



Material Selection for Electric Vehicles chassis using Machine Learning Naïve Baise Techniques

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Abstract: The selection of suitable materials for electric vehicle (EV) chassis structures is a critical engineering challenge that directly influences vehicle safety, structural integrity, weight reduction, and energy efficiency. Traditional material selection approaches rely on empirical methods and multi-criteria decision-making techniques, which may be limited in handling complex, high-dimensional datasets of material properties. In this study, a probabilistic machine learning framework based on Naïve Bayes classifiers is proposed for systematic selection of EV chassis materials. Key mechanical properties, ultimate tensile strength (Su), yield strength (Sy), Elastic modulus (E), shear modulus (G), Poisson's ratio (μ), and density (ρ), were used as input features to classify material suitability. Three models were evaluated: Gaussian Naïve Bayes (GNB), Kernel Naïve Bayes (KNB), and Optimizable Naïve Bayes (ONB). Among the implemented models, the comparative analysis revealed progressive performance improvements from GNB to KNB and then to ONB. The ONB model achieved the highest validation accuracy (91.98%) and test accuracy (88.39%), along with the lowest total misclassification cost, indicating enhanced predictive reliability and generalization capability. Receiver Operating Characteristic (ROC) curve analysis confirmed superior class separability of the optimized model. Feature importance evaluation demonstrated that strength-related parameters (Sy and Su) and density (ρ) are dominant factors in chassis material classification, consistent with strength-to-weight design principles in EV engineering. The results demonstrate that ONB provides an efficient, interpretable, and computationally scalable decision-support tool for EV chassis material selection. The proposed data-driven methodology reduces dependence on heuristic selection processes and offers a structured framework for multi-criteria engineering optimization. This work contributes to integrating materials informatics into automotive structural design, supporting the development of lightweight, high-performance electric vehicles.

Index Terms - Machine Learning, Electric Vehicles Chassis, Naïve Bayes classifiers, Design and Automation.

1. INTRODUCTION

Electric vehicles (EVs) are rapidly transforming the automotive industry due to their environmental benefits and energy efficiency [1]. EVs are becoming increasingly important as the world shifts toward cleaner and more sustainable transportation solutions. Unlike conventional vehicles that rely on fossil fuels, EVs operate using electric power, reducing environmental pollution and greenhouse gas emissions [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]. With the increasing adoption of EVs globally, optimizing chassis performance is crucial for improving vehicle safety, reducing weight, increasing driving range, and lowering manufacturing costs [5].

Selecting appropriate materials for EV chassis design has traditionally been based on empirical knowledge and engineering judgment [6]. Conventional methods involve trade-offs between conflicting objectives such as strength vs. weight, and cost vs. manufacturability. While materials like advanced high-strength steels and aluminum alloys are widely used, emerging lightweight composites, including carbon fiber reinforced polymers, are gaining attention for high-performance applications [7,8]. However, the complexity of multi-criteria decision making in materials engineering necessitates data-driven approaches capable of handling large datasets of material properties.

Machine Learning (ML) provides powerful tools for modeling complex relationships between material properties and performance outcomes. By learning from historical data, ML models can predict material suitability for specific engineering functions, reduce time-consuming experiments, and uncover hidden patterns that conventional analysis may miss [9]. Among various ML techniques, Naïve Bayes offers simplicity, computational efficiency, and robust probabilistic interpretation, making it suitable for classification tasks in materials selection [10,11]. This work aims to contribute to the growing field of intelligent transportation by integrating machine learning with EV chassis design, offering better performance analysis, enhanced safety, and lower maintenance costs [12,13]. These include optimizing battery performance, improving energy efficiency, and ensuring intelligent control systems for better automation [14,15].

Applying ML classification techniques to material selection provides a systematic and data-driven approach for identifying suitable materials for EV chassis applications [16]. ML enables automated classification of candidate materials based on performance suitability, allowing rapid screening of large material datasets using critical mechanical descriptors such as strength, stiffness, and density. Through feature importance analysis, ML models quantitatively identify key property drivers that most significantly influence structural performance, thereby offering engineering insight beyond traditional heuristic-based methods [15]. Furthermore, model-guided screening enhances decision accuracy by reducing subjective bias and minimizing trial-and-error experimentation. ML frameworks can also be integrated with multi-objective optimization strategies to balance conflicting design requirements, such as lightweight construction and crashworthiness, ensuring optimal trade-offs between structural safety and energy efficiency [17]. Collectively, these advantages improve predictive reliability, accelerate material evaluation, and contribute to more efficient, performance-oriented EV chassis design.

