

Analysis of the Performance of Aluminum and Titanium Alloys in Unmanned Aerial Vehicle (UAV) Structures Using Machine Learning Models

Mohanad S. Hasan¹, Amjad M. Bader², Sarah Ahmed Ali Alanbaki³, Raed Mahmoud Al-Azawee⁴
^{1, 2, 3} College of Engineering, University of Diyala, Diyala, 32001, Iraq

⁴Department of Chemistry, College of Education for Pure Science (Ibn Al-Haitham), University of Baghdad, Baghdad, 11001, Iraq

mohaned.s@uodiyala.edu.iq¹, amjadmodher@uodiyala.edu.iq², saraahmadali1992@gmail.com³,
raed.mahmoud2105p@ihcoedu.uobaghdad.edu.iq⁴

Abstract

The dataset used in this research is a well-curated collection of aluminum and titanium alloy samples, compiled from experimentally reported values and reliable literature sources for UAV structural applications. The dataset created using this methodology can simulate engineering practices that use common material systems found in aerospace structures. The dataset provides a comprehensive evaluation of material properties by integrating information from various sources to capture genuine physical, mechanical, fatigue, and operational properties. The study emphasizes the variety of material attributes and the engineering importance of the attributes selected, because these factors determine the accuracy of modeling UAV material selection within a complex multi-criteria system. Each sample's material description includes 12 attributes: density, Young's modulus, yield strength, ultimate tensile strength, fatigue strength, fatigue life, hardness, corrosion resistance, weldability, cost level, and availability. The machine learning models consider both quantitative and qualitative parameters to examine how design requirements interact in nonlinear ways. The selected aluminum and titanium alloys were chosen for this study because they frequently appear in UAV systems, which establishes the dataset as both a theoretical and practical research foundation. The developed machine learning models show improved reliability and generalization, and they provide engineering value for UAV structural design and material selection.

Keywords: UAV structural design; Data-driven material selection; Ensemble learning; Mechanical and fatigue properties; Lightweight aerospace materials

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1. Introduction

The increasing development and practical applications of uncrewed aerial vehicles (UAVs) in civil, industrial, and defense sectors coincide with stringent requirements for material structural properties. UAV structures must meet conflicting requirements such as low weight, high mechanical strength, fatigue resistance, corrosion resistance, manufacturability, and cost-effectiveness; maintaining a suitable balance among these

requirements remains a major challenge in UAV structural mechanics [1].

Aluminum alloy components have traditionally dominated UAV airframe construction because of the material's low density, relatively high strength-to-weight ratio, ease of processing, and low Cost. Titanium alloy components, although denser and more expensive to process, offer strong mechanical properties, fatigue resistance, and corrosion resistance, and could be considered for certain components within a UAV system [2]. However,

choosing between aluminum and titanium alloy components involves many intricate trade-offs that a traditional rule-based selection environment cannot effectively capture [3].

Traditional approaches to material selection in aerospace engineering typically rely on empirical charts, performance indices, or expertise-based methods [4]. Although these methods have helped material scientists identify relevant materials, they usually assume a linear relationship between material properties and performance requirements, which is a major weakness. UAV structural member performance depends on several interconnected variables, including density, modulus of elasticity, yield strength, fatigue resistance, and corrosion resistance. The association between these material characteristics and performance is nonlinear and complicated [5].

In the present scenario, the recent development in machine learning (ML) techniques has been found to have great potential in effectively dealing with complex and high-dimensional problems of interest to the field of engineering, particularly in the field of materials science and design of structures, which do not lend themselves to the application of traditional methods of analysis and design calculation involving the application of statistical techniques; i.e., ML algorithms are more suitable and have been successfully utilized in the solution of problems that are related to corrosion prediction, mechanical property calculation, and material classification, as opposed to the linear modeling approaches. [3], [4] and [5].

These developments led to the present study, which focuses on a machine learning-based framework to assess the structural performance of aluminum and titanium alloys for UAV applications. The approach builds on earlier data-driven research on corrosion-dominated material performance. At the same time, the present work broadens to include basic mechanical properties, fatigue characteristics, and qualitative operational considerations. We analyzed a dataset on widely used aluminum and titanium alloys in UAV structures, considering their physical properties, mechanical properties, fatigue behavior, and qualitative operational features [6].

The key aim of this research is to investigate the potential of various machine learning algorithms to predict and evaluate UAV structural material performance using multiple-criteria input parameters [7]. By comparing different machine learning algorithms, this paper aims to (i) reveal the limitations of using conventional machine learning algorithms, (ii) show the potential of employing modern machine learning algorithms, and (iii) develop an efficient tool for the evaluation of UAV structural materials performance [8]. The general framework of the presented research approach can be extended to evaluate larger sets of materials, performance parameters, and optimization techniques for UAV structural designs.

This paper contributes to the literature by introducing a novel framework for UAV structural materials evaluation that relies on a multi-criteria machine learning model. In contrast to previous research, the study introduces a multi-criteria framework that accounts for multiple material properties and operational characteristics. The paper also compares two materials, aluminium and titanium alloys, in terms of their suitability for UAV construction. In addition, the paper explains machine learning algorithms (SHAP) to improve understanding of the results.

Beyond the general applicability of machine learning algorithms, this research aims to make a specific contribution to material selection for UAVs. Unlike traditional studies that focus on applying machine learning algorithms, this research implements a detailed multi-criteria model that considers the mechanical, fatigue, and operational characteristics of materials simultaneously within a single predictive algorithm.

Moreover, the research focuses specifically on the UAV structural problem through a comparative analysis of two metal alloys. Implementing explainable machine learning algorithms (SHAP) increases the interpretability of the algorithm's predictions by providing physical explanations for the impact of certain material parameters.

The proposed methodology not only uses machine learning algorithms but also attempts to overcome the existing barrier between engineering

decisions and machine learning modelling in UAV material selection. To make the contribution even more novel, the proposed framework complements machine learning algorithms with a multi-criteria evaluation method that makes them more practically relevant. This will be shown by incorporating various material parameters, such as toughness, fatigue resistance, and other performance aspects during actual operations, into a prediction model specific to UAV structural applications.

