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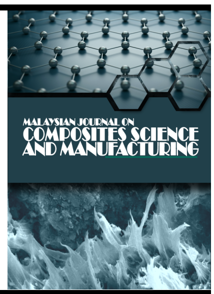

Review of Predictions of Impact Performances and Damages of Fiber Reinforced Composite using Machine Learning Approaches

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ABSTRACT

Fiber-reinforced composites (FRCs) offer high specific mechanical properties like-exceptional strength, lightweight properties, and versatility, but their susceptibility to impact damage poses a significant challenge. Characterizing these while connecting processing methods, microstructure, and environmental factors to impact response has seen limited success through conventional modeling. But with increasing computational power and availability of data, machine learning techniques present opportunities in this domain enabling accurate prediction and robust monitoring of impact performance and damage. This review paper provides a comprehensive examination of the evolving landscape in predicting impact performances and damages of FRCs to optimize composites' design through the lens of different supervised, unsupervised, blended, deep transfer learning and alternative approaches highlighting their strengths, limitations, and suitability for specific tasks. Methods encompassing artificial neural networks (ANNs), support vector machines (SVMs), and convolutional neural networks (CNNs) have exhibited promise in predicting performance and damage parameters respectively. Each section critically evaluates the strengths, limitations, and contributions of these approaches, providing a holistic view of their effectiveness.

1. Introduction

Composite materials are defined as the composition of more than one at least two visually distinct materials which are combined to provide better properties compared to the constituent's individual materials while retaining their respective different properties while contributing desirable attributes as a whole [1]. Fiber-reinforced composites (FRCs) consist of fibers with superior strength and modulus bonded to a matrix with distinct interfaces (boundaries) between them [2]. FRCs are popularly used in engineering and structural applications because of their high performance relating to improved specific strength and stiffness. Currently, the demand for lightweight and high-

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performance structures continues to rise, so understanding the behavior of FRCs under different impact loading conditions becomes imperative for design structures. This is because of withstanding the anticipated impact loads to ensure safety and reliability; to optimize material selection for improving energy absorption; to develop effective non-destructive evaluation techniques for preventive maintenance; to advance the understanding of fundamental mechanisms for developing novel materials with superior impact resistance. Furthermore, due to impact there are extreme changes in energy transfer among the projectile, target resulting energy dissipation and damage dissemination mechanisms for different impact loading velocities in application [3]. Besides, impacts lead to significant damages sometimes barely visible impact damages (BVID) which reduce stiffness, residual strength, service life, and functionality of the components with time. Therefore, it is very crucial to poster these types of damages and to be able to predict damages to get the remaining lifespan under dynamic loadings [4] [5]. Following the perspective existing researches mainly focus on the experimentation and application of finite element analysis for numerical modeling through simulation besides limited and on-going attempts on the application of artificial intelligence (AI) i.e., machine learning (ML) to characterize properties of FRCs including impact performance and damage prediction. So, application of machine learning in the research of FRCs is an exciting foundation of review to predict impact performances and damages. As the extensively deployed experimental testing and analytical models through numerical simulation to predict the induced damage modes subjected to impact loadings by means of finite element analysis (FEA) can waste of tests, components [6] besides real time issue, limited accuracy and high computational cost in capturing the complex relationships between material properties and damage mechanisms. Though, the application of machine learning tools in the research areas of structural applications is not new and quite familiar which is broadly reviewed in [7].

Presently, data-driven algorithm methods have gained popularity in fatigue studies as it can process huge experimental data [8]. Similarly, data science and machine learning techniques (one of the branches of artificial intelligence) have been rapidly growing over the time and being implemented in material science to solve different problems by using a range of statistical and probabilistic approaches. On the other hand, machine learning allows machines to learn automatically from experience and to identify correlations and patterns between input and output data sets [9] which is shown as role of machine learning in FRCs composites in Fig. 1. Nowadays it has become an imperative tool which is widely used in a variety of studies including prediction of material properties, design factors, effect of manufacturing processes, uncertainty quantification, damage identification and structural health monitoring [10]. Combining internet of things and finite element (FE) simulations in the edge using physics-informed neural networks (NNs) or other machine learning techniques for digital twin modeling permits the identification of failures of composites [11]. But, accurate prediction of impact performance and damage remains a complex task, often hindered by the complicated chemistry of material properties, fabrication processes, and loading conditions. Considering those factors, this review encompasses a spectrum of predictions of FRCs performance and damage by machine learning approaches which included supervised learning for classification and regression tasks; unsupervised learning for uncovering hidden patterns; deep learning for extracting complex features; blended and others approaches to guide the formation of composites with enhanced impact resistance and improved performance. Precisely, this review comprehensively examines the current state of the art in machine learning based prediction of impact performance and damage in FRCs to explore a wide range of employed algorithms, types of impact scenarios, damage characteristics with different modes, evaluation with validation of models, effectiveness of approaches followed by challenges and future prospects of research.

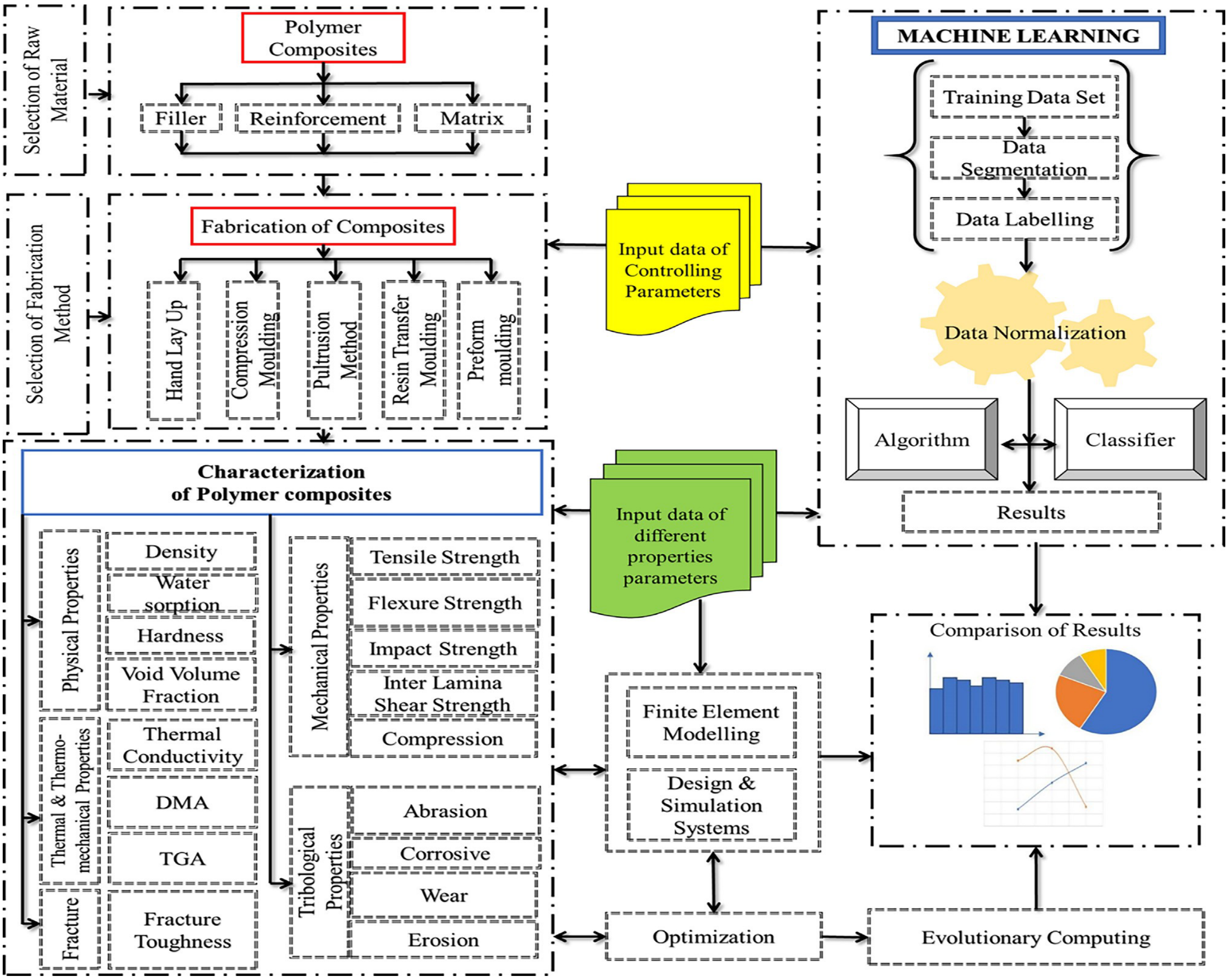

Fig. 1. Role of machine learning in fiber reinforced polymer composites [9]

2. Methodology

This section presents the methodology used in the review. In these steps, we followed some guidelines to select the best and most influential articles related to the topic. The Google Scholar, Scopus database, Science Direct, PubMed, IEEE, Springer Link was used as a screening tool to find the appropriate article papers for the study. Here, following keywords were used in order to find articles that matched the desired topic. The keywords were combined using Boolean operators, resulting in the following search:

(low velocity impact) AND (machine learning)
(low velocity impact) AND (fiber reinforced composite) AND (machine learning)
(low velocity impact damage) AND (fiber reinforced composite) AND (machine learning)

Other filters like year, area, articles etc. were also used to narrow down which showed the substantial results where Google Scholar, Science direct, Scopus and Springer link shows the maximum share. From the search of those databases the first screening has been completed then the abstracts of the selected articles were reviewed. Those did not discuss something related to the subject matter were excluded. Finally downloaded papers of the subject matter are uploaded in reference manager software Mendeley and checked for duplicates where sixteen duplicate articles were excluded to keep the best fitted one for further synthesizing and reviewing which is given in subsequent sections of the presented paper. It may be noted that, the surveys mainly and mostly included journal articles which is one hundred and four; besides three conference papers, two proceedings paper, three books are also included here. The details of published research papers history in different journals, conference, proceedings is shown in Table 1 where it has been found that the maximum fourteen articles have been published in Composite Structures journal; in the same time Composites Part B: Engineering and Composites Science and Technology journal published eight and seven articles respectively. Articles were chosen with the highest level of research outputs and that have been extensively peer-reviewed from 2010 and onwards which is shown in Fig. 2; where it has been found that the number of publication in the specified area have been significantly increased in the recent years. Notably it is to be mentioned here; so far 28 more research articles have been published in 2024 which are included in this review paper.