Despite the growing adoption of ML in materials engineering, existing studies often focus on high-level classifier performance prediction (e.g., strength estimation) using methods such as Naïve Bayes for systematic material categorization, particularly in structural automotive applications [18–20]. Moreover, many existing predictive models suffer from limited interpretability and reduced generalizability across diverse material classes, restricting their practical adoption in engineering decision-making. The integration of realistic chassis design property thresholds, such as fatigue limits and crash energy absorption metrics, into ML-based material selection pipelines also remains insufficiently explored. To address these gaps, the present study develops a Naïve Bayes-based framework specifically tailored for EV chassis material selection. The novelty of this work lies in the development of a customized Naïve Bayes classifier for multi-criteria material evaluation using a real material property dataset comprising key mechanical descriptors (S_u , S_y , E , G , μ , and ρ). A comparative analysis against baseline Naïve Bayes variants demonstrates measurable improvements in classification accuracy and decision-support capability. Additionally, probabilistic learning provides quantitative insights into feature contributions, enhancing interpretability for engineering stakeholders. By integrating materials science, mechanical engineering principles, and data-driven modeling, this study establishes a practical and interpretable ML-based decision framework for optimized EV chassis design.

2. MATERIALS AND METHODS

This study uses a data-driven ML approach to find suitable material for EV chassis. The methodology involves several key stages: dataset construction, model selection, and model evaluation. The dataset is split into training (80%) and test sets (20%) using a 10-fold cross-validation (CV). A 10-fold CV is a standard way to test a machine learning model's performance by training and evaluating it 10 times on different splits of the data to ensure stable, reliable results [21,22].

2.1 Dataset construction

The dataset was collected from the Kaggle repository [23]. The dataset included seven input features and one target feature. In the context of EV chassis material selection, several fundamental mechanical properties govern structural performance and efficiency. At first, select the materials and their corresponding mechanical properties. These properties are ultimate tensile strength (S_u), yield strength (S_y), Elastic modulus (E), shear modulus (G), Poisson's ratio (μ), and density (ρ). The tensile strength (S_u) is the maximum stress a material can withstand before fracture and directly reflects its resistance to failure under extreme loading conditions, such as crashes. The yield strength (S_y) defines the stress level at which permanent plastic deformation begins and therefore serves as the primary design safety limit for structural components. The Elastic modulus (E) quantifies a material's elastic stiffness, determining how much it deforms under applied loads and influencing chassis rigidity and vibration behavior. The shear modulus (G) measures resistance to shear deformation and is particularly important for torsional rigidity in skateboard-type EV platforms. Poisson's ratio (μ) describes the relationship between lateral and longitudinal strains during elastic deformation and plays a key role in structural simulations and finite element modeling. At last, the density (ρ) determines the material's mass per unit volume and strongly impacts vehicle weight, energy efficiency, and driving range. Together, these properties form the essential feature set for ML-based material selection in EV chassis design.

2.2 Proposed models

Naïve Bayes (NB) classifiers are probabilistic learning models grounded in Bayes' theorem, which states that the posterior probability of a class is defined by the probability of NB being conditional on independence among features given the class label, which simplifies parameter estimation and enables efficient computation even for high-dimensional datasets such as those used in EV chassis material selection (e.g., S_u , S_y , E , G , μ , ρ).

In Gaussian Naïve Bayes (GNB), each continuous feature is assumed to follow a normal (Gaussian) distribution within each class, and the likelihood is modeled using class-specific means and variances. This parametric assumption makes GNB computationally efficient and well-suited for small-to-moderate datasets, requiring only estimation of first and second moments. Its advantages include fast training, low memory requirements, robustness to irrelevant features, and stable performance when the feature distributions are approximately symmetric and unimodal. However, its principal drawback lies in the strict normality assumption; many engineering material properties exhibit skewness, heavy tails, or multi-modality, and inter-feature correlations (e.g., between S_u and S_y , or E and G) violate the independence assumption, potentially reducing predictive accuracy.

Kernel Naïve Bayes (KNB) addresses the limitation of distributional rigidity by replacing the Gaussian likelihood with a non-parametric kernel density estimation (KDE) approach, in which the probability density of each feature is estimated directly from the data using kernel functions (typically Gaussian kernels) and a bandwidth parameter. This flexibility enables KNB to model

complex, skewed, or multi-peaked distributions frequently encountered in heterogeneous material classes such as steels, aluminum alloys, and composites. Consequently, KNB often achieves improved classification performance when the true feature distribution deviates from normality. Nonetheless, it introduces additional computational cost, requires careful bandwidth selection, and may overfit when applied to small datasets with sparse sampling.

