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Machine Learning Techniques in Fracture Mechanics a Comparative Study of Linear Regression, Random Forest, and Ada Boost Model

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ABSTRACT

Machine learning approaches have revolutionized the analysis of fracture mechanics by providing efficient alternatives to traditional analytical and empirical methods. This research explores the use of machine learning methods fracture mechanics, focusing on their applications in predicting material behavior and crack propagation. This research evaluates three machine learning models: linear regression, random forest regression, and Ada boost regression, comparing their performance in training and testing phases. Analysis of model parameters, including tree depth, number of trees, and leaf nodes, reveals significant correlations with prediction accuracy and model stability. The results demonstrate that ABR achieved superior performance during training, followed by RFR ($R^2 = 0.98006$) and LR ($R^2 = 0.96297$).

However, experimental data showed mixed results, with LR demonstrating better generalization capabilities ($R^2 = 0.45561$) compared to RFR ($R^2 = 0.15210$) and ABR ($R^2 = 0.02597$). This study highlights the importance of balancing model complexity with computational efficiency and addresses challenges such as data scarcity and knowledge transfer in various fracture mechanics problems. Although machine learning techniques show promising potential in fracture mechanics analysis, especially in atomic-level structural dynamics and crack propagation prediction, the findings suggest that further refinement is needed to improve model generalization and reliability. The research emphasizes the need for standardized validation methods and the power of hybrid approaches that combine physical understanding with data-driven insights. These advances contribute to the continued development of more sophisticated solutions in materials science, especially in applications such as additive manufacturing, structural health monitoring, and risk assessment.

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Introduction

Engineers prefer analytical solutions because of their simplicity and reliability, which makes them more convenient for Applications such as material properties, structural analysis, and design. However, such solutions are not always achievable. A practical alternative is an empirical approach that uses the expertise of engineers and generalizations of experimental and numerical data. For example, ASTM Standard C1421 provides empirical methods for estimating the site-strain stress intensity factor at a crack tip when evaluating the fracture toughness of advanced ceramics. Both analytical and empirical solutions are evaluated for their effectiveness and reliability. Accurate fracture toughness analysis relies this requires a solution that determines the site-strain stress intensity factor at the crack tip under a specific load, based on linear elastic fracture mechanics selection of an appropriate micro cantilever geometry is constrained by practical factors, including the limitations The necessity of precisely controlled fracture occurrence during FIB tooling and loading. However, the commonly used geometries do not allow for highly accurate analytical or empirical solutions across the full range of applicable model dimensions.

The achievable accuracy depends on both the accuracy and quantity of data necessitates the need create a well-balanced dataset that includes both input and target data, and their definition, play a key role in shaping the machine learning process. In this study, Fracture toughness measurements are expected to be fully compliant with the principles of linear elastic fracture mechanics, which treats the calculation of the

plane-strain stress intensity factor as a boundary value problem in linear elasticity [1]. Fracture propagation is the primary cause of failure in brittle materials, a phenomenon that has been extensively studied for over a century due to its industrial importance and scientific interest.

In these materials, atomically sharp cracks propagate through Bond failure. The failure of brittle materials, in contrast to ductile failure abruptly, often at grain boundaries, while in geosynthetic materials, fractures propagate along interstitial spaces. Once initiated, fractures propagate rapidly, governed by locally stored elastic energy. Multiple approaches, including analytical and numerical methods, have been used to analyze material failure at different length scales. Modeling Computational analysis of micro- and mesa-scale fracture mechanics intensive, making direct application to larger components or systems that are important for a variety of applications impractical. However, at the continuous level, fracture networks represent complexities, such as varying Fracture directions and sizes show an important feature. computational challenge, often resulting in the loss of important sub-scale information as the length scales change [2].

A deep learning approach has recently been introduced Predicting fracture patterns in crystal structures Lenard-Jones materials. The method uses Datasets derived from physics-based molecular dynamics simulations and a ConvLSTM-based model to capture spatial-temporal relationships affecting fracture propagation. That has high the breakdown kinetics are driven by chemical complexity and covalent bond breakage. We will explore the calibration of parameters required for accurate fracture predictions, achieve results that agree well with molecular dynamics simulations, Further highlighting the power of the machine learning approach analyze increasingly complex and large-scale material systems [3]. Selective laser melting, a widely used laser powder bed fusion technique, offers high productivity and flexibility. Meanwhile, lightweight Titanium alloys are preferred for weight and stiffness-sensitive structures due to their exceptional strength-to-weight ratio and corrosion resistance. Studies have shown that Ti-6Al-4V components manufactured using selective laser melting exhibit quasi-constant service strength, meeting material-specific design criteria.

However, manufacturing defects introduced during SLM often result in poor fatigue performance of net-shaped components. Therefore, a comprehensive Understanding the impact of defects on the fatigue life of SLM-processed components is of great importance for both academic research and industrial applications. In additive manufacturing, common defects primarily include porosity and lack of fusion defects. Gas pores are typically formed due to gas entrapment or LOF issues caused by unstable keyhole and Insufficient energy input. LOF defects are usually large and irregularly shaped than randomly dispersed gas pores. Both porosity and LOF defects negatively affect fatigue performance by acting as stress concentrations that facilitate Crack formation. Despite minimal porosity (about 0.01%), fatigue failure in SLM-processed Ti-6Al-4V samples mainly originates from surface or near-surface defects [4]. Additive manufacturing (AM), a relatively new technology, uses computer-aided modelling to build structures and components layer by layer, providing a cost-effective and efficient way to produce complex parts. Unlike traditional manufacturing, AM eliminates machining and assembly processes, significantly reducing production time.

Due to these advantages, AM has become the main approach for designing and manufacturing Space, energy and advanced components automotive industries. However, in real-world applications, additive manufacturing components experience frequent cycling loads, making fatigue failure a common concern. To ensure their reliability, it is essential to study fatigue damage mechanisms and develop life prediction models. Titanium alloys are extensively used in mechanical and aerospace engineering for their high strength, low density, and exceptional corrosion resistance, making them increasingly popular for manufacturing with Additive manufacturing technology. Literature reviews suggest that the fatigue behaviour of AM titanium alloys is greatly influenced by imperfections, post-processing conditions, and AM process parameters [5].