Table 1
Publication distributions

No.	Name	Number
1	Composite Structures	14
2	Composites Part B : Engineering	8
3	Composites Science and Technology	7
4	International Journal of Impact Engineering	3
5	Frontiers in Materials	2
6	Materials	3
7	Journal of Nondestructive Evaluation	2
8	Journal of Nondestructive Evaluation	2
9	IEEE Sensors Journal	2
10	Mechanical Systems and Signal Processing	2
11	Journal of Materials Science	2
12	Applied Composite Materials	5
13	JMST Advances	1
14	Hybrid Advances	1
15	Structures	2
16	Structural and Multidisciplinary Optimization	1
17	Reviews on Advanced Materials Science	1
18	Journal of Materials Research and Technology	1
19	Russian Journal of Nondestructive Testing	1
20	Defence Technology	1
21	Journal of Engineering Design and Technology	1
22	International Journal of Mechanical Sciences	2
23	Aerospace Science and Technology	2
24	Heliyon	1
25	Polymers and Polymer Composites	1
26	AIP Advances	1
27	Composites Part A : Applied Science and Manufacturing	1
28	Engineering Structures	3
29	Neural Computing and Applications	1
30	NDT and E International	1
31	Applied Composite Materials	1
32	Chinese Journal of Aeronautics	1
33	Polymers	3
34	Journal of Brazilian Society of Mechanical Sciences and Engineering	1

35	Journal of Composites Science	1
36	Engineering Applications of Artificial Intelligence	1
37	AIAA Journal	1
38	Photonic Sensors	1
39	Journal of Mechanical Science and Technology	1
40	PLOS ONE	1
41	Structural Health Monitoring	1
42	Optical Fiber Technology	1
43	Thin-Walled Structures	2
44	International Journal of Precision Engineering and Manufacturing	1
45	Archives of Computational Methods in Engineering	1
46	Composites Communications	1
47	Computer Networks	1
48	Computer Science Review	1
49	Construction and Building Materials	1
50	Engineering Fracture Mechanics	2
51	International Journal on Interactive Design and Manufacturing	1
52	Materials Today Communications	1
53	Progress in Aerospace Sciences	1
54	Results in Engineering	2
55	Materials Today Proceedings	2
56	33rd Technical Conference of the American Society for Composites	1
57	AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference	1
58	IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA)	1
59	Book/Book Chapter	3
Total		112

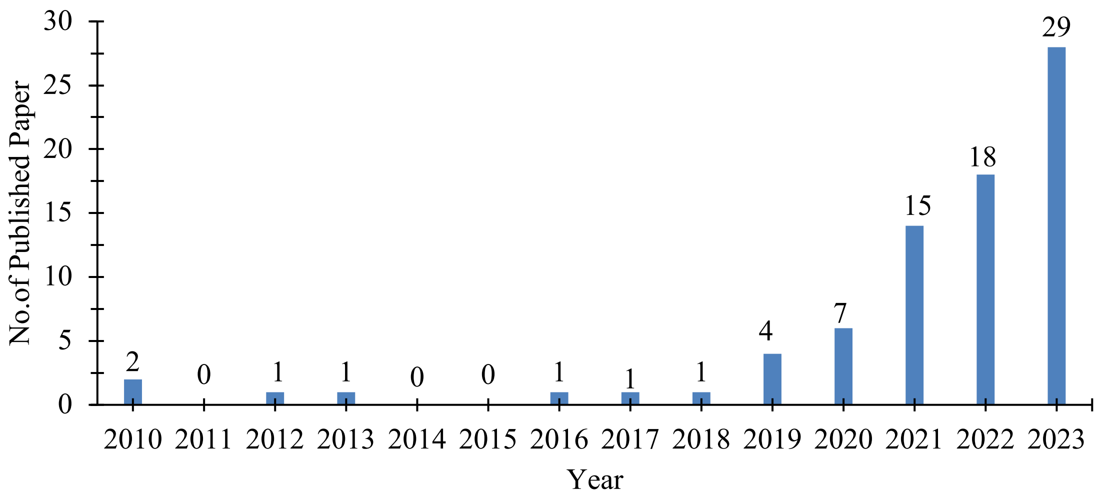

Fig. 2. Publication trend of related research articles

3. Machine Learning Approaches in Predicting Impact Performance and Damage

The field of machine learning (ML) has surged to the forefront of fiber-reinforced composites (FRCs) research, particularly in predicting impact performance and damage. Driven by a thirst for knowledge in this area, researchers have embraced diverse machine learning models and tailored protocols to specific objectives, guided by the type of input data. Notably, these techniques fall into three broad categories: supervised learning (utilizing labelled data for classification and regression), unsupervised learning (revealing hidden patterns in unlabelled data), and reinforcement learning (adapting in dynamic environments) [12] represented in the Fig. 3. Existing research paints a vibrant picture of machine learning's potential in FRCs analysis. From various software applications, as detailed in [13], to bridging the gap between microscopic and macroscopic design parameters using artificial intelligence (as discussed in [14]), machine learning demonstrates its versatility in tackling complex challenges. Furthermore, well-trained machine learning based constitutive models excel at predicting the mechanical behavior of polymers, outperforming classical models in capturing nuances like hardening, softening, creep, and relaxation [15]. While open-source data makes machine learning tools accessible and reduces computational costs [9], the quality and accuracy of datasets remain paramount. Encouraging FRCs researchers to share reliable data from their endeavours is vital for fuelling the advancement of machine learning in this domain [13]. Notably, the successful pairing of machine learning with finite element analysis showcased in [13] demonstrates the effectiveness of such collaborations in generating precise predictions of fiber characteristics from material composition. This review meticulously delves into specific machine learning approaches applied to predict mechanical properties and damage induced by various impact velocities, including low velocities. By dissecting the data, algorithms, inputs, outputs, and achievements of these studies a critical analysis is reviewed as per title classification of different machine learning approaches. So, the current review shows effective evidence of application of machine learning in FRCs impact and damage prediction though there are challenges particularly in data quality and collaboration efforts.

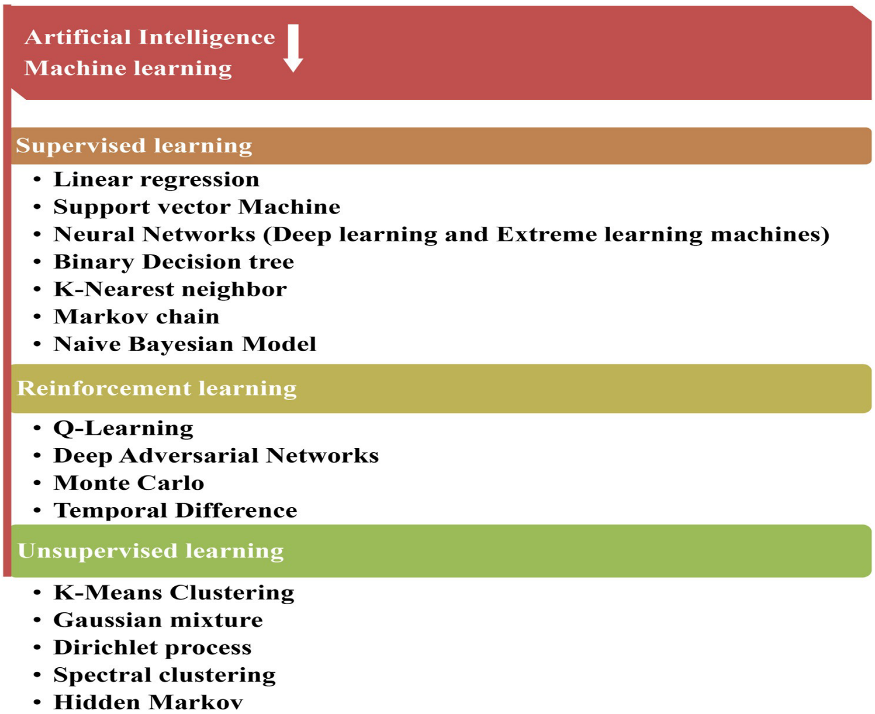

Fig. 3. Classification of machine learning algorithm [13]

3.1 Supervised Approaches

There are different supervised approaches which are employed in impact performance and damage predictions. Supervised methods showed the best results for damage classification and characterization tasks and consequently mostly used while regression or classification method is preferable for acustic emission methodology while CNN is preferable for scanning methods like thermography [16]. The findings of different deployed supervised approaches are reviewed below.

3.1.1 Neural network (Deep learning)

Neural Networks are a dominant class of functions with an extensive range of applications in machine learning and data science as well. Originally presented as simplified models of neurons in the brain, nowadays the biological inspiration plays a less prominent character. The acceptance of neural networks owes to their capacity to combine generalization with computational tractability while neural networks can approximate most rational functions to arbitrary accuracy. Their structure is still simple enough so that they can be trained proficiently by gradient descent [17]. It can be used to learn experiential knowledge from historical data by a number of processing units, which operate in parallel. Activation functions such as sigmoid and the hyperbolic tangent functions are usually used to these units to comprehend nonlinear computations. A neural network usually has one input layer, one output layer, and one or more hidden layers. By fine-tuning the number of hidden layers and the number of units in each layer, different models can be trained to solve different issues [18]. Neural network based approaches are found quite familiar and mostly employed approach in existing literature especially artificial neural network (ANN) and convolutional neural network (CNN) which is a member of deep learning. Besides these; there are other deep learning techniques i.e., long short term memory networks (LSTM), recurrent neural networks (RNNs), generative adversarial networks (GAN), radial basis function networks (RBFN), multilayer perception (MLP) are also found in literature.

3.1.1.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs), mimicking the human brain's structure with neuron-like computational units (shown in Figure 4). It is made up of a more than one layer perceptron, which is typically categorized into three layers: input, hidden, and output. Neurons in the hidden layer receive input signals from the input layer. These signals disseminate through the network, with connection weights and threshold values adjusted in response to training data. This learning occurs in both the hidden and output layers. The output layer makes the final predicted results by integrating the hidden layer's processed information. During the early stages, the weight function (w_{ij}) consists of multiplying and summing corresponding inputs (x_i), followed by a bias (b_i) to obtain y_i which is shown in Eq. (1). This process assists the neural network to learn and predict based on the input data as showed in Figure 4 [19].

$$y_i = \sum_{i=1}^{n} w_{ij} x_i + b_i \tag{1}$$

The output parameter z_i can be obtained by applying activation function f on y is shown in Eq. (2)

$$z_i = f(y_i) \tag{2}$$

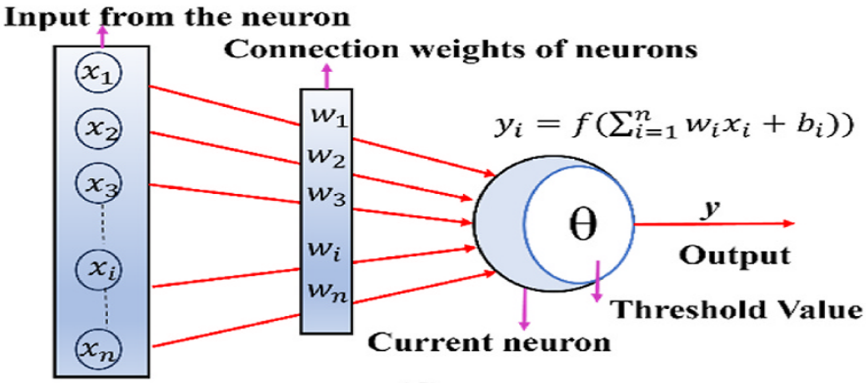

Fig. 4. Illustration of multi-layer perceptron (Artificial Neural Network) [19]

ANN have emerged as a potential tool for predicting the impact properties performance and damage of FRCs [12] which is shown in Table 2 and Table 3. From which Table 2 shows that the application of ANN relies on mainly carbon and glass epoxy composites with the data of experiments, simulation though data augmentation process have been deployed sometimes to increase the required number of data. During model application the dataset is categorized mainly in the ratio of 70%, 15% and 15% respectively for training, testing and validation respectively. The model accuracy found overall 90% with highest of 96%. In the ANN model application the input and output with targeted attributes are composite construction properties, impact or damage properties and their prediction related. On the other hand Table 3 shows the ANN model development information where the model details reveals that mainly sigmoid function is used with Levenberg-Marquardt optimization algorithm to avoid model over fitting by regularization technique and optimize the required parameters as well. Besides, there are maximum 64 neurons, 10 hidden layers, different input and output numbers, learning rates shown in the table. Apart from this, errors and model performance indicators like R square, MSE have been calculated to validate the model by mostly k-fold cross validation besides ensemble, train-test-split and performance metrics calculation method. The findings in the study listed in the Table 2 and Table 3 delves into their strengths and limitations, highlighting their impact on various aspects of FRC performance and damage assessment which are summarized below.