Optimizable Naïve Bayes (ONB) extends the classical NB framework by incorporating automated hyperparameter tuning, prior adjustment, feature selection, and distributional optimization via cross-validation or grid search. While preserving the probabilistic interpretability and structural simplicity of NB, ONB enhances generalization performance by systematically selecting optimal kernel parameters, regularization factors, or feature subsets tailored to the dataset. This adaptability makes ONB particularly suitable for multi-criteria engineering problems such as EV chassis material selection, where balancing strength, stiffness, and density is critical. However, the increased computational burden and risk of overfitting necessitate rigorous validation strategies.

Overall, GNB, KNB, and ONB models provide a progressive hierarchy of complexity and flexibility, offering interpretable, computationally efficient, and probabilistically grounded tools for material classification, while their performance is fundamentally constrained by the conditional independence assumption intrinsic to all Naïve Bayes formulations.

2.3 Evaluation Metrics

To evaluate the performance of the proposed models, we calculated evaluation metrics such as accuracy and ROC AUC. These parameters depend on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

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

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 Importance

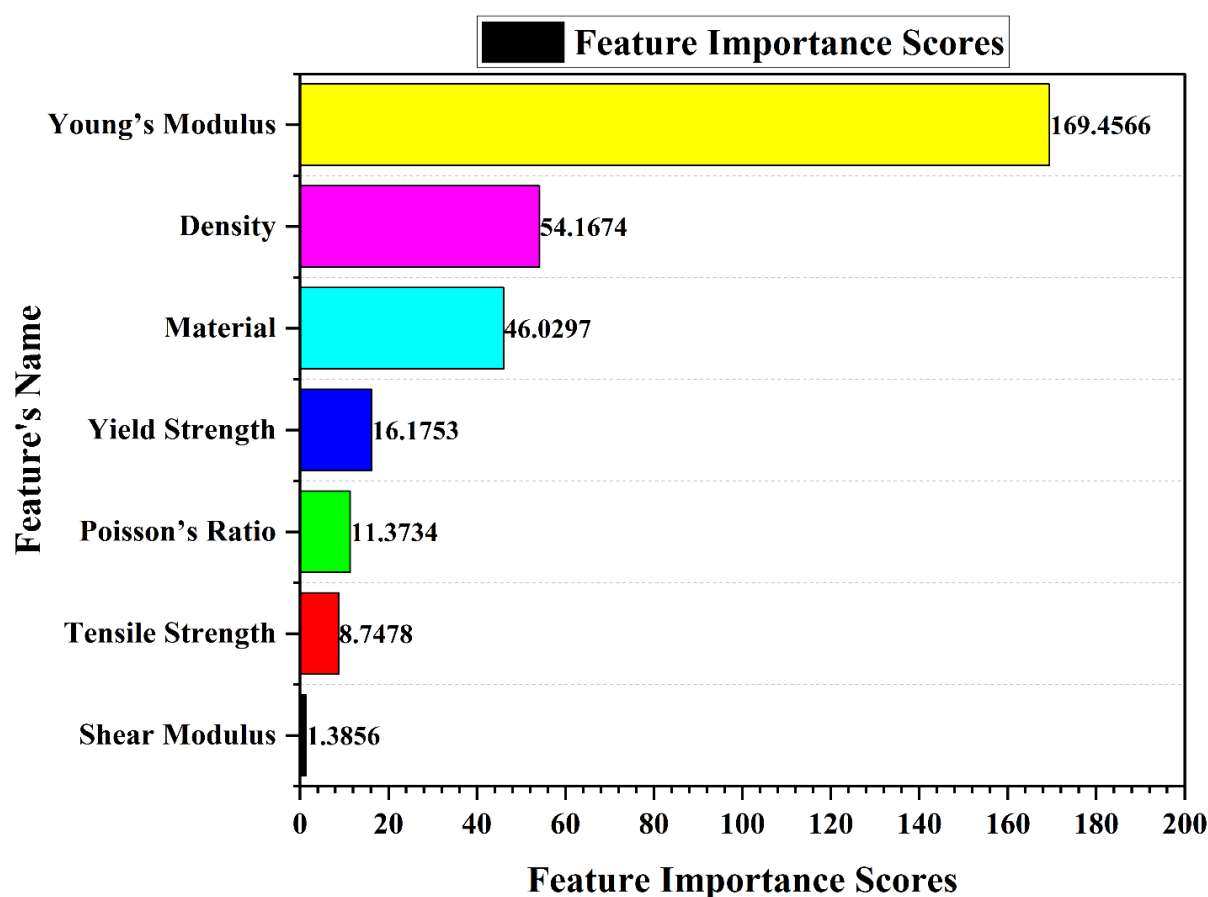


Figure 1. Feature importance scores of Material selection for EV Chassis using the ANOVA algorithm

