Optimizing Material Selection for Electric Vehicle Chassis: A Mechanical Properties Approach

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Keywords: Electric Vehicles (EV) Material Selection Based on Mechanical Properties Using a Data-Driven Approach for Chassis Optimization.

Abstract: It seeks to lay out an extended procedure for choosing materials for an EV chassis by employing significant mechanical properties and machine learning methods. However, with more demand for lightweight, durable, and efficient vehicles, selecting suitable materials for the chassis becomes a crucial factor in enhancing overall performance. The research uses mechanical properties, including strength, weight and durability, from a large data set to make a machine learning model that spots materials with the most promise for improving chassis design. By combining data-driven insights, this approach modernizes the material selection process that will promote better performance, safety and longevity of an EV. In summary, this work advances material selection methodologies and solidifies next-generation EV design savings, thus facilitating sustainable automotive engineering.

1 INTRODUCTION

As many countries are focused on sustainable transportation, the rate of adoption of electric vehicles (EVs) has picked up pace. The automotive sector is focusing on improving EV performance, efficiency, and safety, as governments and industries across the globe are calling for lower emissions and greener alternatives. Chassis the structural framework of the vehicle is one of the critical elements in EV development. Chassis impacts stability, durability, and structural integrity while playing a substantial role in energy efficiency, vehicle range, and overall performance.

The material for chassis construction has a direct bearing on weight, safety and energy consumption of EVs. Historically, material selection processes were largely manual and dependent on engineering experience, frequently involving trial-and-error assessments of materials. Though effective to a certain extent, such methods are innately time-consuming, resource-depleting, and inefficient for the needs of ground breaking EV architecture. As the range of material choices expands and the challenge of striking the balance between strength, mass, and durability becomes more complex, such a daring approach is needed. Therefore, the suitable chassis material should have a tensile strength. This minimizes weight while maximizing energy accumulation. It should also ideally have the right Poisson's ratio to handle mechanical stress and be resistant to fatigue over time.

Hereby you will introduce a data-driven framework that uses technologies and breakthroughs in machine learning and data science to overcome these barriers. Using mechanical property data, a predictive model is established to evaluate and rank materials for high-performance chassis construction. The tensile strength, yield strength, strain, Brinell hardness, density, and elasticity of these key properties are analysed to find the material that offer the critical trade-off between the best combination of strength, weight and performance. By combining feature engineering, regression modeling, and ensemble learning, the model should be able to facilitate the material selection process, where such selection typically has high reliance on human intuition, thus potentially reducing guesswork and prototyping work.

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The aim of this study is two-fold; first, to streamline the process of material selection during EV chassis design; second to facilitate the development of safe and lightweight vehicles which are energy efficient. By automating and enhancing the accuracy of material evaluation, this effort increases the EV manufacturing efficiency while guaranteeing performance and sustainability. Moreover, this framework aligns with the larger sustainability objectives, helping manufacturers create vehicles that lead to lower energy consumption and lower emissions. With EV technology moving forward, data-led approaches will be essential in overcoming the challenges associated with contemporary automotive innovation. This scalable and adaptable framework for material selection time empowers the automotive industry's journey towards sustainable transportation objectives while also enabling design innovation so as to guarantee EVs high performance, safety, and long-term reliability in sectors or markets of future demand.

2 RELATED WORK

Some research has been done in this field and served as the basis of the project. This section describes the previous work done in this field.

To overcome this issue, N. Srivastava (2018) suggests the use of machine learning approaches such as support vector machines, random for rest, and neural networks to accelerate and enhance the prediction of fracture behaviour based on material properties and structural features as opposed to conventional approach based on empirical models and numerical calculations which is slower and cumbersome. Also, paper (Y. Zhang et al., 2022) illustrates how the development of vehicle model of plug-in hybrid electric vehicles (PHEV) can be augmented with different machine learning (ML) methods integrated with a virtual test controller (VTC) through LSSVM and random forest (RF), increasing the accuracy of the model and optimizing control strategies. The work done in (Chen, Qiang, et al., 2020) suggests that with techniques such as reinforcement learning and genetic algorithms, which combined can allow to optimize the selection of materials towards multiple requirements.