The successful integration of machine learning into various physical science research areas is largely due to its high performance and scalability. Previous studies, particularly those focused on fracture problems, have used Machine learning models including random forests and convolutional networks for prediction fracture paths using data from continuous states. However, there is currently no machine learning approach capable of predicting fracture mechanics while capturing microscopic bond-breaking processes from an atomistic perspective, as is seen in All-atom molecular simulations, including molecular dynamics. High computational cost of traditional molecular dynamics (MD) simulations makes fracture mechanics predictions challenging, limiting their applicability for Nan scale materials design.

This study aims to address this issue by introducing a machine learning approach capable of enabling Atomic-scale structural design for advanced materials. To achieve this, we use a specialized neural network It combines a continuous neural network with long short-term memory to learn Also predict the fracture behavior of brittle materials [6]. Data-driven methods such as Machine learning has established a new paradigm in scientific research. Although long established in the field of fracture mechanics, there is limited understanding of two important aspects of data-driven approaches: knowledge extraction and transfer this context, knowledge generally refers to qualitative and quantitative insights into physical phenomena and the relationships in various physical problems. In particular, knowledge extraction and transfer played a key role in the historical development of fracture mechanics. Example, the experimental discovery of size-dependent fracture strength was an early milestone.

A century ago, Griffith developed a quantitative breakdown theory based on thermodynamic principles, which laid the foundation relationship between Relationship between fracture

strength and defect size in brittle materials. Data scarcity presents a significant challenge, as it can lead to knowledge bias due to the inability to reliably estimate accuracy without sufficient data. However, even with limited data, it is essential to integrate rigorous accuracy assessment into the knowledge extraction process. Furthermore, research on Knowledge transfer in data-driven fracture mechanics is lacking. Implementing Machine learning-based knowledge transfer on various fracture mechanics problems remains an open question [7]. Ideally, predicting damage progression in real-world applications would involve directly simulating cracks.

However, finite and discrete element simulations are computationally intensive, often requiring thousands of processor hours to capture macro-scale crack network evolution. This high computational cost arises from the need for very detailed nets to accurately capture crack formation networks individually. Recent advances in computational power and data availability revitalized Machine learning applications. ML methods have been successfully used for classification, regression, bridge metrics, and dimensionality reduction. ML has demonstrated superior performance compared to humans in many tasks, such as gaming, autonomous driving, and pattern recognition. In materials science, ML has recently made significant progress in bridge metrics, especially in fracture mechanics [8]. Composite materials and acoustic emission have long been a part of engineering research. Experimental studies of composite materials using acoustic emission can generate extensive datasets, which poses challenges in data interpretation.

The materials examined in this study are particularly noteworthy because they include both metals and alloys, leading to a wide range of potential damage mechanisms. Acoustic emission has been used to study material behavior since ancient times. A well-known example is the plastic deformation of tin, which produces sounds audible to the naked ear. The first systematic attempts to document these emissions appeared in the twentieth century, with the observation of audible signals in Metals such as tin, zinc, and cast iron. These findings contributed to the development of acoustic emission it was developed by J. Kaiser in the 1950s as a practical approach to assessing concrete damage. Acoustic emission is based on the pressure waves generated by the release of energy when crack surfaces are separated. These elastic waves are detected by sensors attached to the material under investigation, usually using the piezoelectric effect [9]. Exploring structure-property relationships is a fundamental scientific approach with great potential for discovering new materials. However, the vast diversity and complexity of materials make it challenging to fully understand and control these relationships. Data-driven methods for discovering advanced materials use emerging technologies such as big data, artificial intelligence, data mining, and machine learning, which significantly accelerate materials research and development.

Unlike traditional methods that rely on complex theoretical models, extensive simulations, or experiments, data-driven approaches use large datasets to uncover previously unknown relationships. Notably, this approach enables rapid Defining and optimizing design space, allowing for rapid material modifications as needed [10]. The section “Importance of Specialized Engineering and Tools” explores Importance of damage sensing features and related analytical tools. Analyzing Understanding crack initiation and propagation is essential for predicting future performance, identifying potential failure modes, and assessing structural integrity. The analysis of crack propagation is a key aspect of fracture mechanics, a field dedicated to understanding crack propagation in materials. Research in fracture mechanics, which involves empirical and analytical solutions, is a time-consuming process, requires advanced technical expertise, and is also very complex. Diagnosing defects and malfunctions in mechanical systems, components, and devices machines presents significant challenges. These solutions offer a promising alternative to Empirical and analytical methods, while providing accurate and efficient results. ML techniques have been Fracture mechanics is used in various subfields to improve engineering applications [11].

In contemporary mechanical engineering, the pursuit of materials with optimal properties and adaptive functions is of paramount importance. The micro structural arrangement of materials Important in defining the macroscopic properties of composite materials. Composites, which typically consist of two or more distinct materials, exhibit widely different large-scale properties depending on the configuration of their constituent materials. Laminated composites, formed by combining various fibres and matrices, significantly affect the material behavior under different loading conditions. Conventional additive manufacturing methods are time-consuming and limited by the complexity of the adhesive layers, which require placing adhesive between previously fabricated components and manually joining them. However, Additive manufacturing, especially 3D printing, has become a very promising technology that enables the creation of composites with a variety of materials and properties in 3D space.

This advancement overcomes the challenges associated with additive manufacturing and allows for a wide range of material combinations [12]. Conventional methods for predicting fatigue crack growth typically rely on mathematical models, such as the Paris-Endogen model, which relates the stress intensity factor limit to the crack growth rate. While these fracture mechanics principles have been valuable in guiding material selection and structural decisions, data-driven machine learning approaches have been developed as alternatives. Some of these ML methods directly predict crack growth, while others estimate key parameters associated with traditional fracture mechanics models used for crack growth rate prediction. Throughout history, humans have modified their environment to create essential tools and objects. The continuous evolution of structural materials is a prime example. The primary function of any structural material is to effectively support loads. From simple huts built from natural materials to modern skyscrapers constructed from engineered materials such as steel, concrete, and glass, advances in construction materials have shaped the

homes and structures we live in today [13]. The unique Zirconium alloys exhibit desirable physical properties such as low neutron absorption cross section, exceptional mechanical strength, and high corrosion resistance, make them well-suited for nuclear reactor applications. They are commonly used in components such Used in applications such as fuel cladding, pressure pipes, fuel channels, and fuel components gaps. Zirconium exhibits a number of complex properties, including competing sliding Displacement motion, multiple cleavage sites, and mechanisms for divergent twinning patterns, Also a high-temperature phase transition from hexagonal close-packed to body-cantered cubic.