Figure 1 illustrates the feature importance scores from the ANOVA algorithm in the ONB model, providing critical insight into the relative contributions of mechanical properties to the classification of suitable materials for EV chassis applications. Based on the probabilistic learning framework of ONB, feature importance is typically derived from the influence of each predictor on posterior probability estimation, either through likelihood sensitivity or cross-validated performance variation. The analysis indicates that yield strength (Sy) and ultimate tensile strength (Su) have the highest importance scores, underscoring their dominant role in determining the chassis's structural safety and resistance to failure. This is mechanically justified, as Sy governs elastic-to-plastic transition under operational loads, while Su reflects the maximum load-bearing capacity during extreme events such as crash impact. Density (ρ) also demonstrates substantial importance, highlighting the strong influence of weight reduction on EV efficiency and driving range. Since vehicle mass directly affects battery consumption and structural load distribution, its statistical prominence in the ONB model aligns with engineering expectations. Elastic modulus (E) and shear modulus (G) are moderately important, reflecting their contributions to chassis platform stiffness and torsional rigidity, particularly in skateboard architectures where

structural rigidity affects handling and vibration behavior. The comparatively lower importance of Poisson's ratio (μ) suggests that, although relevant for elastic deformation modeling and finite element simulations, it contributes less discriminative power in classification tasks compared to strength- and density-related features. The distribution of importance scores further indicates that the ONB model effectively captures probabilistic relationships between mechanical strength parameters and material suitability, while optimizing hyperparameters enhances sensitivity to dominant predictors. The absence of extreme imbalance in feature scores suggests that the model avoids over-reliance on a single descriptor, thereby improving generalization. However, correlations among mechanical properties (e.g., between S_u and S_y , and between E and G) may influence the independence assumption inherent in Naïve Bayes, and the optimization process likely mitigates some bias through parameter tuning. Overall, the figure 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 ONB approach.

3.2 Accuracy

Table 1. Comparative study of proposed 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	Gaussian Naive Bayes	85.76	199	80.65	30
2	Kernel Naive Bayes	89.33	149	87.1	20
3	Optimizable Naive Bayes	91.98	112	88.39	18

