

Stress, Strain, or Energy? which one is superior predictor of fatigue life in notched Components? a novel Machine Learning-Based framework

A.M. Mirzaei

Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy
School of Aerospace, Transport and Manufacturing, Cranfield University, Bedford MK43 0AL, UK

ARTICLE INFO

Keywords:

Fatigue life prediction
Notch
Machine learning
Additive manufacturing
Carbon fiber laminated composites

ABSTRACT

This paper introduces an efficient framework for accurately predicting the fatigue lifetime of notched components under uniaxial loading within the high-cycle fatigue regime. For this purpose, various machine learning algorithms are applied to a wide range of materials, loading conditions, notch geometries, and fatigue lives. Traditional approaches for this task have mostly relied on one of the mechanical response parameters, such as stress, strain, or energy. This study also concludes which of these parameters serves as a better measure. The key idea of the framework is to use the profile (field distribution represented by some points) of the mechanical response parameters (stress, strain, and energy release rate) to distinguish between different notch geometries. To demonstrate the accuracy and broad applicability of the framework, it is initially validated using metal materials, subsequently applied to specimens produced through additive manufacturing techniques, and ultimately tested on carbon fiber laminated composites. This research demonstrates the effective use of all three parameters in estimating fatigue lifetime, while stress-based predictions exhibit the highest accuracy. Among the machine learning algorithms investigated, Gradient Boosting and Random Forest yield the most successful results. A noteworthy finding is the significant improvement in prediction accuracy achieved by incorporating new data generated based on the Basquin equation.

1. Introduction

Estimating fatigue life is a vital task in the design and maintenance of various mechanical systems and structures. This process involves predicting how many cycles (life) a material can endure before failure due to cyclic loading, a phenomenon commonly encountered in real-world structures [1]. Mostly, fatigue life estimation has relied on empirical relationships derived from extensive experimental testing, focusing on mechanical response parameters, e.g., stress [2], strain [3], or energy [4]. Therefore, these methods can be time-consuming, expensive, and may lack precision for diverse materials or loading conditions. Recently, machine learning (ML) has emerged as a leading solution in the field of materials science and technology [5], specifically fatigue failure [6]. It offers the potential to enhance prediction accuracy by identifying patterns within existing datasets [7,8]. This section provides a review of the current state of the art in fatigue analysis through machine learning, initially exploring its broad applications across various problems and materials, then narrowing down to its use in additively manufactured specimens, and ultimately presenting advanced models to set

E-mail addresses: amir.mirzaei@polito.it, amir.mirzaei@cranfield.ac.uk.

<https://doi.org/10.1016/j.engfractmech.2024.110401>

Received 14 May 2024; Received in revised form 30 July 2024; Accepted 13 August 2024

Available online 17 August 2024

0013-7944/© 2024 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Nomenclature

<i>GB</i>	Gradient Boosting
<i>LR</i>	Linear Regression
<i>MLP</i>	Multi-Layer Perceptron
<i>MSE</i>	The mean squared error
<i>N_f</i>	Number of cycles to failure
<i>R</i>	Loading ratio
<i>R²</i>	The coefficient of determination
<i>RF</i>	Random Forest
<i>VR</i>	Voting Regressor
α	Notch opening angle
ρ	Notch radius
σ_a	Nominal stress amplitude

the context for the problem statement.

ML techniques have significantly improved the predictive accuracy of fatigue life estimation of various materials, as evidenced by several compelling applications. For instance, hybrid physics-informed and data-driven models (HPDM) have proven to be effective, laying a methodological foundation further substantiated by the successful application of the XGBoost model in predicting the fatigue life of high-strength bolts [9]. This approach has also been extended to the prediction of low-cycle fatigue life for lead-free solders, demonstrating ML's reliability across various fatigue conditions [10]. Another illustrative example is the development of a knowledge-based ML framework that integrates empirical formulas with data-driven models, resulting in improved accuracy and resource efficiency [11]. The versatility of ML is further exemplified by its successful application in predicting fatigue life in drilled composite laminates [12]. To emphasize the extensive applicability of machine learning techniques across various materials in the domain of fatigue life estimation, the following can be cited: A588 low alloy steel [13], 316 stainless steel [14], gray cast iron [15], cast aluminum alloy [16], multi-principal element alloys [17], and additively manufactured (AM) parts [18,19]. Moving to multiaxial loading, in a novel twist, image recognition technology has been utilized to extract loading path features for multiaxial fatigue life prediction [20]. Moreover, the fusion of virtual synthetic multiaxial fatigue data with ML models has further enhanced the accuracy of life prediction models, as proposed in [21].

Focusing on AM materials, ML techniques have been effectively employed to tackle the intricate nature of fatigue phenomena inherent to these materials [22]. These methods have consistently proven to be indispensable in this context [23]. The effectiveness of ML in handling uncertainties and optimizing manufacturing processes to enhance fatigue performance is highlighted in studies such as [24–26]. To address the issue of limited fatigue data and to expand the dataset size for Ti-6Al-4 V, Monte Carlo simulation in conjunction with ML models yielded promising results [27]. In noteworthy research [28], ML was combined with natural language processing and computer vision to collect and analyze fatigue and mechanical data from thousands of scientific articles. This resulted in the creation of a comprehensive database, FatigueData-AM2022, which can serve as a benchmark and training set for further ML-driven analyses. The application of machine learning has also extended to predicting microstructural-level fatigue damage [29] and fatigue behavior in various materials and contexts within AM, including laser powder bed fusion materials [14] and non-metallic materials like polymer composites [30].

Advancements in computational frameworks, such as the one proposed in [31], underscore the potential of ML in optimizing fatigue performance. A noteworthy development in this direction is represented in [32], where a Physics-Informed Neural Network was utilized to predict finite fatigue life in defective materials, showcasing the successful integration of traditional physics models with advanced ML techniques. Additionally, in a recent study [33], an enhanced offline prediction approach was introduced for predicting the lifespan of fatigue crack propagation. This method relies on data feedback and highlights the significance of iterative learning and adaptation within machine learning frameworks. It is worthwhile to mention that the emergence of ML techniques has brought about a transformative shift in fatigue life prediction strategies, leveraging innovative computational approaches. For instance, a hybrid model integrating fracture mechanics and ML has excelled in predicting high-cycle fatigue life [34]. A unified physics-informed ML framework has shown significant promise in predicting notch fatigue life, highlighting the effectiveness of incorporating physical principles into ML algorithms [35]. These algorithms, including the application of shallow neural networks and sequence learning models, were utilized to forecast the lifetime under isothermal low-cycle fatigue loading and thermo-mechanical fatigue loading, yielding accurate estimations for these complex loadings [36].

In summary, the integration of machine learning techniques with traditional methods has revolutionized fatigue life estimation, offering enhanced accuracy, adaptability, and efficiency across various materials and loading conditions. This research aims to build upon these advancements, exploring the specific application of ML in fatigue lifetime assessment of notched structures.

The primary aim of this research is to propose a novel framework that incorporates either stress, strain, or energy release rate fields along with machine learning algorithms to estimate the fatigue lifetime of notched components. The originality of the proposed method, in comparison with existing methods in the literature, is twofold:

1- Utilization of response parameter profile: Traditional ML algorithms for failure analyses only use a stress component of the node at the tip of the notch. To distinguish between different geometries, the notch opening angle and notch tip radius values are used as

inputs into the model. In contrast, the proposed method uses a physics-based response parameter of the material (i.e., stress, strain, energy release rate) to obtain the notch effect. For this purpose (under uniaxial loading), the fields of stress, strain, and energy release rate along the notch bisector (where failure is expected), represented by several nodes in this direction, are used as inputs to the model.

2- Identification of the most effective field: This study aims to identify the most effective field among stress, strain, or energy for fatigue life estimation of notched components under uniaxial loading using Machine Learning (ML) models.

In the next section, the ML tools employed for establishing the framework are presented, while the measures and inputs of the model are discussed in Section 4. Finally, the results of predictions by the proposed method for three different materials are presented in Section 5 to demonstrate the validity of the method across various materials. Additionally, in this section, the proposed framework is compared with the TCD approach, and a thorough analysis of the effect of different choices on the inputs of the method is provided.

2. Problem statement

Geometric discontinuities like cracks, notches, and holes, often found in mechanical structures, serve specific design purposes or arise due to wear and environmental factors. These elements, acting as stress concentrators, play a pivotal role in delineating both the load-bearing capability and operational lifespan of the structural component. However, due to its complexity, this topic is less often addressed in the literature [37]. In this paper, a novel framework is proposed to estimate the fatigue life of notched components using ML algorithms, based on various mechanical parameters such as stress, strain, or energy fields.

The inspiration for the proposed framework stems from Neuber's study [38], which introduced a successful approach for fatigue analysis of notched components. This approach later became known as the Theory of Critical Distances [39,40] and has recently been incorporated into the Finite Fracture Mechanics approach [41–43]. These strategies typically depend on the *stress field* around the notch tip to distinguish various notch geometries. Fig. 1 provides a schematic illustration of the stress field corresponding to two distinct notch geometries, indicating that a sharper notch corresponds to different profile and higher stress gradient [44].

On the other hand, studies have shown that certain materials are subject to strain-controlled failure [45]. As a consequence, the strain field is incorporated into our analysis. Finally, the energy release rate, widely used in Linear Elastic Fracture Mechanics (LEFM) and its applications, is utilized in this study for the sake of comparison and completeness. Therefore, three fundamental response parameters are employed in this paper to establish a new framework to estimate the fatigue life of notched components and determine which parameter is more efficient for this task. Note that these fields are discretized by a certain number of nodes, which will be comprehensively explained in Section 5.5. The represented fields are unique for each notch geometry and serve as a measure of the geometric factors of each notch. In Section 4, the framework and its input parameters are presented in detail.

It is worthwhile to mention that linear elastic analysis is employed to derive stress, strain, and energy release rate fields. This methodology is especially pertinent in scenarios involving medium- and high-cycle fatigue loading conditions, where even ductile materials may exhibit linear elastic behavior. However, it is important to note that the proposed approach may not be applicable to materials or conditions that exhibit significant plasticity or non-linear behavior.

3. Machine learning tools

This section provides an introduction to the script and the machine learning algorithms that have been utilized within this study. The script is written in Python and utilizes a variety of data science packages including pandas, numpy, matplotlib, seaborn, and sklearn. Initially, it emphasizes data preprocessing. If *activated*, useful in cases where the original dataset is limited in size (will be elaborated in Section 5.5.4), new data can be synthetically generated using a function that resembles a line in log–log space, with an added noise factor ranging between -0.3 and 0.3 , as shown in Fig. 3. In this scenario, the code ensures that the amount of data for each notch geometry is set to 100. This technique for generating synthetic data mimics real-world scenarios where data often exhibit a

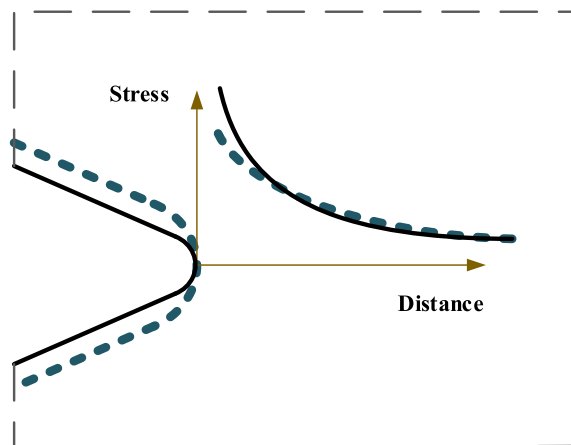


Fig. 1. Schematic illustration of two different notch geometries with their related stress distribution in an infinite medium.

power-law distribution, causing the data to form a straight line in log–log space according to the Basquin equation [46]. Accordingly, in this study, the term *baseline data* refers to the original data, while *enhanced data* refers to the combination of the original and generated data. Note that both the baseline data and the enhanced data are employed, and the results are compared with each other for a more thorough analysis. The noise introduced helps emulate the unpredictable variations typically found in real data, providing a more realistic testing ground for the regression models. This approach offers valuable insights into model performance under varying and potentially noisy conditions. It should be noted that the noise factor should be selected based on different factors like material, notch geometry, environmental conditions, equipment, and other factors. However, for simplicity, the proper values (−0.3 and 0.3) were selected (will be elaborated in Section 5.5.5), which are typical mean values for experimental studies in fatigue [39,47].

To capture complex data relationships, the script initially generates new features by summing the product of applied stress and all other columns, as further explained in Section 4. Subsequently, it handles categorical data (a name related to each notch shape) by converting them into numerical format through one-hot encoding. The script also computes correlations between features and the target variable, applying a feature selection strategy based on a predetermined threshold to retain only the most relevant features. Section 4 discusses the features specific to each problem. Moreover, the script offers flexibility in handling unseen data by either randomly selecting from the dataset or using specific types of data (notch type). Unseen data play a crucial role in evaluating the performance of machine learning models on untrained data. To enhance model performance, the data are normalized using RobustScaler, which effectively handles outliers. Normalizing the data, based on RobustScaler, ensures that all features are on a consistent scale, preventing dominance by features with larger scales and promoting balanced model performance.