However, the contribution goes beyond prediction by employing explainable machine learning algorithms to interpret the relationships

formed. This enables not only predictions but also a more engineering-oriented interpretation of the results. That is why the paper's contribution combines several key aspects into one framework. Table 1 presents a comprehensive overview of the physical, mechanical, fatigue, and operational attributes employed in the machine learning-based evaluation of aluminium and titanium alloys for UAV structural applications. The selected parameters were carefully chosen to represent the key performance requirements governing material selection in lightweight aerospace structures.

Table 1: The key material properties and attributes required for modelling the structural performance of UAV structures, including physical, mechanical, fatigue, and operational characteristics.

Category	Property	Unit / Description
Physical properties	Density	g/cm ³
	Young's Modulus	GPa
Mechanical properties	Yield Strength	MPa
	Ultimate Tensile Strength (UTS)	MPa
	Elongation	%
	Hardness	HB / HV
Fatigue properties	Fatigue Strength	MPa
	Fatigue Life	Cycles
	Fatigue Test Method	Experimental / Standard-based
Operational characteristics	Corrosion Resistance	Qualitative rating
	Weldability	Qualitative rating
	Cost Level	Relative cost classification
	Availability	Market availability level
Application	UAV Usage	Structural application in UAVs

The physical characteristics, i.e., density and Young's modulus, are of critical significance in the determination of the weight efficiency and stiffness of the UAV structures. Density directly affects the airframe's overall mass, which is vital for determining flight endurance and energy requirements.

Mechanical properties such as yield strength, ultimate tensile strength, percentage elongation, and hardness define the material's ability to withstand applied loads and avoid failure. Yield strength defines the point up to which the material can endure permanent deformation. In contrast, ultimate

tensile strength defines the maximum stress the material can withstand before failure. The percentage of elongation helps measure the ductility

of the materials, which is an essential determinant in avoiding brittle failure in UAV structures. Hardness relates to material durability.

Fatigue-related parameters are particularly important in UAV applications because of the cyclic loads caused by aerodynamic forces, propulsion, and takeoff and landing cycles. Fatigue strength and fatigue life define the material's capacity to resist repeated cycles. In contrast, the fatigue test method

provides information on the procedures or tests used to determine properties under fatigue stress.

Operational characteristics relate to the material's resistance to corrosion, weldability, Cost, and availability. In this context, operational characteristics play a crucial role beyond the mechanical properties of the materials. Material corrosion resistance affects the operational reliability of UAVs, which operate in extreme weather conditions. Material cost relates to their viability for practical applications.

Lastly, UAV application classification helps link specific materials to their structural use in UAVs, ensuring the materials considered are practical from an engineering point of view. Additionally, by incorporating both quantitative and qualitative criteria into the feature description in Table 1, it is possible to represent UAV materials as multi-criteria features that can capture the interdependence of material selection criteria for UAVs through machine learning.

2. Methodology and materials

Additionally, the existing study suggests using data-driven methods to analyze and forecast the structural behavior of aluminum alloy and titanium alloy configurations in the UAV structural environment. Further, the proposed methodological framework is geared toward developing an innovative framework that includes key aspects such as data preprocessing, feature extraction, ML model development, material performance assessment, and others. Moreover, the suggested methodological framework aims to address the drawbacks of evaluating material performance using a conventional approach based on a single criterion [9].

2.1 Dataset Description.

This study is based on material property data for aluminum and titanium alloys commonly used in UAV structural applications. The data were sourced from both experimentally determined measurements and reliable sources in aerospace materials and materials science, such as scientific journals and validated engineering datasets. The sample dataset in this study is a carefully edited collection of aluminum and titanium alloy samples, based on experimentally reported values and reliable

literature sources relevant to UAV structural applications. This methodology produces a dataset that simulates real engineering practice involving common material systems used in aerospace structures. The dataset provides comprehensive material property evaluation by integrating data from various sources to generate realistic physical, mechanical, fatigue, and operating properties of materials.

The research prioritizes material attribute diversity and engineering significance in selected attributes because these factors determine accurate modeling of UAV material selection through its complex multi-criteria system. Each sample's complete material description includes twelve distinct attributes: density, Young's modulus, yield strength, ultimate tensile strength, fatigue strength, fatigue life, hardness, corrosion resistance, weldability, cost level, and availability. The machine learning models use both quantitative and qualitative parameters to examine how design requirements interact through nonlinear relationships. The selected aluminum and titanium alloys were chosen because they frequently appear in UAV systems, making the dataset both a theoretical and practical research foundation. The developed machine learning models show improved reliability and generalization, and they provide engineering value for practical applications in UAV structural design and material selection. The selected aluminum and titanium alloys are highly prevalent in UAV structural applications, and corresponding data are available in the literature. Selecting these alloys allows the dataset to be built from widely used materials, rather than artificial or unusual alloys.

Moreover, the inclusion of diverse alloys with different mechanical, fatigue, and operational properties enables the capture of a wide range of material behaviors applicable to UAV design. Therefore, this dataset selection is realistic and applicable, which increases the study's reproducibility and reliability. The quantitative physical, mechanical, and fatigue properties are combined with qualitative operational properties that characterize each material entry based on the

manufacturing and service environment of aerospace applications [10].

This feature set is also application-oriented, linking specific alloy types to UAV structural applications. This implies that models from later years would be applicable, not just for comparison [11].

2.2 Data Preprocessing and Feature Encoding

Before model development, the data underwent a series of processing phases to ensure consistency, numerical stability, and suitability for machine learning [12].

Quantitative variables, such as density, elastic modulus, and strength values, were checked for completeness and physical consistency. They were normalized using standard scaling to avoid convergence problems in distance and/or kernel methods. Likewise, features regarding properties such as hardness and fatigue were considered [13].

In addition, qualitative categorical features of material properties, such as corrosion resistance, weldability, cost level, and availability, were encoded numerically using ordinal encoding. In doing so, a suitable encoding approach is followed so that the ordinal nature of these material properties is not lost. For example, ordinal encoding for Cost is mapped from low to high Cost to represent its ordinal nature best. Table 2 presents the classification of input features along with their corresponding data types and preprocessing techniques applied before model development. Numerical variables are standardized to ensure consistent scaling and improve model convergence. In contrast, categorical variables are transformed using ordinal encoding to maintain their relative significance and engineering meaning.