Table 2
Artificial Neural Network (ANN) application for impact performance and damage prediction in FRCs

Ref.	Composite	Tool	Dataset	Accuracy	Input	Output	Target	Velocity
[25]	Glass fiber reinforced polymer (GFRP)	ANN	70% +15%+15% (training + validation + testing)	-	Immersion time and the elastic modulus	Indentation properties	Effect of adding nano-particles on mechanical properties	-
[21]	Composites plate	ANN	31-Experiment	89.85%	Characteristics of projective experiments	Damage depth and size	Projective damage prediction	-
[20]	E glass epoxy plate and Pipe	ANN	-	High	Thermography readings	Temperature and thermal images	Characterize surface defects	-
[24]	Glass fiber-reinforced epoxy beams	ANN	140+10 (training + testing)-Simulation	-	Delamination scenarios	Delamination location and size are	Delamination severity and location prediction	-
[33]	CFRP plate	ANN	384-Experiment+Augmentation	-	Experimental image results	Impact localization	Prediction of LVI location	Low
[30]	Carbon fiber epoxy	ANN	64296 (50%+50)- (training + forecasting)- Experiment + Augmentation	-	Temperature, pressure, impregnation distance, viscosity	Dynamic impact energy absorption property	Prediction of impact energy	Low
[29]	Carbon/epoxy plate	ANN	200- Experiment+ Simulation	96%	Absorbed energy for different configuration	Absorbed energy prediction	Prediction of the absorbed energy	Low
[22]	Carbon fibre composites	LSTM (ANN)	1000-Simulation	90%	Lamination information	Locations and sizes of delamination	Identification of the delamination	-
[23]	Carbon, E-Glass Epoxy	ANN	70% +15%+15% (training + validation + testing)	-	Longitudinal stress	In-Plane shear stress	Predict biaxial failure	-
[31]	Carbon, epoxy	BP-ANN	752,000-Experiment+Simulation; training: validation: testing=7:2:1	High	Five stress tractions	Corresponding fracture angle	Accelerate Calculation process of Puck inter-fiber failure	Low
[32]	Glass fiber reinforced polymer (GFRP)	ANN	70% +15%+15% (training + validation + testing)	-	Ply orientation, sample thick- ness, height of fall, impact energy	Energy observation and peak force	Predict impact parameters	Low
[27]	3D-printed sandwich beams	DNN-(feed-forward)	92000-Experiment, 70% +15%+15% (training + validation + testing)	-	Thickness, diameter, angle of chiral unit cell, duration of tests	Resultant stresses and strains	Predict mechanical responses and design optimization	-
[28]	E-Glass, Epoxy	YUKI-Deep-ANN	Simulation	-	Mechanical Properties	Crack Properties	Assess behavior and characterization	-

Table 3
Artificial Neural Network (ANN) model development

Ref.	Model Details	Optimization Algorithm	Performance Indicator	Error
[20]	Neurons 10, hidden layer 10, output layer 2	Levenberg-Marquardt	Average percentage difference	18.7, 24.1, 24.8 (depth, width, and length)
[21]	Hidden layer 6	Levenberg–Marquardt	Average percentage difference	9.37%
[22]	Dropout 0.1 - 0.6, sigmoid & tanh function, one hot encoding	Back propagation Through Time (BPTT)	Cross entropy loss	-
[23]	Neurons 2, Hidden layer 5	Nelder-Mead simplex algorithm	RMS	-
[24]	Input 5, Output 3, Hidden layer 1	Gradient descent with momentum and adaptive LR	MSE	-0.55 to 1.1 & -8.8 to 20
[25]	Neurons 5, Input 2, Hidden layer 1, Output 1, 1000 epochs, Sigmoid function, Learning rate 0.01	Levenberg-Marquardt	MSE	-
[26]	Tangent sigmoid function, Input 9, 1000 epochs	Levenverg-Marquardt	MSE, R square 99%	Average 0.55% & 1.36%
[29]	Tangent sigmoid function, few iterations, initial population size 200, Neurons limit [6, 100], number of hidden layers [1,2]	Levenberg–Marquardt	MSE, RMSE	0.18J(Carbon/epoxy), 0.33 J (Glass/epoxy)
[30]	Tangent sigmoid function, output range −1 to + 1, no rule for optimal number of hidden layers and neurons, best configuration 50 neurons in single hidden layer	Levenberg–Marquardt	R-squared ($R2_{adj}$) of 97.46%, MSE	0.02 kJ,
[33]	Hidden layers 2 between 24 nodes and 10 nodes	-	-	Mean error 2.06 mm, Median error 3.13 mm
[33]	Sigmoid function, learning rate 0.2 & 0.01	-	MSE = 0.983, R square = 0.975	Relative error of about 10% - 90%
[31]	Hidden layer 3	Inverse	MAE= 0.1168	Delamination area's length and width= 5.56%, 11%; Peak impact force and maximum displacement = 11.7%, 6.9%.
[34]	Hidden layer 2, (32 & 64 neurons), Sigmoid, ReLU, Leaky ReLU function, improved Adam adaptive optimizer, MSE, Batch Normalization function, learning rate 0.001,0.0001	Inverse model (GAN)	R square =0.97	-

Well-trained ANNs excel at capturing the complex non-linear relationships between design parameters and mechanical properties. Their predictive accuracy and computational efficiency surpass many traditional methods, as demonstrated in [14]. Notably, [20] showcases an ANN coupled with thermal imaging, acting as a live NDT tool for monitoring composite health by revealing de-bonding as the primary defect type. Similarly, a cloud model-ANN hybrid model achieves a remarkable 89.85% accuracy in predicting and evaluating damage degrees in composite plates [21]. Again in pinpointing defects with precision ANN's prowess extends beyond property prediction to defect detection. ANN-based LSTM models deliver impressive defect localization results, boasting accuracy rates near 97%, 90%, and 99.6% for size, horizontal position, and depth, respectively [22]. Furthermore, a method shows promise for complex geometries and diverse materials, although further validation is needed. But in navigating the limits of accuracy challenges remain while a 1-5-5-1 ANN exhibits lower RMS error in predicted failure surfaces compared to analytical methods like Tsai-Wu failure theory [23], which underscores the need for further research on applying machine learning to analytical prediction methods. Similarly, [24] highlights the discrepancy between ANN's delamination detection accuracy in numerical and experimental evaluations, calling for performance improvements. Despite these limitations of optimizing design and performance, ANNs offer valuable insights for design optimization. For instance, FEM, ANN, and experimental data synergy in [25] reveals that Nano-clay and silica composites exhibit superior environmental resistance, with optimized mechanical properties achievable at specific Nano-clay concentrations. Likewise, [26] demonstrates that ANN can successfully analyse various stacking sequences and predict their ballistic limits, opening doors for weight-efficient ballistic performance improvements. Apart from this, DNNs effectively predict mechanical responses compared to conjugate gradient-trained DNNs while RSM-derived polynomial models capture the compressive properties of the beams successfully [27]. Again, machine learning technique optimizes Deep-ANN and fine-tuned Gradient Boosting hyper parameters where YUKI-Deep-ANN and YUKI- Gradient Boosting highlighted superior stability and accuracy in predicting natural frequencies [28].

On the other hand, the versatility of ANNs extends to low-velocity impact scenarios. As noted in [29], they can accurately predict absorbed energy and composite behavior under such loads, provided sufficient training data is available. Back-propagation ANNs also showcase effectiveness in predicting impact energy absorption for blend composites, offering an alternative to traditional methods for optimizing processing parameters for impact resistance [30]. Furthermore, the proposed ANN based new fracture angle search method under LVI for carbon fiber composite is faster, accurate compared with Puck's method and SRGSS algorithm [31] while there are extreme changes in the behavior of fibers and matrix after LVI in GFRP which are predicted by ANN [32]. On the other hand, the fusion of multi-frequency image data with ANNs paves the way for even more precise damage localization, as demonstrated in [33].

In conclusion, ANNs offer a powerful avenue for understanding and predicting the complex interplay between design, performance, and damage in FRCs. Their ability to interpret non-linear relationships, pinpoint defects, and optimize design parameters makes them essential tools for advancing FRC technology. The future lies in exploring advanced ANN architectures like Recurrent Neural Networks for sequence-based data processing and further refining training data acquisition and utilization.

3.1.1.2 Convolutional Neural Network (CNN)

Convolutional neural network (CNN) is another emerging supervised deep neural network (DNN) architecture that is developed from the fully connected feed forward network to avoid fast growth in parameters. The concept is to present convolutional and pooling layers before providing input to a completely connected network. Each neuron in the convolutional layer only associate to partial neurons of the earlier adjacent layer [18]. It also works as human brains (shown in Fig. 5) like ANN which is followed by feed forward neural networks that operate by extracting local features from raw input data in a layer-by-layer for predictions [35]. CNNs consist of convolutional layers, nonlinear layers and pooling layers. The convolutional layers handle fresh input data and produce invariant local features. The non- linear layers apply the activation function such as linear function or gradient based back propagation. The pooling layers pull the most important features by pooling operations such as max and average pooling. Supposing the input data as $x_1, x_2 ...., x_n$ the convolutional process can be described as:

$$c_i = \phi((ux_{i:i+m-1}) + b) \tag{3}$$

where, $x_{i:i+m-1}$ is a concatenation vector, b and ϕ is bias and non-linear activation function. u is a filter vector where: $u \in R^{md}$. A coming map could be given as follows from the beginning through the ending:

$$c_j = c_1, c_2, \ldots, c_{i-m+1} \tag{4}$$

where, index j represents the jth filter [36].

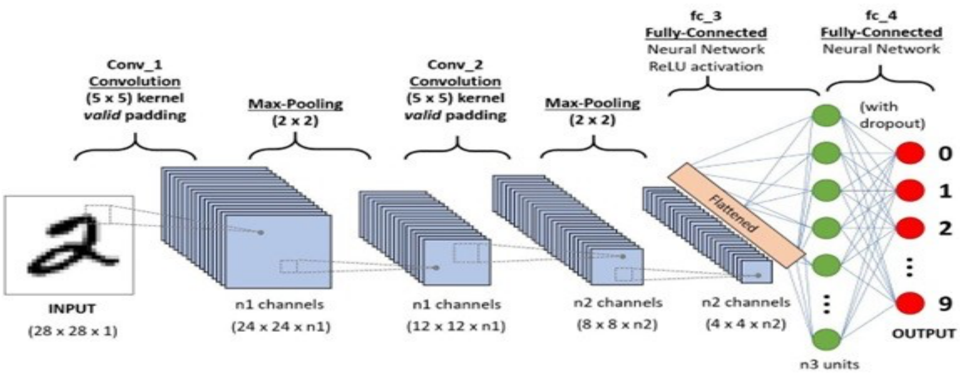

Fig. 5. Convolutional neural networks (CNN)

CNN outperforms regarding damage detection and prediction. Previous studies regarding impact performance and damage prediction (shown in Table 4 and Table 5) of composites reveals that, CNNs excel at extracting local features from raw data through their layered architecture. This makes them ideal for characterizing materials like CFRP, GFRP composites and others. Apart from this Table 4 shows the CNN and deep transfer learning application for impact performance and damage prediction in FRCs where it has been found that the study are mainly carbon fiber composite related where transfer feed forwarded network is widely applied beside CNNs. Experimental, simulation, field, literature data are mainly used for the study to predict impact induced damages where above 90% accuracy achieved for most of the cases. Furthermore, information related to CNNs and feed forward transfer learning model development have been shown in Table 5 where different model details reveals that different convolution layer, pulling layer, number of epochs, padding, kernel size, stride, learning rate and function are employed to achieve desired results of impact image prediction based on input data of images. Beside those parameters different algorithms like batch, Adam, L2 and BPTT are mainly applied for regularization as optimizer. Accuracy, Precision, Recall and F1 score are calculated as performance indicators by confusion matrix besides ensemble, train-test-split and performance metrics calculation method to validate the model. Lastly, available errors for different factors are shown in the table. Following the perspective, the findings in the study listed in the Table 4 and Table 4 highlighting various aspects of FRC's damage classification and prediction are summarized below