In another study, the utilization of ML regression models such as Gradient Boosting (GB) to optimize suspension spring fatigue behaviour has been performed, enabling accurate predictions of fatigue lifespan by determining that tempering temperature is a determining factor in controlling the fatigue behaviour of the material. The study employs feature selection techniques, such as recursive feature elimination (RFE), to determine significant manufacturing parameters impacting the fatigue longevity and show how ML models can optimize material processing to increase material durability (Ruiz, Estela, et al., 2022). A more recent paper surveys the diverse application and intersection of machine learning and material science providing a broad overview of both current application and emerging opportunities (Morgan et al., 2020). One study has demonstrated that, in practice, machine learning models achieve great precision when applied for predicting the lifetime of the EV battery or its other fundamental elements, following this approach to optimize the selection of materials for the car chassis through assessment of their durability or strength for decades (Karthick, K., et al., 2024).

Moreover, the paper (Stoll, Anke, and Peter Benner 2021) details about machine learning methods that are helpful in predicting the material properties such as ultimate tensile strength (UTS) by means of simple experiments, namely, Small Punch Test (SPT). It emphasises how efficient ML is for large material data, identifying structure-property relationships, and improving properties characterization relevant to your project.

Also, about the way in which machine learning can play a major role in rational design and discovery of novel overcoming the challenges with understanding and exploration of extremely large material space, processes and properties as indicated (Moosavi et al., 2020). Summary: It summarizes all the major breakthroughs of the field of machine learning for designing materials, describing the challenges and opportunities of this field, which is related to our project of rating materials for EV chassis based on their properties. A thorough review of the application of machine learning (ML) methods on structural materials, and its promising role in enhancing the discovery and design of unique mechanical properties in materials such as high-entropy alloys (HEAs) and bulk metallic glasses (BMGs) is provided in paper (Sparks, Taylor D., et al., 2020). The role of ML in porosity prediction, defect detection, and process optimization has been established in the study (Liu, Mengzhen, et al, 2024) highlighting the potential for integrating ML algorithm and 3D printing to enhance the quality and strength of mechanical parts. The use of machine learning is having a major impact in predicting mechanical behaviour of steel component manufactured using additive manufacturing

technique and optimizing the 3D printing parameters for achieving desired mechanical properties.

The overall summary and performance of both parametric and non-parametric models was reported (Marques, Armando E., et al., 2020) for the uncertain analysis in regards to the presaging of sheet metal forming, which filled the shortage of using a small subset of individual metamodeling methods for sheet metal forming and often based on subjective performance assessment criteria. Also, study (Wei, Jing, et al., 2018) have indicated that with low computational cost and high prediction performance, machine learning is gradually becoming an indispensable tool for studying in materials science, it can predict properties, discover new materials, and explore quantum chemistry. It highlights the need for improved material databases, new principles in machine learning, and integration of DFT and machine learning for increased accuracy, all of which are applicable to your project on evaluating materials for electric vehicle chassis development. Another paper (Nasiri et al., 2021) describes revolutionization in prediction of mechanical properties and performance of additively manufactured (AM) mechanical parts (Polymers and metals) using neural networks (NN) algorithm and support vector machines (SVM) as optimization tool.

The review of literature emphasizes on the significant role of man known as machine learning in optimal material selection for the chassis of Electric Vehicle. The survey, by reviewing different studies identifies important approaches like metamodel based optimization and reinforcement learning algorithms that have shown effective for improving material performance in aspects like strength, wight and durability. The insights provide validation on the implementation of advanced machine learning algorithms into our project, pushing to optimize the material selection process enabling the field of chassis design for electric vehicles to improve in terms of efficiency and performance.

3 METHODOLOGY

The following section proceeds with all the necessary steps taken to obtain the appropriate model for the optimization in chassis selection. Below in the Figure 1 is the workflow as the system architecture that will help to guide for the best result:

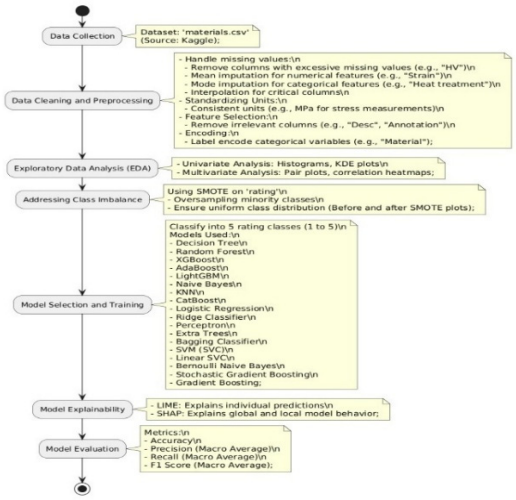

Figure 1: Workflow of methodology.

