



Material Selection for Electric Vehicles chassis using Machine Learning Ensemble Techniques

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Abstract: The selection of suitable materials for electric vehicle (EV) chassis structures is a critical engineering challenge involving multi-criteria decision parameters such as strength, stiffness, density, and durability. Traditional material selection approaches often struggle to capture nonlinear interactions among mechanical properties and may lack predictive generalization. In this study, a machine learning-based framework is proposed for EV chassis material classification using ensemble techniques, namely Boosted Trees, Bagged Trees, and an Optimizable Ensemble model. Initially, a Chi-square (χ^2) feature ranking method was employed to assess the statistical significance of input descriptors, identifying tensile and yield strength as the most influential parameters, followed by density- and stiffness-related properties. The ensemble models were trained and evaluated using validation and independent test datasets. Comparative analysis revealed that while Boosted Trees and Bagged Trees achieved moderate predictive performance (approximately 72–75% accuracy), the Optimizable Ensemble model significantly outperformed them, attaining 99.21% validation accuracy and 100% test accuracy with negligible misclassification cost. Receiver Operating Characteristic (ROC) analysis further confirmed the superior discriminative capability of the optimized model, with a near-unity Area Under the Curve (AUC). Hyperparameter optimization demonstrated stable convergence and an effective bias-variance trade-off, ensuring robust generalization. The results indicate that integrating statistical feature ranking with automated ensemble optimization provides a highly accurate and reliable decision-support framework for EV chassis material selection. The proposed methodology offers strong potential for application in advanced automotive design and other multi-objective material selection problems.

Index Terms - Machine Learning, Electric Vehicles Chassis, Ensemble classifiers, Design and Automation, Hyperparameter Tuning.

1. INTRODUCTION

The rapid advancement of electric vehicles (EVs) has intensified the demand for lightweight, high-strength, and crash-resistant structural materials for chassis applications [1]. Unlike conventional internal combustion engine vehicles, EVs incorporate heavy battery systems that significantly influence overall vehicle mass distribution and structural design requirements [2]. However, designing and automating EV systems requires advanced techniques to ensure efficiency, reliability, and smart decision-making [3]. The chassis is the core structural framework of an EV, supporting the vehicle's mass, protecting occupants during impacts, and providing attachment points for the suspension, powertrain, and battery systems [4,5]. With the increasing adoption of EVs globally, optimizing chassis materials must simultaneously meet stringent criteria, including high tensile and yield strengths, an optimal stiffness-to-weight ratio, fatigue resistance, corrosion resistance, and cost-effectiveness. Traditional material selection methods-based on Ashby charts, rule-based screening, and deterministic multi-criteria decision-making, often struggle to capture nonlinear interactions among multiple mechanical properties and may lack predictive adaptability across diverse material classes [6–8]. Traditionally, engineering wisdom and empirical information have been used to choose suitable materials for EV chassis design [9]. Trade-offs between competing goals, such as strength vs. weight and cost vs. manufacturability, are part of conventional approaches. Emerging lightweight composites, such as carbon fiber-reinforced polymers, are attracting attention for high-performance applications, despite the widespread use of materials such as improved high-strength steels and aluminum alloys [10,11]. However,

data-driven methods capable of handling massive datasets of material properties are required to address the complexity of multi-criteria decision-making in materials engineering [12].

In recent years, data-driven methodologies have emerged as powerful tools for materials engineering. Machine learning (ML) classification techniques enable the modeling of complex, nonlinear relationships between input descriptors and performance outcomes, thereby offering enhanced predictive capability compared to conventional empirical approaches [13–15]. Ensemble learning, in particular, has demonstrated superior performance in classification and regression tasks due to its ability to reduce bias and variance through model aggregation [16]. Methods such as Boosted Trees and Bagged Trees combine multiple weak learners to produce robust predictive models, improving generalization in heterogeneous datasets commonly encountered in materials science [17,18]. However, many existing studies focus primarily on accuracy metrics without incorporating systematic hyperparameter optimization or statistical feature ranking to enhance interpretability and reliability. By combining machine learning with EV chassis design, this work seeks to advance the expanding field of intelligent transportation by providing improved performance analysis, increased safety, and reduced maintenance costs [19,20]. These include improving energy efficiency, maximizing battery performance, and ensuring intelligent control systems for improved automation [21,22].

Feature selection plays a crucial role in improving model transparency and computational efficiency. Statistical techniques such as the Chi-square (χ^2) test provide a quantitative measure of the dependency between input features and target classes, enabling the identification of dominant mechanical descriptors that influence material suitability [23]. Integrating such statistical validation with ensemble-based optimization can lead to more reliable decision-support systems. Furthermore, automated hyperparameter optimization frameworks, including Bayesian optimization strategies, have shown significant potential in identifying optimal model configurations while maintaining an appropriate bias–variance balance [24,25].