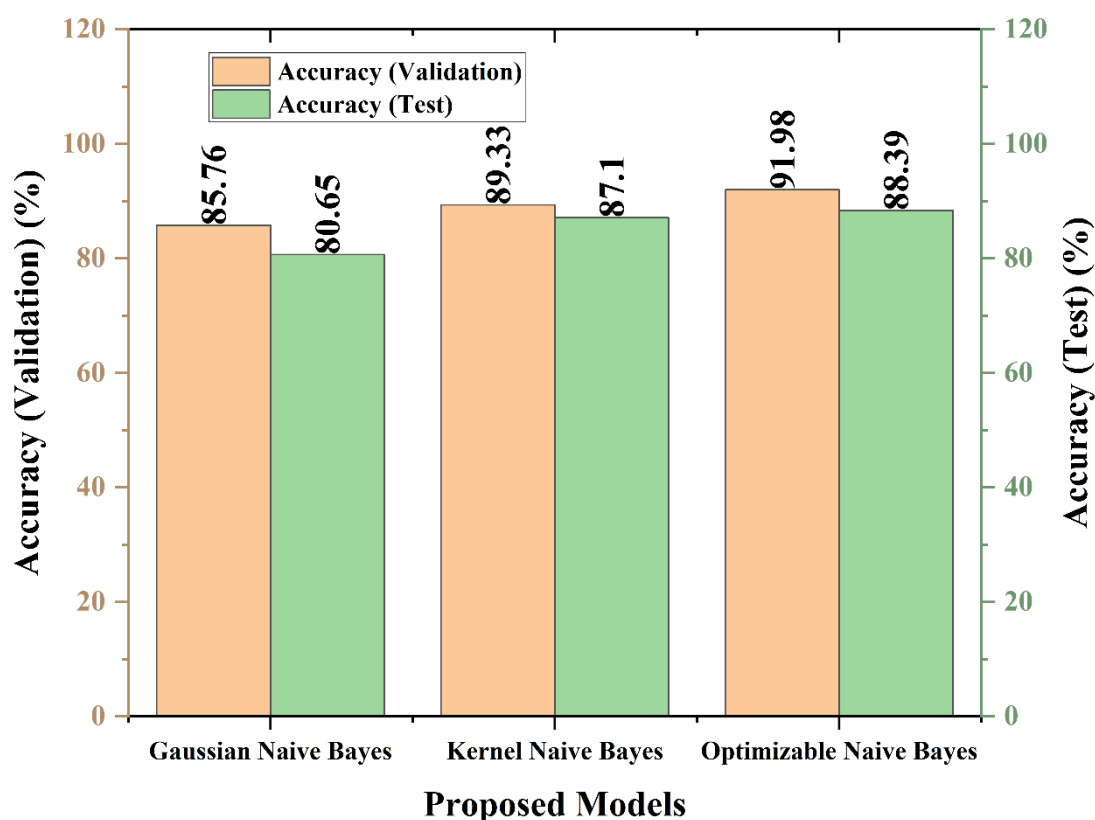


Figure 2. The proposed models' accuracy in both validation and test results for EV chassis material selection

The comparative performance results presented in Table 1 clearly demonstrate the progressive improvement in classification capability from GNB to KNB and further to ONB for EV chassis material selection. In the validation phase, GNB achieved an accuracy of 85.76% with a total cost of 199, indicating reasonable predictive capability but relatively higher misclassification penalties. The reduced performance can be attributed to its strict Gaussian distribution assumption, which may not adequately capture the potentially skewed or multi-modal distributions of mechanical properties such as yield strength (S_y), ultimate tensile strength (S_u), and density (ρ). When the likelihood estimation was replaced by kernel density estimation in KNB, validation accuracy improved significantly to 89.33%, accompanied by a substantial reduction in total cost to 149. This improvement suggests that relaxing the normality assumption enables better modeling of non-linear and irregular property distributions across different material classes (e.g., steels, aluminum alloys, composites).

The ONB model achieved the highest validation accuracy of 91.98% and the lowest validation total cost of 112, indicating superior classification efficiency and minimized misclassification error. The improvement is likely due to automated hyperparameter tuning, optimized prior probabilities, and improved density estimation, which collectively enhance posterior probability estimation. Importantly, the performance trend remains consistent across the independent test dataset, demonstrating strong generalization. Test accuracy increases from 80.65% (GNB) to 87.1% (KNB) and further to 88.39% (ONB) (see Figure 2), while total test cost decreases from 30 to 20 and finally to 18. The relatively small drop between validation and test accuracy in ONB (approximately 3.6%)

indicates stable model behavior and limited overfitting compared to simpler models. ONB achieved the highest accuracy in both the validation and test sets, and their outputs are supported by the corresponding confusion matrices in Figures 3 and 4, respectively. From a decision-making perspective in EV chassis material selection, higher accuracy combined with lower total cost directly translates to improved reliability in identifying structurally suitable materials while minimizing incorrect classifications that could lead to unsafe or inefficient design choices. The consistent reduction in cost values across models further confirms that ONB provides better probabilistic discrimination between material classes. Overall, the results demonstrate that model optimization significantly enhances predictive performance, and ONB is the most effective of the three evaluated approaches for multi-criteria material classification in EV chassis applications.