While experimental studies provide valuable insights into actual material behavior, probing the underlying atomic-scale mechanisms remains a challenge. Computational studies serve as a powerful tool to gain a deeper understanding of these atomic processes. First-principles approaches such as density functional theory provide more accurate energy calculations. However, their use is limited by high computational costs, which limit the size and complexity of the structures that can exist analyzed [14]. These studies use continuous state Fracture prediction data using machine learning. How does a fragility fracture occur due to bond breakage at the atomic level, a machine learning approach capable of predicting fracture mechanics based on microscopic bond breakage data would be very useful for Nan scale material design? Hsu et al. used Molecular dynamics data were used to develop a convolutional long-short-term memory model to predict brittle fracture in a basic Lenard-Jones material. Their research was analyzed crack growth in bimetallic materials by examining different crystal orientations. Recently, Lee Many people developed a deep learning model to investigate fracture mechanisms grapheme, which helps predict its fracture behavior based on crystal orientation. This study aims to improve improving existing approaches by building a machine learning model approach to predict crack propagation in realistic polycrystalline grapheme sheets. Raised -fidelity molecular dynamics simulations provide the dataset for Training and evaluating the model.

A convolutional network is used to capture this microstructure of fractured polycrystalline grapheme, while a bidirectional continuous neural network is used to predict crack propagation [15]. Increasing life expectancy has led to an increase in age-related frailty. Among the medical conditions affecting developed countries, bone-related problems rank behind cardiovascular and neurological diseases, yet they often receive less attention. One of the most significant concerns Hip fractures caused by osteoporosis, a bone disease characterized by loss of bone mass, are common among people over the age of 65. Data -driven approaches offer an alternative by training machine learning (ML) models using Finite element methods or simulation data derived directly from medical data. Machine learning algorithms can automatically capture complex nonlinear relationships between multiple inputs. (e.g., medical and biomechanical data) and multiple outputs. This capability allows finite element methods (FEM) to generate data offline, which can then be used by ML models to Relate inputs such as mechanical properties, geometric mesh, and boundary conditions to outputs such as nodal displacements, stresses, and strains result, ML models can serve as efficient real-time predictors of fracture risk [16]. To model the development of small fatigue cracks, especially those within grains, it is essential to understand Influence of underlying microstructure on cracking behavior. When cracking initiates is considered random and deterministic, predicting small fatigue crack behavior remains an open question. These cracks can propagate along crystallographic directions and specific sites, leading to the process of slip. The behavior of long cracks is well characterized by linear elastic fracture mechanics through the Paris law. However, for small cracks, the propagation rate varies significantly. This behavior, showing considerable variability due to complex interactions with surrounding microstructure.

The development Synchrotron-based X-ray tomography and diffraction methods, combined with in situ loading, has made it possible to obtain essential data on Crack orientation and propagation rate in relation to microstructure. This study uses experimental data on the evolution of fatigue cracks under in situ loading to develop a model explaining the driving force behind small fatigue crack growth [17]. Karpiuk-Prisakari et al. reported that model comparisons depend on the influence of boundary conditions on the resulting crack shape and numerical simulations are aligned with those in previous studies. In addition, their research highlights the important role of boundary conditions in calibrating joint fracture-mechanics models for concrete. Therefore, The main goal of the authors' study design an experiment using a double-end notch concrete model to generate accurate and comprehensive boundary conditions for numerical simulations. Another study used digital image processing reflected light elasticity to determine and evaluate corrosion crack nucleation.

This method provided a quantitative assessment of crack formation due to corrosion, analyzing the distribution of expansion stress at the initial and partial cracking stages. In addition, stress intensity factors also incremental strains was investigated based the optical linear elastic fracture mechanics is based on changes in corrosion exposure time scales [18]. In glasses and amorphous materials, brittle-ductile transitions can be induced by modifying their nanostructure through compositional changes, thermal treatments, and densification. In crystalline materials, fracture behavior is determined by the interplay between dislocation mobility and bond rupture, with plasticity typically originating in defects. However, the mechanisms behind ductility in amorphous materials are unclear, as these materials lack long-range order and do not contain well-defined defects. Although the atomic positions in a stable glassy system are fully known, identifying the soft regions that undergo structural rearrangement remains a significant challenge. Various models have been developed to characterize plastic behaviourglasses, such as elastoplastic theory, soft glass rheology, and shear transformation zone models. In metallic glasses, ductility is associated with localized structural rearrangements called shear transformation zones. In contrast, the brittleness of oxide glasses is due to the absence of such

plastic deformation regions. Although these theories imply the presence of defects within the glass structure, they remain phenomenological and do not provide a precise definition, making it difficult to identify these defects from first principles [19].

MATERIAL AND METHODS

Material

Number of trees: Trees play a vital role in maintaining ecological balance. They it produces oxygen, absorbs carbon dioxide, and serves as a habitat for wildlife. As deforestation continues to increase, planting more trees is essential in the fight against climate change. A hundred trees can greatly improve air quality, prevent soil erosion, and promote biodiversity. They help reduce temperatures and conserve water resources. In cities, trees provide shade, reduce noise pollution, and increase mental well-being. In addition, they support livelihoods by providing fruit, wood, and medicinal materials. Expanding the area of trees is crucial for sustainability, ensuring a healthy environment for future generations. In mathematics and related fields, a number tree is a visual representation of the prime factors of a number, arranged in a pyramid-like structure within a tree-like structure. Commonly called factor trees, they systematically decompose a number into its prime components.