3.1 Data Collection

For retrieving the dataset for this project, the project used dataset included in second most popular data science competitions and official open dataset platform in Kaggle. It provides precise mechanics of strength and other attributes of materials like various grades of steel. Each material is characterized by some important properties related to building EV chassis, including:

– Tensile Strength (MPa): The maximum stress that a material can withstand under tensile stretching.
– Yield Strength (MPa): The stress where a material strains or bends plastically.
– Strain: The degree of deformation permitted in a material before it gets stressed.
– Brinell Hardness Number (BHN): Hardness, an index of durability.
– Elastic Modulus (MPa) & Shear Modulus (MPa): Stiffness & shear deformation resistance.
– Poisson's ratio: Ratio of longitudinal to lateral strain.
– Density (kg/m³): A key parameter affecting not only the weight of the material, but also the energy efficiency of the EV.

This robust dataset provides a strong basis for material selection based on mechanical and structural performance. Data cleaning and pre-processing was conducted before analysis and included the removal of any missing values and ensuring all data was on a uniform scale, preparing the data for the feature engineering and modelling steps.

3.2 Data Cleaning and Preprocessing

So, one of the steps of data pre-processing is called Data cleaning. Ensure that the output of your models' predictions is valid and correct. The model and analysis conducted over the dataset used did therefore rely heavily on data cleaning: the dataset contained columns with missing values or inconsistent parameters that would bias results and mislead model training and compromise predictive performance. High quality data was ensured through the following data cleaning steps:

Handling missing Values: Columns with a lot of empty data (e.g. "HV") were dropped. Mean imputation was applied to numerical features, such as "Strain," while the mode was used for categorical features (e.g., "Heat treatment"). Next, since the material properties are varied in a predictable way based on the underlying physical or chemical principles, missing values in key columns were also processed by interpolation. This method ensured that minimal information loss occurred and that the integrity of the analysis was preserved.

Standardizing Units: All mechanical property columns were verified for consistent units (e.g., MPa for stress measurements).
Feature Selection: Irrelevant columns (e.g., "Desc" and "Annotation") were excluded to focus on features contributing to material classification.
Encoding: Categorical variables, such as "Material" and "Heat treatment," were encoded using label encoding.

3.3 Explanatory Data Analysis

Explanatory Data Analysis (EDA) was conducted to gain insights into the dataset, assess variable distributions, and explore interrelationships between features. Key steps included:

- Univariate Analysis: Histograms and KDE plots were used to understand the distribution of individual variables as shown in Figure 2 and Figure 3 respectively. Likewise, Figure 3 shows a unique pattern between two physical properties i.e. Tensile_strength (MPa) and Strain which show left skewness of the data.
- Multivariate Analysis: Pair plots and correlation heatmap revealed relationships between mechanical properties, such as the strong correlation between tensile and yield strength as shown in Figure 4 and Figure 5.

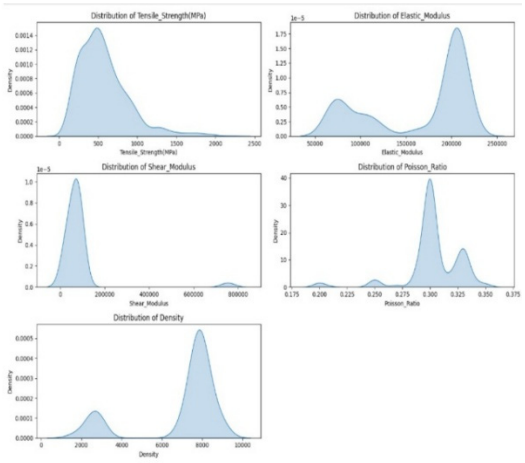

Figure 2: KDE plot.