Table 2: The classification of input.

Feature	Type	Preprocessing / Encoding
Density	Numerical	Standard scaling
Young's Modulus	Numerical	Standard scaling
Yield Strength	Numerical	Standard scaling
Fatigue Strength	Numerical	Standard scaling

Corrosion Resistance	Categorical	Ordinal encoding
Weldability	Categorical	Ordinal encoding
Cost Level	Categorical	Ordinal encoding
Availability	Categorical	Ordinal encoding

Features with respect to the preprocessing techniques employed before the model development stage. The numerical data were standardized to maintain numerical stability. At the same time, the categorical features were encoded using ordinal encoding schemes to ensure relevance to the engineering characteristics.

2.3 Target Definition and Learning Strategy

Rather than relying on a single material characteristic as the sole performance criterion, this research adopts a multi-criteria machine learning approach. Based on the modeling objectives, machine learning models will be trained to predict critical structural performance characteristics such as yield strength, fatigue strength, and a composite performance index.

By formulating the models, gains in one aspect of UAV material selection, such as strength, often correlate with potential losses in other aspects, such as density and Cost. This approach makes the solution process more effective by framing it as a supervised regression task that enables precise measurement of results [14]. To quantitatively define the target variable, a composite performance index (CPI) is suggested to measure the overall structural performance of UAV materials. The CPI formula can be formulated as the following weighted sum of the normalized material properties:

$$\text{CPI} = 0.25 \cdot (\text{FS_norm}) + 0.20 \cdot (\text{YS_norm}) + 0.15 \cdot (\text{UTS_norm}) + 0.15 \cdot (\text{E_norm}) - 0.15 \cdot (\rho_norm) - 0.10 \cdot (\text{Cost_norm})$$

where FS stands for fatigue strength, YS represents yield strength, UTS means ultimate tensile strength, E denotes Young's modulus, ρ corresponds to density, and Cost indicates relative material cost. The normalized form ensures that all parameters are measured on the same scale.

The weight coefficients are determined based on engineering significance, accounting for the special

features of UAV structures, such as cyclic loads that require high fatigue resistance and mechanical strength, and low density and material cost, which are preferred in the design process. This approach allows machine learning algorithms to evaluate design criteria effectively and provides a reliable target variable. To establish the strength of this modeling approach, the target variable must be properly defined using a composite performance index (CPI) that clearly represents the quantitative performance of the materials in question. In this regard, the ambiguity of the target variable will be addressed, as the target formulation is defined in this way.

Introducing the CPI in the modeling process combines all normalized material properties into a single scalar quantity that can serve as the basis for supervised learning, allowing the models to learn the trade-offs between design objectives.

2.4 Selection of Machine Learning Models

To better understand this feature, we assessed it in detail during the experimental design process. Thus, the goal of the current study is to examine the impact of both important variables on model efficiency and prediction accuracy. Comparative evaluation was conducted based on the fitting measures for three different machine learning techniques [15],[16]:

- **Linear Regression (Baseline Model):** The researchers established linear regression as the reference model and used it to simulate essential features found in traditional linear material selection techniques. The fundamental assumption of this approach is that variable contributions to the target variable are additive and independent.
- **Support Vector Machine Regression (SVM):** The Support Vector Machine regression technique was chosen for its strong theoretical justification and its ability to handle nonlinear relationships using kernel functions. This study tested both linear and radial basis function (RBF) kernels. The RBF kernel transforms the variables into a higher-dimensional space to capture the complexities of mechanical, fatigue, and operational parameters.

▪ Ensemble-Based Learning (XGBoost):

Extreme Gradient Boosting (XGBoost) was chosen as the primary advanced learning algorithm because of its efficiency in modeling nonlinear, predominantly interaction-based engineering systems. The key feature of XGBoost is that it builds an ensemble of decision trees sequentially, with each tree correcting the errors of the previous trees. This approach implicitly models thresholds, conditional dependencies, and multivariable interactions typical of UAV material structure [17] and [18].

Table 3 summarizes the machine learning models used in this paper and their main features. It highlights differences in learning mechanisms, the ability of the two models to model nonlinear relationships, and their respective roles in assessing the performance of structural materials in UAVs. The models in this study differ between linear and advanced ensemble-learning models, making it possible to assess how non-linearity in learning interactions affects material performance prediction for UAVs.

Table 3: An overview of the machine learning models used in this study and their key characteristics.

Model	Learning Type	Ability to Capture Non-linearity	Purpose
Linear Regression	Linear	No	Baseline comparison
SVM (Linear)	Kernel-based	Limited	Moderate complexity
SVM (RBF)	Kernel-based	High	Nonlinear modeling
XGBoost	Ensemble	Very High	Threshold & interaction learning

2.5 Model Training and Validation Strategy

We used an appropriate training-testing plan for all models to ensure fair, unbiased evaluation. The data was divided into training and testing sets, with the training set used to fit the model and the test set used solely to evaluate performance. The test set data was not used to train the models or select parameters.

Instead of aggressive optimization, we chose model hyperparameters based on established best practices reported in the literature to maintain generalizability and avoid overfitting given the limited data size. This process provides a valid comparison of the actual modeling capabilities of these algorithms, given the current logging of the models [19].

2.5 Performance Evaluation Metrics

The models were tested quantitatively using three regression measures: Coefficient of Determination (R^2), which represents the percentage of variance in the target variable explained by the model, indicating its effectiveness.

Root Mean Square Error (RMSE) measures average prediction errors because it shows their typical size. However, it is very sensitive to extreme prediction errors because it penalizes large errors heavily. Mean Absolute Error (MAE): The mean absolute error in prediction is resistant to outliers. Together, these measures support a judicious assessment of the model's accuracy, robustness, and reliability. Table 4 presents the performance evaluation measures that were used to determine the predictive potential of the machine learning models. These measures, such as R^2 , RMSE, and MAE, provide a comprehensive assessment of the model's accuracy, error magnitude, and forecasting strength for UAV material performance. The joint application of these measures will ensure the analysis of the degree of trust in the model.