After the data preprocessing, the script employs five regression models for training and validation, utilizing K-fold cross-validation with five folds. The models used encompass Gradient Boosting, Random Forest, Linear Regression, Multi-Layer Perceptron, and a Voting Regressor that amalgamates the aforementioned models. Although hyperparameter tuning can enhance the performance of models, they are trained with their default settings, without any customization or tuning of their parameters. This approach provides a baseline for the performance of models, offering a clear reference point for understanding their natural strengths and weaknesses. On the other hand, by sticking to the default settings, the results can be easily replicated by others. It is worthwhile to note that the primary analyses of hyperparameter tuning using the grid search approach did not significantly impact the results. However, in the future, the effect of adjusting the settings will be studied. Cross-validation is employed to assess the models' ability to generalize to unseen data. The code executes 100 iterations for each regression model, enabling a more comprehensive performance evaluation and accounting for variability in data selection.

In selecting the specific regression models for this study, a diverse and effective approach was considered to predict the fatigue lifetime of notched components. Gradient Boosting and Random Forest were chosen for their proficiency in handling complex non-linear patterns and their consistent success in the study's outcomes. Linear Regression serves as an easily interpretable baseline model, and the Multi-Layer Perceptron is utilized for its ability to explore intricate non-linear relationships. The Voting Regressor uniquely integrates the strengths of all the aforementioned models, providing an additional layer of robustness. Furthermore, an essential consideration in the selection of these models was their relative ease of coding and implementation compared to other more complex machine learning approaches. This decision not only facilitated the model coding process but also ensured a practical and accessible methodology. By combining simplicity in coding with both linear and complex modeling capabilities, this ensemble offers a well-balanced and efficient approach to the prediction task, aligning seamlessly with the multifaceted nature of the variables and conditions investigated.

The workflow of the machine learning tools utilized can be summarized as follows:

Start

1. Data Preprocessing

1.1 Synthetic Data Generation (Optional):

- **Objective:** Augment the dataset if the initial size is limited.
- **Methodology:**
 - o **Data Check:** Verify the size of the initial dataset.
 - o **Synthetic Data Creation:** Fit a line in log–log space (following Basquin equation) and introduce noise to simulate realistic variability, generating additional target data accordingly.

1.2 Feature Engineering:

- **Feature Creation:**
 - o Generate the features by calculating the intended field distributions (stress, strain, or energy) around the notch tip for the load amplitude. This is achieved by multiplying the applied stress amplitude with the near-fields calculated by FEA for an applied stress of 1.
- **Categorical Data Encoding:**
 - o Convert categorical data (e.g., notch shapes) into a numerical format using one-hot encoding.
 - o Add the one-hot encoded columns to the main data frame.
- **Correlation Analysis:**
 - o Calculate the correlation between each feature and the target variable (fatigue life).
 - o Sort features based on their absolute correlation values to identify the most relevant features.
- **Feature Selection:**
 - o Select a number of features based on their correlation with the target variable.
 - o Include one-hot encoded categorical features and any forced features (if specified).
 - o Remove any duplicate features to finalize the list of selected features.

1.3 Handling Unseen Data:

- **Data Splitting:**

(continued on next page)

(continued)

-
- o Separate a subset of data to be used as unseen data for evaluation. This can be done randomly or based on specific criteria (e.g., by excluding a particular notch type).
 - 1.4 Data Normalization:**
 - **Normalization Technique:**
 - o Normalize the data using RobustScaler, which is effective in handling outliers and ensuring consistent scaling across features.
 - 2. Model Training and Evaluation**
 - 2.1 Model Definition:**
 - **Regression Models:**
 - o Gradient Boosting Regressor
 - o Random Forest Regressor
 - o Linear Regression
 - o Multi-Layer Perceptron (MLP) Regressor
 - o Voting Regressor (ensemble model combining the above models)
 - 2.2 Cross-Validation:**
 - **K-Fold Cross-Validation:**
 - o Utilize K-fold cross-validation to evaluate model performance.
 - o Run 100 iterations (episodes) for each model to ensure robustness and reliability of results.
 - 2.3 Model Training:**
 - **Training Procedure:**
 - o Train each model on the training set and evaluate its performance on the testing set.
 - o Calculate and record performance metrics such as R^2 score and Mean Squared Error (MSE) for each fold and each episode.
 - **Best Model Selection:**
 - o Track the best-performing model for each regression method based on the highest R^2 score.
 - o Print the average R^2 score and MSE across all episodes for each model.
 - 3. Model Selection and Prediction**
 - 3.1 Best Model Selection:**
 - **Performance Comparison:**
 - o Compare the average performance metrics of all models.
 - o Select the model with the best overall performance (highest R^2 score and lowest MSE).
 - 3.2 Final Predictions:**
 - **Unseen Data Prediction:**
 - o Use the best-trained model for each regressor to predict fatigue life on the unseen data subset.
 - o Print and compare the original and predicted values for each model.
 - 3.3 Visualization:**
 - **Prediction Plots:**
 - o For each model, create log-log plots comparing the original data and predictions.

End

Having previously described the workflow of the prediction procedure and its constituent components, this section presents a brief introduction to the machine learning algorithms. This presentation offers a more in-depth reasoning behind the choice of the models and their predictive ability for the problem, thus setting the stage for a more comprehensive discussion on the operation and performance of the predictive framework. However, since the models are well-developed, they are not presented in detail, and interested readers are referred to the appropriate references cited in the related sections.

3.1. Gradient Boosting Regressor

Gradient boosting is a machine learning technique where weak predictive models, typically decision trees, are combined to form a powerful ensemble model [48,49]. It is a stage-wise optimization algorithm that can accommodate a variety of loss functions [50]. The principle of gradient boosting involves iteratively building weak learners and adding them to the ensemble model in such a way that the errors of the previous models are minimized. This is achieved by fitting each new model to the residuals or errors of the preceding models:

$$e_i = y_i - F_{m-1}(x_i) \quad (1)$$

where e_i is the residual for the i -th instance, y_i is the actual output for the i -th instance, $F_{m-1}(x_i)$ is the prediction of the $(m-1)$ -th model for the i -th instance. A weak learner is then fit to these residuals. This results in a new model, represented as:

$$F_m(x_i) = F_{m-1}(x_i) + h_m(x_i) \quad (2)$$

where $h_m(x_i)$ is the prediction of the m -th weak learner for the i -th instance.

This iterative process results in an ensemble model, composed of a sum of weak learners:

$$F(x_i) = F_0(x_i) + \sum_{m=1}^M h_m(x_i) \quad (3)$$

where $F_0(x_i)$ is the initial model's prediction for the i -th instance M is the total number of weak learners in the model [51].

3.2. Random Forest Regressor

Random Forest (RF) is a machine learning approach where multiple decision trees, each with unique characteristics, are combined to form a robust ensemble model [52,53]. The fundamental principle of RF lies in constructing a multitude of decision trees and aggregating their predictions to determine the final output. The construction of each tree, denoted by $T_m(x)$, is based on a bootstrap sample drawn from the training set with replacement. To elaborate, in this bootstrap process, each sample is created by randomly selecting data points from the original dataset, allowing the same data point to be chosen multiple times, which contributes to the unique nature of each tree. Further, at each node, a random subset of m variables is chosen out of the total p variables, and the optimal split among these m variables is used to bifurcate the node [54].

The prediction of the RF model for an instance is given by averaging the predictions from all the decision trees. This can be mathematically represented as:

$$F(x_i) = \frac{1}{N} \sum_{m=1}^N T_m(x_i) \quad (4)$$

In this equation, $F(x_i)$ is the RF prediction for the i -th instance, N represents the total number of trees in the RF model, and $T_m(x_i)$ denotes the prediction of the m -th tree for the i -th instance.

Each decision tree independently draws its bootstrap samples from the dataset:

$$D_m = \text{bootstrap}(D), \quad \text{for } m = 1 \text{ to } N \quad (5)$$

where D_m is the dataset for the m -th tree, D signifies the original dataset.

Despite the many advantages of RF, it is crucial to remember that, unlike gradient boosting which builds models in a stage-wise additive manner, decision trees in an RF model are constructed and combined independently.

3.3. Linear regression

Linear regression (LR) is a statistical technique widely used in machine learning to predict a dependent variable based on the values of one or several independent variables [55]. This approach, foundational in statistics and machine learning alike, adopts a systematic method for determining the relationship between predictors and outcomes [56]. The principle of linear regression involves fitting a model to the data in such a way that the sum of squared residuals (SSR) is minimized. The residual for an instance is calculated as the difference between the actual output and the prediction of the model:

$$e_i = y_i - \left(\beta_0 + \sum_{j=1}^n \beta_j X_{ij} \right) \quad (6)$$

where e_i is the residual for the i -th instance, y_i is the actual output for the i -th instance, β_0 is the y-intercept, β_j is the coefficient of the j -th independent variable, X_{ij} is the value of the j -th independent variable for the i -th instance. The model aims to determine the coefficients (β_j) that minimize the sum of squared residuals. This is achieved through techniques such as ordinary least squares (OLS) or gradient descent for larger datasets due to its computational efficiency [57].

The final prediction of the model is given by the equation:

$$Y_i = \beta_0 + \sum_{j=1}^n \beta_j X_{ij} \quad (7)$$

where Y_i is the predicted output for the i -th instance.

While the simplicity and interpretability of linear regression models have made them a mainstay in many scientific disciplines, it is important to bear in mind that these models rely on certain assumptions. These include linearity, independence of errors, homoscedasticity, and normality of errors. Violations of these assumptions can lead to model inaccuracies or misleading results.

3.4. Multi-Layer Perceptron (MLP) Regressor

The Multilayer Perceptron (MLP) is an artificial neural network featuring multiple interconnected layers, each serving a unique role in the model's architecture [58,59]. MLP uses non-linear activation functions and leverages backpropagation for iterative weight adjustment, which minimizes the error between the actual and predicted output.

The process of weight adjustment is expressed as:

$$e_i = y_i - F_{n-1}(x_i) \quad (8)$$

where e_i represents the error for the i -th instance, y_i is the actual output, and $F_{n-1}(x_i)$ is the previous model's prediction for the i -th instance. The weights of the MLP are then updated:

$$F_n(x_i) = F_{n-1}(x_i) + h_n(x_i) \quad (9)$$

where $h_n(x_i)$ denotes the change in the weight for the i -th instance in the n -th iteration.

The iterative process culminates in an MLP model, which is the assembly of layered nodes:

$$F(x_i) = F_0(x_i) + \sum_{n=1}^N h_n(x_i) \quad (10)$$

where $F_0(x_i)$ is the initial prediction for the i -th instance and N is the total number of iterations.

MLPs are used in various applications due to their ability to map input features to continuous output variables. Unlike gradient boosting models, the MLP's layers are interconnected and weights are adjusted simultaneously, enabling MLPs to capture complex non-linear relationships in the data.

3.5. Voting Regressor

The Voting Regressor is a machine learning technique that utilizes multiple base regressors, each trained on the entire dataset, to form an aggregate model by averaging predictions. This ensemble method can include a diverse range of algorithms such as Decision Trees, Support Vector Machines, or Neural Networks as its base regressors [60,61]. The process of averaging helps to reduce variance when the base regressors are prone to overfitting the data [60] and also to decrease bias when they are inclined to underfit the data [62].

Considering its limitations, the standard practice of utilizing uniform weights for ensemble voting regression may prove to be insufficient for improving predictions without the aid of domain knowledge. The performance of the regressor can also be impacted by the different voting methods used, and in some instances, more computationally expensive methods like the single transferable vote may be necessary.

To summarize this section, Table 1 presents an overview of the methodology and key features of all ML models used in this research.

4. Inputs and data for validation

To conduct a thorough evaluation of the proposed framework's performance and reliability in estimating finite fatigue life of notched components, it is essential to work with robust and extensive datasets. This requirement becomes even more critical when determining the most effective parameter between stress, strain, and energy. To achieve this objective, three distinct sets of experimental data were incorporated into the study, encompassing a range of notch geometries, including U-notch, V-notch, and circular holes. They also cover different materials such as steel, Poly Lactic Acid (PLA), and long carbon fiber laminated composites, all subjected to different (uniaxial) loading conditions and ratios. It is worthwhile to mention that experimental datasets that can be used in this study are limited, as fatigue analyses across various notch geometries are notably time-consuming. Each dataset, with its unique characteristics, provides a diverse and comprehensive foundation for our evaluation. This approach allows us to maintain a balance between complexity and comprehensiveness, ensuring that our analysis of the proposed framework's performance remains insightful and concise. Note that the stress-life (SN) diagrams and the geometry of specimens for each dataset are not presented for the sake of brevity. Readers interested in further details are referred to [39,47,63].

In order to calculate the stress and strain distributions, along with the energy release rate, the finite element (FE) commercial package, Abaqus® software, was used. The specimens were modeled under 2D plane stress condition with a highly refined mesh around the notch to ensure proper capturing of stress concentration. For details on numerical modeling, refer to the papers on the

Table 1

A brief presentation of the methodology and the key features of the ML models.