Tree depth: In a hierarchical tree structure, tree Depth is defined as the longest path from the root tip to the leaf tip. It is an important concept in computer science, especially in data structures such as binary trees, decision trees, and search algorithms. Tree depth affects search efficiency, memory consumption, and computational complexity. A deep tree can hinder operations such as searching, insertion, and deletion, while a balanced tree improves performance. In mathematics, tree depth is used in graph theory to explore hierarchical relationships and refine problem-solving strategies. It also plays an important role in algorithm design, affecting recursion depth and execution time. In ecology, tree depth refers to the reach of a tree's root system or canopy. Deep roots improve stability, facilitate water absorption, and enhance nutrient uptake, strengthening the tree's adaptive capacity to environmental changes. Similarly, a dense and extensive canopy provides more shade, promotes biodiversity, and contributes to carbon sequestration. The concept of tree depth is valuable in a variety of fields, from improving data structures in computers to assessing ecological sustainability. Effective management and analysis of tree depth improves efficiency, sustainability, and functionality in a variety of applications, making it a critical component in both natural ecosystems and artificial systems.

Averages Number of tree leaf nodes: Average number tree and leaf nodes It is a key concept in various fields, including computer science, ecology, and mathematics. In data structures, especially in tree-based models such as binary trees and decision trees, the number of leaf nodes significantly affects performance and efficiency. A well-balanced tree maintains an optimal number of leaf nodes, which facilitates efficient search, insertion, and deletion operations. Conversely, an excessively deep and unbalanced tree will slow down calculations and increase complexity. In ecology, the average number of trees in an area affects biodiversity, carbon storage, and climate regulation. Leaf nodes, or leaves, are essential for photosynthesis, oxygen production, and providing shelter for wildlife. A dense population of trees with abundant leaves supports a thriving ecosystem by improving air quality and supporting diverse species.

Minimum number of sample at a leaf Node: Minimum number of samples required at a leaf nodes an important parameter in decision trees and tree-based machine learning models. A high minimum sample value helps prevent over fitting by reducing the model's sensitivity to noise, leading to better generalization. However, setting it too high can limit model flexibility and may cause important data patterns to be overlooked. On the other hand, a low minimum sample size allows for subtler splits, capturing intricate details, but increases the risk of over fitting. Striking a balance between complexity and generalization is essential to improving model performance. The best minimum sample value depends on factors such as dataset size, feature distribution, and required level of detail. Properly tuning this parameter improves prediction accuracy, ensures consistency, and improves decision making in Classification, regression, and many other machine learning applications risk assessment.

Maximum Annual premium equivalent: Maximum Annual Premium Equivalent (APE) is an important metric in the insurance industry, used to estimate gross premium income on an annual basis. It is determined by summing the full value of regular premiums and a percentage of single premiums, typically 10%. This metric allows insurers to measure business performance, compare premium contributions across different policy types, and assess revenue sustainability. A higher APE indicates stronger policy sales and increased recurring revenue, which are essential for long-term profitability. However, placing too much emphasis on increasing APE can increase risk exposure if policyholder retention rates are low. Maintaining a balance between premium growth and policyholder retention is critical to financial sustainability. To maintain a healthy portfolio, insurers analyse APE along with other key indicators such as the sustainability ratio and claims ratio. Effective management of maximum APE supports better financial planning, improves risk management, and enhances overall business strategy.

Instructions for machine learning

Linear Regression: Linear regression is a basic statistical method used to examine the relationship between a dependent variable and one or more independent variables. In its most basic form, simple linear regression considers one independent variable and models their relationship using a linear equation.

$$Y = mx + c$$

In this equation, □ represents the dependent variable, □ represents the independent variable, □ represents the slope, and □ is the intercept. This method uses the least squares technique

to reduce the gap between the actual and predicted values. It is useful for trend forecasting, data-driven decision making, and analyzing variable relationships. Linear regression is widely used for forecasting and risk assessment in fields such as economics, finance, healthcare, and engineering. Its key assumptions include linearity, independence, constant variance (homogeneity), and normality of residuals. Deviations from these assumptions can lead to incorrect predictions. Despite its simplicity, linear regression continues to be an essential tool for data analysis and serves as the basis for many advanced machine learning models.

Random Forest Regression: Random Forest Regression is an ensemble learning method that builds multiple decision trees and combines their predictions to improve accuracy and reduce over fitting. expands on decision tree regression by training multiple trees on distinct data subsets, with the final prediction obtained by averaging the individual tree outputs. This approach improves model stability and generalization by reducing variance and reducing the over fitting problem commonly found in single decision trees. It is useful for both linear and nonlinear relationships, making it a flexible a tool with applications in fields such as finance, healthcare, engineering. Random Forest Regression also produces feature importance scores, which allow us to identify key variables within a dataset. It is highly resilient to noise and handles missing values efficiently. However, it is more computationally demanding than simpler models and may lack the interpretability of traditional regression methods. Despite these limitations, Random Forest Regression remains a widely accepted and powerful tool for predictive modeling, providing an optimal balance between accuracy and adaptability.

Adaboost Regression: Ada boost Regression is an ensemble learning technique that improves prediction It improves accuracy by combining multiple weak learners, typically decision trees, into a single, robust model.. Unlike conventional regression techniques, Ada Boost increases the weight of mispredicted events, ensuring that subsequent models focus more on challenging events. The algorithm works iteratively, repeatedly training the weak models and modifying their influence based on the errors of previous iterations. The final prediction is obtained by combining the weighted outputs of all the weak models. This strategy improves model performance while reducing bias and variance. Due to its ability to handle complex relationships and improve prediction accuracy, Ada Boost regression is widely used in fields such as finance, healthcare, and engineering. However, it is susceptible to noisy data and outliers, as they can be over-weighted, which increases the risk of over fitting. In addition, careful parameter tuning is often required to achieve optimal performance. Despite these limitations, Ada Boost regression remains a very useful technique for transforming weak models into robust prediction structures, making it valuable for many real-world applications.