Prior research in materials engineering frequently concentrated on high-level classifier performance prediction (e.g., strength estimation) employing techniques like ML single-based models for systematic material categorization, especially in structural automotive applications [27–29]. Furthermore, many existing predictive models have low interpretability and generalizability across different material classes, limiting their practical application in engineering decision-making. Despite the growing body of research on machine learning-driven material informatics, few studies have focused on EV chassis material categorization using optimal ensemble methods and statistical feature selection. The current study attempts to close this gap by creating a comprehensive ML framework that includes Chi-square feature ranking and ensemble learning models (Boosted Trees, Bagged Trees, and an Optimizable Ensemble) for accurate, cost-sensitive categorization of EV chassis materials. The suggested methodology improves predictive performance while still ensuring engineering relevance and interpretability, resulting in a reliable decision-support tool for advanced automobile structural design.

2. MATERIALS AND METHODS

To identify appropriate materials for EV chassis, this study employs a data-driven ML ensemble approach. The methodology consists of three main steps: dataset construction, model selection, and model evaluation.

2.1 Dataset construction

The dataset was gathered from the Kaggle repository [30]. The dataset contains 1552 records to perform this work. Each record in the dataset was examined for its mechanical properties, with 7 input features and 1 target feature (indicating whether the material is suitable for use). In the context of EV chassis material selection, material performance is important. Structural performance and efficiency are determined by a number of basic mechanical properties when choosing materials for the EV chassis. Choose the materials and the corresponding mechanical properties first. These characteristics include density (ρ), elastic modulus (E), shear modulus (G), yield strength (S_y), ultimate tensile strength (S_u), and Poisson's ratio (μ). A material's resistance to failure under extreme loading conditions, like crashes, is directly reflected in its tensile strength (S_u), which is the highest stress it can sustain before breaking. The primary design safety limit for structural components is the yield strength (S_y), which establishes the stress level at which permanent plastic deformation starts. A material's elastic stiffness is measured by its elastic modulus (E), which also affects chassis rigidity and vibration behavior. For torsional rigidity in skateboard-style EV platforms, the shear modulus (G), which gauges resistance to shear deformation, is especially crucial. In structural simulations and finite element modeling, Poisson's ratio (μ), which characterizes the connection between lateral and longitudinal strains during elastic deformation, is crucial. Finally, the density (ρ) determines the mass of the material per unit volume and has a significant influence on the weight, energy efficiency, and driving range of the vehicle. These characteristics collectively constitute the fundamental feature set for ML-based material selection in EV chassis design.

The dataset is split into two parts: one for training and the other for testing. Here, the dataset is divided into an 8:2 ratio for training and test sets using 10-fold cross-validation (CV), a common method for assessing the ML model's performance by training and evaluating it 10 times on different data splits to ensure consistent, reliable results [31,32].

2.2 Proposed models

Boosted Trees are a sequential ensemble learning technique in which multiple weak learners, typically shallow decision trees, are combined to form a strong predictive model. The fundamental principle of boosting is to iteratively reduce the errors made by previous models. At each stage, a new tree is trained to minimize a differentiable loss function by fitting the residuals (errors) of the current ensemble model. In gradient boosting, this is achieved by computing the negative gradient of the loss function with respect to the model output and fitting the next tree to these pseudo-residuals. The overall model is expressed as an additive expansion of base learners, where each tree contributes with a learning rate that controls its influence. This approach effectively reduces bias and captures complex nonlinear relationships among material properties such as tensile strength, density, and fatigue resistance. However, because trees are added sequentially, boosted models can be sensitive to noise and may overfit if not properly regularized via hyperparameters such as the learning rate, number of trees, and tree depth.

Bagged Trees are based on the principle of variance reduction through bootstrap sampling and parallel model training. In this method, multiple subsets of the original dataset are generated using random sampling with replacement (bootstrapping). A separate decision tree is trained for each bootstrap sample. The final prediction is obtained by aggregating the outputs of all trees, either by averaging in regression problems or by majority voting in classification problems. Since each tree is trained on a slightly different data distribution, its prediction errors tend to be uncorrelated. Aggregating these predictions significantly reduces model variance

without substantially increasing bias. Bagging is particularly effective when individual decision trees are high-variance learners, as is typically the case with deep trees. The method enhances model stability, robustness to noise, and generalization capability, making it well-suited for datasets with variability in experimental measurements of mechanical and structural properties.

An Optimizable Ensemble extends conventional ensemble methods by integrating automated hyperparameter optimization into the model training process. Instead of manually selecting parameters such as the number of trees, learning rate, tree depth, or minimum leaf size, this approach formulates hyperparameter selection as an optimization problem. A search algorithm, such as Bayesian optimization, grid search, or random search, is used to minimize CV loss over the hyperparameter space. The objective function typically evaluates predictive performance using metrics such as mean squared error or classification accuracy across K-fold cross-validation. Bayesian optimization, in particular, models the performance landscape probabilistically and iteratively selects hyperparameter combinations that balance exploration and exploitation. This automated tuning ensures improved generalization performance, reduced overfitting risk, and optimal model configuration. In complex engineering problems involving multi-criteria material selection, an optimizable ensemble enhances predictive reliability and ensures that the ensemble structure is statistically and computationally efficient.