Model	Methodology	Key Features
Gradient Boosting Regressor	An ensemble learning method that builds models sequentially, each trying to correct errors made by the previous model. It focuses on improving accuracy by combining the predictions of several weaker models.	Efficient with large datasets and complex relationships, reduces bias and variance, but can overfit if not properly tuned.
Random Forest Regressor	An ensemble learning method that creates a "forest" of decision trees during training. Each tree in the forest provides a prediction, and the final prediction is obtained by averaging the predictions of all trees.	Reduces overfitting risk, robust to noisy data, handles large high-dimensional datasets, and provides feature importance insights.
Linear Regression	A simple and interpretable regression method that assumes a linear relationship between input features and the target variable. The model estimates coefficients to minimize the difference between predicted and actual values.	Easy to implement and interpret, assumes linearity which may miss complex patterns, and is sensitive to outliers.
Multi-Layer Perceptron (MLP) Regressor	A type of artificial neural network with one or more hidden layers between the input and output layers. Uses backpropagation for training, adjusting weights to minimize the error.	Models complex non-linear relationships, requires careful hyperparameter tuning, and is computationally intensive, often needing more data for effective training.
Voting Regressor	An ensemble learning method that combines the predictions of multiple different regression models. Each model in the ensemble makes a prediction, and the final prediction is obtained by averaging the predictions of all models.	Combines the strengths of multiple models, improving performance and reducing overfitting, leading to more robust and generalized predictions.

experimental data for each dataset [39,47,63]. The specimens were discretized using 8-node biquadratic elements, and a convergence analysis was performed to verify the independence of the numerical results from the mesh size. To do so, the model's mesh was progressively refined in critical regions (i.e., around the notch tip). Simulations were run with each refined mesh, and the results were compared. Convergence was considered achieved when further refinement did not significantly alter the quantities of interest (stress, strain, and energy). Note that, as each sample required only a linear elastic FE model, a very fine mesh could be considered from the beginning.

This investigation focuses on fatigue failure under uniaxial loading conditions. In this case, it is assumed that the impact of stage II, where the crack growth is perpendicular to the loading direction, is the primary factor governing the overall material strength in the fatigue process zone. As a result, predictive models are based solely on the plane subject to the linear elastic Mode I fatigue damage [39]. Hence, within the scope of the analyses, the terms stress, strain, and energy fields refer to the maximum principal (hoop) stress component along the notch bisector line, the maximum principal strain component along the notch bisector line, and the energy release rate pertaining to a crack situated at the notch tip and growing along the notch bisector line. For the sake of brevity, further information regarding numerical modeling and the extraction of stress, strain, and energy profiles is not mentioned. Then, the stress, strain, and energy fields were extracted up to a sufficient distance where, for example, the stress field reached a (near-) constant value (it is discussed in Section 5.5.3). Also, a total of 10 data points were utilized, with a higher density of points near the notch tip (it is discussed in Section 5.5.1). It is worth emphasizing that to use the field distributions as an input of the ML models, these fields are discretized by a certain number of nodes.

The specimens were simulated under remote stress with an amplitude of 1 (MPa). Therefore, by multiplying the gross stress amplitude (σ_a) from stress-life (SN) data by the stress, strain, or energy fields obtained through FE analyses, the corresponding fields related to each applied stress amplitude are derived. Note that these data, along with the corresponding number of cycles to failure (life) and a name for each notch shape (which is transformed into a numerical form through one-hot encoding), constitute the only input vectors for the problem. In other words, the inputs include the stress-life data, the name of the notch shape, and the fields of stress, strain, or energy release rate for a stress amplitude of 1 MPa. As mentioned in Section 2, each of the stress, strain, or energy fields is unique to a specific notch geometry, and these fields make distinctions between different geometries. For clarity, Fig. 2 illustrates a simplified graphical overview of the various stages within the proposed methodology. All in all, it can be argued that the proposed framework is practical, as it requires only linear elastic analyses for each notch geometry. On the other hand, in terms of machine learning coding, simple algorithms are employed with default settings and without parameter tuning, to make the model more user-friendly. The subsequent section will provide a more detailed discussion of this process, as well as highlighting the key attributes of

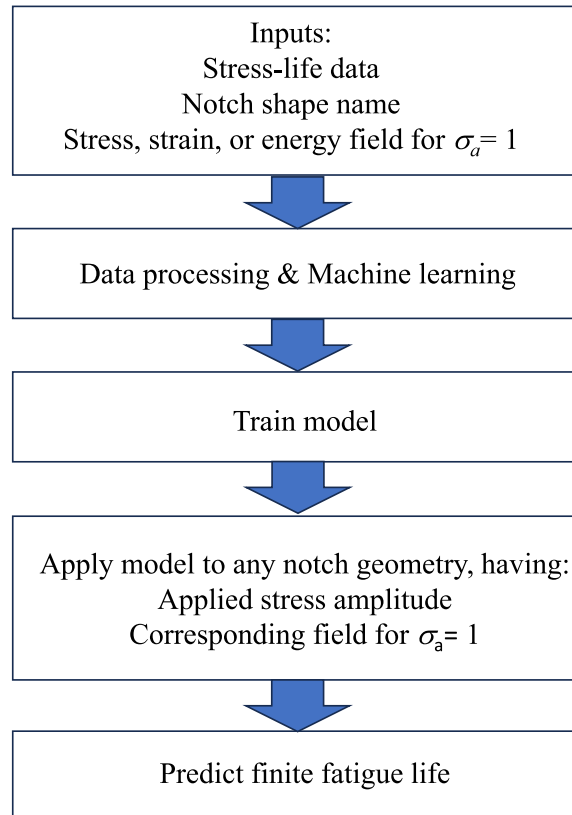


Fig. 2. Simplified graphical overview of the proposed framework.

each dataset, and their distinctive characteristics and significance within the evaluation.

4.1. Validation by specimens made of steel

The first data set comprises specimens made of EN3B steel and encompasses both plain (intact) and notched specimens, with six distinct notched geometries, each tested under tension–tension loading ($R=0.1$) [39]. These tests were conducted under either tensile or bending loading conditions. For the specimens under tensile loading, the specimens were weakened by a single edge V-notch with an opening angle (α) of 60° and a notch tip radius of 0.12 mm, a single edge U-notch ($\alpha = 0^\circ$) with a radius of 1.5 mm, and two central circular holes with two different diameters of 3.5 mm and 8 mm. Specimens under bending loading condition, which were approximately four times thicker than the tensile specimens, contained a single edge V-notch with an opening angle of 45° and a radius of 0.383 mm, as well as a single edge U-notch with a radius of 5 mm. Considering the simplicity of the specimens' geometries and loading conditions, these details are presented here for brevity; readers are referred to the original study [39] for further information.

To illustrate the performance of the code for generating new data, Fig. 3 presents the stress-life diagrams for the plain and V-notch specimens under tension.

As mentioned, if the option of increasing the number of data is activated, it is ensured that the total number of data points (SN data) for each type of notch geometry in enhanced dataset is equal to 100, following the Basquin equation with some noises.

4.2. Validation by specimens made of PLA

To further evaluate the performance of the proposed framework for finite fatigue life estimation, the experimental dataset presented in [63] is considered. These experiments involved testing PLA specimens with three different manufacturing angles ($\theta_p = 0^\circ, 30^\circ, 45^\circ$) under loading ratio of $R=-1$. Apart from the plain specimens, the specimens were configured as double-edge notched tension, with a V-notch with an opening angle of 35° and a notch tip radius of 0.15 mm, as well as two U-notches with radii of 1 mm and 3 mm. An extensive experiment led the authors to argue that the material could be modeled as linear homogeneous and isotropic by averaging the mechanical parameters across the different manufacturing angles [64]. Consequently, the effects of shell thickness and material non-linearities were considered negligible. Thus, the stress–strain behavior was modeled as purely linear elastic, up to the ultimate tensile strength.

4.3. Validation by specimens made of laminated carbon fiber composites

The last dataset consists of specimens made of T300-12 K carbon fiber and Araldite LY 5052 epoxy resin, which were cured using Aradur 5052 Hardener [47]. The testing campaign included a plain specimen, notched specimens – center holed with diameter of 4.2 mm and 6.5 mm – as well as a center cracked specimen with length of 15.4 mm. These specimens were tested under tension–tension loading with a ratio of $R=0.1$ and had $[0/90]_{2s}$ layup. It is important to note that, due to the use of thin-ply laminate configuration, the specimens experienced failure in either the pull-out or brittle failure modes, without any delamination occurring and the failure was along the notch bisector line (perpendicular to the loading direction). Therefore, the characteristics of the failed specimens closely resemble those of isotropic specimens. This behavior enables the use of stress, strain, and energy fields along the notch bisector line for failure analysis and estimation [65].

5. Results and discussion

This section presents the results of the proposed framework applied to various experimental datasets. It also includes a comprehensive examination through several parametric studies to evaluate the impact of different choices on data selection. The predictions for stress, strain, and energy are showcased for both enhanced and baseline data across each dataset. For each dataset, detailed tables

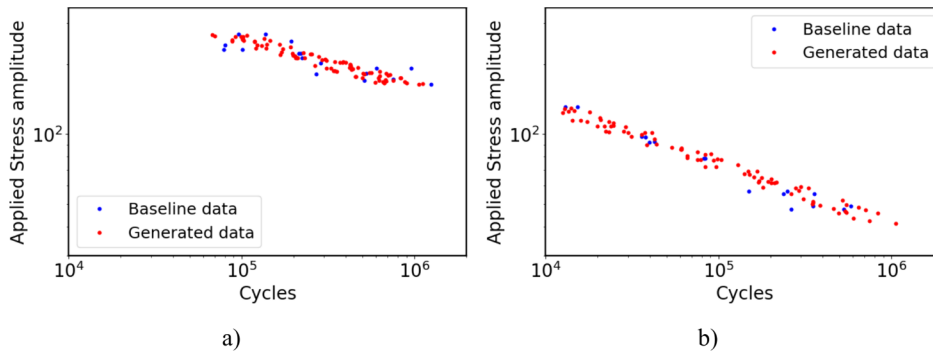


Fig. 3. Stress-life diagrams in log–log form illustrating the baseline and enhanced (baseline + generated) data for two distinct specimens made of steel: a) Plain specimen, and b) V-notched specimen under tension.

are also presented to illustrate the performance of all the ML models.

In order to provide a robust estimation of the model's performance, the results include the average values of the R^2 score and mean squared error (MSE) obtained from 100 different episodes or iterations of the code. Importantly, each episode employs a unique split of training and validation data, generated by a 5-fold cross-validation scheme. This means that in each episode, the model is trained on 80 % of the data and validated on the remaining 20 %, with the specific data points allocated to each subset changing in every episode. Furthermore, the best R^2 score achieved among all model runs, whether for baseline or enhanced data, is highlighted, giving valuable insights into the model's peak performance capability. This strategy of averaging performance metrics across multiple episodes and observing the best score not only gives a more comprehensive and reliable understanding of the model's overall performance but also provides a sense of the model's potential under optimal conditions.

To clarify, the R^2 score and mean squared error (MSE) are calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (N_{f,orig} - N_{f,pred})^2}{\sum_{i=1}^n (N_{f,orig} - N_{f,mean})^2} \quad (11)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (N_{f,orig} - N_{f,pred})^2 \quad (12)$$

where $N_{f,orig}$, $N_{f,pred}$, and $N_{f,mean}$ represent the original (experimental) data of number of cycles to failure, the predicted data, and the mean value of the original data, respectively.

For all three datasets, an initial 10 % of the data is considered as unseen data, and predictions are generated for this subset. These predictions are depicted in Figs. 4-6, where panels a) to c) correspond to cases with enhanced data (shown in Fig. 3), and panels d) to f) represent the baseline data (without any new data production). In all related figures, the horizontal axis represents the estimated life (Predictions), while the vertical axis illustrates the experimental number of cycles (Original Data). The solid black line represents a

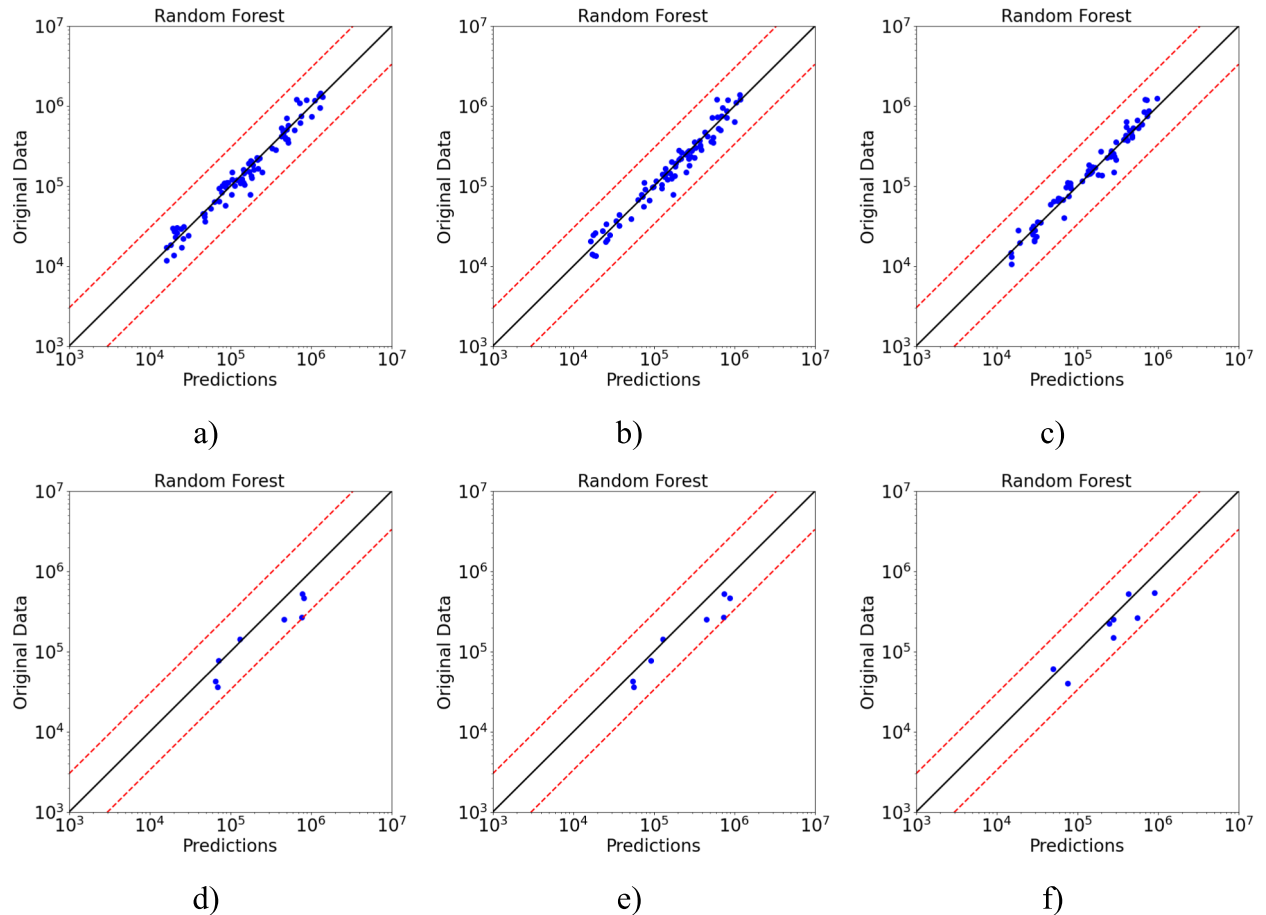


Fig. 4. Comparison of experimental number of cycles to failure and predictions for steel specimens using RF. The figure shows randomly selected samples with 10% of the dataset as unseen data. The analysis includes (a) stress, (b) strain, and (c) energy as measures for the enhanced dataset, and (d) stress, (e) strain, and (f) energy as measures for the baseline dataset.