Table 4
Convolutional Neural Network (CNN) and deep transfer learning application for impact performance and damage prediction in FRCs

Reference	Composite	Tool	Dataset	Accuracy	Input	Output	Target	Velocity
[43]	Carbon fiber reinforced composites	Deep Neural Network learning (CNN)	162 (cracking) + 4500 (breakage & delamination)- Acustic Emission	99%	AE raw time series and frequency-domain sequence data	Damage classification	Technique for time series classification	-
[44]	Short carbon fiber- filled	CNN	-	High	Microstructural image and Young's' modulus	Stress component	Prediction of full-field stress maps	-
[41]	Fiber- reinforced polymer (FRP)	CNN	149- Literature+ simulation	93%	Materials characteristics and impact test parameters	Post impact test parameters	Damage prediction	-
[38]	CFRP	Cascade Region CNN	2500+500 (training + testing)-Field	94.5%	Damage data	Damage identification	Damage prediction	-
[45]	Carbon/epoxy composite laminate	CNN	60+20 (training + testing)- Literature + simulation		Image Data	Impact characterization	Structural health monitoring	-
[40]	Composite laminate	CNN	-	87%-96%	Image data	Damage severity, types	Damage recognition	-
[46]	CFRP	Deep learning (CNN)	-	96.2%-98.36%	Image data	Damage pattern	BVID detection	Low
[47]	CFRP	Deep learning (CNN)	-	99.75%	Image data for different energy	Image classification	Classification of BVID	Low
[48]	Carbon fiber reinforced plastics	Deep learning	70%+30% (training + testing)	-	Scan data of damages	Depth classification	Defects depth estimation	Low

		(LSTM, CNN, CNN- LSTM)						
[42]	Composite laminate	CNN	7:2:1 (training: testing: validation)	90%-96%	NDT image data	Compressive residual strength	Prediction of compressive residual strength after impact	Low
[49]	CFRP	Auto-Regressive (AR)	-	-	Impact test data	Delamination identification	Detection of LVI delamination	Low
[50]	Composite stiffened panel	PNN (T-Bi-LSTM)	1500	-	Stacking sequence	Discrete feature thickness	Predict the buckling load	-
[51]	CFRP	Bi-LSTM	613 (80% training +20% testing)	95%	Damage Images	Damage Images	Classify BVID	-
[52]	Composite laminate	CNN (VQ-VAE)	Simulation data	-	Damage images	Damage images	Forecast damages	Low
[53]	Carbon fiber composite	LSTM (RNN)	9600- simulation data	90%	Damage images	Damage images	Identify lamination defects	-

Table 5
Convolutional neural network (CNN) model development

Reference	Model Details	Optimization Algorithm	Performance Indicator	Error
[37]	Kernel size [1,N/16], Receptive field N/8, connected hidden layers 128 and 8 neurons in softmax classifier with λ = 4, Final output dimension 8, Training epoch 100, Initial learning rate is 0.001, Decay rate 0.5.	Adam with batch size 64	Accuracy, Recall	-
[38]	Convolution kernel size 3 × 3, 1 × 1 expanded to 2, 1;—total 128 convolution kernels, Intersection over Union (IoU) thresholds 0.5, 0.7, and 0.9	Stochastic Gradient Descent	Precision, recall, Kappa coefficient	-
[39]	Neurons 80, 40, 64, 32, 16; 2 Convolution layer 1; Pooling layer 2; GRU layer 1; Hidden layer 3; Output layer 2, 150 Epochs	Neural Network Intelligence	Precision, recall,F1 score	Verification loss value 0.004
[40]	Convolution layer 1,3 & 5;Kernel size 3 x 3, 5 x 5, 10 x 10, Padding 0,1 & 2; Stride 1,2; Pool size 2 x 2, 3 x 3;Stride [11],[22]; Learning rate 0.0001	Back-propagation	Damage classification time	-
[41]	1, 2, 4, 6 convolutional layers, combinations of 4, 8, 16, 32, 64, 128, 256 nodes. Kernel sizes 3 × 3 to 15 × 15; epochs 200; 2 max pooling with 0.5; ReLU	Adam (L2) with batch size 32	Loss function	7%

[42]	ReduceLROnPlateau function; Convolution layer 2,3;Kernel size 3,5,7,11; Kernel number 8,16;	Back propagation	Accuracy	-
[48]	Softmax function, three-layer and four-layer CNN neural network	Batch normalization	Accuracy, Precision, Recall and F1 score	Avg. depth relative error reduced to 8%
[54]	Convolutional layers 4, Pooling layers 4, Output layers 2, 5000 epochs	Gradient descent	Reliability indexes	Average error within 3%
[47]	ResNet function, 50 layers, Final connected layer 5, Learning rate 0.001,Epochs 100	Class Activation Map (CAM)	Cross Entropy, Accuracy	
[55]	Convolution layer (Filter 3 × 3 &2 x 2; 16,32,48,64 Filters), ReLU layer, Max-pooling Layer (Filter 2 × 2, strides 2), SoftMax function	Batch Normalization	Accuracy	-
[43]	Ssliding filters length and stride 1; Convolutions lengths 10, 20, and 40; Number of filters per layer 32 × 4 = 128 ; RELU function; Batch size = 8; Learning rate = 0.001; Epochs = 100	Gradient descent	Accuracy, Precision, Recall, Specificity and F1 score	-
[56]	Initial learning rate 0.01-1;Learning rate drop period 1-5;Epochs 10-30; Filter size for first, second, third convolution layer 3-10, 2-5, 2-5	L2 regularization	Confusion matrix	Max. & avg. error 7.5-10% & 1.1-3.3%
[57]	ReLU and Sigmoid function; Convolutional layer 2; Kernel size 3 x 3; Max pooling layer 3 x 3; Trainable layers 18	Batch normalization	Accuracy, Precision, Recall and F1	-
[50]	SELU activation function, 201-2304 iterations,	Adam optimizer	R square, MSE	-
[52]	15-channel delamination fields (for the delamination forecast network),16-channel inter-laminar damage arrays (for the matrix damage forecast network), 7 and 15 layers	-	MSE	40 % less error
[53]	Dropout range between 0.1 and 0.6, one hot encoding, voting	BPTT	Cross entropy	-

For instance, [37] showcases a 3D terahertz characterization system powered by a CNN, providing a general method for quality control and inspection throughout the composite's lifecycle. Similarly, the Cascade Region-CNN algorithm in [38] effectively detects damage in CFRP composites from diverse data sources like C-scan and A-scan signals. Again, it works for high accuracy damage detection with deep learning. Like, one-dimensional CNNs trained on A-scan signals demonstrate impressive accuracy in damage detection for fiber-reinforced polymer composites, with LSTM variants outperforming other models in recall accuracy [39]. Furthermore, transfer learning approaches like AlexNet-based CNNs achieve high accuracy (87%-96%) in identifying in-service damage severity, offering promising capabilities for real-world applications [40]. Furthermore, CNNs in predicting impact damage and exploring model refinements also hold promise for predicting impact damage in FRCs. The model proposed in [41] predicts impact damage for given stacking configurations, with further improvements achieved through aggregating multiple CNNs. However, the authors highlight the need for investigating the influence of input parameters and increasing data volume for further model refinement. Besides, CNNs application beyond feature extraction there are application towards automated damage assessment. The ability of CNNs to automatically extract damage features from NDT images is a significant advantage. Research findings in [42] demonstrates the effectiveness of CNNs in replacing manual feature extraction, paving the way for faster and more accurate damage assessment. Further explorations of network architectures and hyper-parameter optimization hold promise for further performance improvements.

In summary, CNNs offer a powerful toolbox for FRC damage identification and prediction. Their ability to extract features, classify damage, and predict impact behavior makes them invaluable tools for advancing NDT and design optimization methodologies. So, CNN innovatively can replace the process of manually extracting damaged features from NDT images as it can extract almost all impact damage features and the experiment proved that the highway structure has a better effect on the prediction results where the number of convolution layers and the number, size of convolution kernels has a slight effect on the results.

3.1.1.2.1 CNN based recurrent Neural Network (RNN) and other transfer learning

Deep learning and neural networks based transfer recurrent learning requires a large number of samples and computational resources in order to train the model [35]. Again, in constitutive model construction; deeper neural networks can consider the subtle connections between different parameters, thereby enlightening deeper relationships among the data [58]. On the other hand, deep learning's ability to leverage pre-trained models known as transfer learning; offers significant advantages while deep learning algorithms are more effective for delamination detection and localization in a continuous structural health monitoring method [59]. In [60], a deep learning model for CFRP composite damage detection outperforms SVR and back-propagation neural networks, achieving better accuracy and faster training times. As for example, CNN based multilevel LSTM achieves exceptional accuracy in defect prediction with over 97% for defect size, over 90% for defect horizontal position and 99.6% for depth prediction for carbon fiber composites [53]. Similarly, attention mechanism enhanced spatiotemporal-based transfer deep learning approach effectively categorizes BVID (barely visible impact damages) in CFRP into their respective energy groups, with or without the attention module where the lesser the ratio between higher and lower impact energy higher the possibility of misclassification between them [51]. This highlights the potential of transfer learning for real-world applications where data availability might be limited. Again, deep convolutional neural networks (CNNs) excel at extracting intricate features from images. The InceptionTime model in [43] demonstrates this strength by effectively classifying three tensile damage types in carbon fiber composites (fiber breakage, matrix cracking, and delamination) with an impressive 99% accuracy. This paves the way for automated and precise damage assessment using deep learning techniques. Besides, deep learning extends beyond damage detection, venturing into stress prediction. The CNN-based cGAN model in [44] accurately predicts the full-field stress distribution in composites under specific conditions. However, further research is needed to explore its applicability to other stress and strain components and diverse failure criteria. On the other hand, the physics-informed CGAN model in [61] efficiently designs composite layups, demonstrating its potential for material design problems with changeable architectures. This opens doors for innovative and optimized composite structures. Additionally, fully connected neural networks (FCNNs) showcase versatility in other areas. As demonstrated in [62], FCNNs can determine optimal stacking sequences and predict global deformations of composite laminates in bird strike scenarios. Similarly, CNN based parallel neural network T-Bi-LSTM demonstrates better competence in mining comprehensive stacking sequences of composite stiffened panel than Bidirectional Long Short-Term Memory network (Bi-LSTM) [50]. This highlights their potential for broader application in various loading conditions and structural challenges.

In summary, memory based multilevel recurrent transfer learning offers a transformative approach to FRC analysis and design optimization. Its ability to achieve high accuracy in damage detection, predicts stress distribution, design optimal layups, and predict global deformations under impacts. But, ensuring data availability, mitigating computational demands, and interpreting complex model decisions remain areas for improvement.

