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Recent Advances of Machine Learning in Fracture Mechanics of Quasi-Brittle Materials: A Review

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ABSTRACT

The fracture mechanics of quasi-brittle materials, such as concrete, ceramics, and rocks, pose significant challenges due to their nonlinear stress-strain response, microstructural heterogeneity, and complex failure mechanisms. Traditional numerical and analytical methods often fall short in capturing the full intricacies of fracture propagation and damage evolution in such materials. However, recent advances in machine learning (ML) offer promising solutions to these limitations by enabling data-driven insights and enhanced computational performance. In this review paper, we explore the growing role of ML techniques in the fracture analysis of quasi-brittle materials. By leveraging large and diverse datasets from experiments and numerical simulations, ML models not only complement traditional fracture mechanics approaches but also introduce novel capabilities such as real-time damage prediction, adaptive modelling, and improved generalization across varying material conditions. The integration of data-driven models with physics-based frameworks, especially through hybrid techniques like physics-informed neural networks (PINNs), marks a significant shift in how fracture phenomena are modelled and understood. Key ML methods discussed include artificial neural networks (ANNs), convolutional neural networks (CNNs), and PINNs, with a focus on their respective advantages and implementation strategies. The review highlights how these approaches can enhance safety, efficiency, and predictive accuracy in engineering applications, ultimately making machine learning a transformative tool in the study of quasi-brittle fracture behaviour.

Keywords: Machine learning; fracture mechanics; quasi-brittle materials; crack characterization

INTRODUCTION

Quasi-brittle materials like concrete, ceramics, and composites exhibit complex fracture behavior, transitioning from microcracking to complete failure under critical load (Abuzaid et al. 2024; Lawrence et al. 2024). This makes them essential to study in fields where durability and reliability are key, such as civil and aerospace engineering

(Chin et al. 2024). Accurate prediction of crack propagation is vital for ensuring structural safety, longevity, and cost-effective maintenance.

Classical theoretical models, such as Linear Elastic Fracture Mechanics (LEFM) and Continuum Damage Mechanics (CDM), have served as foundational tools in understanding material failure by relating stresses, strains, and energy release rates (Piska et al. 2024). However, LEFM is based on assumptions of linear elasticity and sharp crack tips, making it inadequate for quasi-brittle materials that undergo distributed microcracking and nonlinear deformation (Da 2024). CDM improves upon this by introducing internal state variables to capture damage evolution, yet it often lacks resolution in highly localized fracture zones and fails to accurately model strain softening and crack path instability (Cheng et al. 2024).

To overcome these limits, nonlocal and gradient-enhanced damage models introduce spatial dependencies, capturing microstructural effects for more accurate fracture predictions (Fazlali et al. 2021; Moghtaderi et al. 2023a, 2023b, 2024a).

Nevertheless, these models are typically integrated into numerical methods, which bring their own limitations. Finite element and other numerical approaches, while versatile, struggle to simulate complex crack paths in heterogeneous materials, particularly under dynamic or large-deformation conditions (Qureshi et al. 2023). Additionally, they require fine mesh discretization and intensive preprocessing, leading to high computational cost and limited scalability for real-time or large-scale applications (Gamra et al. 2024).

Experimental investigations offer valuable data for validating theoretical and numerical models by capturing material behavior under various loading conditions (Bin Azuwa and Bin Mat Yahaya 2024). Tests like three-point bending and impact testing measure crack behavior and toughness (Shin et al. 2023), but they are costly, time-consuming, and often limited by sample variability and environmental factors. Real-time observation of crack growth remains challenging, affecting data accuracy and generalizability (Shin et al. 2022).

Recent developments in machine learning (ML) offer a new pathway to model these complexities efficiently, addressing limitations in traditional theoretical and numerical frameworks. ML approaches can handle high-dimensional, nonlinear, and heterogeneous data, making them ideal for studying the complex fracture behavior of quasi-brittle materials. By learning directly from experimental and simulation data, machine learning models can avoid some of the computational bottlenecks and assumptions inherent in traditional methodologies, opening up new avenues for structural engineering predictive modelling and decision-making.

With advances in computing, machine learning (ML) has become a powerful tool in fracture mechanics, especially for complex behaviors in quasi-brittle materials (Moghtaderi et al. 2024b). Conventional modeling frameworks often falter in capturing the full spectrum of nonlinear crack behavior (Feng et al. 2023), while ML models, including supervised techniques like CNNs and unsupervised ones like K-means clustering, can efficiently analyze large datasets to detect and characterize fracture patterns (Matarneh et al. 2024). Advanced models such as Bayesian neural networks (BNNs) and physics-informed neural networks (PINNs) integrate uncertainty and physical laws, enhancing model reliability (Olivier et al. 2021; Wu et al. 2024). ML also boosts efficiency by reducing simulation and testing needs, enabling real-time monitoring, early crack detection, and preventive maintenance, marking a shift toward proactive, data-driven fracture analysis (Azad et al. 2024).

In this review paper, we look at how machine learning is playing an increasingly important role in fracture mechanics, particularly in the context of quasi-brittle materials. We examine a variety of machine learning techniques, from foundational approaches such as artificial neural networks (ANN) and support vector machine (SVM) to more advanced BNN and PINN, to demonstrate how these tools are being used to address important challenges related to fracture characterization prediction. This review aims to provide insights into how data-driven approaches may enhance physics-based computational models, improve predictive accuracy, and increase the adaptability of fracture analysis, with a focus on the opportunity of ML to address the gaps left by common theoretical, numerical, and experimental methods.

MACHINE LEARNING TECHNIQUES IN FRACTURE MECHANICS

The trend analysis reveals a sharp rise in research on ML for fracture mechanics over the past decade, with a notable increase in publications and citations (Figure 1a), especially for quasi-brittle materials (Figure 1b). The growing interest highlights the potential of ML in addressing complex material failure challenges.