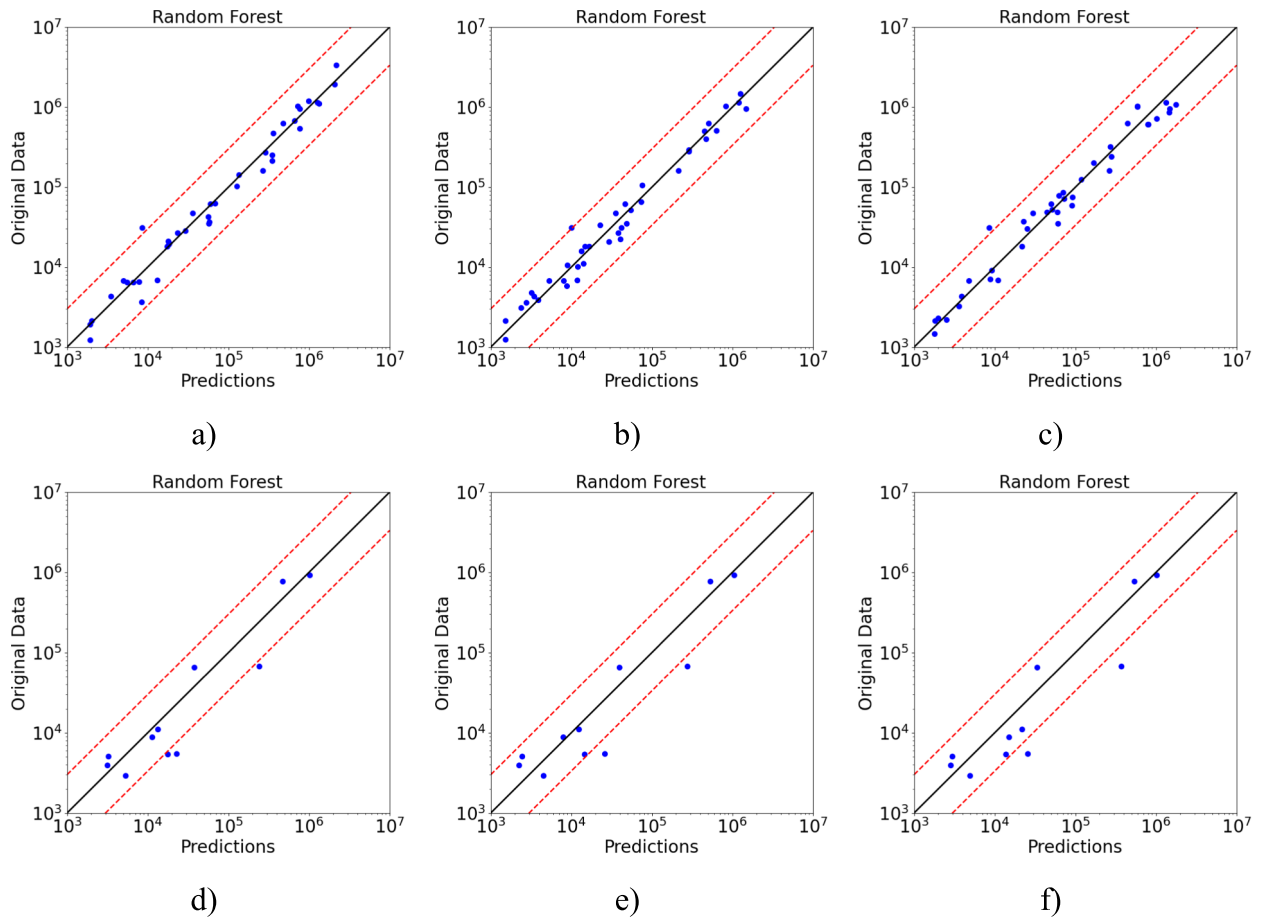


Fig. 5. Comparison of experimental number of cycles to failure and predictions for PLA specimens using RF. The figure shows randomly selected samples with 10% of the dataset as unseen data. The analysis includes (a) stress, (b) strain, and (c) energy as measures for the enhanced dataset, and (d) stress, (e) strain, and (f) energy as measures for the baseline dataset.

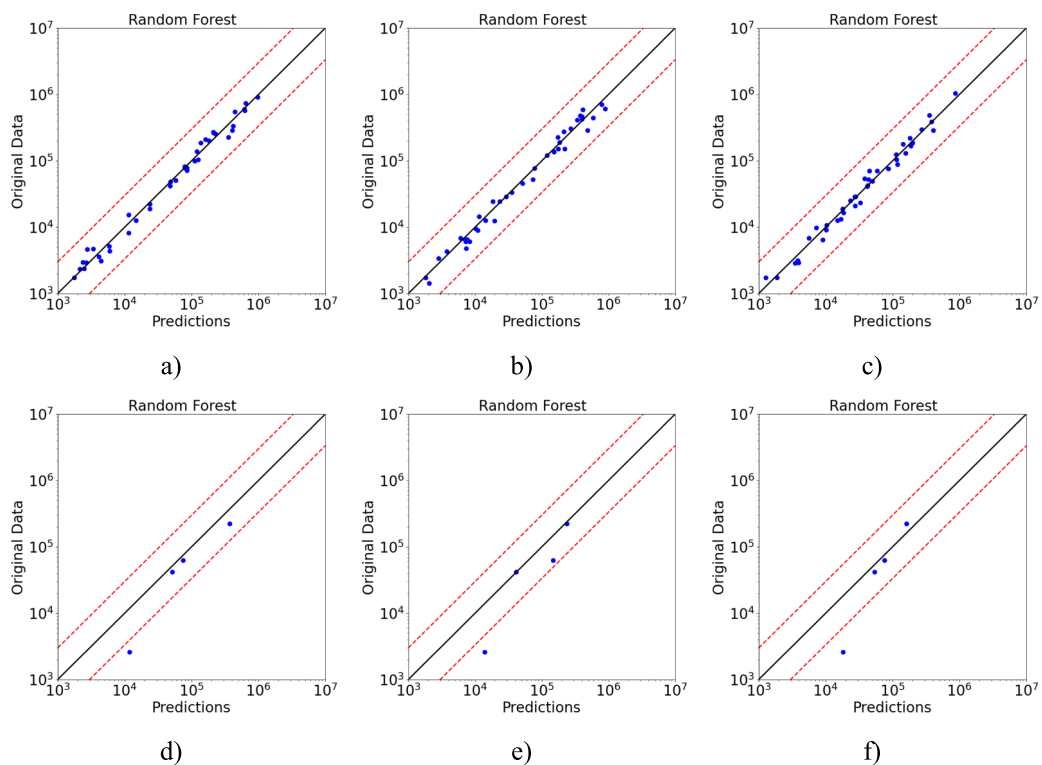


Fig. 6. Comparison of experimental number of cycles to failure and predictions for composites specimens using RF. The figure shows randomly selected samples with 10% of the dataset as unseen data. The analysis includes (a) stress, (b) strain, and (c) energy as measures for the enhanced dataset, and (d) stress, (e) strain, and (f) energy as measures for the baseline dataset.

Table 2

Characteristics and mechanical properties of experimental specimens.

Set No.	Name	Elastic modulus (MPa)	Poisson ratio	Geometric characteristics	R	Loading type
1	Steel	197,400	0.3 [*]	Plain V-notch, $\alpha = 60^\circ$, $\rho = 0.12$ mm U-notch, $\alpha = 0^\circ$, $\rho = 1.5$ mm Circular hole: $\rho = 1.75$ mm Circular hole: $\rho = 2$ mm V-notch, $\alpha = 45^\circ$, $\rho = 0.383$ mm U-notch, $\alpha = 0^\circ$, $\rho = 5$ mm	0.1	Tensile Bending
2	PLA	3476	0.33	Plain V-notch, $\alpha = 35^\circ$, $\rho = 0.15$ mm U-notch, $\alpha = 0^\circ$, $\rho = 1$ mm U-notch, $\alpha = 0^\circ$, $\rho = 3$ mm	-1	Tensile
3	Laminated composites	$E_1 = 102000$ $E_2 = 8500$	$\nu_{12} = 0.29$	Plain Crack, $\alpha = 0^\circ$, $\rho = 0$ mm Circular hole: $\rho = 2.1$ mm Circular hole: $\rho = 6.5$ mm	0.1	Tensile

^{*}It is obtained based on [68].

perfect estimation with zero error. The region above the solid line corresponds to conservative predictions, while the region below indicates unconservative predictions. The dashed red lines represent the scatter bands at 3 and 1/3, following [66,67]. Based on the definitions, a band at 3 represents the line where predictions are three times the experimental value, and a band at 1/3 means that the lower scatter band is one-third of the experimental value. Before presenting the results for different materials, the mechanical properties and other related information for each dataset are presented in Table 2.

5.1. Results for specimens made of steel

Table 3 presents the performance of several machine learning models (Gradient Boosting (GB), Random Forest (RF), Linear Regression (LR), Multi-Layer Perceptron (MLP), Voting Regressor (VR)) for the three different measures (stress, strain, and energy)

Table 3

Evaluation of ML Algorithms for fatigue lifetime prediction with different measures: results for steel specimens.

	Model	R^2 (enhanced)	MSE (enhanced)	Best R^2 (enhanced)	R^2 (baseline)	MSE (baseline)	Best R^2 (baseline)
Stress	GB	0.90	9.29e + 09	0.95	0.45	6.50e + 10	0.97
	RF	0.89	9.72e + 09	0.94	0.51	6.14e + 10	0.95
	LR	0.75	2.24e + 10	0.85	-0.26	1.37e + 11	0.78
	MLP	0.86	1.22e + 10	0.95	0.34	8.01e + 10	0.94
	VR	0.89	1.01e + 10	0.94	0.47	6.72e + 10	0.93
Strain	GB	0.89	8.16e + 09	0.95	0.41	6.65e + 10	0.96
	RF	0.89	8.46e + 09	0.95	0.50	5.94e + 10	0.94
	LR	0.73	2.11e + 10	0.86	-0.27	1.37e + 11	0.78
	MLP	0.85	1.20e + 10	0.96	0.34	8.20e + 10	0.89
	VR	0.88	9.02e + 09	0.94	0.47	6.56e + 10	0.90
Energy	GB	0.89	6.80e + 09	0.95	0.31	7.56e + 10	0.97
	RF	0.89	7.02e + 09	0.96	0.36	7.53e + 10	0.96
	LR	0.68	2.08e + 10	0.79	-0.53	1.51e + 11	0.63
	MLP	0.83	1.09e + 10	0.95	0.20	9.13e + 10	0.85
	VR	0.87	8.13e + 09	0.94	0.32	7.95e + 10	0.93

based on different metrics. The aim is to foster a comprehensive understanding of how different algorithms perform under varying conditions, thereby providing insights into which algorithm and measure pair exhibits the best performance in terms of predictability and precision. It is expected that this detailed presentation of results will contribute significantly to the ongoing discourse in fatigue lifetime prediction using machine learning methods.

Based on Table 3, in examining the stress measure, GB excels on the enhanced dataset with the highest R^2 score (0.90), which represents a high degree of correlation between predicted and actual values. This model also produces the lowest MSE (9.29e + 09), implying fewer prediction errors, and achieves the best R^2 score (0.95). Nevertheless, for the baseline dataset, RF outperforms the other models with the highest R^2 score (0.51) and the smallest MSE (6.14e + 10). For the strain measure, both GB and RF models perform exceptionally well on the enhanced dataset with identical R^2 scores (0.89). On the baseline dataset, RF again performs best, with the highest R^2 score (0.50) and the smallest MSE (5.94e + 10). Notably, GB also produces the smallest MSE (8.16e + 09) and best R^2 score (0.95) on the enhanced dataset, reinforcing its robustness across different measures. When evaluating the energy measure, GB and RF models continue to dominate. Both models generate the highest R^2 scores (0.89) on the enhanced dataset, while RF, once again, takes the lead on the baseline dataset with the highest R^2 score (0.36) and smallest MSE (7.53e + 10). The GB model, consistent with the previous measures, delivers the lowest MSE (6.80e + 09) and highest Best R^2 score (0.95) for the enhanced dataset.