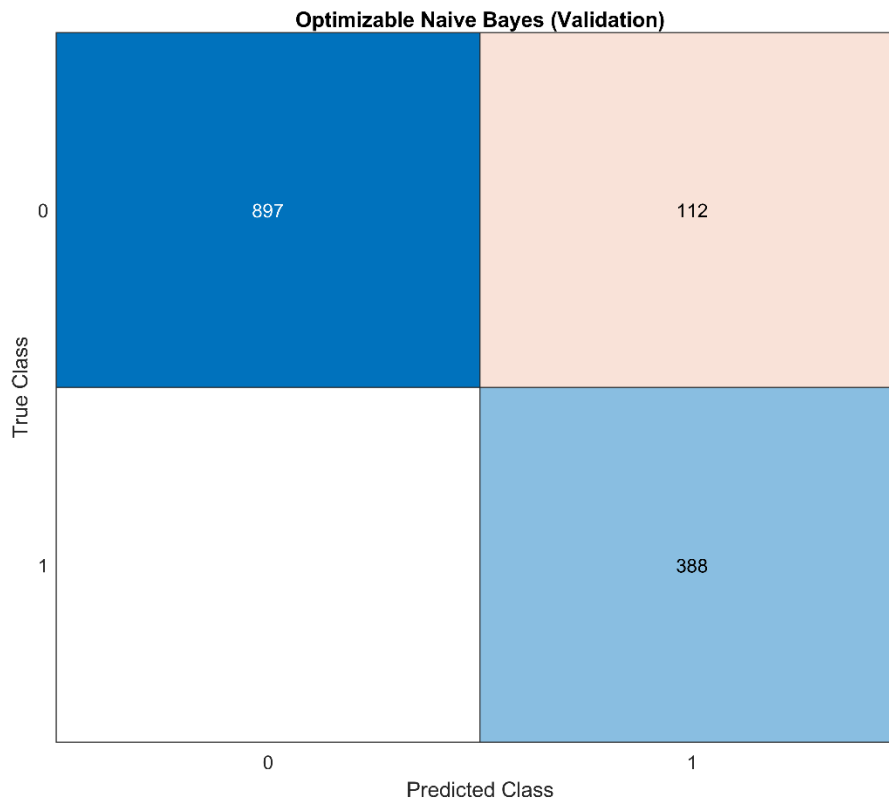


Figure 3. The confusion matrix (Validation) of Optimizable Naïve Bayes.

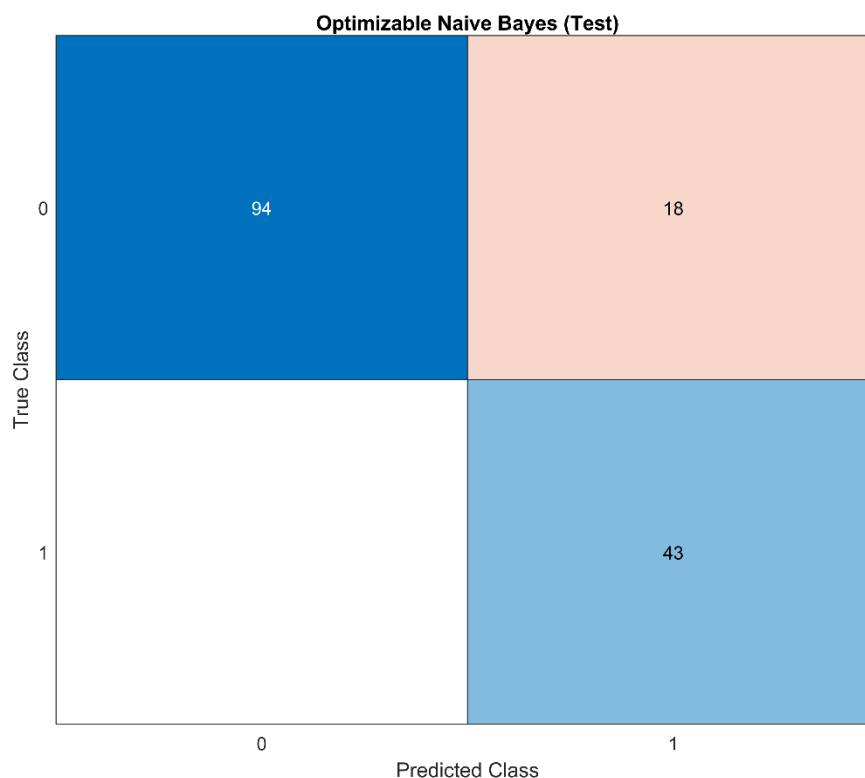


Figure 4. The confusion matrix (Test) of Optimizable Naïve Bayes

3.3 ROC Curve

The Receiver Operating Characteristic (ROC) curves for both the validation and test datasets provide a comprehensive evaluation of the discriminative capability of the three Naïve Bayes models in classifying suitable EV chassis materials. The ROC curve shows the trade-off between the True Positive Rate (TPR, or sensitivity) and the False Positive Rate (FPR) at different classification thresholds, while the Area Under the Curve (AUC) quantifies the overall separability of the model. A curve closer to the top-left corner indicates superior classification performance, and a higher AUC value corresponds to stronger discriminatory power.