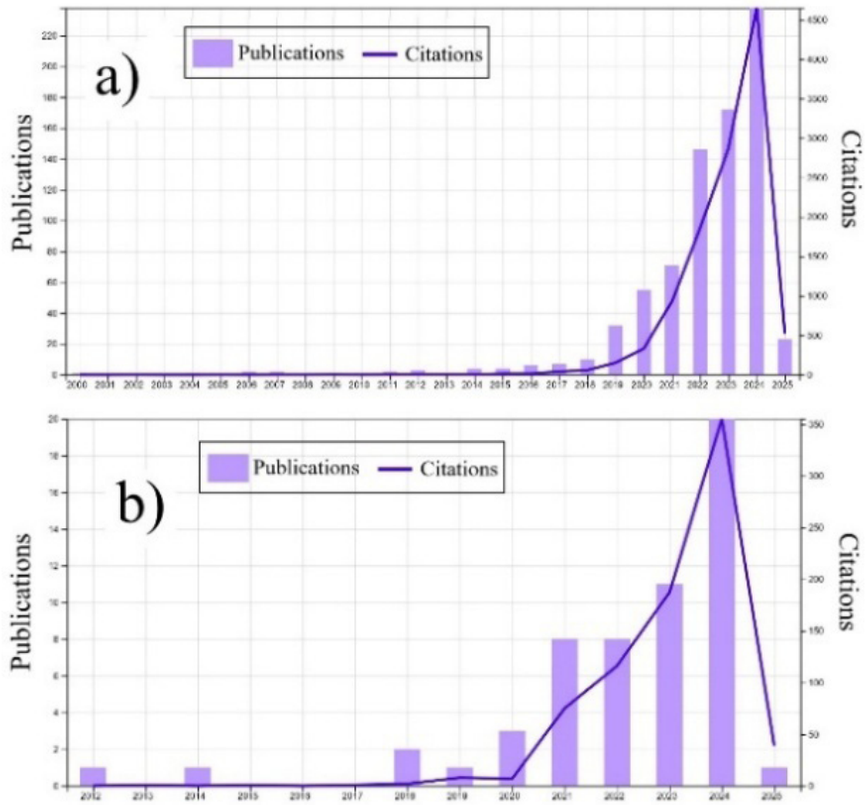

FIGURE 1. Trend analysis based on Web of Science (WoS) sources for publications and citations of a) ML in fracture mechanics. b) ML in fracture mechanics of quasi-brittle materials.

Implementing a ML model in fracture mechanics involves a systematic process, which is shown in flow chart given in Figure 2, starting with data acquisition. By utilizing extensive datasets from simulations and experiments, ML approaches may anticipate crack initiation, growth, and crack paths that are challenging to describe using standard theoretical or numerical models exclusively (Jin et al. 2023).

The next step is data preparation, which ensures input quality through techniques like image processing, data cleaning, normalization, and feature selection. Generative Adversarial Networks (GANs) can also augment limited datasets by generating realistic synthetic data, enhancing model performance and computational efficiency (Loh et al. 2024).

The choice of ML model depends on the data type and research goals (Mohtasham Moein et al. 2023). Neural networks are ideal for image-based pattern recognition, while clustering algorithms classify fracture features effectively (Qiu et al. 2024). After model selection, data is typically split 70–90% for training and 10–30% for testing to ensure generalization (Omar et al. 2022). Model performance is then evaluated using task-specific metrics, such as MSE, MAE, and R^2 for regression as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where y_i, $\hat{y}_i$, $\bar{y}$ and n are actual value, predicted value, mean of the actual values and number of samples, respectively. For classification tasks, where the goal is to assign labels, the accuracy is measured as the proportion of correctly classified instances out of the total instances.

Finally, the outcomes are examined and verified by comparing the findings of the model with criteria from simulations or experiments. This guarantees that the predictions made by the model are accurate and reasonable.

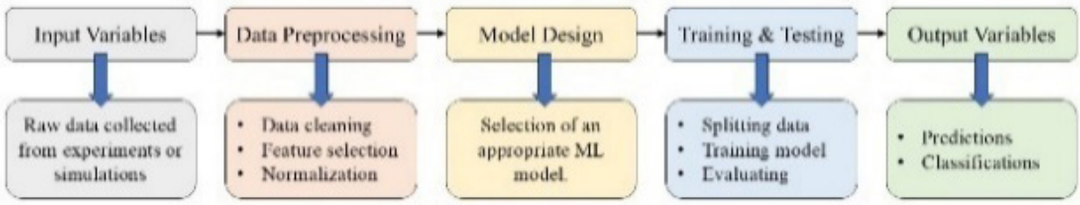

FIGURE 2. Flow chart of ML implementation.

Determining the best architecture and hyperparameters for a machine learning model is an important step towards accomplishing a balance of complexity and performance. An extremely complex model might overfit, meaning it performs well on training data but inappropriately on unidentified data, whereas a model that is overly simple may underfit, failing to capture underlying patterns. Hyperparameter tuning (Khokhar et al. 2021) is critical in this process since it involves deciding on the optimal arrangement of parameters that control the learning process, such as learning rate, regularization strength, and the number of layers and features.

Also, Bayesian optimization is a powerful hyperparameter tuning method that uses a probabilistic model, typically Gaussian Processes, to estimate performance. This methodology is appropriate for applications involving expensive calculations since it learns from previous evaluations to quickly identify optimal hyperparameters (Yuan et al. 2022).

However, significant obstacles persist. First, the quality and quantity of data have a direct impact on model adaptability. Many fracture mechanics problems, particularly in quasi-brittle materials, suffer from inadequate or imbalanced datasets, limiting model applicability. Second, while approaches such as GANs can improve data, they may introduce synthetic noise or implausible patterns if not properly evaluated. Third, interpretability remains a challenge, particularly for deep models like ANN or CNN.

ARTIFICIAL NEURAL NETWORK

ANN is a computer model inspired by the human brain, using artificial neurons to simulate natural neural networks. Learning in an ANN is an optimization process driven by learning algorithms. The network's architecture, consisting of interconnected neurons, determines how they interact. The main goal of an ANN is to process inputs and generate meaningful outputs (Amoosoltani et al. 2021). Figure 3 illustrates a feedforward and backpropagation network, where data moves through layers, and errors are corrected through backpropagation and gradient descent to improve performance.

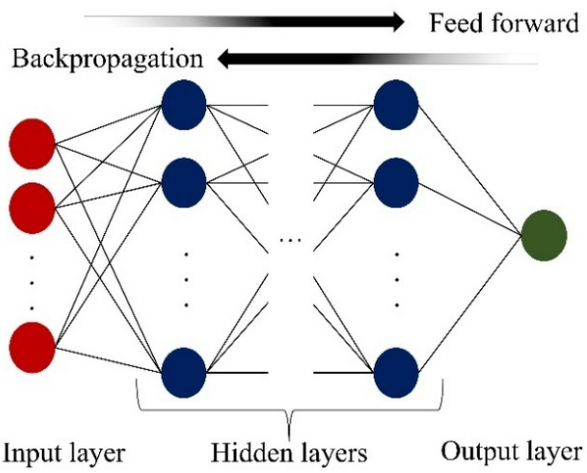

FIGURE 3. General Architecture of ANN model.

Weights in ANN scale input features before they are processed by the activation function (Baek and Chen 2024). The weighted sum of inputs is passed through the activation function, enabling the network to learn complex patterns (Liu et al. 2021). Common activation functions include Sigmoid (σ(x)), ReLU, and Tanh.

Figure 4 depicts the activation function and weights for each neuron, as well as how inputs and outputs are connected.

Typically, ANN is used to predict the fracture parameters and fracture behavior of quasi-brittle materials such as fracture toughness, fracture strength, fracture load, fracture energy, impact load, energy absorption at failure, and failure and damage estimation and crack width prediction.

$$\begin{aligned} \sigma(x) &= \frac{1}{1+e^{-x}} \\ ReLU(x) &= \max(0,x) \\ Tanh(x) &= \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \end{aligned} \tag{2}$$

Table 1 summarizes recent ANN applications in fracture analysis of quasi-brittle materials. It highlights key aspects like materials analyzed, data preparation methods (e.g., experimental tests, simulations), data splitting ratios, input variables (e.g., geometry, material properties), and output goals (prediction or classification). Hyperparameter tuning determines the number of hidden layers, neurons, and activation functions. Performance metrics such as R^2, MAE, and MSE demonstrate model accuracy and reliability, emphasizing ANN's versatility in fracture analysis across different materials and conditions.