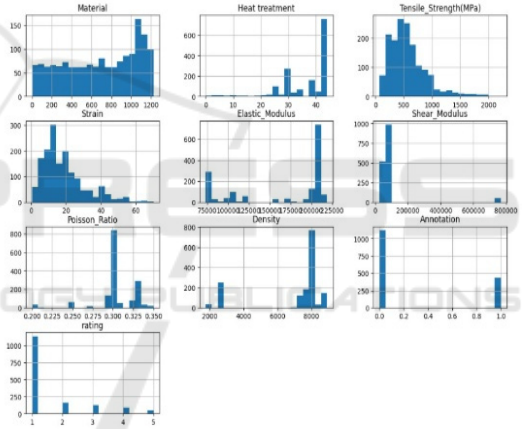

Figure 3: Hist plot.

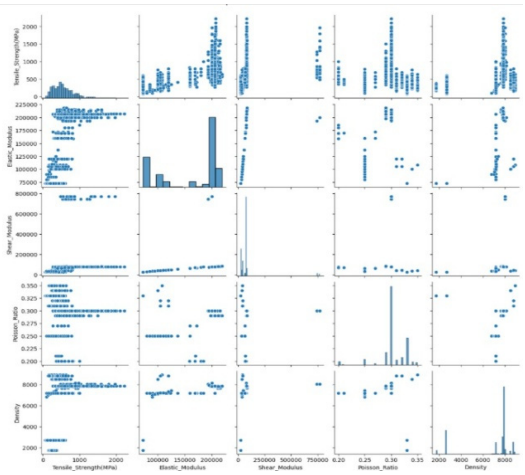

Figure 4: Pair plot.

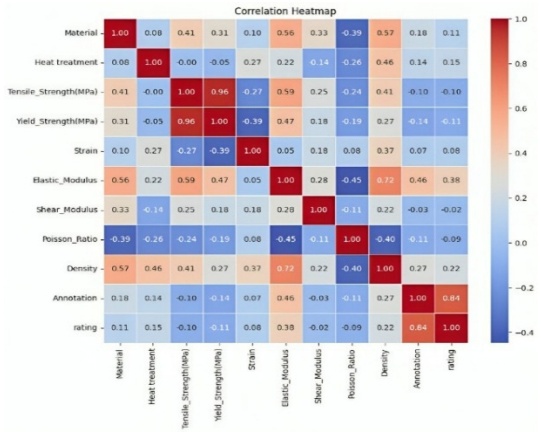

Figure 5: Correlation heatmap.

3.4 Addressing Class Imbalance with SMOTE

The dataset had imbalanced classes in the "rating" target variable, risking biased predictions as shown in Figure 6. SMOTE was employed to oversample minority classes:

- Implementation
  After splitting 80% of dataset into training set and rest of the 20% into testing sets, SMOTE generated synthetic samples for minority classes as showing in Figure 7.
- Results
  The resampled dataset ensured uniform class distribution, improving model learning and fairness.

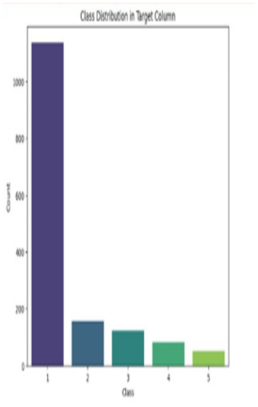

Figure 6: Before employing SMOT

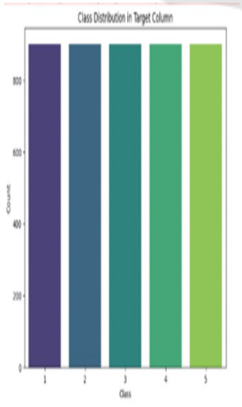

Figure 7: After employing SMOT.

3.5 Model Selection and Training

This study used supervised classification methods to train models using data pertaining to different EVA materials for determination of material rating suitable for EV chassis development. These models include classification models to assign the materials into classes of ratings from 1 to 5. To cover different modeling paradigms the implementation included a wide variety of machine learning algorithms whose diversity ranges from tree-based methods to linear models to boosting algorithms to probabilistic techniques.

The Decision Tree Classifier and Random Forest models were selected for their interpretability and inherent capacity to learn non-linear relationships. Random Forest, being an ensemble learning algorithm, increased prediction accuracy by averaging the accuracy of all individual decision trees thus reducing overfitting. Because of their ability to iteratively improve on weak learners, boosting techniques such as XG Boost, AdaBoost, and Light GBM were also used, in particular, due to its high computational efficiency for large datasets, Light GBM performed particularly well. Comparing with some simpler approaches, Naïve Bayes and K-Nearest Neighbors (KNN)were incorporated. Naïve Bayes serves as a probabilistic baseline, while KNN shows the performance of a distance-based classifier. And so was Logistic Regression for its interpretability and robustness in classification tasks. We included the Cat Boost algorithm, which works efficiently with categorical data, resulting in a reduced need for pre-processing, all while providing the best accuracies.