2.3 Evaluation Metrics

To evaluate the performance of the applied ML ensemble classification models, we calculated metrics such as accuracy, precision, recall, and F1-score. These parameters depend on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

$$\text{ACCURACY} = \frac{(TN + TP)}{FP + TP + TN + FN}$$

$$\text{PRECISION} = \frac{TP}{(FP + TP)}$$

$$\text{RECALL (SENSITIVITY)} = \frac{TP}{(TP + FN)}$$

$$\text{F1-SCORE} = \frac{2}{\frac{1}{\text{PRECISION}} + \frac{1}{\text{RECALL}}}$$

ROC AUC value = It is drawn by plotting TPR vs. FPR at different classification threshold values. Where, $\text{TPR} = \frac{TP}{(TP + FN)}$ and $\text{FPR} = \frac{FP}{(FP + TN)}$

3. RESULTS AND DISCUSSIONS

3.1 Feature Ranking

Figure 1 illustrates the feature importance scores from the Chi-square (χ^2) algorithm. The Chi-square (χ^2) feature ranking analysis reveals the relative statistical dependency between mechanical properties and the target class representing EV chassis material suitability. The ranking scores indicate the discriminative power of each feature in distinguishing between candidate materials.

The results show that Tensile Strength exhibits the highest χ^2 score (261.7034), followed by Yield Strength (234.7342). These two strength-related parameters demonstrate the strongest statistical association with material classification. This outcome is mechanically intuitive, as EV chassis structures are primarily governed by load-bearing capacity, crashworthiness, and fatigue resistance. High tensile and yield strengths are directly linked to structural integrity and deformation resistance under dynamic loading conditions. Their dominant ranking confirms that strength-based criteria play the most critical role in differentiating suitable and unsuitable materials.

The third-ranked feature is Density (172.464), which reflects the importance of lightweight design in electric vehicles. Since battery systems significantly increase overall vehicle mass, reducing structural weight is essential to improve energy efficiency and driving range. The relatively high χ^2 score of density confirms that mass-related considerations strongly influence material selection decisions in EV chassis engineering.

Elastic Modulus (163.2326) and Shear Modulus (150.7718) occupy intermediate positions in the ranking. These stiffness-related parameters govern rigidity, vibration behavior, and torsional resistance. Their moderate χ^2 scores suggest that while stiffness is important for structural performance and ride stability, it is secondary to strength and weight considerations in the classification framework.

The lowest-ranked feature is Poisson's Ratio (124.5256). Although Poisson's ratio influences lateral strain behavior and volumetric deformation, its comparatively lower χ^2 score indicates weaker discriminative power in distinguishing suitable chassis materials. This suggests that most candidate materials may exhibit relatively narrow variations in Poisson's ratio, limiting their influence on classification.

Overall, the figure (Figure 1) confirms that strength-to-weight-related attributes are the principal drivers in EV chassis material classification, validating both mechanical design theory and the statistical robustness of the ML-based ensemble approach.