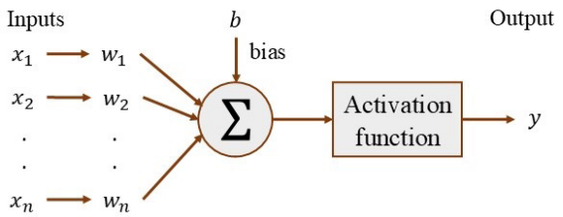

FIGURE 4. Performance of activation function for each neuron in ANN model.

It is clear from the table that experimental and simulation-based data are frequently employed, and each has special benefits. The size of simulated datasets is typically substantially bigger, offering dense, high-resolution data that is appropriate for deep model training. Experimental datasets are smaller because of practical testing limitations, but they are very valuable in helping to root the models in physical realism. Using both sources in a hybrid manner could increase generalizability. Most research use training/testing splits (e.g., 70/30 or 80/20), although the smallest datasets offer issues for model robustness, potentially resulting in overfitting. The input features differ based on the desired property, and include geometrical parameters, material qualities, and loading circumstances. Deeper networks are commonly utilized in models with complicated input spaces or large datasets, whereas shallower models are used when the dataset is small. The choice of activation function is also important: sigmoid is common in early models and for output layers predicting bounded values, whereas ReLU is dominant in hidden layers of more recent and deeper networks due to its efficiency and ability to avoid vanishing gradients. The targeted outputs reflect a wide range of fracture-related applications, from predicting fracture toughness and energy to calculating crack width and failure probability. Most models have high R^2 values. However, such measurements should be evaluated with caution, particularly for smaller datasets where model performance may not be generalizable. Models trained on large amounts of simulation data typically perform well in terms of classification and regression accuracy.

CONVOLUTIONAL NEURAL NETWORK

CNN, a subset of ANN, processes structured grid data like images by utilizing spatial relationships and patterns. Originally designed for computer vision, CNN's ability to learn and extract features directly from data has made it effective in various fields, including fracture mechanics, where it's commonly used for crack detection and identification (Ahila Priyadharshini et al. 2023; Golding et al. 2022; Han et al. 2022; Le et al. 2021; Andy Nguyen et al. 2023; Orinaitė et al. 2023; Sales da Cunha et al. 2023; Tie and Wu 2024; Zhao et al. 2024; Zheng et al. 2020; Zhou et al. 2022). It is also applied for predicting crack patterns (Chang et al. 2022), crack paths (He et al. 2024), and propagation (Yan et al. 2024), as well as damage analysis using fracture data and images (Jin et al. 2022; Li et al. 2023; Mohammadzadeh and Lejeune 2022; Schneider et al. 2021; Wang et al. 2021; Xu et al. 2022).

A typical CNN architecture includes three main layers: the convolutional layer, which extracts features from data using kernels; the pooling layer, which reduces spatial dimensions while preserving key information for computational efficiency; and the fully connected layer, which combines extracted features for classification or regression. Filters in the convolutional layer identify specific features such as edges or textures (Leiyu Chen et al. 2021), and after pooling and convolution layers, the feature maps are flattened into a one-dimensional vector for final processing in fully connected layers. Figure 5 illustrates this architecture and the methodology for evaluating and classifying crack images.

Classical computer vision (CV) methods have been employed since they are simple and low in computing cost. However, these systems are based on personalized characteristics and frequently struggle with complicated material textures. In contrast, CNN automatically learns hierarchical features from image data, allowing for more accurate and resilient fracture and defect detection in quasi-brittle materials.

TABLE 1. Summary of ANN implementation in fracture analysis of quasi-brittle materials (2020 ~ 2024)

Ref	Material	Data Preparation Method	Data size & splitting		Input values	No. of Hidden Layers (No. of Neurons)	Activation function	Output values	Performance metrics
			Training	Testing					
(Xiaotao Li et al. 2022)	Quasi-brittle materials	Simulation	70% (22750)	30% (9750)	3	2 (60,60)	Sigmoid	Fracture toughness	R^2= 0.99
(Niaki et al. 2023)	Polymer concrete composite	Experiment	85% (178)	15% (31)	9	4 (13,12,13,12)	Sigmoid	Fracture toughness	R^2= 0.89 *MAE* = 0.23
(Qiu et al. 2021)	Composites laminates	Simulation	70% (2100)	30% (700)	2	5 (200,150,100,50,30)	Sigmoid	Energy release rate (G_c)	Regression Coefficient (R = 0.99)
(Pakzad et al. 2023)	Steel fiber-reinforced concrete	Experiment	80% (140)	20% (36)	9	4 (9,72,72,72)	Hidden = ReLU Output = Sigmoid	Compressive strength	R^2= 0.89 *MSE* = 36.68 *MAE* = 4.38
(AL-Bukhaiti et al. 2024)	Carbon fiber-reinforced polymer composites	Experiment	70% (98)	30% (42)	17	2 (12,10)	Sigmoid	Fracture strength	R^2= 0.92
(Bahrami et al. 2023)	Various quasi-brittle materials	Simulation	85% (293)	15% (52)	5	2 (10,8)	Sigmoid	Fracture load	R^2= 0.99
(Mirzaiyanrajeh et al. 2022)	Asphalt mixtures	Experiment	80% (682)	20% (170)	14	1 (100)	Sigmoid	Fracture energy	R^2= 0.98
(Xu et al. 2021)	Concrete	Experiment	70% (395)	30% (170)	13	3 (6,6,6)	Tanh	Fracture energy	*RMSE* = 58.9
(Yang et al. 2023)	Alumina ceramic tile	Simulation	80% (256)	20% (64)	10	4 (32,32,32,32)	ReLU	Impact load	*MAPE* = 7%
(Lai et al. 2023)	Fiber–polymer reinforced concrete	Experiment	75% (256)	25% (86)	11	3 (128,64,32)	ReLU	Maximum displacements	R^2= 0.9561 *MAE* = 3.37
(Al-shawafi et al. 2023)	Fiber reinforced concrete	Experiment	70% (8)	30% (4)	6	–	Tanh	Failure strength	R^2= 0.9759 *MAE* = 0.01033 *MSE* = 0.0008
(Jiayun Chen et al. 2021)	Carbon fiber-reinforced polymer composites	Simulation	89% (10000)	11% (1282)	3	2 (6,12)	ReLU and Sigmoid	Failure prediction (0 or 1) (Fail or not fail)	*Accuracy* =97%
(Wan et al. 2023)	Carbon fiber-reinforced polymer composites	Simulation	80% (404000)	20% (101000)	6	3 (32,32,32)	ReLU	Regression: Failure probability (0 ~ 1) Classification: Failure prediction (0 or 1)	*MAE* = 0.85 *Accuracy* =98.1%
(Zhuang et al. 2020)	Various quasi-brittle materials	Simulation	96% (123)	4% (5)	3	4 (100,100,100,100)	ReLU	Loading deflection curves	*RMSE:* Displacement = 0.36 Force = 479.18
(Ganasan et al. 2021)	Reinforced concrete	Experiment	80% (342)	20% (86)	11	–	ReLU	Crack width	*RMSE:* 5%
(Xi et al. 2024)	Reinforced concrete	Simulation	70% (63)	30% (27)	1	1 (3)	–	Crack width	$R^2 \simeq 1$