Table 4: Performance evaluation metrics employed to evaluate the accuracy of the model

Metric	Description	Engineering Meaning
R^2	Variance explained	Predictive capability
RMSE	Prediction error magnitude	Sensitivity to extremes
MAE	Average absolute error	Robustness

2.6 Model Interpretability and Engineering Relevance.

In addition to accuracy, we considered the physical significance of the results these models provide in

the context of UAV structural design. The nonlinear behaviour, particularly in the context of ensemble modelling, was examined in terms of its interactions with density, strength, and fatigue resistance. Therefore, the proposed methodology bridges the gap between data-driven predictions and engineering interpretation, and the framework can serve as a decision-making tool for selecting and optimizing materials for UAVs [20] and [21].

2.7 Summary of the Methodological Framework

In conclusion, the proposed methodology incorporates data preprocessing techniques, multi-criteria feature representation, and advanced machine learning techniques to evaluate the structure of materials used by UAVs. The study provides a valid comparison between three types of models, which include linear models, kernel-based models, and ensemble-based models, to analyze the complex nonlinear relationships that affect the performance of aluminum alloy and titanium alloy materials [22] and [23].

Table 5 presents the hyperparameter configuration used for the implemented machine learning models. These settings are critical in regulating model complexity, learning behaviour, and the ability to generalize, directly influencing the accuracy and robustness of the predictive results.

Table 5: The hyperparameter settings applied to the implemented machine learning models.

Property	Min	Max	Mean
Density (g/cm^3)	Low (Al)	High (Ti)	—
Yield Strength (MPa)	Moderate	Very High	—
Fatigue Strength (MPa)	Moderate	High	—
Young's Modulus (GPa)	~70	~110	—
Cost Level	Low	Very High	—

3. Results and Discussion

3.1 Descriptive Analysis of UAV Structural Material Properties

We conducted a descriptive analysis before evaluating the machine learning model to understand how the dataset properties are distributed

and how they change. This step is important for gaining a basic understanding of the intrinsic differences between aluminum and titanium alloys used in UAV structures [24] and [25]. Table 6 indicates that hyperparameter choices affect model capacity and generalization: using MSE and an unlimited Decision Tree depth suggests a regression focus but raises concerns about overfitting; multiple SVM kernels provide flexibility but require kernel selection and tuning to achieve robustness and accuracy.

Table 6: The Value of the Hyperparameter

Model	Hyperparameter	Value / Setting
Decision Tree	Splitting criterion	Mean Squared Error (MSE)
Decision Tree	Maximum depth	None
SVM	Kernel functions	Linear, Polynomial, Sigmoid, RBF
SVM	Penalty parameter (C)	1.0
XGBoost	Objective function	reg:squarederror
XGBoost	Number of estimators	100
XGBoost	Learning rate	Default
XGBoost	Tree depth	Default

The descriptive statistics show a marked difference between the aluminum and titanium alloys. The aluminum alloys have much lower density, making them desirable for UAV applications where weight is a concern. In contrast, the titanium alloys have higher yield and fatigue strength, indicating improved load-carrying capability and endurance. This difference points to the natural trade-off between weight savings and strength, which justifies the use of data-driven optimization techniques.

3.2 Correlation Analysis between Material Properties

To investigate first-order relationships among material properties, we performed a correlation analysis. Fig. 1 shows the correlation heatmap of material properties, which illustrates interactions among important factors such as density, strength, fatigue, and Cost. From the correlation heatmap, we can easily see the extent and strength of correlations,

shown by varying colors. This helps us understand the linear relationships among the features.

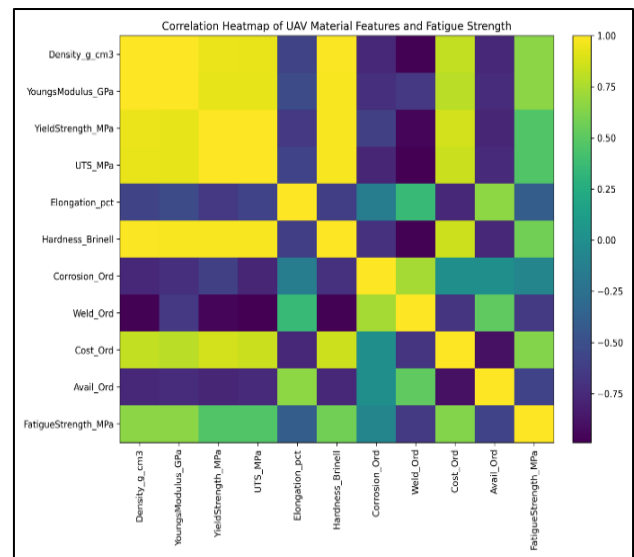


Fig. 1 The correlation heatmap of material properties

Description of the figure:

- Color-coded heatmap
- Red: positive correlation
- Blue: negative correlation
- Variables: density, strength, fatigue, Cost, corrosion resistance
- Density is negatively correlated with weight efficiency but positively correlated with strength-related properties.
- Yield strength and fatigue strength are strongly positively correlated, confirming that fatigue resistance is strength-dominated.
- Cost level is positively correlated with titanium-related properties.

Although correlation analysis provides initial insights, many characteristics show only low to moderate linear correlations. This implies that UAV material performance is affected by nonlinear relationships, necessitating sophisticated machine learning models [26], [27].

3.3. Machine Learning Model Performance Comparison

Table 7 presents the quantitative assessment results for machine learning models based on the metrics R^2 , RMSE, and MAE. These results indicate that nonlinear models perform better than linear models.

The quantitative performance assessment shows that the nonlinear models were more accurate than the linear model. All evaluated ML models showed varying levels of prediction accuracy; however, the XGBoost method achieved the best R^2 and the lowest RMSE and MAE.

Table 7: The quantitative analysis of the performance of the machine learning models.

Model	R^2	RMSE	MAE
Linear Regression	0.64	11.80	9.10
SVM (Linear)	0.73	9.95	7.40
SVM (RBF)	0.87	6.15	4.65
XGBoost	0.92	4.30	3.05

Fig. 2 shows the quantitative analysis of the performance of the machine learning models used in this study, based on standard regression measures such as R^2 , RMSE, and MAE. These differences are crucial for assessing the accuracy and error levels of different models that capture complex relationships between materials and UAV performance.