RESULT AND DISCUSSION

TABLE 1. Machine Learning in Fracture Mechanics

Number of trees	Tree depth	Averages Number of trees leaf nodes	Minimum number of sample at a leaf node	Maximum Annual premium equivalent
1	4	16	8580	29.706
1	5	32	3240	23.828
1	7	64	1296	19.982
1	6	128	240	17.44
1	8	256	88	17.146
256	4	16	430	20.348
256	5	32	106	17.019
256	6	64	51	14.327
256	7	128	50	11.483
256	8	255	50	9.724
512	4	16	93	7.873
512	5	32	50	6.018
512	6	64	50	4.122
512	7	127	50	3.334
512	8	251	50	2.171

Table 1 presents and analysis Application of machine learning in fracture mechanics demonstrates its influence decision tree parameters on prediction performance. The number of trees, tree depth, and number of leaf nodes significantly affect the minimum sample size and maximum annual premium equivalent per leaf node. As tree depth increases, the number of leaf nodes increases, leading to a decrease in both the minimum number of samples per node and the annual premium equivalent. For a tree, increasing the depth from 4 to 8 reduces the maximum annual premium equivalent from 29.706 to 17.146. Similarly, with 256 trees, deeper trees result in lower premiums, decreasing from 20.348 at depth 4 to 9.724 at depth 8. This trend continues with 512 trees, where the premium decreases from 7.873 at depth 4 to 2.171 at depth 8. Notably, models with higher tree counts show greater stability, which is consistently reflected in lower premium equivalents. These insights underscore the effectiveness of machine learning techniques in fracture mechanics, improving prediction accuracy through parameter tuning.

TABLE 2. Descriptive Statistics

	Number of trees	Tree depth	Averages Number of trees leaf nodes	Minimum number of sample at a leaf node	Maximum Annual premium equivalent
count	15	15	15	15	15
mean	256.3333	6	98.73333	961.6	13.63473
std	215.9371	1.46385	89.58752	2271.111	8.130349
min	1	4	16	50	2.171
25%	1	5	32	50	6.9455
50%	256	6	64	88	14.327
75%	512	7	128	335	18.711
max	512	8	256	8580	29.706

The descriptive statistics in Table 2 summarize the main characteristics of the dataset, highlighting the trends of tree-based machine learning models used in fracture mechanics. The mean values indicate that, on average, the models have 256 trees, a tree depth of 6, and 98.73 leaf nodes. The minimum and maximum values show considerable variation, with the number of trees varies from 1 to 512, and the tree depth ranges from 4 to 8. Distribution of the maximum annual premium equivalent is similarly broad, with a mean of 13.63 but a range of 2.171 to 29.706. The standard deviation values indicate significant spread, especially in the number of leaf nodes (STD = 89.59) and the minimum number of samples per leaf node (STD = 2271.11), indicating a high degree of variation in model complexity. Quarterly values further reveal that half of the models have tree depths between 5 and 7, with a median of 6, while the median premium equivalent is 14.327. These insights explain the varying structural configurations of machine learning models in fracture mechanics and their impact on predictive consistency. The data suggests that increasing tree depth and number improves model granularity, contributing to improved predictive performance.

Effect of Process Parameters

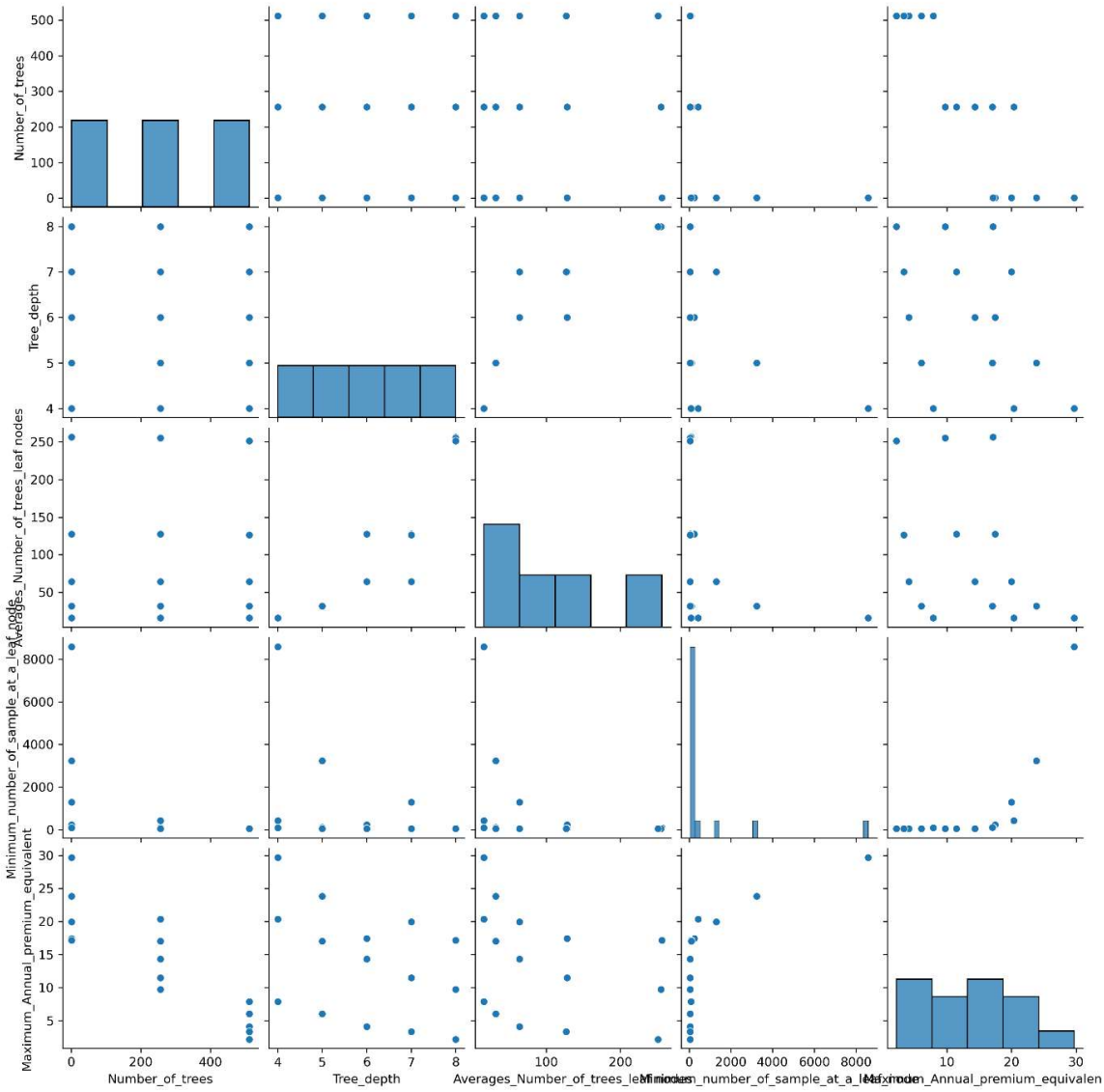


Figure 1. Scatter plot depicting different Machine Learning in Fracture Mechanics