3.1.1.2.2 Hybrid convolutional Neural Networks (CNN) for LVI

There are some hybrid approaches found in the literature to adapt low-velocity impact induced damage classification, identification and prediction. Hybrid deep learning models combining CNNs with LSTMs leverage the strengths of both approaches. As demonstrated in [48], a CNN-LSTM model reduces error in ultrasonic detection of damage in CFRPs under low-velocity impact. Investigating the use of polymer sheets for creating artificial defects can further enhance accuracy. Lastly, there are some challenges and opportunities for future advancements have been identified in literature despite their successes. Like, layup angle and thickness uncertainties, impact strength variations, and boundary condition complexities add noise to model inputs, requiring consideration in future research [54]. Again, CNN based surrogate auto encoder model titled VQ-SM has better performance and robustness on the small dataset to provide full-field damage forecasting for composites under LVI and improving the performance of the “generative” surrogate model [52]. Similarly, another autoregressive approach in [49] successfully identifies delamination-induced damage in composite plates using a reduced number of sensors, demonstrating its potential for high-performance materials. Additionally, another hybrid model differentiating damage patterns caused by slightly different impact energies remains a challenge, as observed in [47]. But data augmentation techniques hold promise to address data imbalances and improve training efficiency described in [55].

3.1.2 Support vector machine (SVM)

Support vector machine (SVM) is a supervised machine learning algorithm that can be used to solve classification and regression problem (shown in Fig.6). The aim of SVM is to maximize the margin between different classes by a finest separating hyper plane in the features. To distribute the input vectors into feature space, different kernels like linear, polynomial, and radial can be used. Kernel function selection is very crucial to achieve a low false alarm rate for binary classification [50].

It maps input features to a converted basis vector and then predicts based on that mapping. In regression tasks, a variant of SVM titled as Support Vector Regression (SVR) is used to guess real value functions. Unlike traditional regression methods, SVR computes error as the distance between the predicted and margin value. The margin zone consists of a predicted value (center) f(x), and width of 2ε. Error is only considered when predictions drop outside of this interval [19]. A decision function f(x) is constructed by Eqn. 5 where $\phi(x_i)$ denotes a nonlinear mapping function. w is a weight coefficient, and b is a bias coefficient [63]. After solving the function f(x) in SVM, to optimize the function $\kappa(x, x_i)$ symbolizes the kernel function, while $\hat{a}_i$ and a_i are the Lagrange multipliers shown in Eqn. (6). These components are used in the optimization to define the optimal hyper plane or regression function [19].

$$f(x) = \prec w, \phi(x_i) \succ + b \tag{5}$$

$$f(x) = \sum_{i=1}^{n} (\hat{a}i - ai)\kappa(x, xi) + b \tag{6}$$

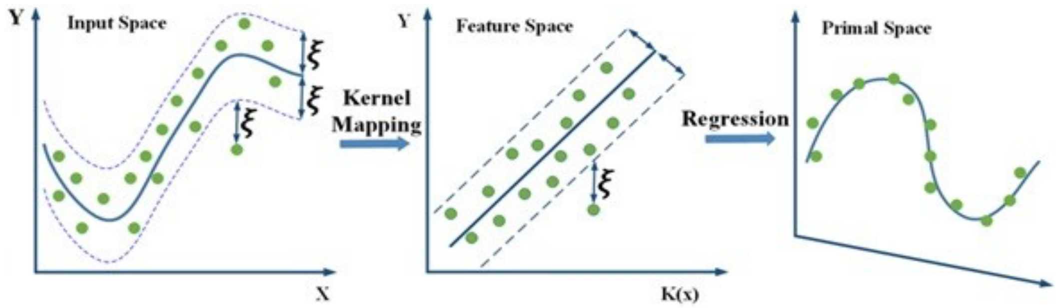

Fig. 6. Support vector regression (SVR)

SVM is effectively applied for pinpointing impact location with precision. Apart from this the application of SVM in predicting impact performance and damage shown in Table 6 and Table 7. In Table 6 it has been found that SVM and its different extensions are applied mainly for carbon fiber composites where above 90% accuracy achieved to predict impact induced characteristics, void contents and location. On the other hand in Table 7 it has been found that Radial basis function and Polynomial function kernel have been widely deployed for the prediction where k-fold cross validation, RMSE and confusion matrix are employed as performance parameter. In the listed studies of Table 6, 7 it is revealed that, SVM's key strengths lies in its ability to accurately localize impact events.

Table 6
Support vector machine (SVM) application for impact performance and damage prediction in FRCs

Ref.	Composite	Tool	Dataset	Accuracy	Input	Output	Target	Velocity
[68]	Polymeric Sandwich structure	SVM	70%+30% (training + testing)	98%	Compressive tests data	Stress and deformation	Prediction of the nonlinear response	-
[70]	CFRP	SVM	-	92.30%	Impact responses	Damage state	Determination of impact damage	-
[71]	CFRP	Regression	-	99.85%	Image data	Void content and location	Effect of void location and content	Low
[66]	FRP composite laminate	Extended support vector regression (C-XSVR)	200+50 (training + testing)-Experiment	-	Images of impact induced damages	Fiber/matrix damage, energy absorption, force deflection curves	Prediction of impact process stages	Low
[72]	CFRP	Least Square Support Vector Regression (LS-SVR)	-	-	Impact responses	Impact location and energy of impact	Impact localization and severity estimation	Low

Table 7
Support vector machine (SVM) model development

Reference	Model Details	Performance Indicator
[63]	Ranges of threshold factor and weight coefficient [0.5, 0.95] and [0.5, 1]; Weight coefficient 0.99; Population size 30; Maximum number of iterations 100	30 times under 5-fold cross validation for RMSE
[65]	Radial basis function (RBF) kernel, Polynomial function kernel	R square = 0.976 RMSE = 0.174%
[73]	Jacobian polynomial kernel function	R-square, root mean square error (RMSE), Relative error
[72]	A classifier with two classes, single input, single output, Bayesian Inference	Performance Index (PI), Euclidian distance
[68]	C=50-2300, Hyper-parameter (Lambda) = 1e7, Epsilon («)= 0.1, Kernel option = 800-1600, Kernel =Gaussian, Radial basis function kernel	Correlation coefficient, Root mean square error
[70]	Radial basis function (RBF) kernel, Polynomial function kernel	4-fold cross-validation, accuracy, precision, recall, average precision

For instance, [64] showcases an SVM model that predicts impact location within 2 inches of the actual point using only four Fiber Bragg Grating Sensors (FBGSs), demonstrating its potential for real-time damage assessment. Similarly, the BDSS-SVR approach achieves satisfactory localization accuracy (average error 3.065 mm) with a minimal number of impact features, making it a robust method for feature selection in low-velocity impact scenarios [63]. However, challenges remain. The need for separate v-SVR models for each coordinate can be time-consuming, prompting further research into multi-output SVR models combined with BDSS for improved efficiency. Again, for porosity detection and reliability assessment SVMs extend beyond impact localization, offering valuable insights into other critical aspects of FRC health. Terahertz time domain spectroscopy combined with SVR analyses porosity in GFRP samples, paving the way for non-destructive on-line detection of this crucial parameter [65]. Furthermore, the ENV (experimental-numerical-virtual) modelling framework in [66] utilizes SVMs for impact analysis, enabling reliability/risk assessments for FRP laminates, potentially preventing catastrophic failures. Besides, SVMs are applied for delamination detection as part of structural health monitoring (SHM) and impact energy estimation. Meanwhile, LS-SVR algorithms coupled with advanced signal processing techniques estimate impact energy with high accuracy (mean error of 3 J) for various impact scenarios in carbon epoxy composites [67]. Furthermore, beyond localization SVMs are applied for classification and feature selection where researches revealed that classification-based SVM models (one presented in [68]) can reconstruct the non-linear compressive response of composite structures with high accuracy (over 98%), even with incomplete data. Additionally, one-class SVMs with appropriate pre-processing techniques excel at anomaly detection and classification which outperform popular methods like k-nearest-neighbours (KNNs) in identifying structural defects [69]. Similarly, extreme learning machines (ELMs) are also used besides SVMs for damage analysis and prediction. Some previous studies compare SVMs with other machine learning algorithms like Extreme Learning Machines (ELMs) for delamination prediction in CFRPs. While both methods offer accuracy, SVM demonstrates superior performance in classifying the delamination interface; while regression tasks is superior in predicting location and size of defects compared to ELM. This highlights the importance of choosing the appropriate algorithm based on the specific prediction task.

Despite having some issues, refining SVMs can be more fruitful for the future of FRCs as SVMs offer a versatile toolbox for FRC damage analysis and prediction. However, challenges remain in terms of computational efficiency, feature selection optimization, and integration with other machine learning techniques.

3.1.3 Decision trees

Decision trees are widely used non-parametric supervised machine learning models which are deployed for classification and regression [Gradient Boosted Regression Trees (GBRT) shown in Fig. 7 as example] composed of a root node, leaf nodes, and branches [35]. The concept behind decision tree learning methods is simple: try out to expand a decision tree by switching a leaf node with a decision node for minimizing the overall empirical risk as much as possible [74]. Each node of the decision tree presents a feature, each branch presents the conjunction of features that proceed to classification, and each leaf node presents a specific class. The decision tree is constructed to exploit the information gain of each variable split, which consequences in a variable ranking. ID3 and C4.5 are recognized algorithms to shape decision trees spontaneously [18]. The variation with regression trees is that decision trees predict categorical values where regression trees predict continuous values. In those types of algorithms, data stream is in the form of:

$$(X, y) = (x_1, x_2, x_3, \ldots, x_k, Y) \tag{7}$$

where x_1, x_2, x_3..., x_k are the predictor variables and Y is the target variable [36].

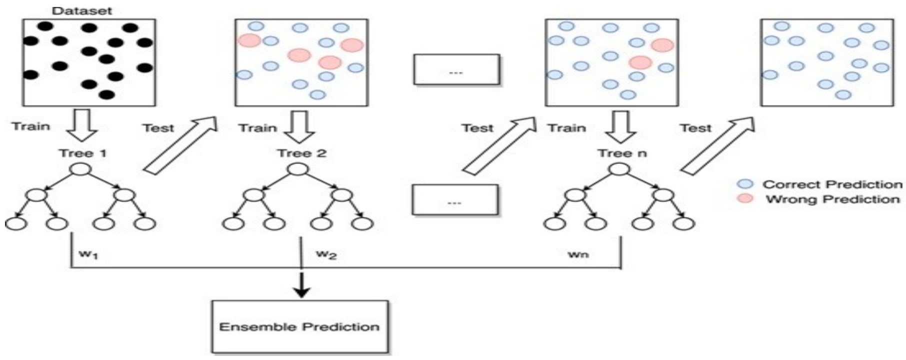

Fig. 7. Gradient boosted regression trees (GBRT)

Previous studies regarding application of decision trees and also their ensemble methods reveals that, decision trees hold promise in predicting ballistic impact resistance and energy dissipation (few examples shown in Table 8). As demonstrated in [75], they outperform support vector and random forest regression in accurately predicting these parameters for unidirectional FRCPs. However, this approach currently overlooks the influence of crucial factors like fiber types, matrix materials, and micro-structural topologies, requiring further refinement for comprehensive analysis. Besides, they are applied for online monitoring with gradient boosting as it is a powerful decision tree-based learning method which offers impressive accuracy and efficiency for online prediction of compression-after-impact (CAI) strength in carbon/glass hybrid laminates subjected to multiple impacts [76]. This opens doors for its application in online structural integrity monitoring of high-performance composite structures, paving the way for proactive maintenance strategies. Again, decision tree-based multi-task learning schemes offer a unique perspective. As shown in [77], they outperform single-task learning in terms of accuracy, performance, and effectiveness. This new approach, with a common layer for shared information, successfully infers dent depth and local volume, demonstrating their high correlation with impact damage in CFRP laminates. This highlights the potential of multi-task learning for problems with multiple inter-related objectives.

Despite successes in previous researches, decision trees face limitations. The relatively smaller number of research studies compared to other machine learning algorithms suggests a need for further exploration. Additionally, refining decision tree models to consider the influence of diverse factors like fiber types and micro-structural topologies is crucial for broader applicability in FRC analysis. So it can be concluded as, decision trees offer a valuable tool for understanding and predicting the behavior of FRCs under various loading conditions. Their potential for accurate ballistic resistance prediction, online CAI strength monitoring, and multi-task learning for uncovering hidden correlations makes them a promising avenue for future research.

