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Materials With the Help of Mechanical Properties for Electrical Vehicle Chassis using Machine Learning Methods

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Abstract

Material science is a fast-growing research field where artificial intelligence is applied in a variety of applications to provide accurate solutions to the problem. Due to its generalizability, noise tolerance, and fast computation, machine learning algorithms have emerged in recent years as a potent tool for creating correlations between data, and are finding use in materials science. In this research work electric vehicle chassis material selection is done based on the mechanical properties of the material and this is done using machine learning techniques. Machine learning techniques, like logistic regression, K-Nearest Neighbor, Decision Tree, Random Forest, Naïve Base, XGBoost and AdaBoost techniques are used for the same. The stacking technique is also used which combines a variety of ML algorithms for enhanced performance and is observed that the stacking technique gives better accuracy compared to other classifiers. Binary class, as well as multiclass problems, are taken that will give solutions to the electric vehicle chassis selection material. Accuracy scores of different algorithms are compared and found that stacking works reasonably better compared to others.

Keywords: *Artificial Intelligence, Classification, Electric Vehicle, Machine Learning, Stacking*

1.0 Introduction

The material science or metallurgy field has been growing so fast for a few decades[1,2]. Material innovation and selection of the right material for a specific purpose is one of the main goals of material science research[3]. Compared to conventional materials, composite materials are widely used in many areas, especially in the automotive industry, which are used lighter in weight[4]. Modern approaches to materials research are best known for their capacity to make full use of the vast amounts of data at present, to accelerate the materials research process, and to achieve an appropriate balance between practical experimental requirements and a low error rate.

In the present digitization era, machine learning techniques are used in many areas related to the mechanical engineering field as well as other fields. Many new technologies are evolving to strengthen the existing technologies. Machine learning is the technique that mainly works based on data driven and many areas will

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benefit from these technologies. Materials scientists are using ML techniques more often to find hidden patterns. The development of new materials depends on people's ability to discover new materials and determine complex connections among them[5].

Even in the material science field ML techniques are nowadays widely used in a variety of applications like material property predictions, material discovery and many more other applications[6-8]. It seems possible to achieve the design of materials that meet specific property requirements and the development of synthesis steps to create these materials. This can be done through closed-loop active learning strategies or by utilizing advanced generative algorithms to reverse the prediction pipeline. Finding new material is a very important theme of material science engineering as well and proper usage of existing material is also very greatly required for the development of proper devices[9,10]. Fuel economy and emission control are two important challenges in the automotive industry[11]. This can be attained through electric vehicles. In this research, we are going to concentrate on a selection of materials for electric vehicle chassis creation. Right material selection using machine learning contains two parts: learning as well as prediction of the material. Right material selection can be done by using a variety of properties of the materials here mechanical properties of the materials are considered and the final goal of this work is to select the suitable material for electric vehicle chassis.

Despite whether a vehicle is an electric or IC Engine, numerous factors impact the fuel efficiency and range in its design. While selecting the electric vehicle material need to concentrate more on less weight and emission control[12,13]. The chassis is a very important component of the vehicle[14]. The weight of the electric vehicle affects the overall efficiency of the vehicle so to optimise the efficiency of the vehicle we need to decrease the weight of the vehicle. While lightweighting the vehicle we can concentrate on chassis, suspension and brake system[15]. The automotive chassis serves as the structural framework for an automobile, providing support and attachment points for key mechanical components such as the engine, axle assemblies, tyres, brakes, and steering system. It is widely recognized as the most vital element of a vehicle, as it imparts strength and stability in various operating conditions[16]. Nowadays, most cars use steel, aluminium alloys, and composites as their three primary foundation materials when creating the body panels[17]. In the process of designing the chassis, we need to consider many properties of the materials like strength of the material, elastic property, density, etc. Only selecting the material based on less-weight criteria is not the ideal way of selecting the material for chassis manufacturing. Instead of that few more properties as mentioned above also we need to consider it. The vehicle chassis plays a crucial role as it provides a base for the body and other components. When designing a chassis, it is essential to consider factors such as extreme stress, extreme deflection, and equilateral stress. The goal is to create car structures that are both lightweight and rigid (stiff)[18].