3.6 Model Explain Ability with LIME and SHAP

Machine learning models, that includes likes of Random Forest Classifier, which are complex are often perceived "black boxes" due to their lack of interpretability. In order to address this, LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive ex Planations) were applied to explain and interpret the predictions made by the model. LIME was applied to predictions on the test set to identify how features like "Tensile Strength (MPa)" or "Density" influenced the model's decision for individual materials as shown in Figure 8. Unlike other interpretable techniques, LIME and SHAP offers both global and local interpretability, thus it is the best for the understanding of the model behaviour and individual predictions as a whole. SHAP values were calculated to identify the features contributing most to the classification task across the entire dataset as shown in Figure 9.

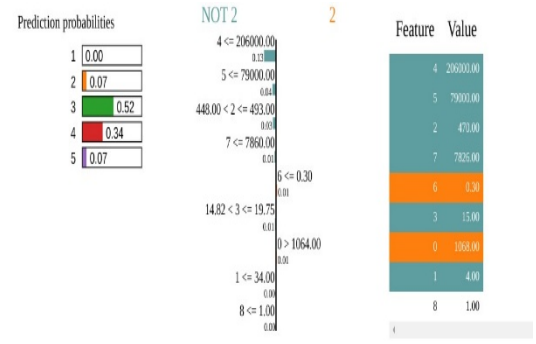

Figure 8: LIME implementation on Random Forest Classifier.

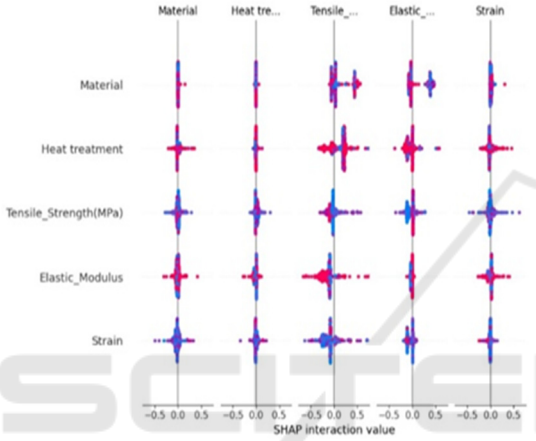

Figure 9: SHAP implementation on Random Forest Classifier.

3.7 Model Evaluation

- Accuracy: The fraction of number of correct predictions to the total number of predictions made. It measures how well the model correctly predicts or classifies the target class.
- Precision (Macro Average): Measures the proportion of positively predicated instances that are actually correct. It focuses on True Positives (TP) through minimisation of False Positives (FP).
- Recall (Macro Average): Gives the proportion of correctly identified actual positive instances, by the model. Therefore, it is also known as True Positive rate or sensitivity.
- F1 Score (Macro Average): It is calculated as the harmonic mean of precision and recall, providing a balance between the aforementioned metrices i.e. Precision and Recall. It becomes essential when there is an imbalance between the classes.

These metrics provide a broad understanding about the performance of model taking an account of different aspects of classification effectiveness and including the trade-offs between incorrectly predicated instances like false positives and false negatives.

4 RESULT AND ANALYSIS

Table 1 presents the performance metrics results for various classifiers. The table reports the performance of each model using four common classification metrics i.e. accuracy, precision, recall, and F1 score. These metrics give you a decent idea of how much the models can (or cannot) predict (train) — and hence they're desirable on that basis. Between the evaluated models XGBoost, Random Forest Classifier and LightGBM been as best performing models having accuracy of 0.95 and the fairness for precision, recall and the F1 score is 0.95 respectively. This result shows that the ensemble technique works well on the results from boosting approach and bagging approach which is capable of dealing the complex data distribution and at the same time prevent from over fitting. The high F1 scores also show the trade-off between precision and recall of these models is balanced and thus can be said the models are robust for practical use. The Decision Tree, Gradient Boosting, and Extra Trees classifiers also performed quite well, with accuracies between 0.93 and 0.94, and consistently high precision, recall, and F1 scores. All these methods use tree-based algorithms that also perform well for non-linear relationships in the datasets. These display the best predictive power although not quite as strong as the top ensemble models.