3.1.4 Bayesian networks

Bayesian network is a supervised model that uses probability of statistical learning theorem to predict classes within a given set of data which enables the calculation of probabilities for their associated variables including classes [12]. Similar to Bayesian networks are Naive Bayes Networks, a simplest form of Bayesian Networks. The computation of the approach is generally based on the assumption that all the attributes are conditionally independent given the value of the class C. Here, independence stands for probabilistic independence, that is A independent of B given C whenever for all possible values of A, B and C, whenever $P_r(C) > 0$ [36].

$$P_r(A|B, C) = P_r(A|C) \tag{8}$$

Previous studies revealed that, one of the key strengths of Bayesian network lies in its ability to accurately estimate the probability densities for each model input parameter. This allows researchers to identify physically meaningful relationships between design variables and mechanical properties, even when limited data is available [78]. However, further exploration beyond open-hole tensile tests is necessary to validate its applicability to a wider range of mechanical scenarios. Again, Bayesian optimization is also applied for precision impact damage localization as it can be seamlessly integrated with other analysis techniques, amplifying their capabilities. For instance, the fusion of Discrete Wavelet Transform (DWT) and short-time Fourier Transform, when trained with Bayesian-optimized hyper-parameters, achieves impressive accuracy in impact location and damage extent estimation for smart composites [45]. Data augmentation further enhances accuracy, highlighting the potential of this approach for real-time damage assessment. Again, to optimize design for strength and efficiency the power of Bayesian optimization extends beyond damage prediction to guiding the design of optimal composite laminates. Frameworks in [79] utilize it to identify stacking sequences that maximize strength while remaining efficient to manufacture. Additionally, [80] demonstrates how combining classical laminate theory with Bayesian optimization can lead to superior layup angles for carbon fiber composites, optimizing both mechanical properties and production time by utilizing non-conventional angles.

In summary it can be concluded that, Bayesian optimization can be successfully employed integrating with complex multi-scale models and incorporating heterogeneous material properties remain areas for further research. Additionally, balancing computational efficiency with accurate model fitting requires further optimization strategies. So it can be summarized as, Bayesian optimization is able to unveil probabilistic relationships between design parameters and mechanical properties. Combined with its potential for precise damage prediction and optimal design makes it a valuable asset for advancing FRCs technology.

3.1.5 Hybrid

Besides different individual classification and regression-based supervised machine learning approaches of damage and properties prediction, there are a number of researches found where hybrid approach combining both of them is employed to propose the best-fitted model which is shown in Table 8 and Table 9. From which, Table 8 shows the hybrid machine learning application for impact performance and damage prediction in FRCs where the approaches are mainly employed for carbon fiber composite laminate and neural network is applied combined with support vector machine, decision tress, K nearest neighbours, regression and some ensemble methods. These approaches mainly applied to predict different characters and damages of composites which are induced for impacts based on different inputs of composite properties achieved from experimental data and simulation data. On the other hand Table 9 shows the information (model details and performance indicator) of applied hybrid models which revealed that mostly as usual structure of model with k-fold cross validation besides ensemble, train-test-split and performance metrics calculation method have been deployed as discussed in the earlier individual sections of machine learning approach.

Table 8
Hybrid machine learning application for impact performance and damage prediction in FRCs

Ref.	Composite	Tool	Dataset	Accuracy	Input	Output	Target	Velocity
[76]	Carbon/ glass laminate	XGBoost + SHapley Additive exPlanation	80%+20%	-	Impacts, DBIP, impact energy	CAI strength	Compression-after-impact (CAI) strength prediction	-
[83]	Composite laminate	ANN, RF	-	90%	Natural vibration frequencies with delamination	Delamination parameters	Assessment of the delamination	-
[90]	CFRP	Radial Basis Function interpolation	-	High	Impact responses	Damage pattern	Impact localization	-
[96]	CFRP	Decision tree based multi-task learning	75%+25%	70%-80%	Impact tests results and damage images	Impactor shape and delamination extent	Predicting impact damage-related information	Low
[87]	CFRP	Regression and random forest	-	80%	Stacking sequence, impactor shape, and impact energy, damage image	Impactor shape, delamination area and length	Impact damage prediction	Low
[86]	CFRP	PCA, Pearson correlation, K-means++ clustering	-	-	Damage images	Damage images	Damage classification and evolution	Low
[81]	Composite	PCA and DT	2124- Simulation (80%+20%)	-	Defect depth, size, and thickness	Defect character	Prediction of defect & characterization	-
[91]	CFRP	ANN and DT (XGBoost)	Training +Testing + Validation	-	Peak amplitude, duration, rise time, ringing count, energy, RMS voltage, average signal level, and peak frequency	Residual Compressive Strength	Prediction of residual compressive strength	-

[92]	Composite	ANN, GA	5000- Simulation (70%+15%+ 15%)	-	Stacking sequence	Peak stress	Optimization for stacking sequence	-
[82]	CFRP	Kullback–Leibler& Renyi divergence, Hellinger distance	-	-	Damage image	Damage image	Image segmentation o	Low
[85]	Carbon fiber, Polyurethane & Epoxy	PCA, SVM, KNN,DT, RF, NN	25-Experiment (70%+30%)	Ada: 87.83%, 90.54% NN: 97.29%, 98.52%	Damage image	Damage image	Impact damage estimation & localization	-
[95]	Composite	DT, Ensemble DT, KNN,SVM	5 groups each of 20%- Simulation	DT: 81.1-85.4 SVM: 85.9,86.2 KNN 86.0, 86.3 (%)	Stacking sequence	Loading types and locations	Design of a piecewise-integrated bumper beam	-
[93]	Textile Composite	ANN, SVM	420-Experiment	-	Properties of fabric and thread	Mechanical properties	Predict physical properties	-
[89]	Carbon fibre composites	Gaussian Process Regression, ANNs & Multiple Linear Regression	3000-Simulation	-	Micro & meso scale properties	Stiffness matrix	Uncertainty quantification of mechanical properties	-
[94]	Fiber-Metal Laminate	ANN, GA	9000- Simulation (80%+10%+ 10%)		Core density, thickness, applied load	Sandwich structure properties	Multi-objective optimization	-
[19]	Kevlar and carbon with Epoxy	Linear & polynomial regression, SVR, ANN	33-Experiment (80%+20%)	80%, 89%, 94% 96%	Impact energy, laminate thickness	Impact force, displacement & absorbed energy	Evaluate impact behavior	-
[88]	E-glass and epoxy	Ensemble tree, SVR, ANN, K-NN	700- Simulation (80%+20%)	96-99%	Mechanical properties	Damage Properties	Predict damage properties	-

Table 9
Hybrid machine learning model development

Reference	Model Details	Performance Indicator
[76]	**DT:** Number of estimators =30, 50, 100, 300, 500; Maximum depth of tree = 3, 4, 5, 6, 7; **ANN:** Learning rate = 0.01, 0.05, 0.07, 0.1, 0.2	5-fold cross-validation; MSE = 1.7355, 3.2729; R-Square = 0.9977, 0.9960
[97]	**NN**: Multi-layer, 10 neurons, 3 hidden layers, 1 output layer; **RF:** Single decision tree; 10 principal components	RMSE
[84]	**NN:** 2 hidden layers (76 and 36 neurons), Adam optimization & ReLU activation function, Learning rate = 0.8; **KNN:** Number of neighbors 5; DT: Tree depth = 5; **SVM:** Polynomial and RFB kernels (gamma = 0.001 and C = 100)	MSE
[81]	**Ensemble:** Bootstrap aggregating (e.g., Random Forest or Extra Trees) and boosting (e.g., XGBoost), 1500 trees (estimators), Learning rate = 0.1.	k-fold cross-validation R2 = 0.92 to 0.99
[91]	**NN:** 3, 6, 9, 12, and 15 layers, 10 iterations and 15 neurons; **DT:** Grid search for learning rate, maximum depth of trees, and number of estimators	10-Cross fold validation R square = 0.9910, RMSE = 2.9174
[92]	**NN:** 2 hidden layer, 14 and 10 neurons, tangent sigmoid and pure linear unit function, Levenberg-Marquardt optimization; **GA:** Number of Population 100 Selection 50, Crossover 60 Mutation 5%, Number of Generation Value 200	Validation error = 20.12, FEA error = 0.12%, MSE=12.77, R square=0.99996
[85]	**SVM:** Gaussian RBF kernel (gamma = 0.5, c = 1000,8000); **KNN:** K=5,8; DT: depth 10,14;13 estimators, learning rate 0.1; RF: trees 17,16 ; **NN:** Adam with ReLU and SoftMax, 8 hidden layer and 5 output, learning rate 0.05 and 0.01, epochs 80 then 25and 50 epochs; **t-SNE:** perplexity = 50 and 40, No. of iterations = 2000	Categorical cross entropy loss
[95]	**DT:** Max. no. of splits 1~1209; Split Criterion: Gini's diversity index, Towing rule, Maximum deviance reduction; Ensemble **DT:** Max. no. of splits 1~1209, No. of learners 10~500, Learning rate 0.001~1; **SVM:** Kernel function- Gaussian Linear & Quadratic Cubic, Kernel scale 0.001~1000, Box constraint level 0.001~1000, Multiclass method; **KNN:** Number of neighbors 1~605, Distance metric- City block, Chebyshev Correlation, Cosine, Euclidean Hamming, Distance weight- Equal Inverse, Squared inverse	K-fold cross validation
[93]	**NN:** Leaky ReLU, Population size 50, Cross over 70%, Mutation 30%, 30 generations, 100 Epochs, No. of neurons 2 (min) and 30 (max), Learning rate 0.05, 0.2; **SVM**: Linear, polynomial, or RBF kernel	K fold, gradient descent optimization RMSE
[89]	**GPR:** Radial Basis Function (RBF), Mat´ern function (Mat) with ν = 3/2, Rational Quadratic (RQ), Exponential Sine Squared (ESS) and Dot Product (DP); **NN:** ReLU, 20 neurons, 2 hidden layer; MLR: Just simple in python of scikit learn	K fold Cross validation, R square ≥ 0.99 and NRMSE $< 10^{-7}$

Apart from this, a proposed models based on PCA and DT provides an effective benchmark which can be applied in health monitoring of composite materials [81]. On the other hand, Kullback-Leibler divergence is proven as the most appropriate measure compared to Hellinger distance and Renyi divergence for automatic image segmentation of impact damage in CFRP composite [82]. A compelling example of hybrid model proposed in [83], which combines Random Forests (RF) with ANN-based Principal Component Analysis (PCA). This approach, trained on offline data, effectively detects delamination and other defects like cracks, cavities, and fiber breaks in laminated plates online. This demonstrates the potential of hybrid models for real-time damage assessment, encompassing a wider range of damage types than traditional methods. Again, in [84], four machine learning algorithms (MPL, KNN, SVM, DT) are combined to predict four out of six damage properties in Glass/Epoxy laminates which shows high accuracy (4%-6% error) while PCA outperforms ICA in terms of the amount of variance captured per feature for impact damage estimation and localization in composite sandwich under LVI [85]. But in another study; PCA, Pearson correlation and K-means++ clustering shows that, the primary stage is controlled by matrix peeling while the second half of the loading shows matrix peeling supplemented by fiber fracture but future studies require to characterize the damage evolution by recording the long-waveform AE signals of the CFRP under LVI [86]. So these showcase the effectiveness of hybrid models for multi-task learning, where multiple damage properties are estimated simultaneously. However, further research is needed to incorporate other crucial damage characteristics like high-velocity impact, compression-after-impact, and transverse impact for a more comprehensive assessment.