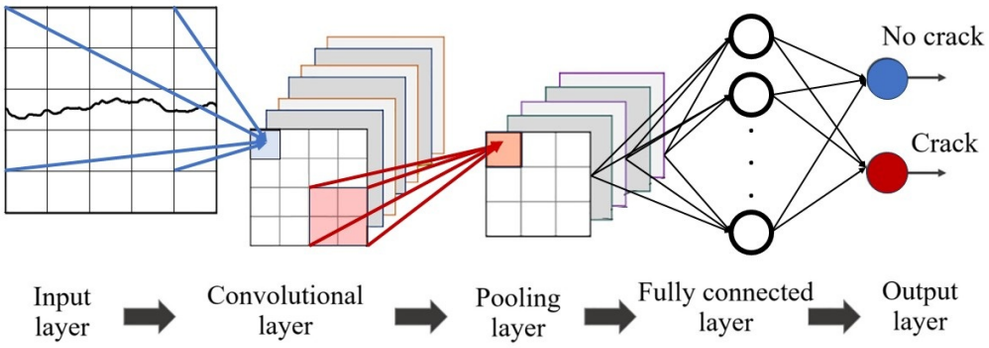

FIGURE 5. An example of CNN architecture for crack detection (Sales da Cunha et al. 2023)

LONG SHORT-TERM MEMORY

Long Short-Term Memory (LSTM) is a form of Recurrent Neural Network (RNN) that is designed to address the limitations of traditional RNN, including the problems of missing and expanding gradients during backpropagation. LSTM is extremely successful for learning from sequential data due to their ability to remember long-term dependencies via unique gating methods. The architecture of an LSTM unit is depicted in Figure 6, where h_{t-1}, h_t, C_{t-1} and, C_t represent the previous unit's output, the current output, the memory state passed from the previous unit and the updated memory state, respectively.

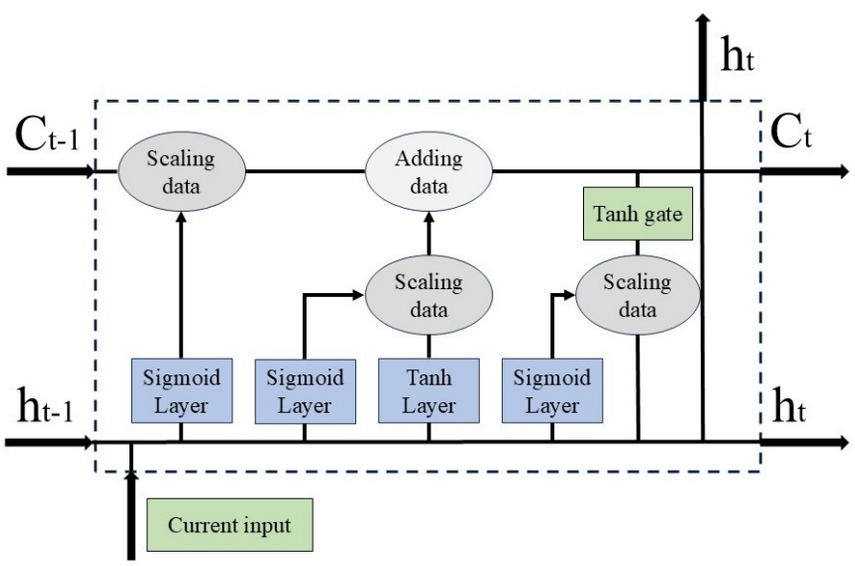

FIGURE 6. The architecture of an LSTM unit (Nguyen et al. 2019)

Due to the outstanding prediction ability of LSTM for time series data, it is used for failure estimation under dynamic and impact loading (Fernández-Godino et al. 2021; Reiner 2023), estimation of flexural loading capacity based on observational corrosion-induced crack width distribution (Zhang et al. 2021) or real-time classification of acoustic emission cracks dataset for structural health monitoring (SHM) (Siracusano et al. 2021).

An example of LSTM implementation can be seen in Figure 7 that compares the relationship between compressive strength and the age of concrete specimens in days obtained by a simple three-point load experimental test on single-edge notched beams.

SUPPORT VECTOR MACHINE

SVM is a supervised learning method that is commonly used for classification and regression (with an extension as support vector regression (SVR)) applications. Its base is in determining the best hyperplane that separates data points from distinct classes by the greatest margin. In fracture mechanics, SVM has evolved as a reliable tool for crack patterns identification (Wang et al. 2024) and crack and failure mode classification (Sun and Zhou 2023; Yue et al. 2021) and SVR is also used for fracture toughness (Albaijan et al. 2023; Albaijan, Samadi, et al. 2024; Alshaiji et al. 2022; Hu et al. 2023; Mahmoodzadeh et al. 2023;

Meybodi et al. 2022; Talebi et al. 2024; Ziamiavaghi and Toufigh 2023), crack width (Yuan et al. 2023), residual strength (Zhang et al. 2022), compressive strength (Zhang et al. 2024) and damage prediction (Feng et al. 2020, 2021; Ramian and Elhajjar 2024).

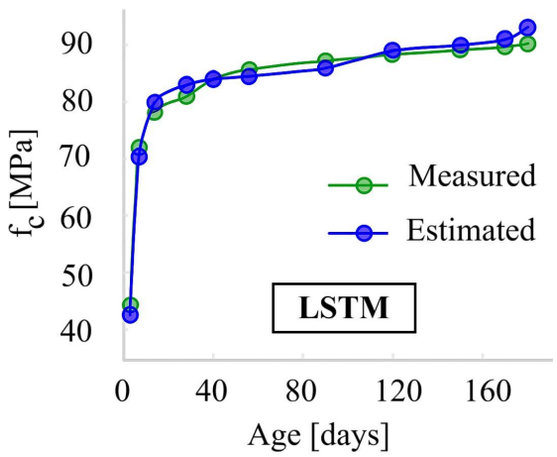

FIGURE 7. An example of LSTM model for compressive strength prediction. (Albaijan et al. 2024)

For linearly separable data in a 2D space, this hyperplane is a straight line, while in higher dimensions, it becomes a plane or hyperplane.

The margin is the distance between the hyperplane and the nearest data points (called support vectors). Figure 8 shows the components of SVM such as optimized hyperplane and support vectors.