Before starting to design an EV chassis, first and foremost selection of material for the same comes into the picture. Good material selection matters a lot in the overall performance of the vehicle[19]. There are a variety of materials available, and the selection of materials based on property is a challenging task. To increase experimental efficiency and lower the error rate, great efforts are being made to develop more appropriate approaches that combine conventional experimental methods with advanced data processing techniques. The AI techniques are applied to many industries and given that the automobile industry is a prominent one, material selection also plays an important role[20]. This ML technique can provide a convenient, fast and greater solution to the material selection of chassis. Based on the different properties of various materials, the algorithm decides which most suitable material for the chassis is.

The behaviour of a material under external load conditions, such as "tension, compression, and shear forces", is defined by its mechanical properties. These things play an important task in the choice of materials during the design of products and processes. They serve as a standard for comparing the advantages of different materials and aid in the decision-making process. Therefore, a thorough understanding of the mechanical properties of engineering materials is essential for choosing the appropriate materials for specific applications. Material selection involves determining which materials will be used for a particular application. So, using ML algorithms by considering the mechanical property of the material we can decide if any material is suitable for electric vehicle chassis manufacturing.

2.0 Proposed Methodology

In this work, a material dataset with mechanical properties is considered. From that, suitable features are considered and given to the machine learning model. The ML model is built and validated concerning various criteria and the result is displayed. The whole process is shown in Figure 1.

2.1 Data Selection and Processing

The utilisation of good quality data can avoid the consideration of incorrect, misplaced, or redundant information. As a result, researchers must gather data from reliable databases. For this work data is collected from Kaggle. The dataset includes mechanical characteristics of materials used in machines, where properties of materials like Aluminum Alloy 1060-H12, Aluminum Alloy 1060-H14(of various series), Aluminum Alloy Alclad of various series, Aluminum Bronze, Architectural bronze, BS, Cartridge brass, Copper Alloy, CNS, High Leaded Tin Bronze, DIN, Grey cast iron, High Leaded Tin Bronze, JIS, Magnesium, Cast iron, Red Brass, NF, Nickel silver, Steel, yellow brass, etc, are considered. The dataset is taken from Kaggle[21]. In that, a dataset of a total of 15 mechanical properties of the materials which are designed for machine designs are considered. There were some missing values observed in some sets of features and to get rid of that data preprocessing was done and finally, only six features were considered for further processing. Features like Ultimate Tensile Strength (Su) which is represented by MPa, Yield Strength (Sy) in MPa, Elastic_ Modulus (E) in MPa, Shear_Modulus (G) represented in MPa, Poisson's_Ratio (mu) in Units of Length and Density (Ro) in kg/m^3 are considered for building the machine learning model for select the suitable materials for an EV chassis.

The point at which a material fails is known as the ultimate tensile strength. It represents the material's ability to resist an applied load. Brittle materials have an ultimate tensile strength close to the yield point, while ductile materials can have a higher ultimate tensile strength. The yield point is the point on a stress-strain curve that marks the transition from elastic behaviour to plastic behaviour. Below the yield point, a material will deform elastically and return to its original shape when the stress is removed. The elastic modulus measures the material's resistance to elastic deformation, with low-modulus materials being flexible and stretchy, and high-modulus materials being rigid and less prone to stretching. The shear modulus measures the ratio of shear stress to shear strain in a material. Poisson's ratio indicates a material's ability to thicken when compressed or thin when stretched. It is the negative ratio of transverse or lateral strain to axial or longitudinal strain.

$$\text{Elastic Modlus} = \frac{\text{Stress}}{\text{Strain}} \tag{1}$$

$$\text{Shear Modulus} = \frac{F * l}{A * \Delta_x} \tag{2}$$

Where F is the force acting on the body, l is the initial length, A is the area and Δx is the change in length.

$$\text{Poisson's ratio} = -\frac{d\epsilon t}{d\epsilon a} \tag{3}$$

Where, is a strain in the direction of load i.e., transverse strain and is a strain at a right angle to load i.e., axial strain.

In Equation 4, the term "density" refers to the mass of a material per unit volume. This shows the compactness of the construction material.