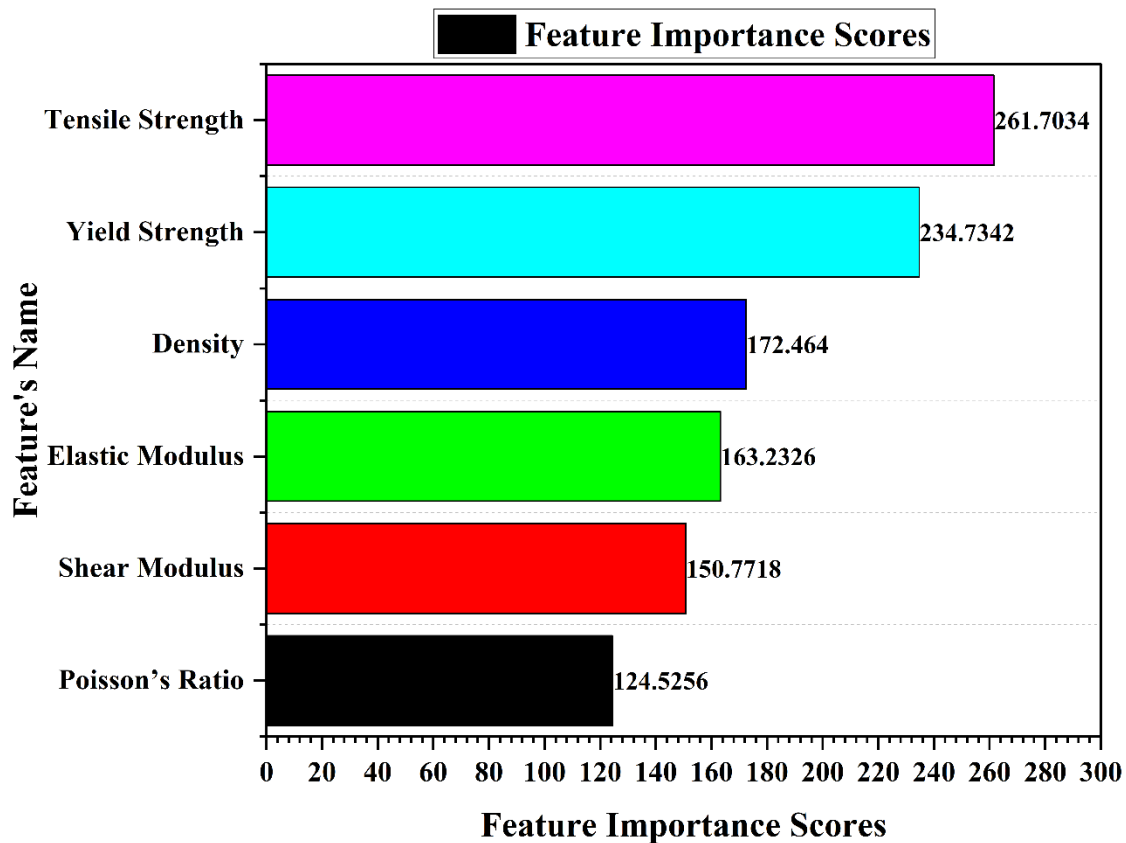


Figure 1. Feature importance scores of Material selection for EV Chassis using the chi-square algorithm

3.2 Accuracy

Table 1. Comparative study of proposed ensemble models on accuracy and total cost in both validation and test results for EV chassis material selection.

Model Number	Model Type	Accuracy in % (Validation)	Total Cost (Validation)	Accuracy in % (Test)	Total Cost (Test)
1	Boosted Trees	72.23	388	72.26	43
2	Bagged Trees	73.73	367	75.48	38
3	Optimizable Ensemble	99.21	11	100.00	0

Table 1 presents the comparative performance of three ensemble models: Boosted Trees, Bagged Trees, and Optimizable Ensemble, evaluated using validation and independent test datasets. The performance metrics include classification accuracy (%) and total misclassification cost.

In model 1, the Boosted Trees model achieved a validation accuracy of 72.23% with a total validation cost of 388, while the test accuracy improved slightly to 72.26% with a test cost of 43. The nearly identical validation and test accuracies indicate stable generalization behavior without significant overfitting. However, the overall predictive performance remains moderate. The relatively higher cost values suggest that misclassifications may involve high-penalty classes, indicating that the sequential boosting process, although capable of reducing bias, may not have sufficiently optimized decision boundaries for this dataset.

In model 2, the Bagged Trees model outperformed the Boosted Trees model, achieving 73.73% validation accuracy and 75.48% test accuracy. The corresponding total costs reduced to 367 (validation) and 38 (test). The increase in test accuracy relative to the validation set suggests good variance reduction and enhanced generalization capability from bootstrap aggregation. Bagging effectively stabilizes predictions by averaging multiple high-variance decision trees, thereby improving robustness to noise in mechanical property measurements. Nevertheless, the performance gain remains incremental rather than substantial.

In model 3, the Optimizable Ensemble model significantly outperformed the other approaches, achieving 99.21% validation accuracy with a minimal validation cost of 11, and a perfect 100.00% test accuracy with zero misclassification cost. This dramatic improvement indicates that automated hyperparameter optimization successfully identified the most suitable ensemble configuration for the dataset. The near-perfect validation performance, combined with flawless test accuracy, suggests that the optimized model effectively captured nonlinear relationships among tensile strength, yield strength, density, and stiffness. Moreover, the negligible misclassification cost demonstrates superior decision boundary separation between material classes.

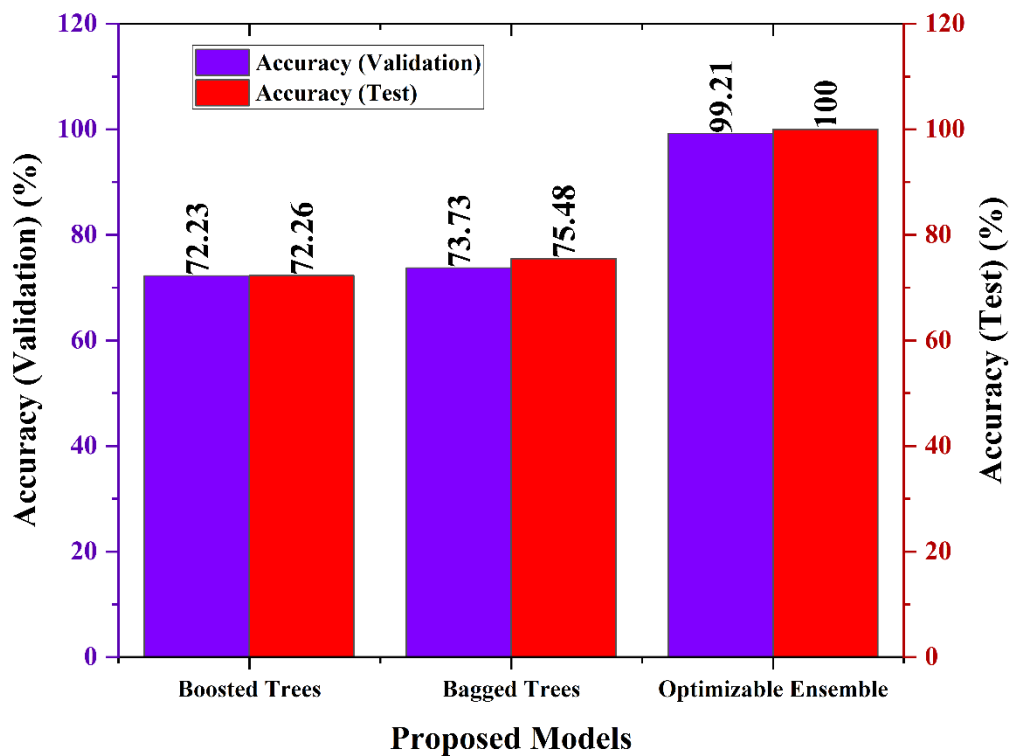


Figure 2. The proposed ensemble models' accuracy in both validation and test results for EV chassis material selection