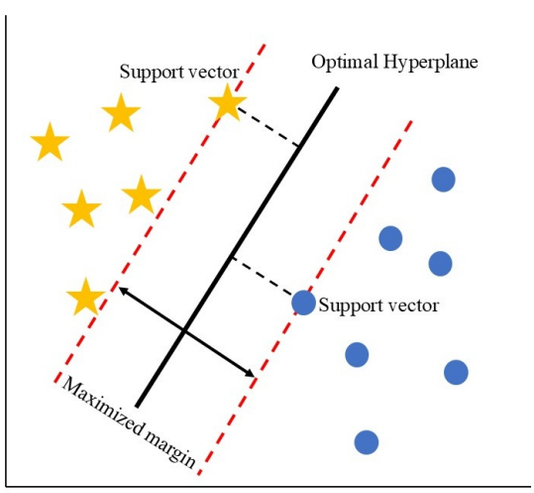

FIGURE 8. The components of SVM (Omar et al. 2023)

The flexibility of SVM comes from its ability to transform data into higher-dimensional feature spaces using kernel functions. To handle non-linearly separable data by mapping it to a higher-dimensional space where it becomes linearly separable Radial Basis Function (RBF) kernel is used as

$$K(x_i, x_j) = exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (3)$$

where γ is a hyperparameter that controls the influence of a single training example.

Figure 9 shows the performance of RBF compare to the linear, polynomial and Sigmoid function to predict fracture toughness when the mix design, material and fracture properties are complicated.

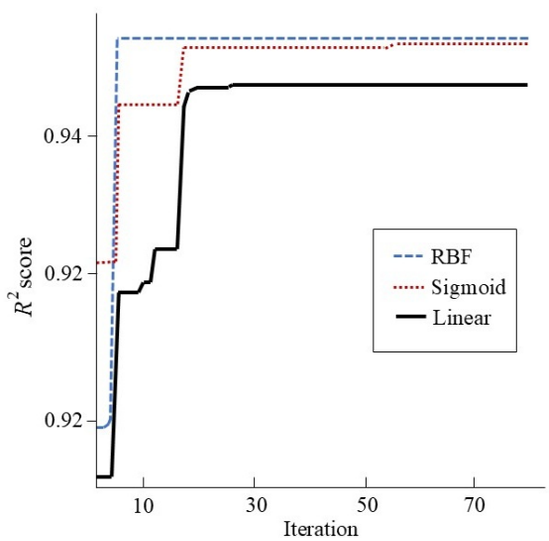

FIGURE 9. Comparison of RBF to other kernel functions in SVR for fracture toughness prediction. (Ziamiavaghi and Toufigh 2023)

K-MEANS CLUSTERING

K-means clustering is one of the most used unsupervised machine learning techniques for categorizing data into specific groups or clusters. K-means is designed to minimize variation within each cluster by repeatedly allocating data points x_i to clusters C_k and updating the cluster centroids (Alipour et al. 2021).

$$C_k = \left\{x_i \middle| \|x_i - \mu_k\|^2 \leq \|x_i - \mu_j\|^2, \forall j \neq k\right\} \quad (4)$$

where C_k is the set of points assigned to the k-th cluster and μ_k is the centroid of the k-th cluster as

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \epsilon C_k} x_i \quad (5)$$

The objective of K-means is to minimize the within-cluster variance, which can be expressed as:

$$J = \sum_{k=1}^{K} \sum_{x_i \epsilon C_k} \|x_i - \mu_k\|^2 \quad (6)$$

where K is the number of clusters and J is the cost function as the sum of squared distances from each data point to its cluster centroid. Therefore, the algorithm of K-means clustering can be written as the algorithm given in below (Benaimeche et al. 2022).

Algorithm 1: K-means Clustering

1: **Initialize**
Select K cluster centroids μ_k randomly from the dataset $x_i=\{x_1,x_2, ..., x_n\}$
Set the number of clusters K.
2: **While** the change in the cost function $\Delta J \neq 0$
3: Assign each data point to the cluster according to Eq. (4).
4: Recalculate the centroids of each cluster according to Eq. (5).
5: Calculate the cost function according to Eq. (6) and compute its change (ΔJ).
6: **End**

In fracture analysis of quasi-brittle material K-means clustering can be used for fragmentation analysis (Lyu et al. 2024), damage evaluation analysis and monitoring for SHM (Liu et al. 2024; Zhang et al. 2023) and also classification of fracture types based on impact fracture test results (Lee et al. 2021).

K-means clustering has recently been used in RVE-based fracture analysis of quasi-brittle materials to reduce computing complexity while maintaining accuracy in capturing microstructural behaviors (Chaouch and Yvonnet 2024). The approach divides macro-scale integration points into clusters depending on their stress σ and strain ε states, with each cluster represented by a single microscale representative volume element (RVE) computation. This eliminates the need to do individual RVE computations for each integration point, which can be computationally expensive.

K-NEAREST NEIGHBORS

K-Nearest Neighbors (KNN) is a simple yet useful machine learning technique implemented in classification and regression applications. In fracture mechanics, KNN can be used as a baseline method for predicting and identifying mechanical behavior of quasi-brittle materials (Hadzima-Nyarko et al. 2020; Haruna et al. 2024; Kumar et al. 2023; Mangalathu et al. 2020; Qing and Li 2024). Unlike model-based techniques that utilize training to optimize parameters, KNN is an instance-based learning algorithm, which means it uses the complete dataset during inference. KNN performs by determining the k k-nearest neighbors of a given query point in the feature space using a specific distance metric, such as Euclidean distance.

DECISION TREES

Decision Trees (DT) are foundational ML models employed to address classification and regression problems, also referred to as classification and regression trees (CART) (Sun and Zhou 2023). DT works by dividing the dataset into subsets depending on feature values, generating

a tree-like structure in which each internal node represents a decision rule and each leaf node corresponds to the final output. Figure 10 demonstrates the schematic structure of DT model.

Different types of decision trees (DT), such as Decision Tree Regressor (DTR) for regression tasks, Classification and Regression Trees (CART) for both classification and regression, Regression Trees (RT), Extra Tree Regressor (ETR), and Chi-squared Automatic Interaction Detector (CHAID) (Albaijan, Samadi, et al. 2024), enhance model adaptability.

These models are widely used in quasi-brittle material fracture analysis, including failure mode classification and predictive tasks like compressive strength, fracture toughness, and fracture energy (Daghigh et al. 2020; Motevalizadeh et al. 2022; Xiao et al. 2021). ETR, an ensemble learning method, uses multiple complete decision trees to improve prediction accuracy and prevent overfitting by randomizing split points. Bagging Trees (BT) and Random Forest (RF) are ensemble methods that use multiple decision trees to enhance performance while reducing overfitting, with RF improving BT by introducing randomness at each split (Han et al. 2021; Lan Ngoc Nguyen et al. 2023).

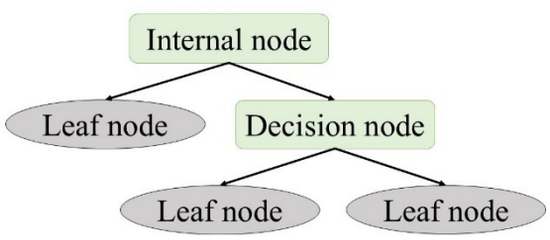

FIGURE 10. Schematic structure of DT.

Unlike ETR, which trains each tree on the entire dataset, boosting approaches like AdaBoost (Son and Yang 2022) train models sequentially, focusing on rectifying previous errors, which reduces bias and variance, making it effective for complex datasets (Fang et al. 2022).