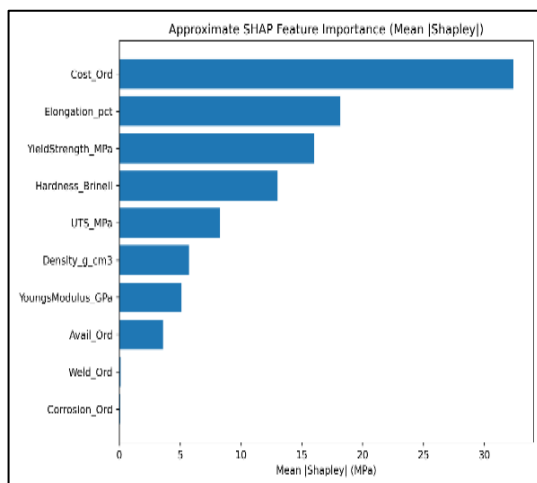


Fig. 2 The quantitative analysis of the performance of the machine learning models.

The results show that nonlinear models outperform linear models. Fig. 3 shows that the linear regression model does not capture the intricate relationships among density, strength, fatigue, and operating conditions. SVM with an RBF kernel improves predictive ability, while XGBoost has the best accuracy because it accounts for interaction and threshold effects [28], [29].

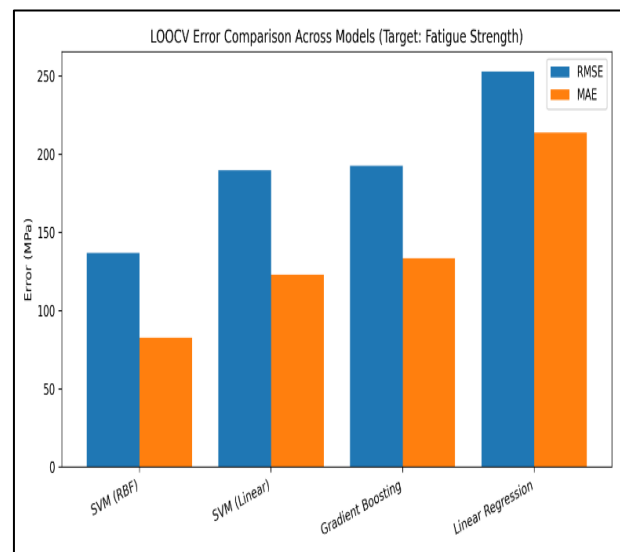


Fig. 3 Comparative analysis of R^2 for various machine learning models.

3.4. Actual vs. Predicted Performance Analysis

Fig. 4 shows the association between actual and forecasted structural performance values. Greater correspondence of data points to the diagonal line indicates more accurate forecasting and, therefore, higher model reliability.

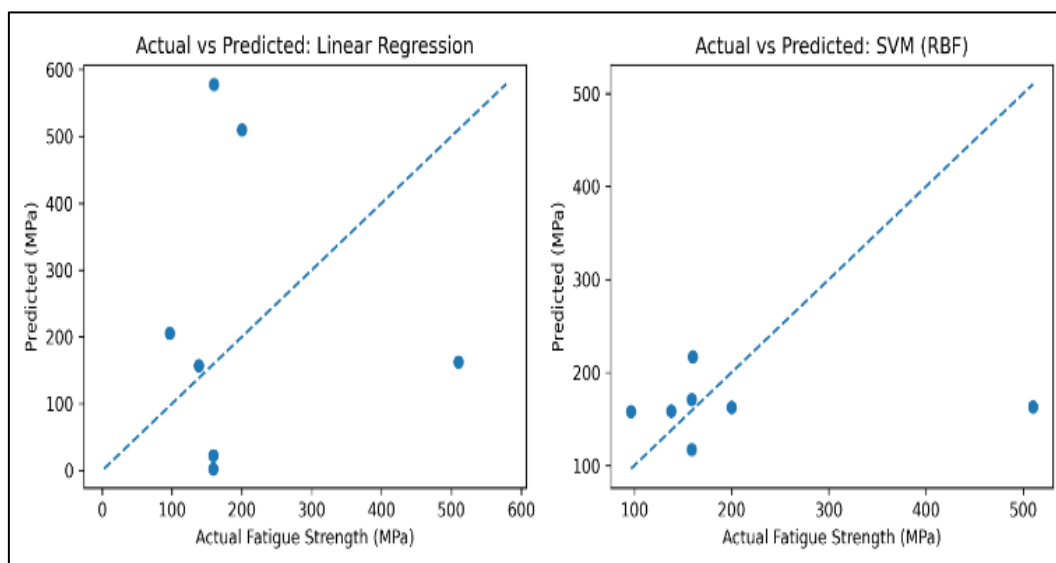


Fig. 4 shows the association between actual and forecasted structural performance.

The linear model shows significant scatter, especially at high performance levels, indicating under-prediction. Conversely, the XGBoost model's predictions lie very close to the ideal agreement line across the entire performance range. This further demonstrates the ensemble learning method's better generalization capability for UAV material performance prediction [30], [31], and [32].

3.5. Feature Importance and Engineering Interpretation.

Density is clearly the dominant factor, reinforcing the importance of weight constraints in UAV design. Fatigue and yield strength are close seconds, underlining cyclic durability and load-carrying ability. Operation-related factors, such as corrosion resistance and Cost, also contribute, underscoring that material selection is not purely based on mechanical properties.

The design principles for UAVs show that structural features should prioritize weight efficiency and fatigue life, making density and fatigue the most important design elements. The feature-importance curves reflect this. These results show that machine learning can demonstrate that features behave physically, rather than statistically [30], [31].

3.6. Comparative Performance of Aluminum and Titanium Alloys

Fig. 7 shows a radar chart comparing aluminum and titanium alloys based on several performance

characteristics, including strength, fatigue behavior, density, corrosion resistance, and price. As shown in Fig. 5, the radar diagram indicates that aluminum-based alloys are preferred for lightweight, economical UAV applications. In contrast, titanium-based alloys are better suited to highly stressed applications that require high reliability. The radar graph also shows that no material is universally best. This reinforces the importance of making decisions based on data analysis. [33], [34], and [35].