Figure 1 presents a scatter diagram matrix that shows the relationships between key machine learning parameters in fracture mechanics. The plot visualizes the relationships Explain the relationship between the number of trees, tree depth, and the average number of leaf nodes, minimum sample size, and maximum annual premium equivalents. The patterns suggest that increasing tree depth and number generally reduces premium equivalents, improving model performance. The scatter of points indicates the variation in model performance, with dense clusters indicating optimal parameter combinations. The histograms on the diagonal provide distributional insights for each variable. This visualization helps to understand how different configurations affect prediction accuracy and consistency in fracture mechanics applications.

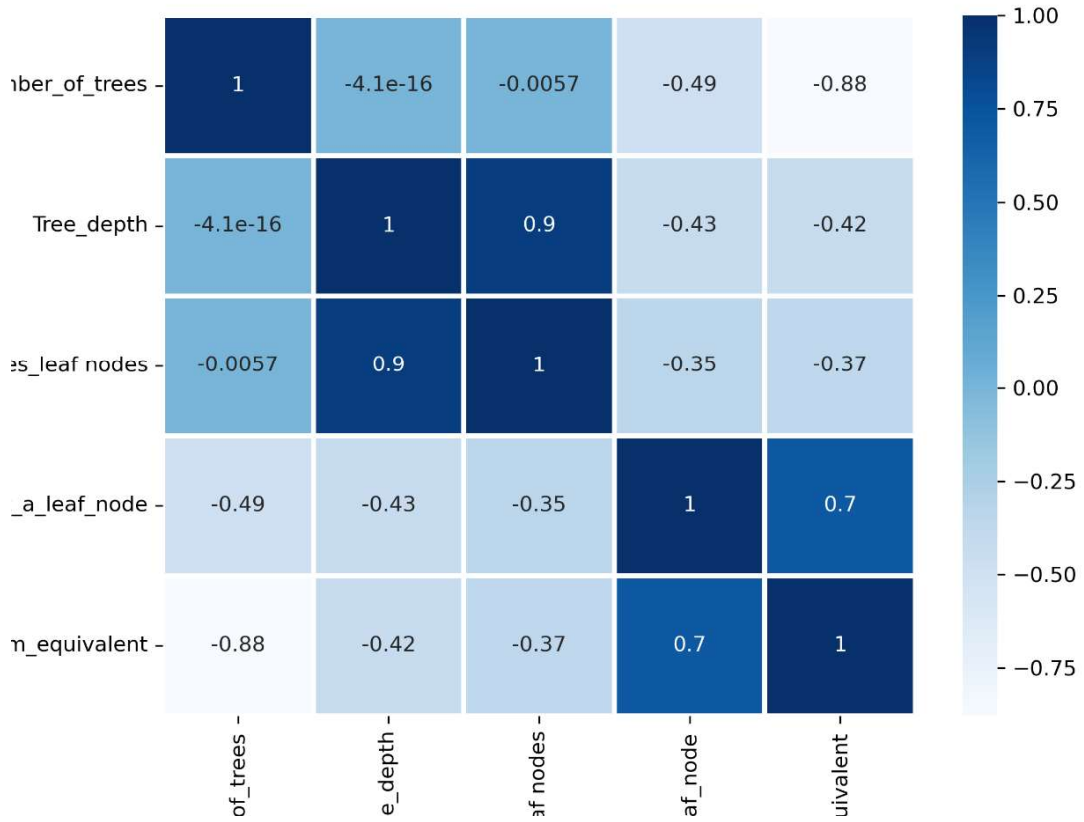
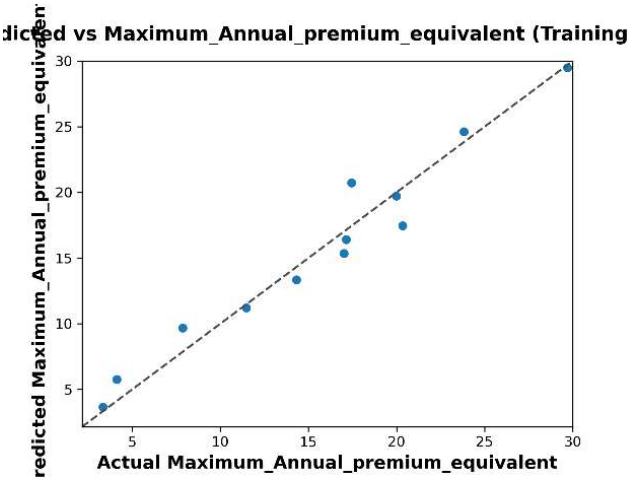
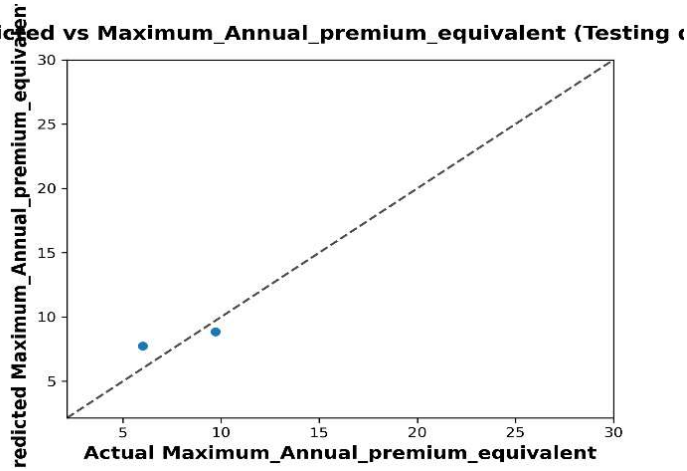