AdaBoost Regressor (ABR) applies this to regression tasks, improving predictions (Mahmoodzadeh et al. 2023; Pakzad et al. 2023; Zhang et al. 2024). Gradient Boosting, including methods like CatBoost (Kim et al. 2022) and XGBoost (Amjad et al. 2023; Fakhri et al. 2022; Ferdousi et al. 2021), optimizes the loss function at each step, with XGBoost using second-order Taylor expansions for optimization. Histogram-Based Gradient Boosting Regressor (HGBR), or LightGBM (Lai et al. 2023; Mangalathu et al. 2020), uses histograms to reduce computational complexity, making it suitable for large datasets.

SVM, KNN, DT, and k-Means clustering all take distinct approaches to fracture mechanics in quasi-brittle materials: SVM offers reliable non-linear prediction of fracture parameters (such as toughness or failure load), frequently surpassing linear methods but necessitating careful kernel tuning to prevent overfitting; KNN is a straightforward, interpretable regression tool that performs exceptionally well in predicting compressive and flexural strength, but it has trouble with large feature sets and distance scaling; DT and their pruned or ensemble versions provide unambiguous decision rules that can classify failure modes or estimate cracking thresholds; as well, k-Means, although not directly predictive, helps fracture mechanics by clustering fracture patterns or grouping material behaviors, improving data-driven preprocessing and exploratory analysis prior to predictive modelling.

Table 2 describes ML models based on their statistical performance in predicting fracture energy using R^2 and MSE measures (Albaijan et al. 2024). Among the models, SVR had the highest accuracy. LSTM and Gaussian Process Regression (GPR) followed, both demonstrating excellent predictive performance. In this situation, models such as DTR and XGBoost performed less well. The ranking shows that, while ensemble methods like Random Forest (RF) and Extra Trees Regression (ETR) produced moderate results, kernel-based and deep learning models like SVR and LSTM are better suited for capturing the complex, nonlinear behavior associated with fracture energy prediction in materials.

TABLE 2. Comparison of the ML models through the ranking score of statistical metrics to predict fracture energy. (Albaijan et al. 2024)

ML Model	R^2	Score	MSE	Score
KNN	0.9379	4	98.98	4
SVR	0.9897	1	16.40	1
DTR	0.8652	8	214.90	8
LSTM	0.9804	2	31.22	2
GPR	0.9745	3	40.74	3
XGBoost	0.9018	7	156.62	7
RF	0.9280	5	114.37	5
ETR	0.9156	6	134.57	6

Figure 11 compares the performance of five machine learning models (KNN, DT, SVR, GPR, and XGBoost) in predicting fracture toughness using five statistical metrics (R^2, MAE, RMSE, MAPE, and VAF) reported by (Fakhri et al. 2022). Each colored section of the horizontal bars represents the ranking contribution of a certain statistic, with a lower total score indicating better overall performance. KNN outperformed the other models,

achieving the lowest total ranking score, showing good predicted accuracy and consistency across all metrics.

This demonstrates that, while sophisticated ensemble models like XGBoost are useful in many domains, simpler models like KNN can be more effective for specific fracture mechanics problems, particularly when working with smaller or well-structured datasets.

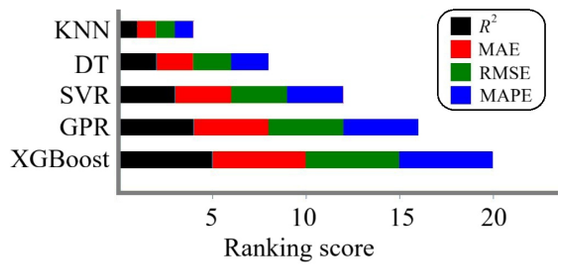

FIGURE 11. Comparison of models' performance for fracture toughness prediction. (Fakhri et al. 2022)

EXTENSIONS OF ML TECHNIQUES

Naïve Bayes (NB) is a probabilistic machine learning algorithm based on Bayes' Theorem, widely employed in classification problems. It determines the posterior probability of a target class based on input features, assuming feature independence. While this assumption may simplify the reality of the situation, NB is computationally effective and has demonstrated strong performance in applications involving the classification of failure modes in quasi-brittle materials (Haruna et al. 2024; Mangalathu et al. 2020; Sun and Zhou 2023). The Bayes' Theorem is expressed mathematically as

$$P(Y|X) = \frac{P(X|Y) \cdot P(Y)}{P(X)} \tag{7}$$

where $P(Y|X)$, $P(X|Y)$, $P(Y)$ and, $P(X)$ are posterior probability of the target class Y given the features X, likelihood of the features X given class Y, prior probability of the target class Y and, evidence or marginal probability of the features X, respectively.

Bayesian Neural Networks (BNN), on the other hands, is an extension of standard neural networks that incorporate probabilistic analysis through Bayesian inference. BNN learns probability distributions rather than weight and bias point estimates (Shi et al. 2024). The model output is expressed as a distribution rather than a single number, accounting for uncertainty.

Gaussian Process Regression (GPR) as a non-parametric, probabilistic machine learning technique widely used for evaluating critical responses like maximum displacements under dynamic and impact loading conditions (Lai et al. 2023) or fracture toughness under acid environment (Albaijan et al. 2023) due to its ability to quantify uncertainties where data are limited and variability is high.

Graph Neural Networks (GNN) is effective tool for modelling fracture mechanics since they can analyze graphical-structured data, with nodes and edges representing material constituents and their interactions. GNN is ideal for capturing complex geometries such as crack patterns, particularly when paired with voronoi diagrams to express spatial and topological relationships (Wang et al. 2024). GNN also incorporates physical restrictions and domain knowledge, which improves accuracy and computing efficiency.

Gene Expression Programming (GEP) is an evolutionary algorithm that combines the concepts of genetic algorithms (GA) with genetic programming (GP). It develops computer programs which arrange interactions between input and output variables. The GEP technique creates interpretable models that link variables by using fixed-length chromosomes and expression trees (Albaijan et al. 2023; Althoey et al. 2022).

More recently, a new framework was presented by (Quek et al. 2024) for approximating fracture paths in random heterogeneous materials using neural network and probabilistic approaches, as well as Hamiltonian Monte Carlo Simulation. This approach is applied to phase-field fracture models, demonstrating excellent accuracy and computational efficiency in predicting crack paths along a range of fracture toughness domains. The finite element discretization is compared to reference phase-field damage and ML framework predictions, which correctly capture the fracture path and damage zones.

Table 3 gives a comparative review of some advanced machine learning models, including BNN, GPR, GNN, and GEP. Each column in the table represents a specific capability or requirement of the model. The "Interpretable" column indicates if the model's internal decision-making process is clear and understandable to users, which is vital in safety-sensitive applications such as structural engineering. The "Uncertainty" column indicates if the model can produce confidence estimates or probabilistic results—an important feature when dealing with changing or limited data. The term "Scalable" denotes to a model's capacity to handle

big datasets efficiently without incurring excessive computational costs; for example, models with cubic temporal complexity, such as GPR, struggle to scale, but GNNs are better suited to large-scale, graph-based fracture data.