Besides, the study in [87] utilizes a hybrid approach involving ridge regression, logistic regression, and Random Forest (RF) to analyse the relationship between dent surface characteristics and internal damage in CFRP laminates. Notably, this model reveals that local volume, dent surface gradient, and pure dent depth all contribute to damage characterization. Again, ensemble tree boosting, SVR, ANN, KNN for predicting the damage behavior of E-glass/Epoxy composite shows that, the best-performing model for higher surface areas of the indenter increased is KNN as it can capture complex and nonlinear relationships between the input features and the target variable with better accuracy and precision [88]. While, Gaussian Process Regression (GPR) compared to ANNs, and Multiple Linear Regression (MLR) is found superior for underlying the relationships between the micro-scale and macro-scale mechanical properties [89]. These highlight the potential of hybrid models to uncover hidden relationships and refine existing damage assessment methodologies. Furthermore, the hybrid model in [70] combines SVM with a radial basis function (RBF) kernel for impact damage detection in CFRP using sensors. This approach achieves an impressive accuracy of 92.30%, showcasing the potential of hybrid models for precise damage localization and identification whereas a novel radial basis function interpolation approach reduces error by around 90% at different energy levels, with an estimated location error below 10 mm [90].

Following the perspectives, more hybrid algorithm applications are found in the literature to predict different impact properties and performances by targeting the design optimization of composite materials. Such studies reveal that, impact resistance and residual compressive strength of CFRP decreased as the impact energy increased while the rate of decline in residual compressive strength slowed with respect to impact energy predicted by ANN and DT (XGBoost) [91]. Similarly, deployment of linear regression, polynomial regression, SVR, ANN suggests that, the impact force increased by 118.5 % in CFRP and 175.8 % in Kevlar composite, while the hybrid layer showed a 101.4 % increase upon impact from 16J but for absorbed energy. While, with the increase of laminated layers carbon fiber laminate absorbs 4.8 times more energy and Kevlar fiber and hybrid composites absorb 3 times more. On the other hand, application of ANN and GA shows that, the peak stress can be reduced by 37.3% with the burst pressure while the burst pressure can be increased by 13.4% by optimizing the stacking sequence [92]. Moreover, regarding design optimization earlier researches shows that, the application of ANN and SVM finds the optimal accuracy and predictive models shows superior performance for physical properties to enhance materials' design, process optimization, and product performance. But further research recommended for image-based analysis and spectral imaging to extract rich structural and compositional information from composites [93]. Again, a newly elaborated methodology based of ANN and GA demonstrates accuracy for optimum design of composite sandwich fabricated from honeycomb core and laminated face sheets [94] while DT, Ensemble DT, KNN,SVM application to design piecewise-integrated composite bumper beam shows that 3D implementation produces better results compared to 2D [95].

In summary; integrating diverse algorithms, optimizing hyper-parameters for each component and ensuring computational efficiency require further research. Additionally, exploring hybrid models for more complex tasks like damage prognosis and remaining life prediction is a promising avenue for future investigation. Lastly, hybrid machine learning models offer a powerful and versatile approach for FRCs damage prediction and property estimation. Their ability to combine the strengths of individual algorithms expands damage detection capabilities, uncover hidden relationships, and achieve high accuracy.

3.2 Unsupervised Approaches

There are a minimum number of attempts (some examples shown in Table 10) found in the literature regarding application of unsupervised machine learning approaches for impact performance and damage oriented research as they do not have corresponding output and the achieved results might not be as much of accurate. This is because of unlabelled input data and unawareness of algorithms about exact output in advance though they help to find useful insights from the data. Previous literature shows that, K-means is prominently employed approach which classifies a set of unlabelled data into different clusters. K represents the number of preferred clusters which have a great impact on the algorithm performance. The function of k-means presents the distance between data and related centroids. K-means allocate each data to a cluster with the centroid that is adjacent to the data. The procedure of updating centroids based on an allotted data point will be continual until no data point or centroid varies [18]. For an initial set of k-means m_1, $m_2 .... m_n$ proceed by alternating between two steps [36]:

a. Allocate instances to the clusters whose mean have the least squared Euclidean Distance:

$$S_i^t = x_p : ||x_p - m_i^t||^2 \leq ||x_p - m_j^t||^2 \; \forall j, 1 \leq j \leq k \tag{9}$$

b. Compute the new mean centroids of clusters:

$$m_i^{(t+1)} = 1/|S_i^{(t)}| \sum x_j \in S_i^{(t)} x_j \tag{10}$$

Table 10
Unsupervised machine learning model development

Reference	Composite	Tools	Model Details	Performance Index	Target
[98]	Carbon fiber reinforced laminate	K means	Partitioning-based data clustering, T2 modules, Bivariate	Correlation matrix (R)	Damage assessment
[99]	Carbon/glass fiber–reinforced hybrid	Fuzzy c-means	3 Clusters	Silhouette index, Davies–Bouldin index	Cluster analysis of acoustic emission signals and tensile properties
[101]	Carbon fibre reinforced polymer	PCA) and the K-means++	3 and 4 Clusters	Silhouette index, Davies–Bouldin index	Fatigue damage monitoring
[102]	Flax/carbon fiber hybrid reinforced polymer	K means	4 Clusters	-	Effect of volume ratio and hybrid mode on LVI properties

Apart from this, earlier researches reveals K-means as a clustering method which divides the unlabelled multidimensional dataset into different clusters of similar properties [9]. Another study [98] demonstrates how K-means clustering of bivariate data can effectively characterize the structural behavior and non-destructively monitor damage in CFRP specimens. This approach classifies different damage mechanisms by clustering acoustic emission (AE) signals into relevant categories, highlighting its potential for real-time damage assessment. Again, Fuzzy C-means (FCM), another valuable unsupervised tool, further expands the possibilities which works as soft cluster algorithm to make each input vector for representing the similarity with one vector shared with each cluster with a function. The value of membership parameter of this algorithm is between 0 and 1. Research in [99] combines FCM with both AE and digital image correlation (DIC) data. This powerful combination unlocks insights into the damage process of composites, providing information on both internal (AE) and external (DIC) damage manifestations. This opens doors for comprehensive damage characterization in a single framework. On the other hand, beyond characterization unsupervised methods can even predict impact location. The k-order sum of squares of deviations proposed in [100] successfully predicts impact positioning for carbon fiber composites under different energy levels. Additionally, [101] utilizes a combination of Principal Component Analysis (PCA) and K-means++ to identify damage modes in CFRP laminates based on AE and DIC data. The clusters obtained align well with microscopic observations of the fracture surface, validating the approach's accuracy. Furthermore, K-means can also reveal hidden relationships between material properties and damage behavior. In [102], cluster analysis of AE signals in hybrid fiber reinforced polymer composites reveals a gradual increase in peak frequency with increasing carbon fiber content. This suggests a link between fiber content and damage mechanisms, providing valuable insights for material design and optimization.

Apart from the reviewed studies, it can be summarized that unsupervised learning methods are underutilized in research related to predicting the impact performance and damage of fiber-reinforced composites primarily because the problem is inherently a supervised learning task. Supervised methods are better aligned with the research goals, provide more interpretable results, and are more effective at making accurate predictions. However, unsupervised learning methods could still play a complementary role in data exploration, anomaly detection, and dimensionality reduction. So, the application of unsupervised approaches for impact performance and damage oriented research can be further explored by selecting appropriate distance metrics, optimizing cluster numbers, and integrating with other algorithms to refine predictions. Additionally, exploring more complex unsupervised techniques like self-organizing maps and deep clustering holds significant potential for uncovering even deeper insights into FRCs damage processes.

3.3 Alternative Approaches

Besides different familiar supervised and unsupervised approaches of machine learning application in the area of impact performance and damage, there are some other approaches also incorporated by the researchers. Like, outlier analysis (OA) offers a unique perspective on impact detection and categorizes impact events. By using machine learning or data-driven methods, OA can identify and categorize impact events based on structural response data. This approach can differentiate damaged and non-damaged features, classify failure modes, and even detect the presence of subtle damage, making it a valuable tool for early damage assessment. Another approach i.e., Genetic Algorithm effectively applied for simulating progressive damage for design optimization. In [103], a genetic algorithm simulates both intra-laminar damage (tension and compression) and inter-laminar damage (delamination) in carbon fiber reinforced polymers under low-velocity impact.

This enables researchers to optimize design parameters based on realistic damage scenarios, leading to more robust and resilient structures. Again, structure genome (SG) based machine learning offers a powerful tool for designing 3D woven lattice structures (WLSs). By analysing existing WLSs and their performance data, SG models can accurately predict compression strength and modulus [104]. This allows researchers to learn from existing designs and create new optimized WLSs with improved performance which pave the way for intelligent material design. Furthermore, the multi-output random forest regression model in [105] demonstrates the potential of machine learning for real-time structural performance monitoring. By considering void content and location; this model predicts force-time, displacement-time, and energy-time curves with high accuracy and speed, making it a valuable tool for online assessment of low-velocity impact behavior in structures. Additionally; logistic regression, combined with the Probability of Detection (POD) criterion, offers a unique approach in predicting the visual detection probability of impact damage [106]. This model with an accuracy of nearly 85% can account for factors like dent depth and diameter, detection type, distance, and personnel qualifications which provide valuable insights into the human factor in damage assessment. On the other hand, another comparative study regarding fused deposition modeling (FDM) Parameters optimization for Improving tensile strength showed that, the performance of the particle swarm optimization (PSO) algorithm works well than response surface methodology (RSO) algorithm [107].

From the above discussion it can be concluded that, the landscape of FRCs damage analysis and prediction is expanding beyond the boundaries of conventional machine learning. Outlier analysis, genetic algorithms, structure genome models, multi-output regression, and logistic regression offer alternative perspectives and valuable insights into impact behavior and damage detection. But, OA requires careful selection of features and robust distance metrics, while genetic algorithms can be computationally expensive. SG-based models need large datasets for training, and multi-output models require careful optimization of hyper-parameters.

3.4 Preview and Summary Discussion

a) Traditional vs ML: There are various researches carried out by the researchers based on the application finite element analysis (FEA) and machine learning (ML) to predict impact performance and damage of fiber reinforced composites (FRCs) considering data mostly generated from experimental test, simulation and sometimes combined including use of data augmentation technique. As per reviewed studies, ML models excel in providing fast, accurate predictions for low-velocity impact damage when trained on high-quality data. They are particularly useful for real-time applications and scenarios where computational efficiency is critical while FEA provides detailed, physics-based predictions of damage mechanisms but can be computationally expensive and requires accurate input parameters. On the other hand, hybrid approaches combining ML and FEA offers a promising direction, leveraging the strengths of both methods to improve accuracy, efficiency, and applicability in practical settings. So, both FEA and ML models have demonstrated efficacy in predicting low-velocity impact damage in fiber-reinforced composites. The choice between them, or the decision to employ a hybrid approach, depends on specific requirements such as the desired balance between computational resources with efficiency, accuracy, the availability of data for model training, real-time predictions and the level of detail required in damage analysis.

b) Library and framework: Machine learning algorithms aided design of reinforced polymer composite and hybrid material systems is widely reviewed in [13], where different libraries with frameworks are deployed to apply different machine learning techniques as part of design optimization of reinforced and hybrid polymer composites. Among them Tensor Flow, PyTorch, MATLAB are mostly deployed libraries with Scikit-learn, Keras frameworks besides Weka, R-language, RapidMiner. Regarding different libraries and frameworks application reviewed studies disclose that, the choice of ML libraries and frameworks for FRCs damage prediction depends on the specific requirements of the research or application. But in general; TensorFlow library with Keras and Scikit-learn framework have been ideally applied for large-scale, production-ready deep learning models where it shows high computational efficiency and accuracy. Similarly, PyTorch is well-suited with Scikit-learn for research like prototyping where it shows good performance with accuracy on smaller to medium-sized datasets. Additionally, MATLAB is conveniently used for smaller datasets as traditional ML models, especially in multidisciplinary engineering environments which shows less efficient for large-scale or deep learning applications compared to others.

c) Model comparison for consideration: Most machine learning algorithms are used to predict the mechanical performances of composites for design optimization besides some applications of impact induced damage analysis. Though existing literature shows deployment of different software for the implementation of different machine learning approaches but there are some strength, weakness of those applied traditional and deep learning models through different software which are found in [35]. Finally, on the basis of evidence found in [13], [35] and in the earlier literatures regarding machine learning-based impact performance and damage prediction, design of reinforced composites, statistical index analysis based on training and testing scores; summary is presented in Table 11. From the Table 11 it is revealed that present literature on impact performance and damage prediction for FRCs relies on few machine learning techniques i.e., neural networks (ANN, CNN), regression and classification (SVM, DT) besides deep learning and unsupervised learning (mostly K-means) though they all have certain considerations for applications.