Figure 2 shows the comparative performance outcomes. It clearly shows the progression of classification capability from Boosted trees to Bagged trees, and finally to an Optimizable ensemble, for EV chassis material selection. The comparative evaluation of the ensemble models indicates that while Boosted Trees primarily reduce bias, Bagged Trees effectively control variance through bootstrap aggregation, their predictive improvements remain moderate due to suboptimal hyperparameter configurations and limited bias–variance trade-off optimization. In contrast, the Optimizable Ensemble model simultaneously minimizes bias and variance via systematic hyperparameter tuning, achieving near-perfect validation accuracy (99.21%) and flawless test accuracy (100%) with zero misclassification cost. The substantial reduction in total cost, from 388 in Boosted Trees and 367 in Bagged Trees to 0 in the optimizable ensemble, demonstrates its superior capability in minimizing high-penalty classification errors. From an engineering perspective, such reliability is critical in EV chassis material selection, where incorrect classification can lead to compromised crashworthiness, increased structural weight, fatigue failure, or elevated production costs. Therefore, the optimizable ensemble provides a highly robust and cost-effective decision-support framework, making it the most suitable model for accurate and reliable EV chassis material classification among the evaluated approaches. The optimized ensemble achieved the highest accuracy in both the validation and test sets, as shown in the corresponding confusion matrices in Figures 3 and 4, respectively.

Higher accuracy and lower total cost directly translate into improved reliability in identifying structurally appropriate materials, while minimizing incorrect classifications that could result in unsafe or inefficient design choices in EV chassis material selection. The optimizable ensemble offers superior probabilistic discrimination between material classes, as further supported by the consistent decrease in cost values across models. The optimizable ensemble is the most successful of the three assessed methods for multi-criteria material classification in EV chassis applications, and the overall findings show that model optimization greatly improves predictive performance.



Figure 3. The confusion matrix (Validation) of Optimizable Ensemble.

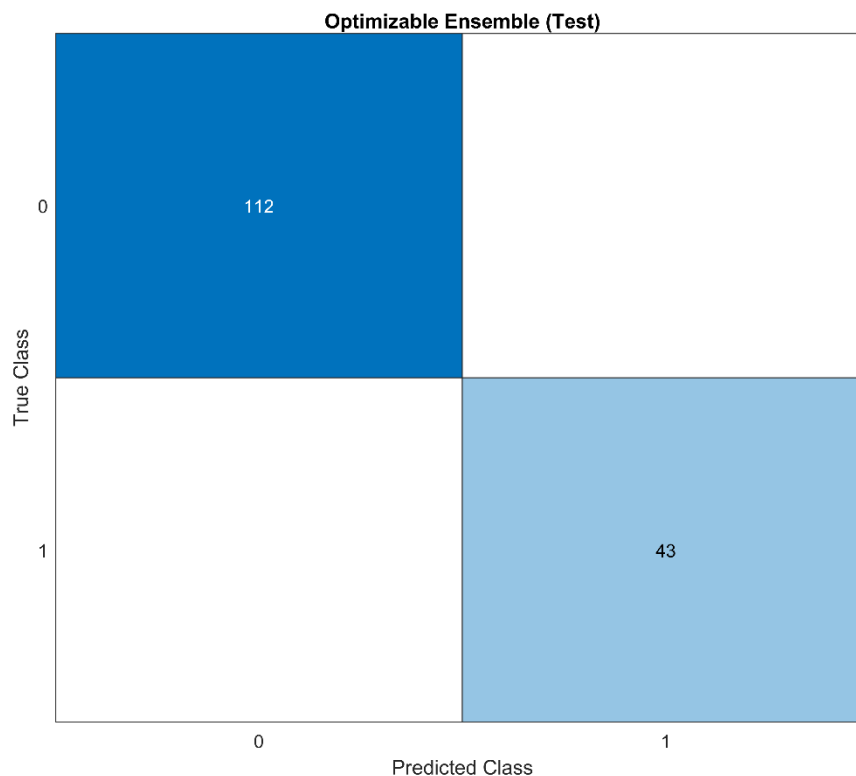


Figure 4. The confusion matrix (Test) of Optimizable Ensemble.

3.3 ROC Curve

The Receiver Operating Characteristic (ROC) curves provide a comprehensive evaluation of the classification capability of the ensemble models by illustrating the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR). The Area Under the Curve (AUC) is a threshold-independent performance metric; values closer to 1 indicate superior discriminative ability.