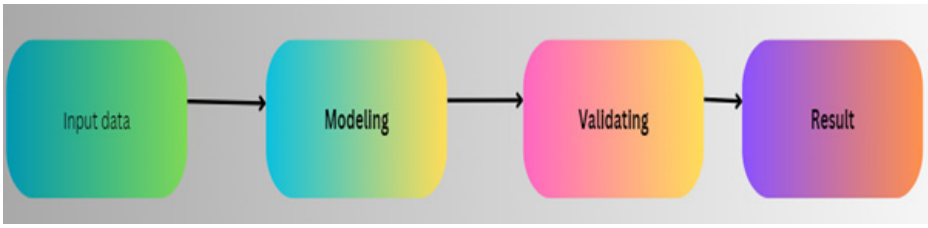


Figure 1. Machine learning model building process.

$$\text{Density} = \frac{\text{Mass}}{\text{Volume}} \quad (4)$$

There are two models developed for material selection, in which one just gives a yes, or no response means we can select a particular material based on the mechanical property of that i.e. The label contains Yes or No values. In another scenario, multi classifier concept is used where material selection is done with priority based on the scale of range 1-5. Instead of using a binary column, we require a column with values ranging from 1 to 5. In this context, a value of 5 indicates a highly suitable material for the chassis, while a value of 1 represents a material that is not suitable for the ladder frame chassis. Initially, all the materials used in the industry for chassis are identified. The average of all the values is then calculated to create a range.

2.2 Model Construction

The learning model is constructed using a variety of ML algorithms and results are compared at the end to check the suitability of the model concerning this algorithm. Logistic Regression (LR), K-Nearest Neighbours (KNN), Decision Tree (DT), Random Forest (RF), Naïve Base (NB), XGBoost (XGB) and AdaBoost (AdaB) technique are used to build the model in this work. Since each of these machine learning algorithms has advantages and disadvantages of its own, they can be used for various types of data and problem scenarios. With the above techniques stacking algorithm is also used to get good result.

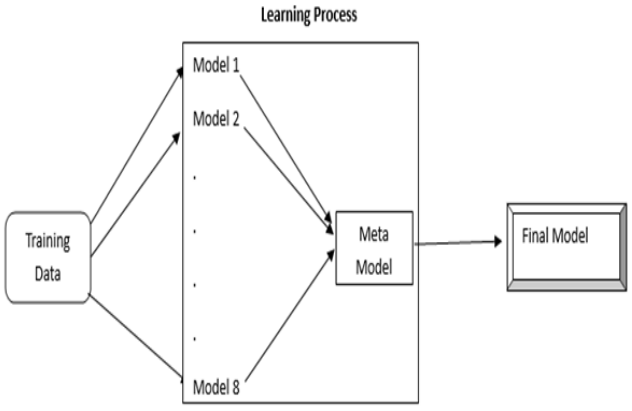


Figure 2. Stack model framework.

Stacking is a method used in ensemble learning, where multiple ML models are combined for better results. The stacking technique is used to create a more accurate predictive model by combining multiple individual models. Unlike traditional ML models, stacking learns the relationship between the predictions made by each model and the actual values. This allows stacking to determine the optimal combination of models in the ensemble, resulting in improved performance. The ensemble consists of two or more base models which fit the training data and predict out-of-sample data (level 0 models) and a higher-level meta-model that fits the predictions from the base models and learns how to best combine them (level 1 model). Figure 2 shows the general framework of a stacked model.

The stack model works as follows, first, separate the dataset into K-Folds, and apply K-Fold cross-validation. Set aside one of the folds and train multiple independent base models using the remaining folds. Use the base models to predict the held-out fold. Repeat these steps K times to obtain out-of-sample predictions for all K folds. Use all the out-of-sample predictions as features (training data) for the meta-model. Finally, predict the output using the meta-model.

2.3 Evaluate the Model

In this proposed system, LR, KNN, DT, RF, NB, XGB and AdaB are tried to build the material selection model. Also, the stacking model is constructed by using the above eight models. The model is constructed for both binary and multi-classification. Accuracy evaluation metrics are used to compare the performance of the model. Accuracy is a commonly used and straightforward evaluation metric that measures the number of correctly predicted data points.