FIGURE 2. Correlation heat map between the process parameters and the responses

Figure 2 presents a correlation heat map illustrating the relationships between process parameters and response variables in machine learning, as in machine learning for fracture mechanics. Darker shades indicate stronger interactions, while lighter shades indicate weaker interactions number of trees shows a strong negative correlation with the maximum annual premium equivalent (-0.88), indicating that increasing the number of trees reduces premium costs. Tree depth and number leaf nodes show a strong positive correlation (0.9), indicating that deeper trees result in more leaf nodes. Minimum number of samples required for a leaf node moderately correlated with premium equivalent (0.7). These insights help to optimize model configurations for better predictive performance.

Linear Regression (LR)



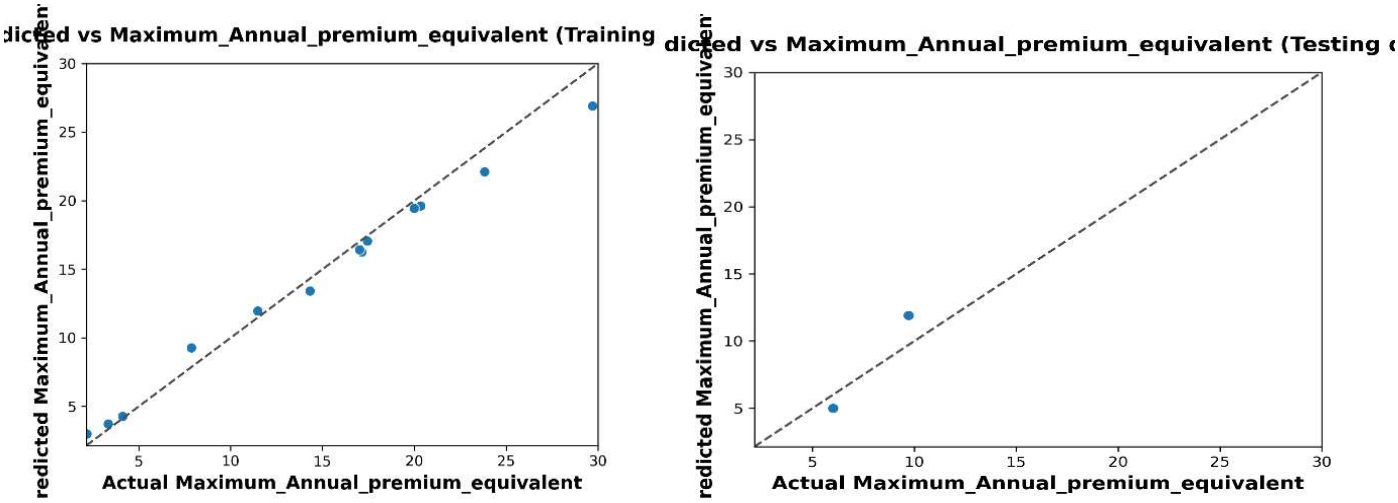


a) b)

FIGURE 3. Predictive accuracy of linear regression model in Machine Learning in Fracture Mechanics Training; (b) testing.

Figure 3 evaluates the predictive accuracy of a linear regression model in machine learning for fracture mechanics. Substructure (a) represents the training data, where the predicted values closely match the actual values. Diagonal, indicating a strong model fit. Substructure (b) shows the test data, where fewer points are plotted, indicating limited test samples. The model performs well in training, but shows some deviations in testing, indicating possible over fitting. The dashed diagonal line serves as a good reference, where correct predictions would be. These plots help to assess model generalization, guiding improvements in training strategies for improved predictive reliability in fracture mechanics applications.

Random forest regression

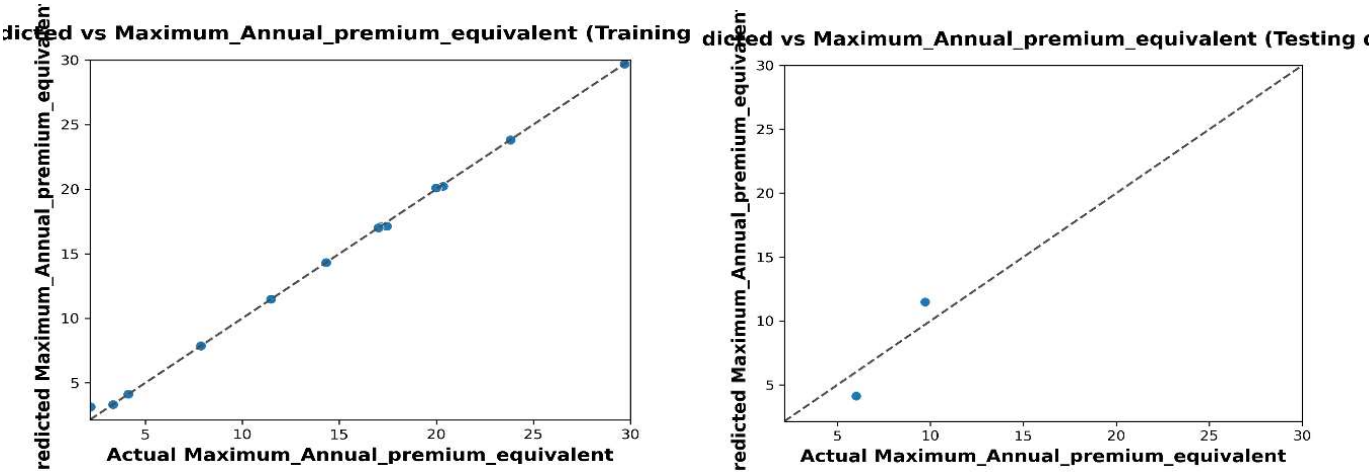


b)

Figure 4. Predictive accuracy of the random forest regression model in Machine Learning in Fracture Mechanics a) train b) test

Figure 4 illustrates the predictive accuracy Application of Random Forest Regression Model in Machine Learning fracture mechanics. Subset (a) shows the training results, where predicted values closely match actual values along the diagonal, indicating robust model performance. Subset (b) presents the testing phase, which exposes a limited number of data points with some deviation from the ideal diagonal, suggesting possible mismatches or limited test data. This model demonstrates high accuracy in training, but generalization may require further improvement. These graphs highlight Reliability and performance of the model predicting fracture mechanics outcomes, supporting its use in structural assessments.