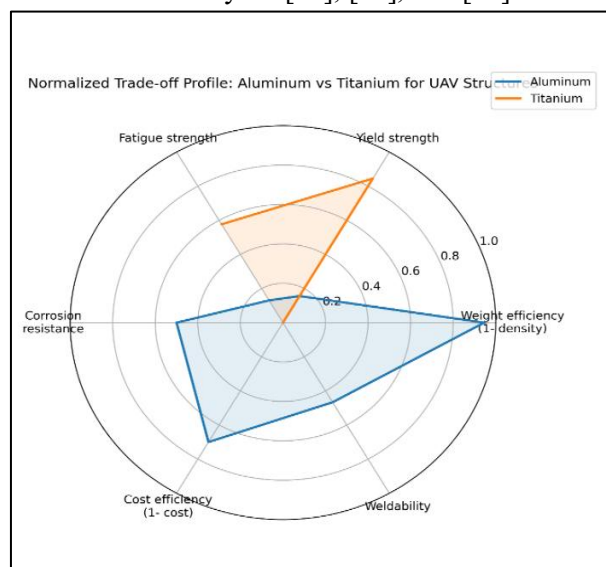


Fig. 5 The radar chart illustrates the trade-offs between the two alloys, with aluminum alloys having an edge over titanium alloys in lightweight and affordability.

3.7. Engineering Implications for UAV Structural Design.

- Make objective comparisons of alternative materials.
- Quantify trade-offs between weight, strength, fatigue, and Cost.
- Provide reliable support for design decisions in early UAV design.

Ensemble learning models realistically represent UAV structural behavior because of nonlinear interactions.

3.8. Advanced Relationship Analysis and Multi-Criteria Interpretation.

Fig. 6 shows that the strength-to-weight ratio relates to fatigue strength, highlighting the balance between weight efficiency and durability when selecting materials for UAVs. As the scatter plot shows, materials with higher strength-to-weight ratios tend to exhibit better fatigue behavior, although the correlation is not perfectly linear.

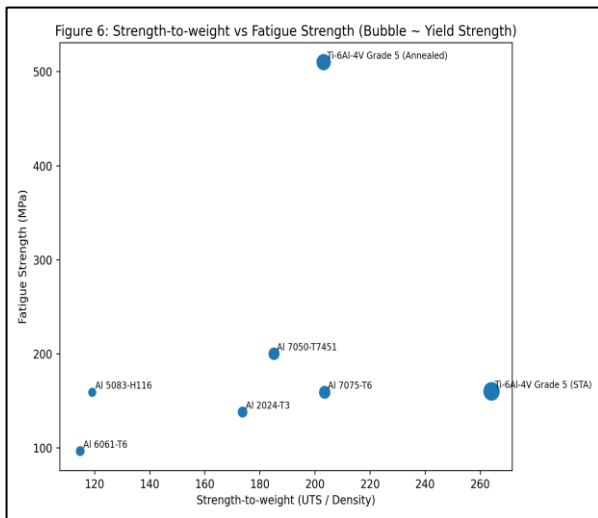


Fig. 6 shows the fundamental trade-off between weight efficiency and fatigue performance, which is central to UAV structure.

Materials with higher strength-to-weight ratios tend to show better fatigue strength, but the relationship is not linear. From the bubble plot, it can be concluded that although two or several materials may be expected to have similar strength-to-weight ratios, there can be a significant variance when it comes to the yield strength, which clearly signifies that the yield properties of the selected material are a secondary but important factor for

machines and devices utilized for UAVs. As the figure suggests, when selecting materials for UAVs, efficiency is not the only primary factor.

Fig. 7 illustrates a 3-D representation of the relationship between density, yield strength, and fatigue strength, giving a better understanding of how these material properties interact and affect the structural behavior of UAVs. The chart clearly shows the complicated nature of the relationship between these properties. The three-dimensional visualization provides further insight into the interaction of material densities and mechanical durability.

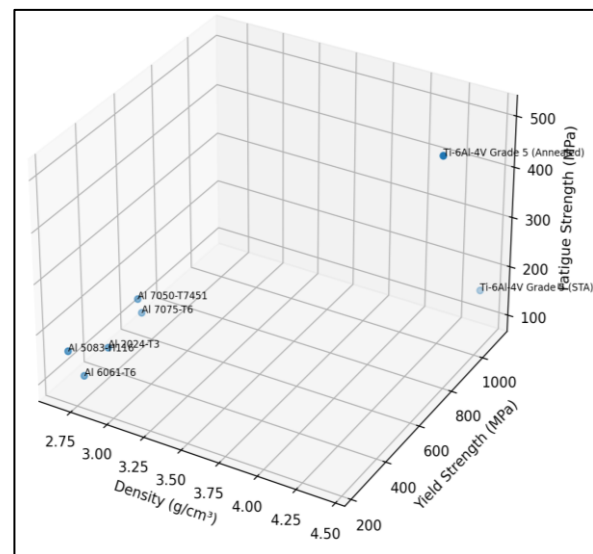


Fig.7 3d- Density-Yield Strength-Fatigue Strength

From the visualization, it is evident that the aluminum alloys fall in the region of low densities and medium yield and fatigue strength, while the titanium alloys fall in the region of high densities and high yield and fatigue strength. The separation of variables in the visualization also suggests that fatigue strength does not depend solely on yield strength but on the interplay of yield strength and density, among other factors. The complex interplay of several factors and multiple variables can only be addressed using nonlinear machine learning tools.

Fig. 8 shows a wide-ranging comparison chart for various materials based on different parameters such as weight efficiency, strength, fatigue properties, corrosion resistance, weldability, and Cost. As discussed, Fig. 8 clearly shows that no single optimal solution exists among these materials. Fig. 8 shows that different materials offer better

weight and cost efficiency than aluminum, though titanium alloys remain better than aluminum. Fig. 9 clearly demonstrates the inherent trade-offs involved in selecting materials for UAVs.