3.0 Results and Discussions

Mechanical properties of machine design materials for electric vehicles are considered. In the experiment "Ultimate Tensile Strength (Su), Yield Strength (Sy), Elastic Modulus (E), Shear Modulus (G), Poisson's Ratio (mu) and Density (Ro)" features are considered. In a binary classifier, the class label 'use' contains a binary value. At the end of this model construction based on the

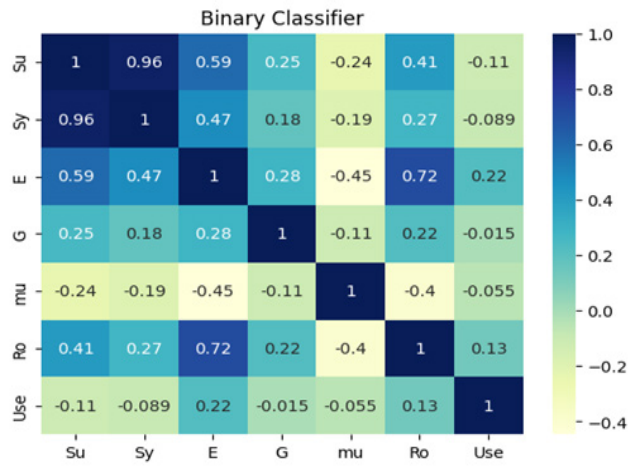


Figure 3. Correlation matrix dataset used for binary classification.

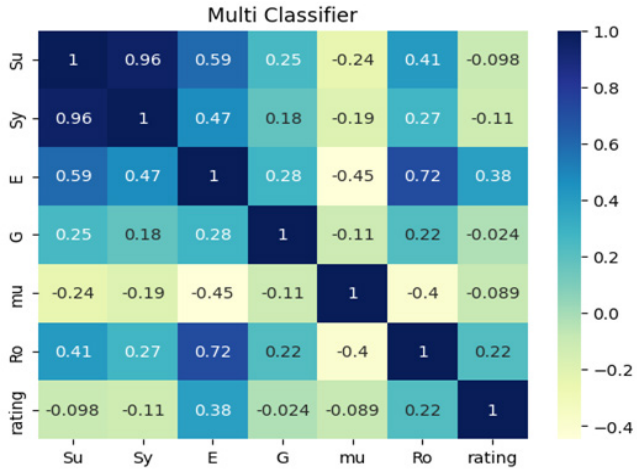


Figure 4. Correlation matrix dataset used for multi-classification.

Table 1. Result of different classifiers for both binary and multi-classes

	LR	KNN	DT	RF	NB	XGB	AdaB	Stacking
Binary Classifier	0.8669	0.9779	0.9987	0.9987	0.8387	0.9981	0.9981	0.9989
Muliti Classifier	0.6576	0.9379	0.9875	0.9888	0.6980	0.9895	0.8209	0.9931

mechanical properties of any new material we can decide, whether the material is suitable for an EV chassis or not.

The correlation matrix is a table that displays the correlation coefficients concerning variables is called a correlation matrix. In each cell of the table, the inter-relationship of two variables is displayed. In exploratory data analysis, this method is frequently employed to investigate correlations between variables or to find multicollinearity between predictors in regression analysis. Relationships are a linear link between two variables, strength and direction are measured by its coefficient. The range of the correlation coefficient ranges from -1 to 1. A correlation value of 1 indicates a perfect positive linear relationship, a correlation value of -1 indicates a perfect negative linear relationship and a correlation value of 0 indicates no linear link between the variables. The relationship between different features and target class is given in Figure 3.

The purpose of a binary classifier is to categorize data into one of two groups or classes. In contrast, when more than two classes need to be predicted, a multiclass classifier is employed. Every input instance is assigned to one of several classes by it. The decision between the two classifier types is based on the application and data availability. Both classifier types are essential in a variety of machine-learning applications.

A multiclass classifier is applied for scenarios where a rating of the material is considered as a class label. A rating of 5 shows that the material is highly appropriate for the electric vehicle chassis, whereas a rating of 1 indicates that the material is not suitable for the EV chassis. So, one to five scales are considered and the relationship between different features and target class is given in Figure 4.

Then feature set is given to different ML algorithms i.e., LR, KNN, DT, RF, NB, XGB, AdaB and stacking techniques. In this experiment, two material selection models are built in that the first one is very simple i.e., binary classifier and the second one is a multi-classifier whose result is given in Table 1.