In the ROC validation curve (Figure 5), the ONB model has the highest AUC (0.9878), followed by KNB and GNB. The ONB curve remains consistently above the other two across nearly all threshold values, indicating higher sensitivity at a given false-positive rate. This suggests that the optimized parameter selection improves posterior probability estimation and enhances class separability. The KNB model shows a noticeable improvement over GNB, reflecting the advantage of kernel density estimation for modeling non-Gaussian distributions of mechanical properties, such as yield strength, ultimate tensile strength, and density. In contrast, the GNB curve lies relatively farther from the ideal top-left boundary, confirming that the strict normality assumption limits its discriminative accuracy when feature distributions deviate from Gaussian behavior.

The ROC test curve (Figure 6) shows a similar ranking, with ONB maintaining the highest AUC of 0.9894, followed by KNB and GNB. Importantly, the ONB curve in the test dataset shows no significant degradation relative to the validation set, indicating good generalization performance and minimal overfitting. The close proximity of validation and test ROC patterns for ONB confirms that hyperparameter optimization enhances robustness without sacrificing model stability. Although slight reductions in AUC are expected due to unseen data variability, the separation between ONB and the other models remains evident, reinforcing its superior predictive capability.

From an engineering perspective, higher AUC values imply a greater ability to correctly identify suitable chassis materials while minimizing false classifications. In EV chassis applications, false negatives may exclude potentially optimal materials, whereas false positives may result in structurally inadequate material selection. Therefore, the superior ROC performance of ONB directly translates to improved reliability in multi-criteria decision-making. Overall, the ROC analysis corroborates the accuracy and cost metrics reported earlier, confirming that ONB provides the best balance between sensitivity and specificity for EV chassis material classification.