Given that BNN estimates posterior distributions via variational inference or Monte Carlo sampling, they need significant processing resources. Bayesian Torch libraries improve training efficiency on complicated fracture datasets by converting deterministic models to Bayesian and supporting GPU acceleration. GNN, on the other hand, benefit from GPU-accelerated frameworks such as PyTorch Geometric and DGL, which optimize message-passing and mini-batching to speed up training for graph-structured data, which is typically used to construct crack networks. GPR has long suffered from cubic computational complexity, rendering it unsuitable for huge datasets. GEP, while computationally lighter, performs well on ordinary CPUs.

TABLE 3. Comparison boxes of four advance ML techniques

Method	Interpretable	Uncertainty	Scalable
BNN	X	✓	X
GNN	X	✓	✓
GPR	✓	✓	X
GEP	✓	X	✓

TRENDS IN ML-BASED FRACTURE MECHANICS

Figure 12, created using VOSviewer, shows the growing use of machine learning (ML) in fracture mechanics. It highlights a network of keywords from studies between 2020 and 2024, emphasizing key research areas like damage modeling, crack characterization, and structural health monitoring. Central concepts like "quasi-brittle materials," "damage," and "machine learning" dominate, linking traditional mechanics with advanced ML methods. The rising use of PINNs is notable, as they integrate physical laws into ML models, improving their reliability and interpretability.

PINNs offer an effective approach for solving partial differential equations (PDEs) in fracture mechanics by integrating governing equations such as stress-strain relationships and crack propagation laws. This allows models to learnfrom limited data while maintaining physical accuracy, particularly in areas like peridynamics, where traditional methods face challenges with discontinuities and nonlocal effects (Eghbalpoor and Sheidaei 2024; Jafarzadeh et al. 2024; Cong Tien Nguyen et al. 2023; Han Wang et al. 2024; Xiao Xu et al. 2021; Yang et al. 2024; You et al. 2023). Unlike conventional machine learning models that depend on large datasets, PINNs leverage physical information encoded in PDEs to guide learning, enabling precise predictions in fracture mechanics, including crack propagation, stress-strain relationships, damage prediction, and classification (Wei et al. 2022; Zheng et al. 2022; Zhou and Yu 2024; Dong et al. 2023; Deng et al. 2024; Ge and Tagarielli 2024; Pantidis and Mobasher 2023; Shi and Beer 2024).

PINNs approximate u with a neural network u_θ, where θ denotes the network parameters. The training method reduces a loss function that includes physical restrictions.

Therefore, the loss function for the data section that ensures the model fits available data is defined as

$$\mathcal{L}_{data} = \frac{1}{n}\sum_{i=1}^{n}\left(u_\theta(x_i,t_i) - \hat{u}_\theta(x_i,t_i)\right)^2 \tag{8}$$

And, the physics residual loss function which enforces the satisfaction of the governing PDE:

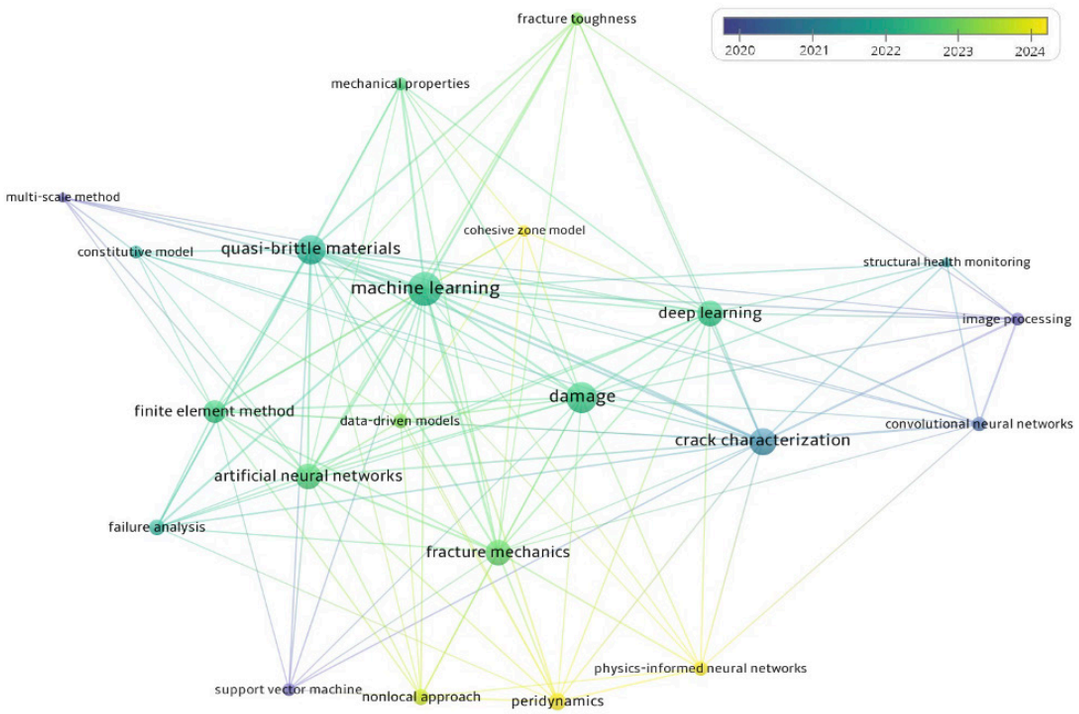

FIGURE 12. Keyword mapping of journal articles related to ML implementation in fracture mechanics of quasi-brittle materials.

$$\mathcal{L}_{physics} = \frac{1}{n}\sum_{i=1}^{n}\left(\mathfrak{D}[u_\theta(x_i,t_i),\lambda] - f(x_i,t_i)\right)^2 \tag{9}$$

where $\mathfrak{D}$, u and, λ are differential operator, the unknown solution and, material parameters, respectively.

Boundary conditions and initial condition also can be handled based on datasets with $\mathcal{L}_{boundry}$ and $\mathcal{L}_{initial}$, respectively. And, the total loss function can be considered as

$$\begin{aligned}\mathcal{L}_{total} = {} & \mathcal{L}_{data} + W_{physics}\mathcal{L}_{physics} \\ & + W_{boundary}\mathcal{L}_{boundary} \\ & + W_{initial}\mathcal{L}_{initial}\end{aligned} \tag{10}$$

where $W_{physics}$, $W_{boundry}$ and $W_{initial}$ are weighted of physics, boundary conditions and initial condition loss, respectively.

A thorough assessment of the PINN developed to accurately predict brittle damage in materials is given in (Eghbalpoor and Sheidaei 2024). Internal force residuals, deformation gradient regularization, damage evolution, boundary condition enforcement, and a linearized physics-based term are among the physically motivated elements that make up the total loss function. Annealing coefficients are used to weight each of these components, controlling their influence during training. The findings show that adding the linearized physics-based loss greatly increases its predictability and rate of convergence, allowing it to reach lower overall loss values in fewer training epochs.

The ability of the model to learn complicated spatial characteristics, like sharp gradients and crack-like discontinuities, with high fidelity is demonstrated by the qualitative comparison of the true displacement field and the PINN's predicted output. The incredibly high accuracy of the model is shown in the MAE rating. When precise deformation prediction is crucial, the application of PINN in brittle fracture analysis is highly supported by this quantitative and visual data. The benefits of PINN, which incorporate physical laws into neural network training and allow for robust and interpretable learning even in highly nonlinear or data-sparse regimes, are more generally demonstrated by this method. PINN provides a viable approach to modeling intricate damage processes in quasi-brittle materials by coordinating data-driven learning with domain-specific physics.