Ada Boost Regression



b)

FIGURE 5. Predictive accuracy of Ada Boost Regression model in Machine Learning in Fracture Mechanics algorithm a) train b) test

Figure 5 demonstrates the predictive accuracy of the AdaBoost regression model in machine learning for fracture mechanics. Subset (a) illustrates the training phase, where the predicted values align almost perfectly with the true values on the diagonal, indicating an excellent model fit. Subset (b) presents the testing phase, showing fewer data points with small deviations from the best diagonal, suggesting possible over fitting or limited testing samples. This model exhibits high accuracy in training, but generalization may require further validation. These graphs provide insights into the performance of the AdaBoost model, highlighting its potential effectiveness in fracture mechanics prediction and structural analysis.

TABLE 3. Regression Model Performance Metrics (Training Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	LR	Linear Regression	0.96297	0.96297	2.39816	1.54860	1.21115	3.29437	0.02205	0.87593
Train	RFR	Random Forest Regression	0.98006	0.98255	1.29162	1.13650	0.90777	2.80387	0.00850	0.71550
Train	ABR	AdaBoost Regression	0.99873	0.99877	0.08216	0.28664	0.11776	0.97550	0.00556	0.00000

Table 3 provides regression model performance metrics for the training dataset, comparing linear regression (LR), Random Forest Regression and AdaBoost Regression. R^2 and explained variance score (EVS) indicate the models' ability to explain data variance, with ABR achieving the highest values (0.99873 and 0.99877 respectively. The mean square error and the root mean square error show that ABR has the lowest values(0.08216 and 0.28664), indicating minimal prediction errors. The maximum error (Maximum Error) is the lowest in ABR (0.97550), indicating high reliability. Meanwhile, the mean square logarithmic error (MSLE) is relatively low across all models, with ABR again performing better (0.00556). Overall, these metrics highlight ABR as the most accurate model, followed by RFR, while LR shows relatively higher errors. The results suggest that Ada Boost effectively reduces regression prediction biases, making it a strong choice for machine learning applications in fracture mechanics. These findings provide a clear comparison of model performances, guiding the selection of the most appropriate regression approach for structural analysis and predictive modeling.

TABLE 4. Regression Model Performance Metrics (Testing Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Test	LR	Linear Regression	0.45561	0.50957	1.86922	1.36719	1.29767	1.72811	0.02778	1.29767
Test	RFR	Random Forest Regression	0.15210	0.25220	2.91137	1.70628	1.60239	2.18868	0.02948	1.60239
Test	ABR	AdaBoost Regression	0.02597	0.02733	3.34445	1.82878	1.82750	1.89600	0.06113	1.82750

Table 4 compares linear regression, Random Forest Regression and AdaBoost Regression are used to perform regression. model performance metrics for testing the data. R^2 and explained variance score (EVS) indicate the predictive ability of the models, with LR achieving the highest R^2 (0.45561) and EVS (0.50957), indicating moderate generalization. In contrast, RFR and ABR show significantly lower R^2 values (0.15210 and 0.02597), indicating weak performance on unobserved data. The mean square error and root mean square error (RMSE) further confirm the relative superiority of LR, lowest values (1.86922 and 1.36719). Mean absolute error and mean absolute error (Med AE) reinforce this, as LR again shows lower errors (1.29767). The maximum error (Maximum Error) is the lowest in ABR (1.89600), but its higher

MSE and RMSE indicate an overall decline in prediction accuracy. The mean squared logarithmic error (MSLE) is low across models, but is the highest in ABR (0.06113), indicating potential scaling issues. Overall, the experimental results show that none of the models generalize exceptionally well, although LR performs relatively well. The reduced accuracy compared to the training results indicates over fitting in RFR and ABR, which requires further adjustment for better generalization.

CONCLUSION

The integration of machine learning approaches in fracture mechanics and materials science represents a significant advance in understanding and predicting material behavior. This review highlights several key advances and implications for future research and applications. Machine learning techniques have shown significant potential in addressing the computational challenges traditionally associated with fracture mechanics analysis. From predicting crack propagation patterns to estimating fatigue life, ML models provide efficient alternatives to conventional analytical and empirical methods.

The success of deep learning approaches, particularly in capturing atomic-level structural dynamics through specialized neural networks combining RNN and LSTM architectures, represents a significant breakthrough in this field. The application of ML in diverse domains, from additive manufacturing to bioengineering, illustrates its versatility and broad impact. In additive manufacturing, ML has proven particularly valuable in understanding the influence of manufacturing imperfections on fatigue performance, especially in materials such as Ti-6Al-4V. However, there are challenges in implementing ML approaches. Data scarcity continues to be a significant limitation, leading to knowledge bias. The need for rigorous accuracy assessment and effective knowledge transfer across various fracture mechanics problems is paramount. In addition, the balance between model complexity and computational efficiency needs to be carefully considered.In the future, the integration of ML with traditional fracture mechanics principles offers promising directions for future research. The development of hybrid approaches that combine physical understanding with data-driven insights will lead to more robust and reliable prediction methods.

The potential for real-time predictive capabilities, especially in applications such as structural health monitoring and risk assessment, offers exciting opportunities for practical implementation. As this field continues to evolve, emphasis should be placed on developing standardized methods for validating ML models in fracture mechanics applications. This includes establishing clear criteria for model selection, data quality assessment, and performance evaluation. Furthermore, integrating ML approaches with emerging technologies in materials characterization and testing may provide new avenues for generating high-quality training data.In conclusion, while machine learning has already demonstrated significant potential in transforming our approach to fracture mechanics analysis, its full impact has yet to be realized.

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