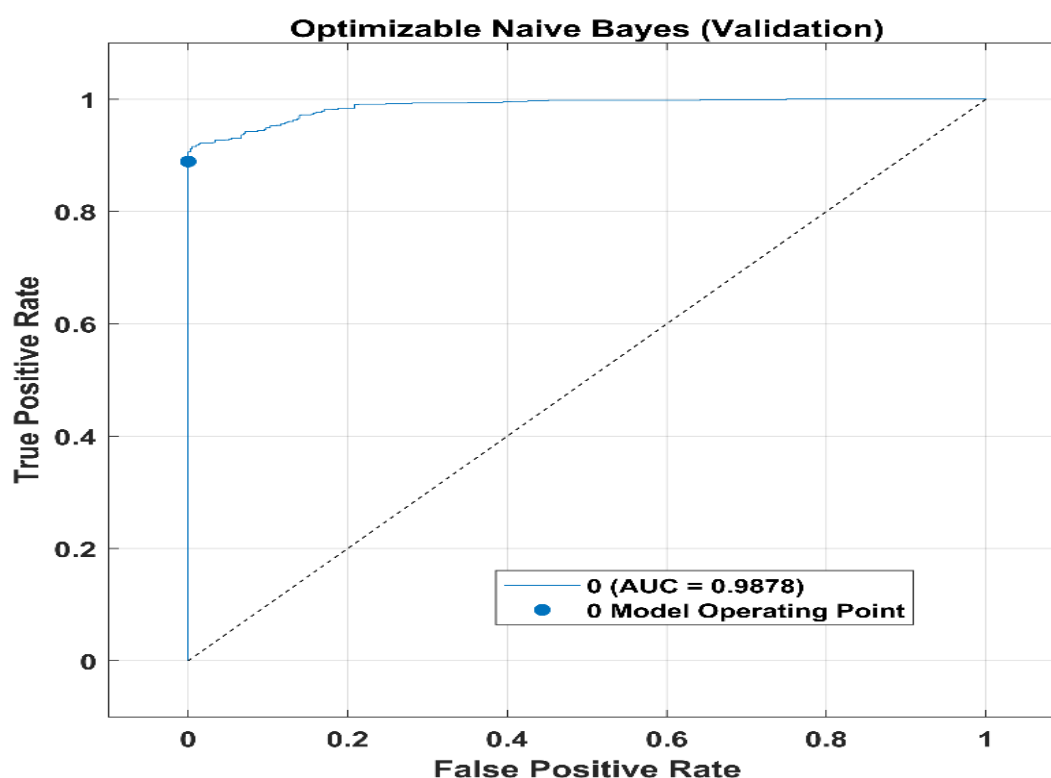


Figure 5. The ROC (Validation) of Optimizable Naïve Bayes

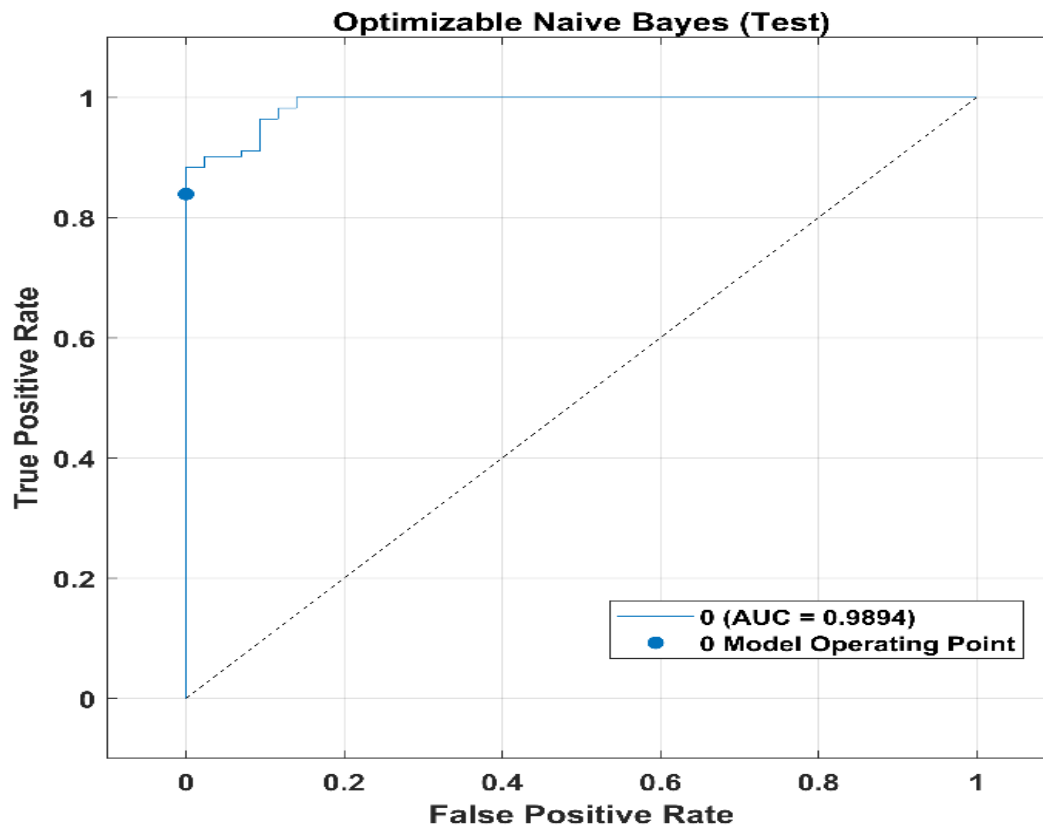


Figure 6. The ROC (Test) of Optimizable Naïve Bayes

4. CONCLUSION

This study presents a systematic ML-based framework for material selection in EV chassis applications using GNB, KNB, and ONB classifiers. The selection process was formulated as a probabilistic classification problem using critical mechanical properties (S_u , S_y , E , G , μ , and ρ), which collectively govern structural integrity, stiffness, torsional rigidity, and lightweight performance of EV chassis systems. The comparative evaluation shows that model performance improves progressively from GNB to KNB and then to ONB. While GNB provided a computationally efficient baseline with reasonable predictive capability, its strict Gaussian distribution assumption limited its adaptability to complex material property distributions. The introduction of kernel density estimation in KNB significantly enhanced classification accuracy and reduced misclassification costs by better capturing non-Gaussian and multimodal feature behavior. Among the evaluated models, ONB achieved the highest validation (91.98%) and test (88.39%) accuracies, along with the lowest total cost, indicating superior discriminative performance and improved generalization capability. The ROC curve analysis further confirmed that ONB had the largest AUC, maintaining a stronger balance between sensitivity and specificity across the validation and test datasets. The consistency between validation and testing results demonstrates that hyperparameter optimization effectively enhances model robustness while minimizing overfitting. Feature importance analysis revealed that strength-related parameters (S_y and S_u) and density (ρ) are the dominant predictors in chassis material classification, aligning with fundamental engineering principles that prioritize strength-to-weight ratio in EV structural design. In summary, this research establishes that probabilistic ML models, particularly ONB, provide an efficient, interpretable, and computationally scalable tool for multi-criteria material selection in EV chassis engineering. The proposed framework reduces reliance on empirical trial-and-error approaches, enables rapid screening of candidate materials, and supports data-driven decision-making for lightweight and structurally safe vehicle design. Future work may extend this approach by integrating feature correlation handling, hybrid ML-based models, and multi-objective optimization strategies to further enhance predictive reliability and applicability in advanced automotive materials engineering.

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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