CONCLUSION

This paper explores the integration of machine learning (ML) in the study of fracture mechanics in quasi-brittle materials such as concrete and ceramics, where traditional theoretical and numerical methods often fall short due to nonlinear behavior and material heterogeneity. ML techniques like CNNs, SVMs, and K-means are applied for crack detection and damage assessment, while advanced models like Bayesian and physics-informed neural networks enhance prediction by incorporating uncertainty and physical constraints. These methods not only improve reliability and reduce computational costs but also enable real-time monitoring and data augmentation through models like GANs. The paper emphasizes the synergy between data-driven approaches and physics-based models, showcasing their potential to transform fracture analysis. Table 4 highlights the performance of various ML algorithms across different materials and applications, providing guidance on model selection based on task-specific data and goals.

RESEARCH GAPS AND FUTURE CHALLENGES

Despite advancements in machine learning (ML) for fracture mechanics, challenges such as data availability, generalization, interpretability, computational efficiency, uncertainty quantification, and integration with traditional models limit widespread adoption.

A major hurdle is the lack of high-quality experimental and simulation datasets, exacerbated by the complexity and cost of fracture testing in quasi-brittle materials. Future research should focus on developing large-scale, publicly accessible datasets and leveraging data augmentation techniques like GANs.

Additionally, ML models often struggle to generalize across diverse materials and conditions, and their complexity hinders interpretability, which is critical for safety applications. PINNs and explainable AI (XAI) can improve model transparency and generalization. The high computational cost of advanced models limits their real-time applicability, necessitating the development of more efficient models.

TABLE 4. Comparison of ML techniques selected for a specific task in fracture analysis of quasi-brittle materials

Ref	Material	Number of data used	Number of Inputs	Output Values	ML Techniques Employed	Best ML Technique Recommended
Khokhar et al. 2021)	Fiber reinforced concrete	387	15	Tensile strength	ANN, SVM, CART, GPR, XGBoost	XGBoost
(Dai et al. 2022)	High strength fiber reinforced concrete	255	15	Compressive strength	ANN, BT, Adaboost	BT
(Pakzad et al. 2023)	Steel fiber reinforced concrete	176	9	Compressive strength	MLR, RF, KNN, SVR, GB, XGBoost, AdaBoost, ANN	SVR
(Lai et al. 2023)	Fiber polymer reinforced concrete	342	11	Maximum displacements	SVR, GPR, XGBoost, Catboost, RFR, LightGBM, ANN	ANN
(Al-shawafi et al. 2023)	Fiber reinforced concrete	12	6	Failure strength	ANN, MLR	ANN
(Nguyen et al. 2019)	L-shape concrete	470	–	Damage evolution	ANN, LSTM	LSTM
(Albaijan, Mahmoodzadeh, et al. 2024)	Concrete	500	4	Fracture energy	RF, DTR, GBR, HGBR, SVR, GPR, KNN, ETR, MLR, LSTM, XGBoost	SVR
(Xiao Wang et al. 2024)	Cementitious materials	1069	2	Crack pattern identification	SVM, GNN	SVM
(Sun and Zhou 2023)	Quasi-brittle	250	9	Failure modes classification	NB, SVM, DT, RF, GB	SVM
(Albaijan et al. 2023)	Reinforced concrete	420	5	Fracture toughness	DTR, SVR, ANN, KNN, GPR, XGBoost, RF, ETR, GBR, HGBR,	ETR
(Albaijan, Samadi, et al. 2024)	Reinforced concrete	420	6	Fracture toughness	MLP, NRBF, KNN, CHAID, CART, LSSVM, DNN, GEP	CHAID
(Hu et al. 2023)	Rock	297	14	Fracture toughness	SVM, ANN, CNN, RBFNN, RF	SVM
(Mahmoodzadeh et al. 2023)	Quasi-brittle	1715	5	Fracture toughness	SVR, ETR, XGBoost, RF, ANN, KNN, GPR, GBR, DTR, HGBR	ETR
(Meybodi et al. 2022)	Rock	24	3	Fracture toughness	MLR, MNLR, SVR	SVR
(Talebi et al. 2024)	Asphalt mixtures	675	4	Fracture toughness	SVR, ETR, GBR	ETR
(Yuan et al. 2023)	Cementitious materials	619	3	Crack width	SVR, XGBoost, RF	RF
(Zhang et al. 2022)	Concrete	1000	8	Residual strength	SVM, ANN, RF	RF
(Zhang et al. 2024)	Fiber reinforced concrete	465	8	Compressive strength	SVM, ANN, AdaBoost, GB	GB
(Ramian and Elhajjar 2024)	Composite	51	4	Cohesive zone parameters	SVR, ANN, RF	ANN
(Omar et al. 2023)	Polymer composite	560	3	Crack growth	KNN, RR, LASSO	KNN
(Qing and Li 2024)	Cementitious composites	501	13	Compressive strength	LR, KNN, RF, XGBoost	RF
(Haruna et al. 2024)	Concrete	12	5	Failure modes classification	DT, KNN, NB	KNN

continue ...

... cont.

(Kumar et al. 2023)	Concrete	87	7	Failure loads	KNN, RF, XGBoost	XGBoost
(Mangalathu et al. 2020)	Reinforced concrete	393	8	Failure modes classification	NB, KNN, DT, RF, XGBoost, AdaBoost, LightGBM, CatBoost	RF
(Hadzima-Nyarko et al. 2020)	Concrete	457	6	Compressive strength	ANN, KNN, RT, RF	ANN
(Xiao et al. 2021)	Concrete	736	8	Fracture energy	RR, CART, GB	GB
(Daghigh et al. 2020)	Nano-composites	15	5	Fracture toughness	DTR, KNN, ABR	ABR
(Kim et al. 2022)	Fiber reinforced polymer composite	855	6	Bond strength	HGBR, RF, XGBoost, CatBoost	CatBoost
(Amjad et al. 2023)	Self-healing concrete	1054	7	Crack width	CNN, XGBoost, ANN, MLR	XGBoost
(Fakhri et al. 2022)	Concrete	560	6	Fracture toughness	SVR, GPR, DT, KNN, XGBoost	XGBoost

Moreover, ML's deterministic predictions ignore uncertainty in fracture behavior, making it essential to integrate probabilistic methods and stochastic frameworks for more reliable predictions. Lastly, limited integration between ML and traditional fracture mechanics models reduces model robustness, suggesting the need for hybrid approaches combining ML with physics-based theories to improve prediction accuracy across various scenarios.

To support effective application, researchers and practitioners are encouraged to select ML techniques based on task-specific needs: for example, CNN are well-suited for image-based crack detection, support vector machines SVM perform reliably in classification tasks, while physics-informed neural networks PINN are ideal for integrating governing fracture equations into the learning process. Equally important, interdisciplinary collaboration between ML experts and fracture mechanics engineers is crucial to develop robust, interpretable, and domain-relevant solutions.

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DECLARATION OF COMPETING INTEREST

None

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