Decision Tree, Random Forest and XGBoost algorithm also give good accuracy i.e. 99.87%, 99.87%, 99.81% and 99.81% respectively for binary classification. Even for multiclassifier systems also Decision Tree, Random Forest and XGBoost algorithm works well with 98.75%,

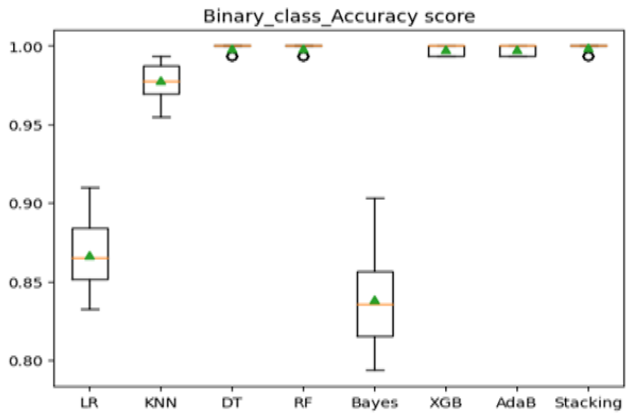


Figure 5. Classification accuracy score of binary class concerning different ML techniques.

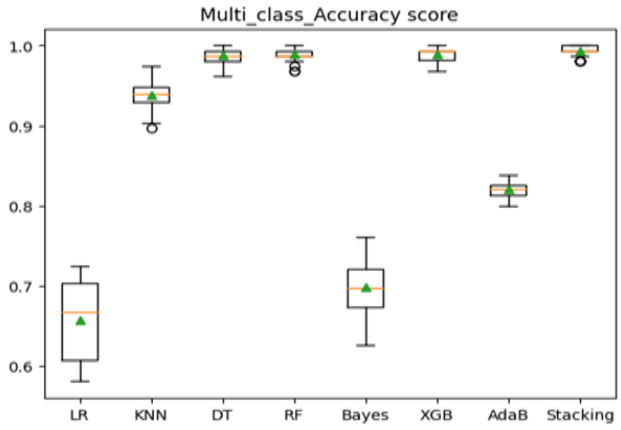


Figure 6. Classification accuracy score of multi-class concerning different ML techniques.

98.88% and 98.95%. Table 1 observed that the stacking technique gives marginally more accuracy compared to other techniques for both scenarios i.e., 99.89% and 99.31% for binary and multi-classifiers. Meta-learning is used in stacking to maximize the utility of base models by enhancing overall performance. Because the qualities of each model are merged to improve the stacking model's prediction capacity, the stacking model performs better than any of the individual models mentioned above.

Figure 5 gives the plot of the accuracy score of classifiers for binary classes and Figure 6 gives the plot of the accuracy score of different classifiers for multi classes i.e., one to five scale of material selection for EV chassis. Here we can observe the accuracy-score of different classifiers.

4.0 Conclusion

In this proposed work, a machine learning model is built for the right material selection for electric vehicle chassis using mechanical properties of the materials such as Ultimate Tensile Strength, Yield Strength, Elastic Modulus, Shear Modulus, Poisson's Ratio and Density. Logistic Regression, K-Nearest Neighbours, Decision Tree, Random Forest, Naïve Base, XGBoost and AdaBoost and stacking techniques are applied to the dataset. Both binary and multi-classifiers model is built on material selection. In multi-classifiers, the material selection is done with the priority-based scale of range 1-5. The Decision Tree, Random Forest, XGBoost, and AdaBoost algorithms exhibit good accuracy rates of 99.87%, 99.87%, 99.81%, and 99.81%, respectively, for binary classification. Similarly, for multiclass classification, the Decision Tree, Random Forest, and XGBoost algorithms perform well with accuracy rates of 98.75%, 98.88%, and 98.95%. The stacking technique yields slightly higher accuracy compared to other techniques in both scenarios, achieving 99.89% and 99.31% accuracy for binary and multiclass classifiers, respectively. In future work, more features can be used and can extend with work with other algorithms.