The LR model consistently underperforms across all measures and datasets, suggesting it may not be suitable for this specific task due to its simplicity, as it assumes a linear relationship between input features. In contrast, the GB and RF models, which are known for their ability to handle non-linearity in data, excel in this task. The MLP and VR models deliver moderate performance, with R^2 scores that are consistently lower than those of GB and RF, but higher than LR. This suggests these models' performances fall in between, implying they might benefit from further tuning or the addition of more relevant features.

After evaluating the performance of models using R^2 and MSE scores, RF is utilized to illustrate estimations for unseen data. In this context, a random selection of 10 % of the data is made to represent the unseen portion. Fig. 4 illustrates the models' predictions for the dataset related to steel.

Fig. 4 supports the findings presented in Table 3. It confirms that, for the enhanced data, energy is identified as the most effective measure. Conversely, for the baseline data, strain (followed closely by stress) emerges as the preferred measure. It is worth noting that, despite variations in notch geometries, loading conditions, and specimen thicknesses, all measures consistently yield promising results for predicting fatigue lifetime. In Section 5.5.4, a comprehensive discussion will be provided to explain why the enhanced data exhibits higher accuracy compared to the baseline data.

5.2. Results for specimens made of PLA

Regarding the dataset related to PLA specimens, Table 4 provides a thorough comparison of R^2 and MSE scores for different measures and algorithms for the analysis of PLA data. By presenting the comprehensive set of performance metrics, Table 4 facilitates a deeper comprehension of the respective strengths and weaknesses of each model within the specified measures.

Examining the stress measure, RF outperforms other models on the enhanced dataset with the highest R^2 score (0.87), and the lowest MSE (3.60e + 10). Interestingly, both GB and RF achieve the same Best R^2 score (0.97). On the baseline dataset, RF performs well again with the highest R^2 score (0.61) and the smallest MSE (8.13e + 10). GB, however, reaches the maximum Best R^2 score of 1.00. Moving on to the strain measure, RF consistently delivers excellent results. It leads on the enhanced dataset with an R^2 score of 0.88 and the smallest MSE (3.19e + 10). For the baseline dataset, RF also exhibits superior performance with the highest R^2 score (0.59) and the smallest MSE (8.39e + 10). Both GB and RF achieve nearly perfect Best R^2 scores on both datasets, marking them as standout performers. When it comes to energy as a measure, RF comes out on top for the enhanced dataset with the highest R^2 score (0.82) and the lowest MSE (5.18e + 10).

On the baseline dataset, VR achieves the highest R^2 score (0.50), while RF retains the smallest MSE (9.90e + 10). The GB model, on

Table 4

Evaluation of ML Algorithms for fatigue lifetime prediction with different measures: results for PLA specimens.

	Model	R^2 (enhanced)	MSE (enhanced)	Best R^2 (enhanced)	R^2 (baseline)	MSE (baseline)	Best R^2 (baseline)
Stress	GB	0.86	4.08e + 10	0.97	0.57	8.78e + 10	1.00
	RF	0.87	3.60e + 10	0.97	0.61	8.13e + 10	0.97
	LR	0.42	1.65e + 11	0.59	−0.05	1.57e + 11	0.71
	MLP	0.82	5.21e + 10	0.97	0.45	9.66e + 10	0.92
	VR	0.84	4.77e + 10	0.96	0.58	8.29e + 10	0.94
Strain	GB	0.86	3.83e + 10	0.98	0.53	9.36e + 10	1.00
	RF	0.88	3.19e + 10	0.98	0.59	8.39e + 10	0.99
	LR	0.42	1.59e + 11	0.58	−0.05	1.57e + 11	0.71
	MLP	0.82	5.00e + 10	0.97	0.48	9.36e + 10	0.93
	VR	0.84	4.41e + 10	0.94	0.57	8.40e + 10	0.92
Energy	GB	0.78	6.20e + 10	0.97	0.38	1.10e + 11	0.99
	RF	0.82	5.18e + 10	0.96	0.48	9.90e + 10	0.98
	LR	0.40	1.62e + 11	0.60	−0.05	1.57e + 11	0.71
	MLP	0.78	6.19e + 10	0.95	−1.30	3.19e + 11	0.86
	VR	0.80	5.97e + 10	0.94	0.50	9.33e + 10	0.91

the other hand, reaches the highest Best R^2 score for both datasets, reiterating its capability to achieve flawless predictions under certain conditions. The LR model shows a consistent underperformance for all measures and datasets, which indicates a possible inability to capture complex relationships in the data. Conversely, GB and RF models, known for handling non-linear data patterns effectively, prove their worth in this context. The MLP and VR models demonstrate average performance, with R^2 scores and MSEs generally lower than GB and RF, but higher than LR. This might indicate that these models might have room for optimization or might perform better with additional or different input features.

Fig. 5 visually demonstrates the results obtained from the analysis of both the enhanced and baseline data using the RF algorithm, for different measures of stress, strain, and energy for the dataset relating to PLA specimens.

Referring to Fig. 5, it can be difficult to determine which measure is best since the predictions based on stress and strain are similar. Nevertheless, for all measures, most of the data falls within the scatter band of 3 and 1/3. This indicates the robustness and validity of our models for different notch geometries and a wide range of fatigue lives. Overall, the outcome of this analysis is particularly encouraging as it underscores the models' ability to manage the high variance inherent in the baseline data, even when the effect of the manufacturing angle is not considered. These findings demonstrate the potential and versatility of the framework in estimating fatigue lives.

5.3. Results for specimens made of laminated composites

Here, a comprehensive evaluation of multiple predictive algorithms for various measures is provided, each applied to a dataset pertaining to composite materials. Table 5 exhibits the R^2 and MSE scores attained by each model for the different measures and across both the enhanced and baseline datasets. Through this comprehensive examination, the potential strengths and limitations of each algorithm when dealing with advanced composite materials under fatigue loading are demonstrated.

Looking at the stress measure, both GB and RF models exhibit superior performance on the enhanced dataset, achieving an identical R^2 score of 0.93, with RF registering a slightly lower MSE (2.35e + 09). Moreover, both models attain an identical high Best R^2 score of 0.98. As for the baseline dataset, RF once again outshines the other models with an R^2 score of 0.27 and the smallest MSE (2.12e + 10).

Table 5

Evaluation of ML Algorithms for fatigue lifetime prediction with different measures: results for laminated composites specimens.

	Model	R^2 (enhanced)	MSE (enhanced)	Best R^2 (enhanced)	R^2 (baseline)	MSE (baseline)	Best R^2 (baseline)
Stress	GB	0.93	2.51e + 09	0.98	0.03	2.68e + 10	0.98
	RF	0.93	2.35e + 09	0.98	0.27	2.12e + 10	0.99
	LR	0.72	9.84e + 09	0.84	−92.24	2.53e + 11	0.96
	MLP	0.84	5.95e + 09	0.98	−0.91	3.53e + 10	0.99
	VR	0.92	3.01e + 09	0.97	−9.96	4.77e + 10	0.99
Strain	GB	0.90	3.27e + 09	0.97	0.21	2.15e + 10	0.99
	RF	0.91	2.96e + 09	0.98	0.35	2.03e + 10	1.00
	LR	0.73	9.17e + 09	0.85	−92.24	2.53e + 11	0.96
	MLP	0.81	6.46e + 09	0.97	−0.31	3.10e + 10	0.96
	VR	0.90	3.43e + 09	0.96	−10.22	4.63e + 10	0.99
Energy	GB	0.92	2.37e + 09	0.98	−0.45	3.14e + 10	0.97
	RF	0.93	2.11e + 09	0.98	−0.91	2.97e + 10	0.97
	LR	0.74	8.19e + 09	0.87	−92.24	2.53e + 11	0.96
	MLP	0.67	1.07e + 10	0.94	−2.33	4.04e + 10	0.98
	VR	0.92	2.55e + 09	0.98	−11.42	5.40e + 10	0.99

RF also achieves the highest Best R^2 score (0.99) on the baseline dataset. Moving to the strain measure, RF maintains its strong performance. It outperforms the other models on the enhanced dataset with an R^2 score of 0.91 and the smallest MSE ($2.96e + 09$). The GB and RF models both achieve nearly perfect Best R^2 scores, highlighting their superior predictive power. On the baseline dataset, RF once again leads with the highest R^2 score (0.35), the lowest MSE ($2.03e + 10$), and an ideal Best R^2 score of 1.00. In the case of the energy measure, RF again delivers the highest R^2 score (0.93) and lowest MSE ($2.11e + 09$) for the enhanced dataset, showing its consistent performance across different measures. On the baseline dataset, however, none of the models achieve a positive R^2 score, pointing to a potential difficulty in modeling the baseline energy measure accurately.

Overall, LR shows the poorest performance across all measures and datasets, having the lowest R^2 scores and highest MSEs. Conversely, the GB and RF models showcase their robust performance, especially RF, which leads in many categories. The MLP and VR models fall in between, not quite reaching the performance of the GB and RF models, but surpassing LR.

In order to further examine the models' performance, the next step involves estimating RF performance on a randomly selected 10 % of the data, which was considered as unseen data, across different measures for both the enhanced and baseline datasets. The predictions of these models for the dataset associated with long carbon fiber composite materials are presented in Fig. 6.

Observing Fig. 6, it becomes evident that for the unseen data, all of the measures deliver exceptional performance when applied to the enhanced dataset. All predictions fall within the scatter band of 3 and 1/3, indicating a high level of accuracy. However, the accuracy of predictions for the baseline dataset seems to falter, a conclusion that aligns with the results presented in Table 5. This discrepancy could be attributed to the small size of the dataset, which contains a total of just 33 data points. Furthermore, there are only four geometries in this dataset. Despite this, given the inherent high scatter observed in the analysis of composite materials, the obtained results can still be deemed satisfactory.

After a comprehensive examination of the provided tables, several salient points and patterns emerge that warrant discussion.

I) It is evident that the ensemble models, GB and RF, consistently outperform the other models across all three materials. This upholds the principle of ensemble learning, which leverages the collective knowledge of numerous 'weak' learners to generate robust and reliable predictions.

II) There is a noticeable underperformance of the LR model compared to its counterparts. The complexities and potential non-linear patterns inherent in data may be a significant challenge for this model, leading to its diminished performance. This observation underscores the need for employing more sophisticated models capable of handling the inherent intricacies of such data.

III) An interesting trend is the performance improvement all models exhibit when applied to the enhanced dataset compared to the baseline dataset. This aligns with a common machine learning principle that a larger volume of high-quality data often leads to enhanced predictive accuracy. This observation may also suggest that the enhanced data could be inherently superior in quality (this behavior will be further discussed in detail later in this section).

IV) The performance of the MLP and VR models varies across different scenarios. While they perform reasonably well in certain instances, they fall short in comparison to the ensemble methods. This inconsistency necessitates a more detailed investigation to pinpoint the conditions favorable for these models.

V) A notable pattern is the overall models' superior performance when utilizing stress as the measure, as opposed to strain or energy, across all three materials. This may indicate that the factors influencing stress are less complex or more linearly configured, thereby aligning favorably with the mathematical formulations used by these models. Additionally, the inherent structure of the stress-life diagrams used as inputs for the framework for all the measures may contribute to this trend.

It is worth mentioning that based on [69], that stress-based approaches generally outperform energy-based ones, particularly under uniaxial loading conditions, although this superiority may not hold under multiaxial loading, as discussed in [70]. Note that, as mentioned in [71], it is hard to determine which component serves best in all cases, since it may depend on the material or loading conditions. For instance, considering the strain-controlled nature of fracture initiation in bone [72], criteria of this type are expected to yield better results for failure prediction in such materials. Furthermore, the enduring significance of stress-based fatigue analyses, as underscored in Shigley's Mechanical Engineering Design [73], reinforces the widespread adoption of stress as the optimal mechanical response parameter for estimating fatigue lifetime across diverse materials. This observation aligns with our findings across various materials, highlighting stress's paramount importance in fatigue analysis.

The results presented in this section demonstrated the effectiveness of employing models with their default settings. This approach offers several benefits, including establishing a baseline for performance, ensuring reproducibility, simplifying the analysis process, laying a foundation for more detailed studies, and facilitating benchmarking and comparative analyses.

5.4. Comparing the results of proposed framework with those of TCD

To gain a deeper understanding of the model's performance, it is essential to compare it with other existing methodologies. For this comparison, a well-established model grounded in fracture mechanics called the Theory of Critical Distances (TCD) [39,40] is utilized. The TCD employs stress distribution to predict the lifetime of notched components. It utilizes stress-life data from both plain and cracked (notched) specimens to calibrate the inputs of the models and predict the fatigue lifetime of notched components. For brevity, only the last dataset (composite materials) is used, and the results of the TCD and the proposed framework, considering only the RF algorithm with stress as the measure, are compared. For further information regarding implementation of TCD for calculating fatigue lifetime of notched components in laminate composites, the reader is referred to [47]. It is worth noting that the comparison of results aims to provide a clearer perspective on the performance of various approaches to complex problems, such as the fatigue life analysis of notched components with different shapes, rather than to demonstrate the superior accuracy of the proposed framework.