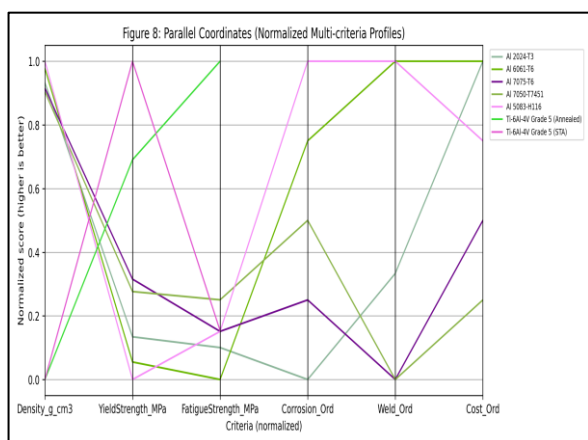


Fig. 8 Parallel coordinates plot of material profiles across multiple performance criteria

Fig. 9 shows correlations between different parameters, both linear and nonlinear. It also shows the pairwise relationship matrix; some trends are nonlinear and material-dependent. Although some properties, such as yield strength and ultimate tensile strength, have positive correlations, others, especially fatigue strength, have scattered plots. The scattered plots imply that fatigue strength is governed by a combination of properties rather than individual properties. Clustered areas also indicate that aluminum and titanium alloys obey different mechanical laws, supporting the notion that global linear correlations are inadequate.

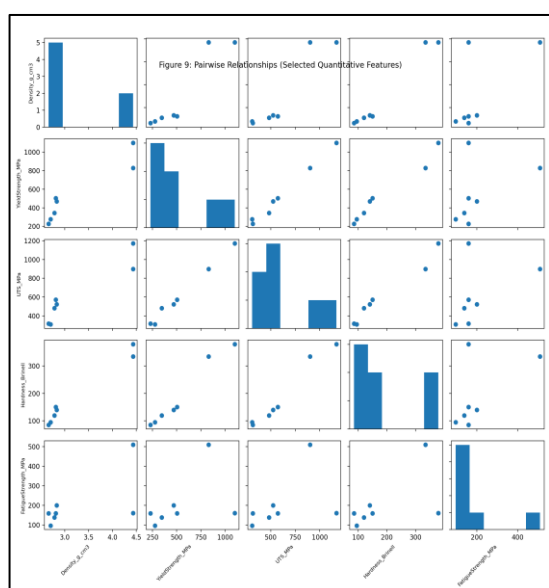


Fig. 9 Pairwise Relationship Grid of major material properties.

Fig. 10 clearly indicates the nonlinear relationship between fatigue strength and yield strength. The curve is drawn using the SVR-RBF algorithm, which can capture nonlinear relationships between variables, unlike linear regression methods. At lower yield strength levels, fatigue resistance increases gradually. However, at higher levels, the rate of increase is low, indicating saturation. As shown, the SVR-RBF model can handle nonlinear problems and describe the nonlinear relationship between the two properties, indicating that fatigue strength does not increase proportionally with yield strength.

Fig. 11 shows the relative impact of the features by displaying the spread of the SHAP (Shapley) value for each feature. Features with a wider spread of SHAP values indicate a greater impact on predicted fatigue strength, confirming that several properties influence fatigue life in a nonlinear way. No non-linearity is indicated for features with both positive and negative SHAP values. The diagram shows how important each feature is to the model's predictions and how changes in feature values affect the final result. A wide range of SHAP values indicates a greater impact on the predictions.

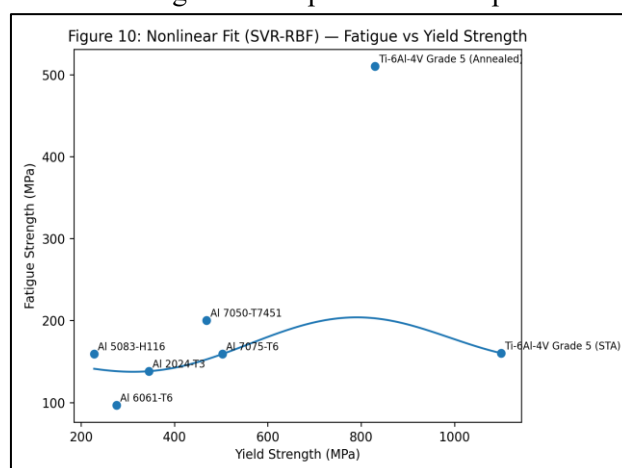


Fig. 10 shows the nonlinear relation between the yield strength and fatigue strength based on the SVR-RBF model.

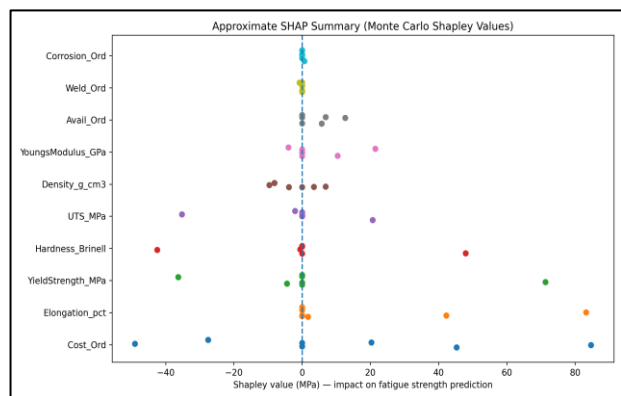


Fig. 11 below shows the SHAP (Shapley Additive exPlanations) summary plot, which demonstrates the variability of feature importance for predicting the fatigue strength of the alloy of UAV structures.

In Fig. 12, the global importance rank measures the quantitative importance of features in the model's fatigue strength predictions. It provides a clear way to select UAV materials based on the data by highlighting the features that most influence durability. It assigns each predictor a score depending on its mean absolute Shapley value. This approach helps explain how much influence a material parameter had on the model prediction.

