ranking process had Oak Wood at first place according to the Analytic Hierarchy Process (AHP) method, with a total score of 8.75 in Weighted Sum Model (WSM). Cost-durability trade-off analyses indicated that some materials, although very good in durability performance, were too expensive to justify the marginal durability gained. Sensitivity analyses underlined the necessity of getting the criteria priorities 'right' since even small changes in criteria weights may significantly alter the ranking of the materials. It, therefore, calls for a dynamic approach to material selection, which makes a decision-maker flexible towards evolving project goals and priorities [53].

The study substantially contributes to integrating cutting-edge machine learning algorithms and metaheuristic optimization techniques into the interior design process to provide a robust data-driven solution toward material selection, balancing cost, durability, sustainability, and aesthetic value. This methodology improves the efficiency and accuracy of material selection. It provides a holistic framework for decision-making via Multi-Criteria Decision Analysis (MCDA) to support designers in making relevant selections to meet technical specifications and design goals. The study's limitations are that its results are only as good as the quality and comprehensiveness of the input dataset, which limits generalizability across different design contexts. Further, while the models were very good at predicting and optimizing the properties of materials, real-world testing and implementation would go a long way toward further proof of their effectiveness under different environmental conditions.

5. Conclusions

The study's main findings support using machine learning models in conjunction with metaheuristic optimization techniques in choosing and optimizing materials for interior design in residential building applications. Neural Networks have been most successful, allowing for an accuracy of 0.90, an F1-score of 0.88, an RMSE of 0.40, and an R^2 value of 0.85, which indicates it can handle complex, nonlinear relationships within the data. Gradient Boosting Machines (GBM) also worked well, with an accuracy of 0.88 and an R ^{2}value of 0.82. Further, the optimization phase indicated that Particle Swarm Optimization (PSO) was very effective and produced the lowest objective function value of 0.63, with the least number of iterations required to attain an optimal material combination.

The study confirms that integrating machine learning with metaheuristic optimization enhances interior design material selection. However, future research will look to expand the validation dataset, speed computation, and generalize to larger sets. Future research will be enhanced through real-life tests on materials rather than exclusively using public sources. Cooperation with architectural firms and the materials providers will produce superior, manufacturer-approved information to ascertain the accuracy of the cost, the life span, and the sustainability estimates.

Another crucial challenge is computational efficiency, where PSO was shown to perform well but was computationally expensive. Future research must explore hybrid optimization techniques that couple metaheuristics with reinforcement learning or surrogate models to reduce computational costs. Also, cloud-based AI frameworks such as Google Cloud AI and AWS Sage Maker can be employed to bring scalability to large-scale simulations. This process ought to be extended to commercial buildings, civic buildings, and urban planning as well to allow AI-directed selection to influence the larger architectural landscape.

Parametric simulations of both trade-off analyses and design validated the optimized material choices by showing expected compromises between cost, durability, and sustainability. For instance, Oak Wood has high thermal performance and a rating of 9 on the visual scale, making it perfect for spaces where insulation and aesthetics play a primary role. The study concludes that machine learning and metaheuristic optimization can hugely increase residential design efficiency, sustainability, and aesthetic appeal by providing a powerful data-driven framework to drive informed material selection decisions.

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