In most real-world situations, predicting the lifetime of an unseen notch geometry becomes necessary. The dataset related to

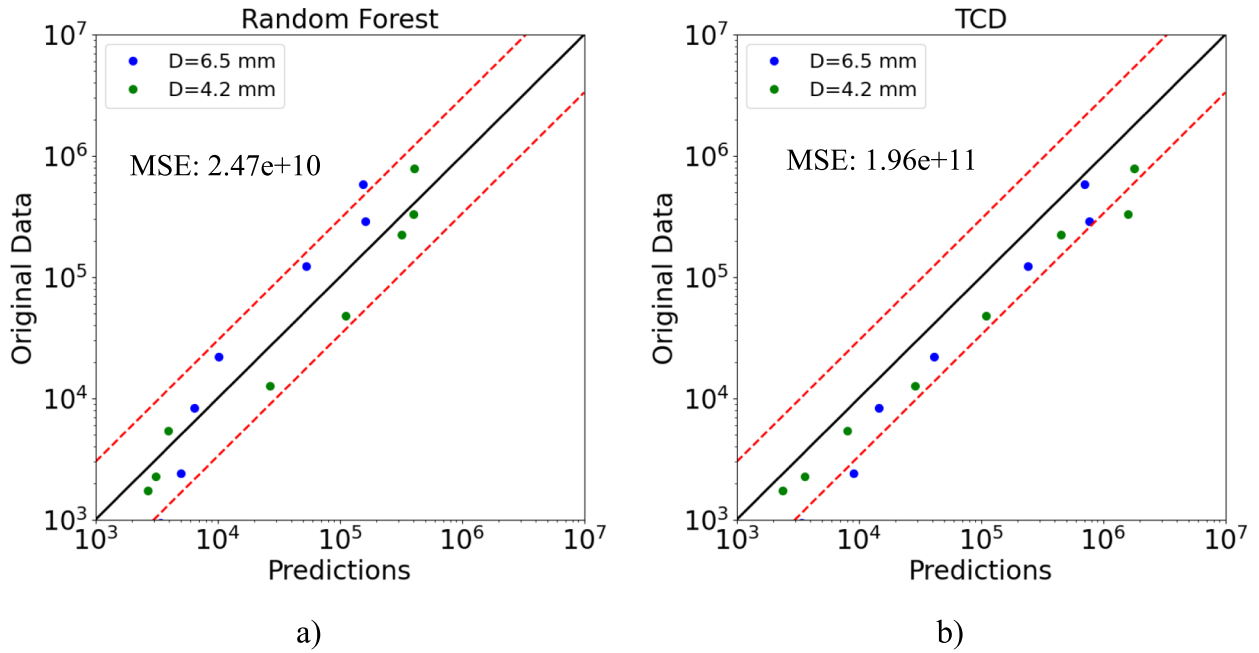


Fig. 7. Prediction of fatigue lifetime for notched components in composite materials based on: a) the proposed framework utilizing the RF algorithm, and b) TCD.

composite materials comprises two distinct notched specimens, as well as plain and cracked specimens. For input characterization, TCD requires stress-life data from plain and cracked specimens. However, in order to increase the number of data for employing RF for predictions, the data related to one notch geometry was designated as unseen data, while the other notch geometry, along with plain and cracked specimens, was employed to train the model. This resulted in the code being executed twice, once for each notch geometry. The model was trained on the remaining portion of the data, augmented with enhanced data (100 data points for each type, except for the one being predicted). Fig. 7 displays the results of both models for these two notched geometries, along with their corresponding MSE values.

The comparative analysis presented in Fig. 7 showcases the superior predictive performance of the proposed framework, by employing the RF algorithm, as compared to the TCD. This advantage is underscored by a significant reduction in the Mean Squared Error (MSE) values for the proposed model ($2.47e + 10$) as opposed to the TCD model ($1.96e + 11$). Additionally, RF predictions exhibit a more balanced distribution around the solid line, representative of perfect predictions, thereby demonstrating the proposed model's proficiency in predicting the fatigue lifetime of notched components in composite materials. On the other hand, the TCD model's predictions tend to deviate below this line, landing in the unconservative region, thus suggesting a potential overestimation of fatigue life and risking unexpected component failure.

5.5. Examination of key influential parameters

After demonstrating the effectiveness of the framework, it is necessary to study the influence of several key parameters, including the effect of density and number of data points, as well as path length. For this purpose, the data related to the composite materials are utilized, following the section on the real-world case study (using the Random Forest model and stress as the measure). It is worthwhile to emphasize that for the sake of simplicity and brevity, the composite data are chosen as they represent the latest set of data and exhibit the most complex material behavior. On the other hand, they serve merely as a representative example for analyzing the model's behavior with respect to different factors, and using another set of experimental data would result in similar conclusions. Furthermore, for the sake of better comparison, only the results related to the notch geometry with $D=4.2$ mm are presented. Note that in each subsection, only one parameter of interest is altered while the remaining parameters are kept consistent with those in the other analyses.

5.5.1. Effect of density of data

Four different types of data selection, each having the same total number of points from the stress distribution, are considered to analyze the effect of data density. Note that here, higher data density refers to a higher number of data points close to the notch tip. In Fig. 8a, the stress distribution is shown as a solid black line, with different markers representing varying densities. From Type I to Type IV, the number of points in closer proximity to the notch tip increases to better capture the stress concentration, keeping the total number of points constant. In Type I, 10 points were chosen at equal distances.

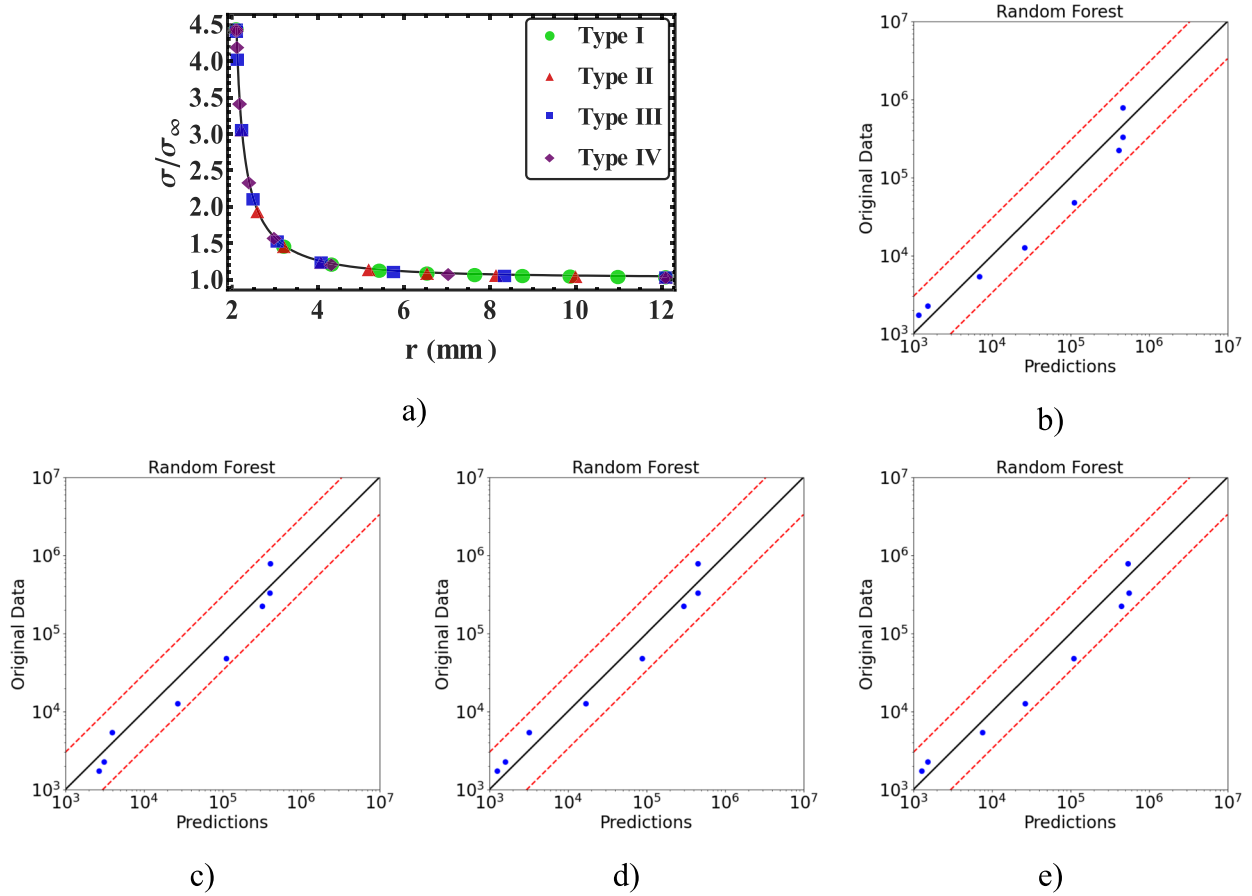


Fig. 8. a) Visualization of the stress distribution along with four different data densities. The solid black line represents the stress distribution, with varying data selection types represented by different points along the line. b) results for type I, c) results for type II, d) results for type III, and e) results for type IV.

From the analysis presented in Fig. 8, it is clear that the model's performance remains remarkably consistent despite variations in density of data. This illustrates the robustness of the model and underscores its stability and reliability. Regardless of the alteration in data density close to the notch tip—a transition from Type I to Type IV—the model effectively preserves its predictive power, offering accurate estimates of fatigue lives. As mentioned in Section 4, our analyses employed a density similar to Type II.

5.5.2. Effect of number of data points

The quantity of data points representing stress, strain, or energy distributions is also optional. As previously stated, 10 data points were considered for each case in the analyses. However, Fig. 9 depicts the impact of varying the quantity of data points on the predictive capability of the framework. It is noteworthy that, in all cases (except panel a) with one data point), the first and last data points of the path along the notch bisector line are used as inputs, and the number of points in between is different. As in the literature the peak stress at the notch tip is frequently used to estimate the fatigue life, panel a) represents this case.

With the exception of cases a) and b), the model's performance appears to remain largely stable, regardless of the number of data points, suggesting its effective capacity to capture and interpret essential data patterns. This characteristic not only confirms the model's reliability but also underlines its flexibility. Conversely, a comparison between cases a) and b) with the other scenarios underscores the importance of considering some intermediate data points between the first and last ones to better reflect the profile of the field in the analysis. It is important to emphasize that this section underscores the effectiveness of the proposed method's concept, particularly when compared to existing methods in the literature that typically rely on using only one data point, usually located at the tip.

5.5.3. Effect of path length

The selection of input data also involves determining the distance from the notch tip from which data should be selected. This decision inherently influences both the representation of the stress distribution and the consequent performance of the model. To meticulously investigate this parameter, data were collected from three distinct distances from the notch tip: 5 mm, 7.5 mm, and 10 mm. The outcomes of these considerations are depicted in Fig. 9.

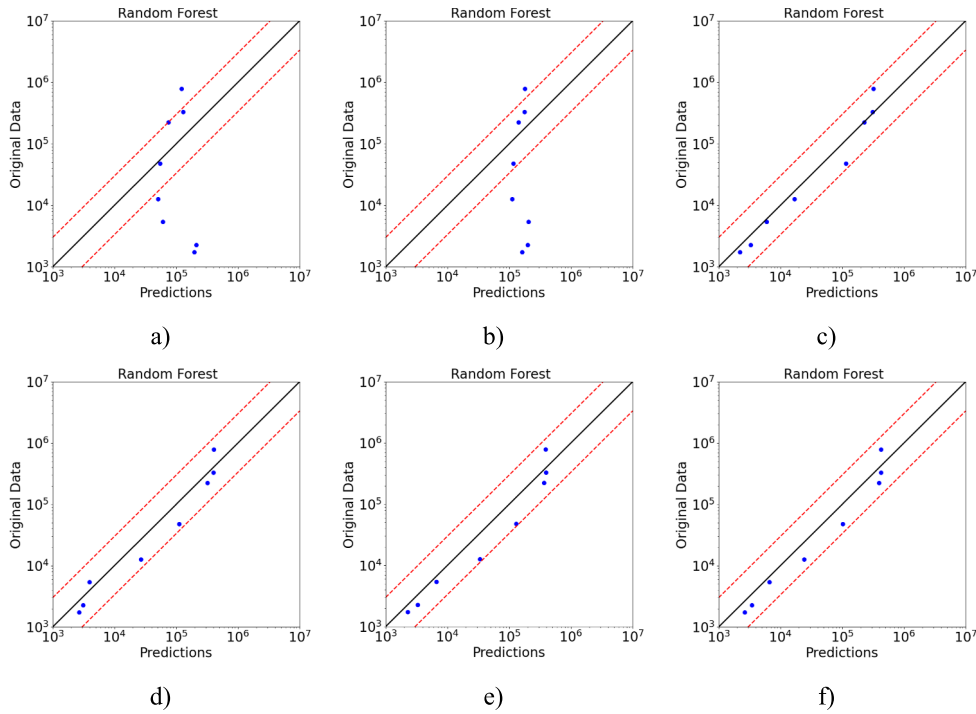


Fig. 9. Performance analysis of the model for different number of data points: a) one, b) two, c) five, d) ten, e) fifteen, and f) twenty.

Fig. 10 offers an enlightening representation of the model's performance in relation to variations in the path length from the notch tip. As can be inferred from the figure, there is a positive correlation between an increase in path length and an enhancement in model performance. This trend can be scientifically rationalized. In the context of stress distribution, when the path length is sufficiently long, it allows the stress distribution to converge towards a fixed value which is for example the applied stress amplitude for sufficiently large ligament. This convergence is vital because it enables the model to capture the transition from the localized stress concentration around the notch to the global stress state. It provides a comprehensive view of the stress scenario, encompassing both the localized stress near the notch tip and the uniform stress distribution at a distance from it. This broad perspective enhances the model's predictive capability, facilitating a more comprehensive view of behavior under various loading conditions, thereby improving its performance.