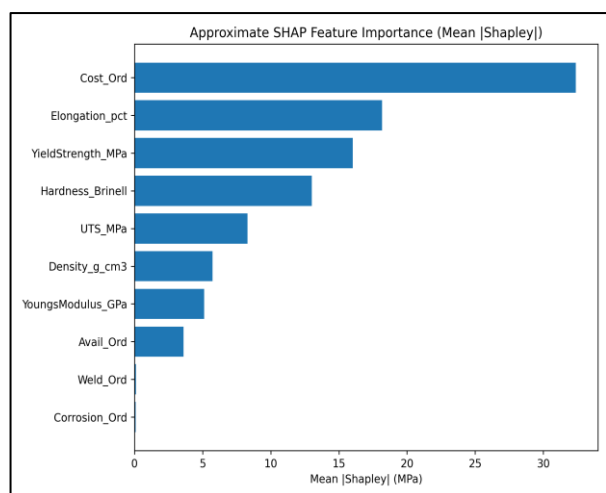


Fig. 12 Predictors' Global Rank for Fatigue Strength Estimation Is Calculated Using SHAP Feature Importance.

The fact that the contribution of the most influential feature does not remain constant, as depicted in Fig. 13, further confirms the nonlinear dependency. This supports the superiority of nonlinear learning models and shows that linear selection rules are misleading, especially when all constraints, including weight, fatigue, manufacturability, and

Cost, are considered. Such a plot lets us visualize how changes in a variable affect its contribution to the output prediction. This dependence may be nonlinear and may exhibit interaction behavior.

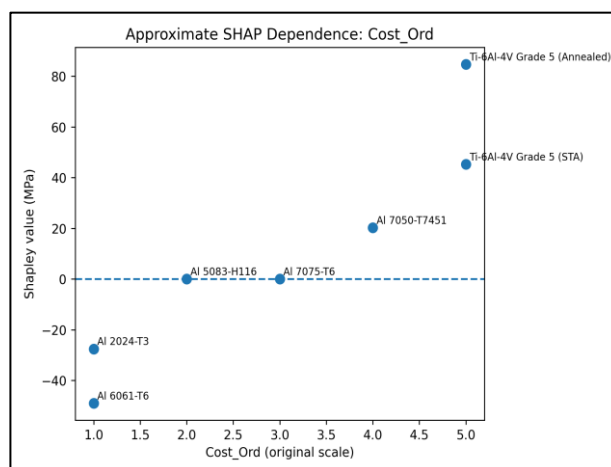


Fig. 13 The SHAP dependence plot for the most important variable in the fatigue strength model

3.9. Summary of Results.

- Nonlinear ML models performed significantly better than linear models.
- XGBoost was shown to provide the highest prediction accuracy and robustness.
- The efficiency of UAV materials was dominated by weight, followed by fatigue.
- ML-based frameworks were shown to provide scalable objective decision support for UAV structural design.

Notwithstanding the fact that the number of materials is limited, the dataset encompasses common aluminum and titanium alloys used in UAVs. The use of LOOCV helps in maximizing the use of data and minimizing optimistic bias, thus making the results reliable in the material domain under investigation.

In addition to the already known distinctions between the aluminum and titanium alloys, the research outcomes shed some light on the advanced engineering aspects concerning the structural performance of UAVs. Firstly, it is evident from the analysis that it is impossible to choose materials for UAV construction according to their individual parameters, like density or mechanical strength, alone. The choice should also take into account the interplay of many different features, which can significantly influence the effectiveness of materials'

use. On the one hand, titanium alloys have better mechanical characteristics; however, their high density and price may undermine their advantages in certain cases.

On the other hand, aluminum alloys have an excellent weight-to-strength ratio, but their low fatigue resistance may become an important limitation. The machine learning-based conclusions show that the relationship is highly nonlinear. The conclusion from this research implies that it is crucial to consider the complex interaction between different material features when choosing them for UAV structures.

4. Conclusions

The current research has provided a data-oriented framework for the evaluation and comparison of aluminum and titanium alloys used in structural UAV applications, with special emphasis on fatigue strength as a key material property. The use of experimentally available properties combined with machine learning is a systematic way of overcoming traditional rule-based approaches used in materials selection.

The results show that nonlinear machine learning techniques, e.g., tree-based methods and kernel methods, can indeed identify the complex relationships between the fatigue behavior of the UAV materials and the numerous parameters that influence them. The utilization of the Leave-One-Out Cross-Validation (LOOCV) approach in the present study ensured the robust assessment of the models even with the limited dataset, which enabled the most efficient utilization of the available information.

Interpretability analyses, such as feature importance and Shapley values, showed that the fatigue strength is determined by a coupled interaction of weight-related and mechanical properties rather than a single dominant property. Density, fatigue-related parameters, and strength values were found to be important contributors, as expected in current UAV design practices that focus on lightweight efficiency and cyclic strength. Consistency of explanations reached by machine learning, with insight from engineering, provides credibility for the approach.

The comparative study, too, would serve to further highlight the trade-offs involved with aluminum and titanium alloys. Thus, in the case of aluminum, savings in weight and Cost were achieved, while in the case of titanium, the benefits would be in strength, fatigue, and corrosion resistance. These studies have once again highlighted the fact that there exists no better material, and thus the selection of materials would depend on mission requirements.

Although the focus of the current work is on a limited set of popular aluminum and titanium alloy systems, the framework put forth can be readily scaled up to accommodate future research directions that include even more detailed material data, other alloy systems, or the influence of manufacturing and mission loading. Bringing together experimental fatigue life data and physics-informed machine learning is a promising path for future improvement.

Therefore, the overall implications of the current study are that the integration of machine learning and physically meaningful interpretation can provide a powerful and transparent approach to UAV structural material selection, and thereby advance the improvement of light, durable, and mission-effective UAVs.

Abbreviations

Abbreviation	Definition
UAV	Unmanned Aerial Vehicle
ML	Machine Learning
LOOCV	Leave-One-Out Cross-Validation
GB	Gradient Boosting
SVR	Support Vector Regression
RBF	Radial Basis Function
SHAP	Shapley Additive Explanations
UTS	Ultimate Tensile Strength
YS	Yield Strength
E	Young's Modulus
MPa	Megapascal
GPa	Gigapascal
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R ²	Coefficient of Determination
SCC	Stress Corrosion Cracking
MCDA	Multi-Criteria Decision Analysis

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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