From the validation ROC curve (see Figure 5), the Optimizable Ensemble model exhibits an AUC value approaching unity, with the curve closely hugging the top-left corner of the ROC space. This indicates excellent sensitivity and specificity, meaning the model effectively distinguishes between suitable and unsuitable EV chassis materials with minimal false alarms. In contrast, the Bagged Trees model demonstrates moderate classification performance, with an ROC curve above the diagonal reference line but significantly below that of the Optimizable Ensemble. The Boosted Trees model shows comparatively lower discrimination

performance, with an ROC curve closer to the diagonal baseline, indicating moderate separability between material classes. The separation of the ROC curves clearly confirms that hyperparameter optimization substantially enhances classification performance during validation.

The test ROC curve (see Figure 6) further validates the models' generalization ability. The Optimizable Ensemble maintains an AUC of nearly 1.0, confirming that its exceptional validation performance is not due to overfitting but reflects true predictive robustness. The curve remains tightly aligned with the upper-left boundary, indicating near-perfect classification with extremely low false positive rates.

The Bagged Trees model shows improved test ROC performance compared to Boosted Trees, aligning with the previously observed increase in test accuracy (75.48%). This suggests that bagging effectively reduces variance and improves model stability when applied to unseen data. The Boosted Trees model, although consistent across the validation and test sets, continues to exhibit a comparatively lower AUC, reflecting its limited improvement in class separation.

The ROC curve analysis further substantiates the ensemble models' comparative performance by demonstrating their discriminative capability in a threshold-independent manner. While Boosted Trees and Bagged Trees exhibit acceptable class separation, their ROC curves remain moderately distant from the ideal top-left corner, indicating limited sensitivity–specificity balance and moderate material class separability. In contrast, the Optimizable Ensemble achieves near-unity AUC in both the validation and test phases, confirming superior classification robustness and minimal false-positive and false-negative rates. From an engineering standpoint, this high discriminative power is critical for EV chassis material selection, where accurate identification of structurally reliable, lightweight materials ensures enhanced crashworthiness, durability, and energy efficiency while minimizing the risk of recommending unsuitable materials that could lead to structural failure or economic loss. Therefore, consistent with the accuracy and cost-based evaluation, the ROC curve analysis conclusively establishes the Optimizable Ensemble as the most reliable, generalizable, and statistically superior model for EV chassis material classification.

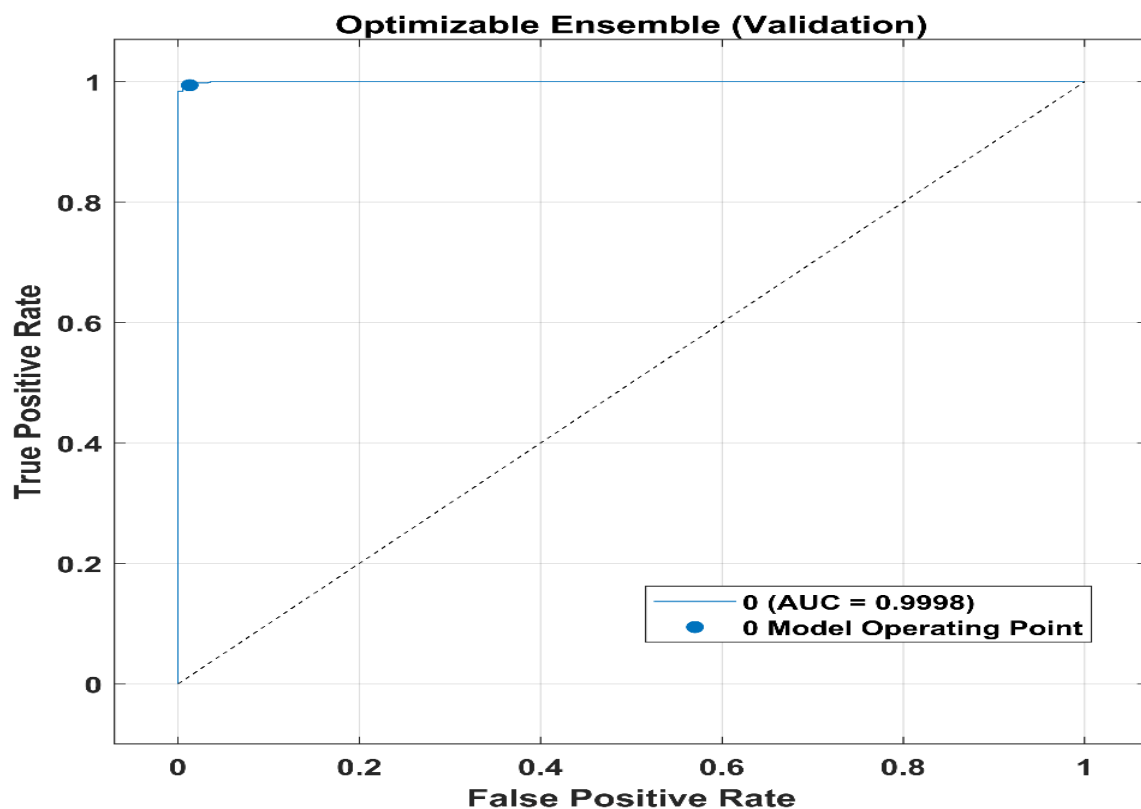


Figure 5. The ROC (Validation) of Optimizable Ensemble.