5.5.4. Effect of number of generated data

This segment investigates how the quantity of data points in the enhanced dataset affects the model's performance. Similar to previous scenarios, the results pertain to the composite material, however, the unseen data were chosen randomly. The other parameters remain consistent with the primary analyses throughout the paper. Six different cases are considered, with the number of data

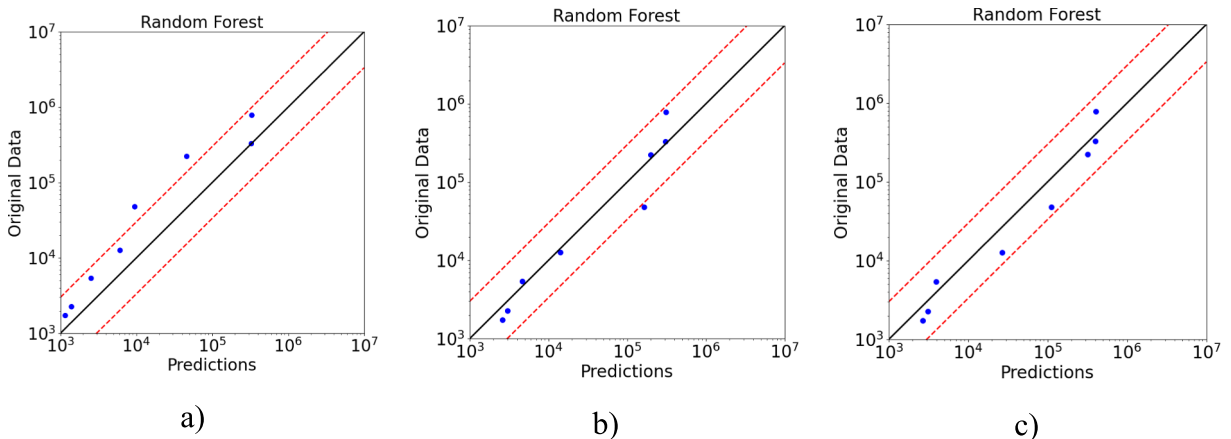


Fig. 10. Performance analysis of the model for different distances from the notch tip (path lengths): a) 5 mm, b) 7.5 mm, c) 10 mm.

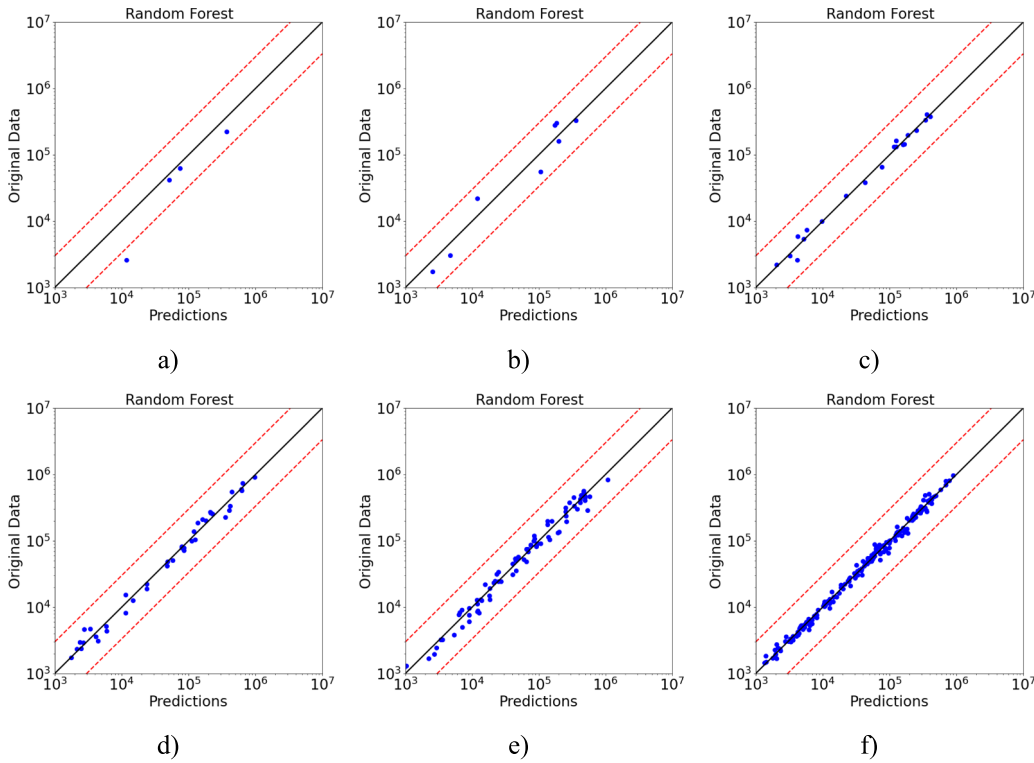


Fig. 11. Performance analysis of the model for different quantities of data points in the enhanced dataset: a) none, b) 20, c) 50, d) 100, e) 200, and f) 500.

points increased from the original dataset to 500 for each specimen. The outcomes of this study are displayed in Fig. 11.

The figure demonstrates a significant increase in the model's accuracy as data points are augmented, despite considerable noise in the generation of new data. This enhancement in performance of the proposed machine learning framework with increasing the number of data points in the enhanced datasets can be attributed to several factors:

1. **Expansion of training examples:** Machine learning algorithms, such as Random Forests, typically exhibit superior performance when provided with a larger number of examples to learn from. In the context of a dataset with limited size, the model may suffer from a shortage of sufficient information to decipher the governing patterns within the problem.
2. **Reduction of overfitting:** Properly increasing the quantity of data can bolster the model's robustness by mitigating overfitting. Overfitting refers to a scenario where the model excessively adapts to the noise in the training data (considering the high scatter in fatigue data), leading to suboptimal performance on new, unseen data. The inclusion of additional data (and consequently, more noise) in the dataset strengthens the model's resistance to noise, thereby reducing the likelihood of overfitting.
3. **Bias-Variance trade-off:** This principle states that an increase in bias leads to a decrease in variance, and vice-versa. By generating more data, we have subtly increased the model's bias, making it more generalized. At the same time, this decrease in variance lowers the model's susceptibility to overfitting and enhances its performance on unseen data.

5.5.5. Effect of noise factor of generated data

The response of the model effectiveness to the noise factor is explored in this section. The analysis is run again with the data points of the enhanced dataset. As in the previous examples, the discussion centers on composite materials, and other variables are in line with the main analysis throughout the manuscript. Three scenarios are considered; noise factor from -0.1 to 0.1 in scenario a), -0.3 to 0.3 in scenario b) which is similar to prior cases, and -0.5 to 0.5 in scenario c). The results of this analysis are shown in Fig. 12.

The analysis presented in Fig. 12 highlights the model's consistent and reliable performance across various noise levels in the enhanced dataset, underscoring its robustness and stability. This characteristic is particularly valuable, given that fatigue testing in experimental settings often exhibits significant variability. The framework's ability to maintain accurate predictions despite the presence of a high noise factor like 0.5 in the data is a testament to its effectiveness in dealing with real-world challenges, making it a reliable tool for interpreting experimental fatigue tests with high levels of scatter.

It should be noted that the employed machine learning algorithms are generally more robust to noise than others. Ensemble approaches like Gradient Boosting and Random Forest reduce error by aggregating several models. Despite being sensitive to outliers, Linear Regression concentrates on average trends, making it less sensitive to random noise. The MLP Regressors have good generalization abilities (if properly regularized), allowing them to effectively filter out noise. Finally, the Voting Regressor, which uses

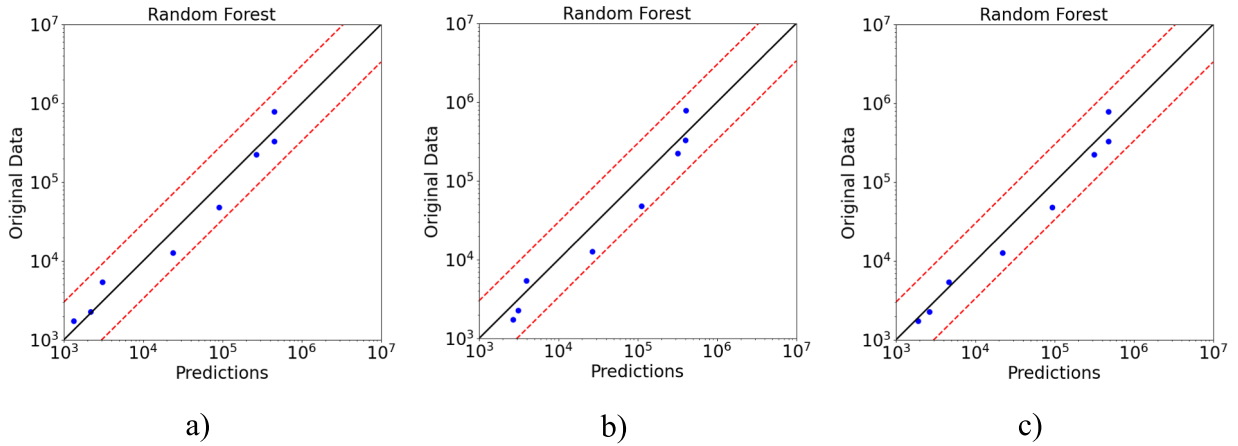


Fig. 12. Performance analysis of the model for different noise factors in the enhanced dataset: a) -0.1 to 0.1 , b) -0.3 to 0.3 , c) -0.5 to 0.5 .

diverse types of models, is also more resistant to noise because the noise resistance of some models offsets the error of others. The degree of robustness of these models depends on the type of noise, its amount, the complexity of the model, and how it is configured during training, among other factors.

After illustrating the high performance of the model across three representative datasets, notably, involving different materials, and comparing these results with other approaches, it has been demonstrated that the model exhibits strong performance in terms of stability and reliability under various parameter selections. This behavior suggests that the proposed framework provides a robust basis for studying fatigue analysis of notched components. However, it is worthwhile to note that this manuscript was limited to uniaxial loading conditions within the high-cycle fatigue regime. To maintain brevity, the results for three different cases were shown, and further analysis might be needed for a more in-depth conclusion. However, it should be noted that the experimental data on the fatigue of notched components with different geometries in the finite life region are limited. Despite this, the framework's high-accuracy predictions for the samples tested highlight its significant potential.

This research establishes a foundation for future studies aimed at exploring alternative machine learning algorithms and optimization techniques, as well as the tuning of hyperparameters, with the objective of further enhancing the performance of the fatigue life prediction framework. From a mechanical standpoint, a potential improvement could be achieved by extending the model to account for multi-axial and variable loading conditions, broadening its scope and applicability.

6. Conclusions

A robust framework based on machine learning algorithms was proposed to estimate the finite fatigue life of notched components under uniaxial loading conditions. The novelty of the framework lies in its ability to distinguish different notch geometries by employing the profile of mechanical response parameters, such as the stress field, strain field, and energy release rate, as measures. In other words, based on the mechanical response fields that are unique for each notched sample, the ML models are trained to estimate the notch effect on fatigue life. Three distinct datasets were used for validation, covering a wide range of materials, such as steel, PLA, and carbon fiber composites, and notch geometries under different uniaxial loading conditions. The following conclusions can be drawn:

- I. All measures utilized in the framework contribute to a reasonably accurate estimation of fatigue lifetime; however, the stress measure proved to be the most effective.
- II. The study highlighted the effectiveness of machine learning models within the framework, specifically Gradient Boosting and Random Forest. Furthermore, a comparison with the TCD model highlighted the superior predictive performance of the proposed framework.
- III. The impact of some parameters on the performance of the framework was carefully analyzed, providing valuable insights into its robustness and stability under various conditions. The framework consistently maintained its predictive accuracy, regardless of changes in data density or noise factors, and converged quickly as the number of total data points representing the field distributions increased. However, it was demonstrated that the path length of the field distribution needs to be sufficiently long to capture both local and nonlocal features.
- IV. It was observed that enhancing the number of data points, in accordance with the Basquin equation (with some added noise), improves the framework's performance by possibly providing more training examples, reducing overfitting, and facilitating a better bias-variance trade-off.

CRediT authorship contribution statement

A.M. Mirzaei: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgements

The author acknowledges the funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No 861061 – NEWFRAC Project. The support of Prof. Pietro Cornetti during the project is gratefully acknowledged.