5.0 References

1. Zhu Y. Introduction to heterostructured materials: A fast-emerging field. Metall Mater Trans. 2021;52(11):4715-26. https://doi.org/10.1007/s11661-021-06438-8
2. Johnson NS, Vulimiri PS, To AC, Zhang X, Brice CA, Kappes BB, Stebner AP. Invited review: Machine learning for materials developments in metals additive manufacturing. Addit Manuf. 2020; 36:101641. https://doi.org/10.1016/j.addma.2020.101641
3. Correa-Baena JP, Hippalgaonkar K, van Duren J, Jaffer S, Chandrasekhar VR, Stevanovic V, Wadia C, Guha S, Buonassisi T. Accelerating materials development via automation, machine learning, and high-performance computing. Joule. 2018; 2(8):1410-20. https://doi.org/10.1016/j.joule.2018.05.009
4. Wazeer A, Das A, Abeykoon C, Sinha A, Karmakar A. Composites for electric vehicles and automotive sector: A review. Green Energy and Intelligent Transportation. 2023; 2(1):100043. https://doi.org/10.1016/j.geits.2022.100043

5. Shetty V, Shedthi BS, Shashishekar C. Application and challenges of machine learning techniques in mining engineering and material science. J Mines Met Fuels. 2023; 71(11). https://doi.org/10.18311/jmmf/2023/36099
6. Li J, Lim K, Yang H, Ren Z, Raghavan S, Chen PY, Buonassisi T, Wang X. AI applications through the whole life cycle of material discovery. Matter. 2020; 3(2):393-432. https://doi.org/10.1016/j.matt.2020.06.011
7. Shetty V, Shedthi S, Kumaraswamy J. Predicting the thermodynamic stability of perovskite oxides using multiple machine learning techniques. Mater Today Proc. 2022; 52:457-61. https://doi.org/10.1016/j.matpr.2021.09.208
8. Panchal JH, Kalidindi SR, McDowell DL. Key computational modelling issues in integrated computational materials engineering. Computer-Aided Design. 2013; 45(1):4-25. https://doi.org/10.1016/j.cad.2012.06.006
9. Liu Y, Zhao T, Ju W, Shi S. Materials discovery and design using machine learning. J Materiomics. 2017; 3(3):159-77. https://doi.org/10.1016/j.jmat.2017.08.002
10. Batra R, Song L, Ramprasad R. Emerging materials intelligence ecosystems propelled by machine learning. Nat Rev Mater. 2021; 6(8):655-78. https://doi.org/10.1038/s41578-020-00255-y
11. Mallick PK, editor. Materials, design and manufacturing for lightweight vehicles. Woodhead publishing; 2020. https://doi.org/10.1016/B978-0-12-818712-8.00008-2
12. Davies G. Materials for automobile bodies. Butterworth-Heinemann; 2012.
13. Edwards K. Interaction between functional and human-centred attributes in materials selection. Materials Experience, Butterworth-Heinemann; 2014. p. 287-99. https://doi.org/10.1016/B978-0-08-099359-1.00020-5
14. Nazaruddin N, Syehan A, Heryana G, Adhitya M, Sumarsono DA. Mode shape analysis of EV-bus chassis with reverse engineering method. IOP Conference Series: Materials Science and Engineering. 2019; 694(1):012002. https://doi.org/10.1088/1757-899X/694/1/012002
15. Sri CT, Kumar MNG, Madhuri BVSA, Harika GK, Sateesh B. Design and development of electric moped chassis. Intj Conference on Industrial Engineering and Operations Management. 2022; 321-9. https://doi.org/10.46254/IN02.20220133
16. Baskar GP, Kulkarni A, Salvi Gauri S. Finite element analysis of fire truck chassis for steel and carbon fibre materials. Journal of Engineering Research and Applications. 2014; 4:69-74.
17. Babu AR, Sairaju B, Amirishetty S, Deepak D. Automotive chassis design material selection for road and race vehicles. J Mech Eng Res Dev. 2020; 43(3):274-82.
18. Kumar S, Girgoswami R, Shukla A, Shinde P, Rathod NT. Design and analysis of chassis for electric vehicles. Int Res J Eng Technol. 2021; 8(8):3195-9.
19. Khan F, Hossain N, Mim JJ, Rahman SM, Iqbal MJ, Billah M, Chowdhury MA. Advances of composite materials in automobile applications- A review. J Eng Res. 2024. https://doi.org/10.1016/j.jer.2024.02.017
20. Kamran SS, Haleem A, Bahl S, Javaid M, Prakash C, Budhhi D. Artificial intelligence and advanced materials in the automotive industry: Potential applications and perspectives. Mater Today Proc. 2022; 62:4207-14. https://doi.org/10.1016/j.matpr.2022.04.727
21. Available from: https://www.kaggle.com/code/purushottamnawale/material-selection-using-random-forest/input