While the Logistic Regression and Naive Bayes models were relatively lower in accuracy (0.67 and 0.61 respectively) due to the simplicity of their models. Although these models are good performing in precision and recall layout, they show low performance with regard to handling complex data as explored by the low F1 score. Again, the Support Vector Machine (SVC) and Stochastic Gradient Descendent (SGD) models had even lower accuracies at 0.49 and 0.37 respectively suggesting that linear models or models sensitive to feature scaling are not effective for this dataset.

To my surprise the Perceptron model failed to meet the expectation, achieving an accuracy of 0.06 and an F1 score of 0.04. Such information is not available when working with single-layer neural networks and is something more complex data problems may need to go through before a defined solution can be rendered, which is exactly what deep

learning does. Table 1 show the Model Evaluation Metrics for Various Classifiers.

Table 1: Model Evaluation Metrics for Various Classifiers.

Model	Accuracy	Precision	Recall	F1 Score
k-Nearest Neighbour	0.90	0.71	0.72	0.71
Logistic Regression	0.67	0.37	0.42	0.37
XGBoost (eXtreme Gradient Boosting)	0.95	0.95	0.95	0.95
Decision Tree	0.94	0.94	0.94	0.94
Random Forest Classifier	0.95	0.95	0.95	0.94
Ridge Classifier	0.82	0.82	0.82	0.82
Perceptron	0.06	0.76	0.06	0.04
Extra Trees	0.93	0.93	0.93	0.93
Bagging Classifier	0.93	0.93	0.93	0.93
Support Vector Machine (SVC)	0.49	0.79	0.49	0.58
Linear SVC	0.67	0.74	0.67	0.69
Naive Bayes	0.61	0.81	0.61	0.67
Bernoulli Naive Bayes	0.84	0.79	0.84	0.80
AdaBoost	0.85	0.79	0.85	0.81
LightGBM	0.95	0.95	0.95	0.95
Stochastic Gradient Descent (SGD)	0.37	0.77	0.37	0.43
CatBoost	0.93	0.93	0.93	0.93
Gradient Boosting	0.94	0.94	0.94	0.94

The Ridge Classifier and Bernoulli Naive Bayes models achieved an accuracy of 0.82 and 0.84, respectively, giving a moderate performance evaluation. These models could have been useful in scenarios where computational simplicity and interpretability were prioritized over absolute predictive accuracy.

Finally, the high-performing AdaBoost (0.85 accuracy) and Cat Boost (0.93 accuracy) further emphasize the effectiveness of boosting algorithms in improving model accuracy and generalization. These methods demonstrate their ability to correct weak learners iteratively, resulting in strong overall performance.

5 CONCLUSION AND FUTURE SCOPE

From the evaluation results we did, it is mentioned in the article that classifier model like XG Boost, Random Forest and Light GBM performed better. XG Boost, as a gradient boosting implementation was able to achieve an accuracy of 0.95 and an F1 score of 0.95(0/1), showing that it both manages the more complicated data patterns, as well as catching most of them. For instance, Random Forest Classifier got a score of 0.95 accuracy, which is super high, and precision, recall, F1 scores are low levels, indicating good generalization and robustness of the architecture. And Light GBM also got high accuracy (0.95) and F1 score (0.95), which continues to suggest its ability to handle large datasets along with accurate predictions. This presented occasional boost in accuracy due to their ability to provoke their learning performance and strengths of diverse base learners and as we already discussed they are Mixed decision trees and gradient. Due to their cumulative strengths — XG Boost, Random Forest and Light GBM are the best possible models for real-world deployments in situations where robustness, accuracy and efficiency are key. The above study shows perceptible improvements in the choice of EV chassis material which improve both performance and sustainability of automotive design.

The results of the current study are expected to be useful for future research on improvements to the proposed framework and applications in various contexts. In addition, more mechanical properties and a larger diversity of materials could have helped expand the dataset and increase the model's versatility and accuracy. For instance, hybrid algorithms that integrate ensemble with neural networks, or other methods, will further improve predictive capabilities by utilizing the benefits of both algorithms. This would not only enhance the efficiency and performance of electric vehicles but also play a crucial role in sustainable engineering within the automotive sector.

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