References

- [1] Stephens RI, Fatemi A, Stephens RR, Fuchs HO. Metal fatigue in engineering. John Wiley & Sons; 2000.
- [2] Shokrieh MM, Lessard LB. Progressive Fatigue Damage Modeling of Composite Materials, Part I: Modeling. *J Compos Mater* 2000;34:1056–80.
- [3] Mirsayar MM. A novel multiscale model for mixed-mode fatigue crack growth in laminated composites. *Int J Mech Sci* 2023;255:108470.
- [4] Mandegarian S, Taheri-Behrooz F. A general energy based fatigue failure criterion for the carbon epoxy composites. *Compos Struct* 2020;235:111804.
- [5] Juan Y, Dai Y, Yang Y, Zhang J. Accelerating materials discovery using machine learning. *J Mater Sci Technol* 2021;79:178–90.
- [6] He L, Wang Z, Akebono H, Sugeta A. Machine learning-based predictions of fatigue life and fatigue limit for steels. *J Mater Sci Technol* 2021;90:9–19.
- [7] Wei J, Chu X, Sun X-Y, Xu K, Deng H-X, Chen J, et al. Machine learning in materials science. *InfoMat* 2019;1:338–58.
- [8] Yu H, Hu Y, Kang G, Peng X, Chen B, Wu S. High-cycle fatigue life prediction of L-PBF AlSi10Mg alloys: a domain knowledge-guided symbolic regression approach. *Philos Trans R Soc A Math Phys Eng Sci* 2024;382:20220383.
- [9] Zhang S, Lei H, Zhou Z, Wang G, Qiu B. Fatigue life analysis of high-strength bolts based on machine learning method and SHapley Additive exPlanations (SHAP) approach. *Structures* 2023;51:275–87.
- [10] Long X, Lu C, Su Y, Dai Y. Machine learning framework for predicting the low cycle fatigue life of lead-free solders. *Eng Fail Anal* 2023;148:107228.
- [11] Lian Z, Li M, Lu W. Fatigue life prediction of aluminum alloy via knowledge-based machine learning. *Int J Fatigue* 2022;157:106716.
- [12] Khayyam H, Shakhosravi NA, Jamali A, Naebe M, Kafieh R, Milani AS. GMDH-Kalman Filter prediction of high-cycle fatigue life of drilled industrial composites: A hybrid machine learning with limited data. *Expert Syst Appl* 2023;216:119425.
- [13] Yang W-K, Hu B-L, Luo Y-W, Song Z-M, Zhang G-P. Understanding geometrical size effect on fatigue life of A588 steel using a machine learning approach. *Int J Fatigue* 2023;172:107671.
- [14] Zhang M, Sun C-N, Zhang X, Goh PC, Wei J, Hardacre D, et al. High cycle fatigue life prediction of laser additive manufactured stainless steel: A machine learning approach. *Int J Fatigue* 2019;128:105194.
- [15] X. Teng, J. Pang, F. Liu, C. Zou, X. Bai, S. Li, Z. Zhang, Fatigue Life Prediction of Gray Cast Iron for Cylinder Head Based on Microstructure and Machine Learning, *Acta Metall. Sin. (English Lett.)* (2023).
- [16] Utpat VS, Kulkarni SG. Analysis of Various Machine Learning Algorithms for Cast Aluminium Alloy to Estimate Fatigue Strength. *J Inst Eng Ser D* 2023;104:61–70.
- [17] Sai NJ, Rathore P, Chauhan A. Machine learning-based predictions of fatigue life for multi-principal element alloys. *Scr Mater* 2023;226:115214.
- [18] Bao H, Wu S, Wu Z, Kang G, Peng X, Withers PJ. A machine-learning fatigue life prediction approach of additively manufactured metals. *Eng Fract Mech* 2021;242:107508.
- [19] Zhan Z, Ao N, Hu Y, Liu C. Defect-induced fatigue scattering and assessment of additively manufactured 300M-AerMet100 steel: An investigation based on experiments and machine learning. *Eng Fract Mech* 2022;264:108352.
- [20] Zheng Z, Li X, Sun T, Huang Z, Xie C. Multiaxial fatigue life prediction of metals considering loading paths by image recognition and machine learning. *Eng Fail Anal* 2023;143:106851.
- [21] He G, Zhao Y, Yan C. Application of tabular data synthesis using generative adversarial networks on machine learning-based multiaxial fatigue life prediction. *Int J Press Vessel Pip* 2022;199:104779.
- [22] Wan HY, Chen GF, Li CP, Qi XB, Zhang GP. Data-driven evaluation of fatigue performance of additive manufactured parts using miniature specimens. *J Mater Sci Technol* 2019;35:1137–46.
- [23] Chen J, Liu Y. Fatigue modeling using neural networks: A comprehensive review. *Fatigue Fract Eng Mater Struct* 2022;45:945–79.
- [24] Wang L, Zhu S-P, Luo C, Liao D, Wang Q. Physics-guided machine learning frameworks for fatigue life prediction of AM materials. *Int J Fatigue* 2023;172:107658.
- [25] Shi T, Sun J, Li J, Qian G, Hong Y. Machine learning based very-high-cycle fatigue life prediction of AlSi10Mg alloy fabricated by selective laser melting. *Int J Fatigue* 2023;171:107585.
- [26] Maleki E, Bagherifard S, Guagliano M. Correlation of residual stress, hardness and surface roughness with crack initiation and fatigue strength of surface treated additive manufactured AlSi10Mg: Experimental and machine learning approaches. *J Mater Res Technol* 2023;24:3265–83.
- [27] Li J, Yang Z, Qian G, Berto F. Machine learning based very-high-cycle fatigue life prediction of Ti-6Al-4V alloy fabricated by selective laser melting. *Int J Fatigue* 2022;158:106764.
- [28] Zhang Z, Xu Z. Fatigue database of additively manufactured alloys. *Sci Data* 2023;10:249.
- [29] Pierson K, Rahman A, Spear AD. Predicting Microstructure-Sensitive Fatigue-Crack Path in 3D Using a Machine Learning Framework. *JOM* 2019;71:2680–94.
- [30] Sharma A, Mukhopadhyay T, Rangappa SM, Siengchin S, Kushvaha V. Advances in Computational Intelligence of Polymer Composite Materials: Machine Learning Assisted Modeling, Analysis and Design. *Arch Comput Methods Eng* 2022;29:3341–85.
- [31] Wang X, Miao C, Hao D. Machine learning-assisted fatigue performance optimization for cutout geometry of orthotropic steel bridge decks. *Case Stud Constr Mater* 2023;18:e01962.
- [32] Salvati E, Tognan A, Laurenti L, Pelegatti M, De Bona F. A defect-based physics-informed machine learning framework for fatigue finite life prediction in additive manufacturing. *Mater Des* 2022;222:111089.

- [33] Sun L, Huang X. Prediction of fatigue crack propagation lives based on machine learning and data-driven approach. *Sci: J. Ocean Eng*; 2022.
- [34] Li H, Zhang J, Hu L, Su K. Notch fatigue life prediction of micro-shot peened 25CrMo4 alloy steel: A comparison between fracture mechanics and machine learning methods. *Eng Fract Mech* 2023;277:108992.
- [35] Hao WQ, Tan L, Yang XG, Shi DQ, Wang ML, Miao GL, et al. A physics-informed machine learning approach for notch fatigue evaluation of alloys used in aerospace. *Int J Fatigue* 2023;170:107536.
- [36] Bartošák M. Using machine learning to predict lifetime under isothermal low-cycle fatigue and thermo-mechanical fatigue loading. *Int J Fatigue* 2022;163:107067.
- [37] Wu Z, Kou H, Chen N, Zhang M, Hua K, Fan J, et al. Duality of the fatigue behavior and failure mechanism in notched specimens of Ti-7Mo-3Nb-3Cr-3Al alloy. *J Mater Sci Technol* 2020;50:204–14.
- [38] H. Neuber, Theory of notch stresses: principles for exact calculation of strength with reference to structural form and material., (1961) 293p. file://catalog.hathitrust.org/Record/102014224.
- [39] Susmel L, Taylor D. A novel formulation of the theory of critical distances to estimate lifetime of notched components in the medium-cycle fatigue regime. *Fatigue Fract Eng Mater Struct* 2007;30:567–81.
- [40] Taylor D. Geometrical effects in fatigue: a unifying theoretical model. *Int J Fatigue* 1999;21:413–20.
- [41] Mirzaei AM, Cornetti P, Sapora A. A novel Finite Fracture Mechanics approach to assess the lifetime of notched components. *Int J Fatigue* 2023;107659.
- [42] Leguillon D. Strength or toughness? A criterion for crack onset at a notch. *Eur J Mech* 2002;21:61–72. <https://www.sciencedirect.com/science/article/abs/pii/S0997753801011846>.
- [43] Weißgraeber P, Leguillon D, Becker W. A review of Finite Fracture Mechanics: crack initiation at singular and non-singular stress raisers. *Arch Appl Mech* 2016;86:375–401.
- [44] Mirzaei AM, Ayatollahi MR, Bahrani B, Berto F. A new unified asymptotic stress field solution for blunt and sharp notches subjected to mixed mode loading. *Int J Mech Sci* 2021;193:106176.
- [45] Nalla RK, Kinney JH, Ritchie RO. Mechanistic fracture criteria for the failure of human cortical bone. *Nat Mater* 2003;2:164–8.
- [46] O.H. Basquin, The exponential law of endurance tests, in: *Proc Am Soc Test Mater*, 1910: pp. 625–630.
- [47] Mirzaei AM, Mirzaei AH, Shokrieh MM, Sapora A, Cornetti P. Fatigue life assessment of notched laminated composites: Experiments and modelling by Finite Fracture Mechanics. *Compos Sci Technol* 2024;246:110376.
- [48] Natekin A, Knoll A. Gradient boosting machines, a tutorial. *Front Neurobot* 2013;7.
- [49] Friedman JH. Greedy Function Approximation: A Gradient Boosting Machine. accessed July 9, 2023 *Ann Stat* 2001;29:1189–232. <http://www.jstor.org/stable/2699986>.
- [50] Sigrist F. Gradient and Newton Boosting for Classification and Regression. *Expert Syst Appl* 2021;167.
- [51] A. Guryanov, Histogram-Based Algorithm for Building Gradient Boosting Ensembles of Piecewise Linear Decision Trees, in: W.M.P. van der Aalst, V. Batagelj, D. I. Ignatov, M. Khachay, V. Kuskova, A. Kutuzov, S.O. Kuznetsov, I.A. Lomazova, N. Loukachevitch, A. Napoli, P.M. Pardalos, M. Pelillo, A. V Savchenko, E. Tutubalina (Eds.), *Anal. Images, Soc. Networks Texts*, Springer International Publishing, Cham, 2019: pp. 39–50.
- [52] T.K. Ho Random decision forests *Proc 3rd Int Conf Doc Anal vol 1* 1995 *Recognit* 278 282.
- [53] Breiman L. Random Forests. *Mach Learn* 2001;45:5–32.
- [54] Schonlau M, Zou RY. The random forest algorithm for statistical learning. *Stata J* 2020;20:3–29.
- [55] Galton F. Regression Towards Mediocrity in Hereditary Stature. accessed July 9, 2023 *J Anthropol Inst Gt Britain Irel* 1886;15:246–63. <http://www.jstor.org/stable/2841583>.
- [56] Maulud D, Abdulazeez AM. A Review on Linear Regression Comprehensive in Machine Learning. *J Appl Sci Technol Trends* 2020;1:140–7.
- [57] Matloff N. Statistical regression and classification: from linear models to machine learning. CRC Press; 2017.
- [58] Rosenblatt F. The perceptron: A probabilistic model for information storage and organization in the brain. *Psychol Rev* 1958;65:386–408.
- [59] Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. *Nature* 1986;323:533–6.
- [60] Hastie T, Tibshirani R, Friedman JH, Friedman JH. The elements of statistical learning: data mining, inference, and prediction. Springer; 2009.
- [61] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. others, Scikit-learn: Machine learning in Python. *J Mach Learn Res* 2011;12:2825–30.
- [62] Breiman L. Bias, variance, and arcing classifiers (Technical Report 460). Calif: Stat. Dep. Univ; 1996.
- [63] Ezech OH, Susmel L. On the notch fatigue strength of additively manufactured polylactide (PLA). *Int J Fatigue* 2020;136:105583.
- [64] Ezech OH, Susmel L. Fatigue strength of additively manufactured polylactide (PLA): effect of raster angle and non-zero mean stresses. *Int J Fatigue* 2019;126:319–26.
- [65] Green BG, Wisnom MR, Hallett SR. An experimental investigation into the tensile strength scaling of notched composites. *Compos Part A Appl Sci Manuf* 2007;38:867–78.
- [66] Gates N, Fatemi A. Notched fatigue behavior and stress analysis under multiaxial states of stress. *Int J Fatigue* 2014;67:2–14.
- [67] Gates N, Fatemi A. Multiaxial variable amplitude fatigue life analysis including notch effects. *Int J Fatigue* 2016;91:337–51.
- [68] Akçay FA, Oterkus E. Prediction of fracture toughness of metallic materials. *Eng Comput* 2023;39:81–8.
- [69] Hu Z, Berto F, Hong Y, Susmel L. Comparison of TCD and SED methods in fatigue lifetime assessment. *Int J Fatigue* 2019;123:105–34.
- [70] Branco R, Costa JD, Borrego LP, Berto F, Razavi SMJ, Macek W. Comparison of different one-parameter damage laws and local stress-strain approaches in multiaxial fatigue life assessment of notched components. *Int J Fatigue* 2021;151:106405.
- [71] Che FX, Pang JHL. Fatigue Reliability Analysis of Sn–Ag–Cu Solder Joints Subject to Thermal Cycling. *IEEE Trans Device Mater Reliab* 2013;13:36–49.
- [72] Ritchie RO, Kinney JH, Kruzic JJ, Nalla RK. A fracture mechanics and mechanistic approach to the failure of cortical bone. *Fatigue Fract Eng Mater Struct* 2005;28:345–71.
- [73] R.G. Budynas, J.K. Nisbett, J.E. Shigley, Shigley's mechanical engineering design, 9th ed, McGraw-Hill, New York SE - xxi, 1082 pages: illustrations; 27 cm., 2011.



DSPACE

<https://dspace.org/>

Stress, strain, or energy? Which one is superior predictor of fatigue life in notched components? A novel machine learning-based framework

Mirzaei, Amir M.

2024-10-01

Elsevier

<https://doi.org/10.1016/j.engfracmech.2024.110401>

Mirzaei AM. (2024) Stress, strain, or energy? Which one is superior predictor of fatigue life in notched components? A novel machine learning-based framework. Engineering Fracture Mechanics, Volume 309, October 2024, Article number 110401