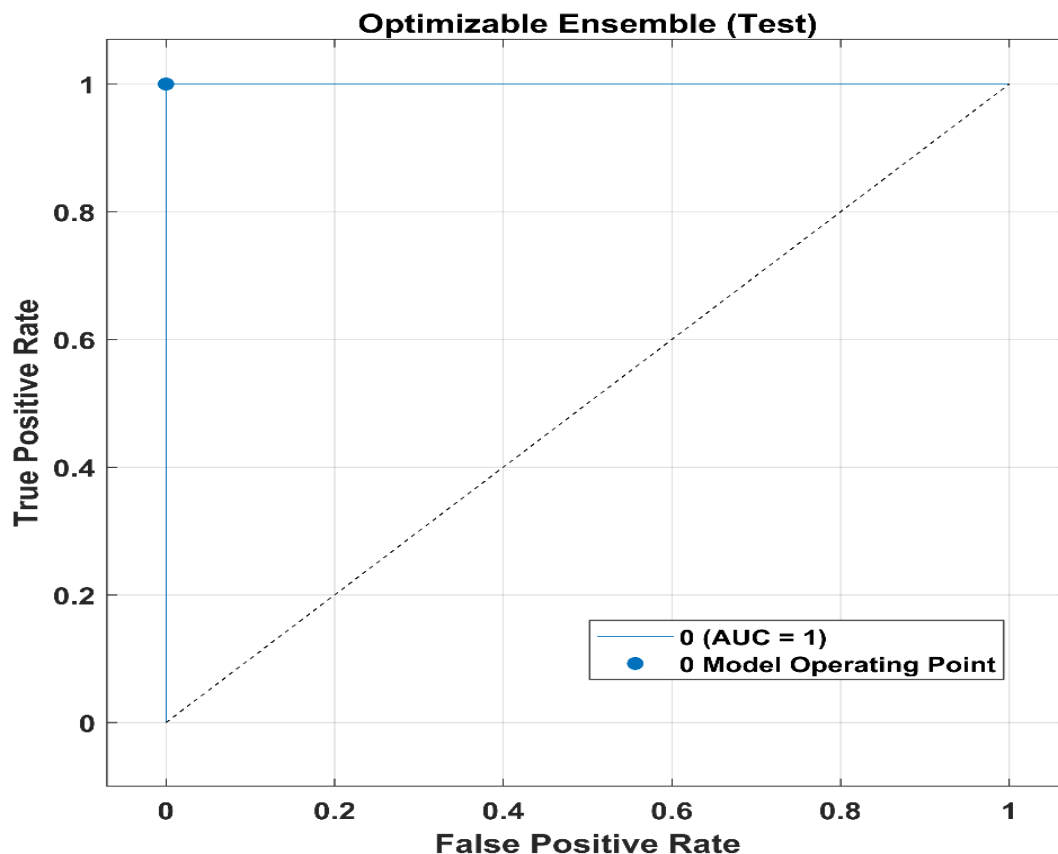


Figure 6. The ROC (Test) of Optimizable Ensemble.

3.4 Hyperparameter Optimization

Figure 7 shows the Bayesian Optimization results for hyperparameter optimization of the optimizable ensemble models. There are 30 iterations, and 28 show the best hyperparameter. The hyperparameter optimization figure shows the performance progression of the optimizable ensemble model during the automated search. The plot typically shows the objective function value (e.g., classification error or cross-validation loss) versus the number of optimization iterations. A clear decreasing trend in the objective function is observed as the optimization progresses, indicating that successive hyperparameter combinations progressively improve model performance.

In the initial iterations, the model exhibits relatively higher validation error, reflecting suboptimal parameter configurations. As the optimization process continues, the algorithm explores different combinations of critical parameters such as the number of learners, learning rate, maximum tree depth, and minimum leaf size, and gradually converges toward an optimal configuration. The rapid decline in loss during early iterations suggests effective exploration of the hyperparameter space, while the stabilization of the curve in later iterations indicates convergence to a near-global optimum.

The final optimal point corresponds to the minimum observed validation loss, which aligns with the previously reported near-perfect validation accuracy (99.21%) and zero misclassification cost on the test dataset. This confirms that automated hyperparameter tuning significantly improves both bias–variance balance and generalization.

From a statistical learning perspective, the smooth convergence behavior suggests that the optimization algorithm successfully balanced exploration and exploitation, avoiding local minima and overfitting. The absence of erratic fluctuations in the objective function further indicates model stability during tuning.

From an engineering standpoint, this optimized configuration ensures reliable decision boundaries for EV chassis material selection, minimizing the risk of structural misclassification. The hyperparameter optimization process, therefore, plays a crucial role in transforming a conventional ensemble model into a highly accurate and robust predictive framework.

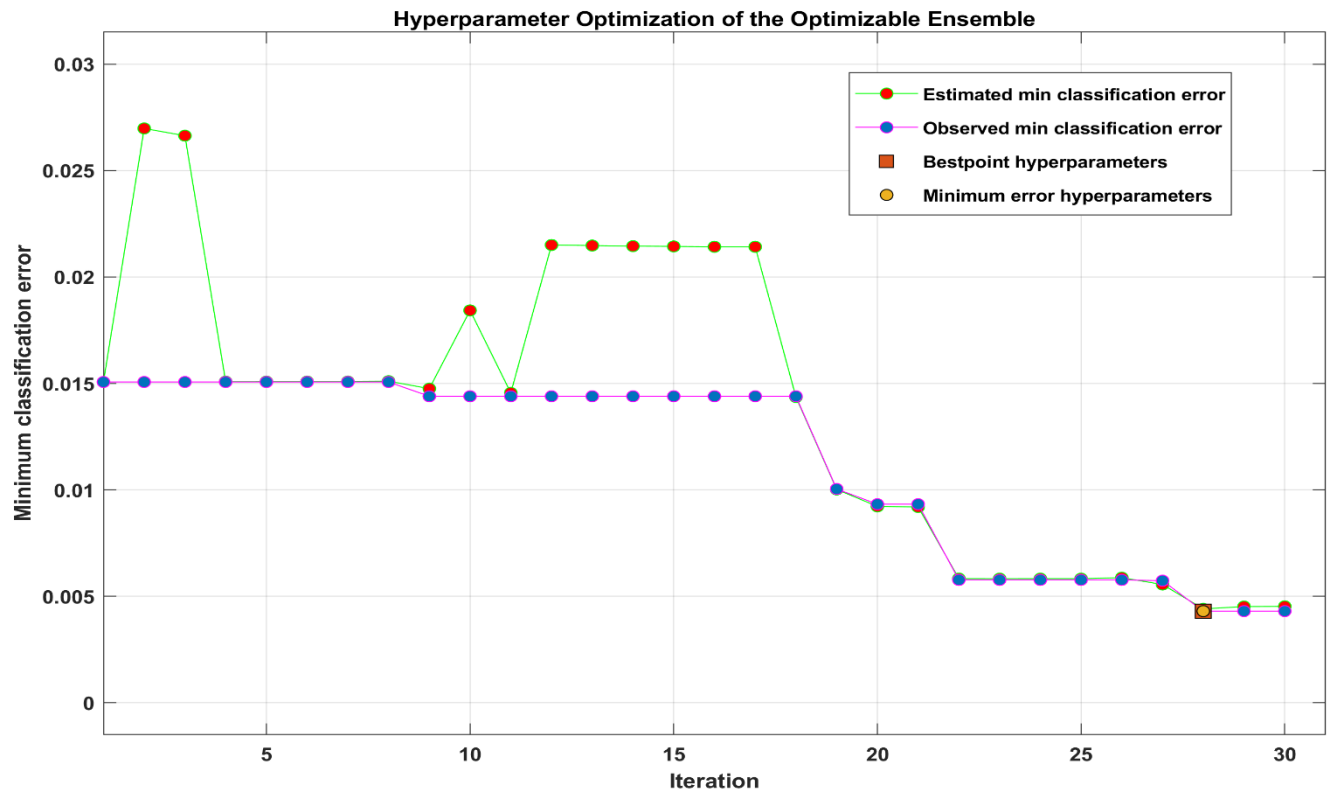


Figure 7. The plot of minimum MSE vs. iteration during the hyperparameter optimization of the Optimizable Ensemble model for EV Chassis material selection.

4. CONCLUSION

This study presented an ML-based framework for EV chassis material selection using ensemble methods, including Boosted Trees, Bagged Trees, and an Optimizable Ensemble. The Chi-square feature ranking analysis established tensile strength and yield strength as the most statistically significant predictors, followed by density and stiffness-related parameters, thereby confirming the engineering relevance of the selected mechanical descriptors. Comparative model evaluation demonstrated that while Boosted Trees and Bagged Trees provided moderate classification performance with reasonable generalization, their predictive accuracy and cost reduction were limited. In contrast, the Optimizable Ensemble model achieved superior performance, with 99.21% validation accuracy and 100% test accuracy, accompanied by negligible misclassification cost. The ROC curve analysis further validated its near-perfect discriminative capability, and the hyperparameter optimization results confirmed stable convergence toward an optimal bias–variance balance without overfitting.

From an engineering perspective, the proposed optimized ensemble framework ensures reliable identification of structurally suitable, lightweight, and high-strength materials, thereby reducing the risk of incorrect material selection that could compromise crashworthiness, durability, or manufacturing efficiency. Overall, the findings demonstrate that integrating statistical feature ranking with automated ensemble optimization provides a robust, accurate, and cost-effective decision-support system for EV chassis material classification. The proposed methodology offers strong potential for extension to other multi-criteria material selection problems in advanced automotive and structural engineering applications.

Data availability

Data will be made available on request.

Informed consent

Not Applicable.

Ethical approval

Not Applicable.

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Conflict of Interest

The authors declare no conflict of interest, or financial or otherwise.

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