Table 11
Summary of different ML techniques' application for impact performance and damage prediction for FRCs

Sl. No	Technique	Type	Key features	Consideration for applications
1	Artificial Neural Network (ANN)	Supervised	Design optimization, performance and damage prediction	Exploring advanced architectures for sequence-based data processing, further refining training data acquisition and utilization
2	Convolutional Neural Network (CNN)		Damage identification and prediction	Effects of no. of convolution layers and the number, size of convolution kernels
3	Support Vector Machine (SVM)		Damage analysis and prediction	Computational efficiency, feature selection optimization and integration with other techniques
4	Decision Trees (DT)		Performance and prediction	Multi-task learning integration for uncovering hidden correlations
5	Bayesian Optimization		Design optimization and damage prediction	Computational efficiency with accurate model fitting
6	Hybrid techniques		Damage detection and prediction, property estimation	Optimizing hyper-parameters, computational efficiency
7	Unsupervised techniques	-	Impact and damage analysis	Appropriate distance metrics, optimizing cluster numbers and integrating with other algorithms
8	Deep Learning (DL)	-	Damage analysis, design optimization	Data availability, computational demands, interpreting complex model decisions
9	Alternative techniques	-	Impact behavior, damage analysis and prediction	Selection of features and robust distance metrics, computational cost, large datasets, optimization of hyper-parameters

d) Model validation: Studies of predicting the impact performance and damage of fiber-reinforced composites, ML models are typically validated using a most combination of different methods like cross validation, train-test-split, performance metrics, and ensemble. Though, the cross-validation methods are consistently applied in most studies to ensure that the model's performance is not dependent on a single train-test split. But, the choice of validation technique depends on the size and nature of the dataset, the complexity of the problem, and the specific goals of the research. Robust validation ensures that the models are accurate, reliable, and capable of generalizing to new data. It is further to be mentioned regarding validation that, in the application of machine learning models the overfitting issue is addressed through a combination of regularization, early stopping, feature selection, ensemble methods, and independent validation. These strategies ensure that the ML models generalize well to new data and provide accurate predictions of impact performance and damage.

e) Environment and ethics: The reviewed studies show very few environmental or ethical implications of using machine learning for FRCs materials design and impact prediction. As for example, a study shows that composites containing nano-clays show higher resistance to severe environment according to FEM, ANN, and experimental data [25]. On the contrary another review study mentioned that, it is tough to guarantee that the ML algorithms will perform well in industrial environments [12]. However, the use of ML for FRC materials design and impact prediction has significant environmental and ethical implications. Different ML models can contribute by different ways to sustainability by optimizing the use of eco-friendly materials, reducing waste, and improving energy efficiency. Additionally, ethical considerations such as bias, transparency, job displacement, and data privacy must be addressed to ensure responsible and equitable use of ML technologies. By leveraging the strengths of different ML models, researchers and practitioners can develop innovative solutions that promote sustainability and ethical practices in the design and manufacturing of FRCs.

f) Best fitted model: Review and evidence on performance metrics shows that, deep learning technique especially convolutional neural network is best fitted for damage identification and prediction as evidence found in present literature that it can extract all images of induced damages. While artificial neural network and classification, regression based technique i.e., support vector machine are best fitted for property estimation and design optimization because of high performance in capturing training data patterns and predicting properties with high correlation coefficients. Though, all have some issues like number and size of convolutional layer, computational cost, integration with other techniques, hidden co-relations. Besides, the performance of models is subjective to different factors, including model type, training dataset size, input parameters (material type, material content, and manufacturing processes), and the statistical index used to assess the performance [108].

g) Future model features: To improve the prediction of fiber-reinforced composites (FRCs) impact performance and damage requires incorporating a wide range of key factors and features into future machine learning (ML) models. Future ML models for predicting the impact performance and damage of FRCs should incorporate a comprehensive set of features including material properties (like fiber type and properties, matrix properties, interface properties); structural characteristics (like lay-up configuration, geometric features, manufacturing defects**,** reinforcement architecture); loading conditions (like impact energy and velocity, loading rate, impact angle and location, multiple impacts); environmental factors (like temperature, humidity and moisture, chemical exposure, UV radiation, ageing and fatigue) and data-driven insights (like experimental, simulation, sensor, historical). Advanced features such as multiscale modeling, damage mechanisms, nonlinear behavior, and uncertainty quantification can further enhance the accuracy and robustness of these models. By integrating physics-based knowledge and real-time data; ML models can provide more reliable and actionable predictions, enabling the design of safer and more efficient composite structures. Additionally, incorporating sustainability and eco-friendly features can support the development of environmentally responsible FRCs.

3.5 Challenges & Opportunities

Machine learning (ML) and, to a growing extent, deep learning (DL) is revolutionizing the field of composite materials, offering promising tools for predicting their properties and damage behavior. While different limitations exist (outlined in[13]), the insights gained from these approaches have been valuable [35] for predicting impact performance and damage of FRCs. But, there is need to bridge the gap between simulation and reality. Current research primarily focuses on simulated data or test specimens, achieving high accuracy in controlled environments. However, studies on real structures are scarce and often show lower accuracy. Bridging this gap; through robust ML techniques implemented in real-world settings is crucial for improving effectiveness and generalizability [109]. Again, machine learning-based damage recognition in composites often relies on k-means clustering. While this approach has yielded promising results, future work should prioritize ensuring the accuracy of clustering labels and minimizing quantization error. Additionally, exploring more advanced methods especially deep learning models that go beyond k-means can potentially lead to even more accurate and robust damage detection [110]. On the other hand, integrating non-destructive evaluation (NDE) with AI techniques like ML and DL holds immense potential for designing and manufacturing high-quality and sustainable fiber-reinforced polymer composites [111]. For that, it is necessary to extend the application of data-driven methods in multiscale and multi-physics modelling to enhance computational efficiency and interpretability of failure mechanisms in composite modelling [112]. This synergy can unlock new possibilities in material characterization, leading to the discovery of novel multi-functional composites. Lastly, the latest advancements in ML, such as hybrid algorithms, adaptive and reinforced learning, physics-informed ML, and multi-fidelity modelling, offer exciting opportunities for composite materials research. Integrating these techniques can open up countless possibilities for exploring trends, patterns, and efficient computational relationships to improve the characterization of existing composites and pave the way for the development of new materials with unique functionalities [113].

Present studies have some pressing challenges, limitations which exhibit the future research directions. Among different challenges and limitations; quality, consistency and availability of dataset, generalization across materials and conditions, selection of hyper parameters issue for accuracy and generalization, interpretability and trust issue due to black box nature, integration of physics based knowledge, multiscale and multi physics phenomena, uncertainty quantification, experimental verification, prediction of overall mechanical properties, computational resources with cost and time issue are prominent and demanding. So, despite of promising potential with several challenges machine learning and deep learning offer a powerful toolkit for predicting properties and damage in composite materials. But, addressing the limited availability of large datasets for composites by data augmentation technique, combining physics based model with ML and hybrid models, enhancing model interpretability by explainable AI technique, multi-scale modelling, fostering collaboration between ML researchers and experimentalists or material designers and developing domain-specific AI models tailored to the unique characteristics of composite materials are crucial steps towards realizing the full potential of ML in this field [13][35].

As per above discussion on mentioned challenges, few can be summarized under scalability as most pressing one in machine learning application in FRCs impact and damage prediction. There are significant scalability concerns to more FRCs complex composite structures or real-time damage detection systems in industrial settings. These concerns arise from the increasing complexity of the structures containing high dimensionality, multiscale phenomena and nonlinear behavior of materials, real-time damage detection systems, industrial deployment robustness, data quality and availability, compatibility with existing system, computational resources utilization, regulatory standards and ethical consideration. The scalability concerns are significant but can be addressed through a combination of technical and organizational solutions. Key strategies include optimizing model complexity, leveraging edge and cloud computing, improving data quality, and ensuring robust integration with existing systems. By addressing these challenges, ML can be effectively scaled to meet the demands of industrial applications, enabling more accurate and efficient damage detection and prediction in FRCs complex composite structures. Despite of those challenges, the following potential opportunities can be breakthroughs to revolutionize the design, analysis, and maintenance of FRC structures, enabling safer and more efficient applications across industries.

i. ML models can be integrated with sensor data to enable real-time monitoring and damage prediction in FRC structures which can lead to develop lightweight, edge-computing ML models for real-time SHM in aerospace, automotive, and civil infrastructure applications.
ii. ML can be used to optimize FRC layups, material compositions, and geometries for improved impact performance. Combine ML with generative design algorithms can be used to create novel FRC architectures with enhanced damage resistance.
iii. ML can bridge the gap between different length scales (e.g., micro, meso, macro) to provide a comprehensive understanding of FRC damage mechanisms by integrating data from molecular dynamics simulations, micromechanical models, and macro-scale experiments.
iv. ML can be used to create digital twins of FRC structures, enabling real-time updates and predictions based on sensor data and environmental conditions by integrating ML with IoT (Internet of Things) and digital twin technologies for predictive maintenance and lifecycle management.
v. ML can identify anomalies in FRC structures (e.g., manufacturing defects, impact damage) and predict their progression over time by developing unsupervised or semi-supervised ML models for anomaly detection and prognostics in FRCs.
vi. Combining ML with physics-based models can improve accuracy, interpretability, and generalization by developing hybrid models that leverage the strengths of both approaches, such as physics-informed neural networks (PINNs) or ML-enhanced FEA.
vii. ML models that quantify uncertainty can improve decision-making in design and maintenance by developing Bayesian ML frameworks or ensemble methods for uncertainty-aware predictions in FRC applications.
viii. ML can optimize the additive manufacturing process for FRCs, ensuring consistent quality and performance by using ML to predict and control defects.
ix. ML can predict the impact of environmental factors (e.g., temperature, humidity) and aging on FRC performance and damage by developing models that account for long-term environmental degradation and fatigue in FRCs.

4. Conclusion

The application of machine learning techniques in predicting impact performances and damages of FRCs represents a promising avenue for advancing the field. This review has meticulously explored the diverse landscape of machine learning applications in predicting impact performance and damages of FRCs. The strengths of regression models, the adaptability of classification techniques, the depth of neural networks, and the collective power of ensemble methods provide a rich toolkit for researchers and engineers. However, acknowledging the existing challenges, the review has emphasized the immense potential of machine learning for not only enhancing characterization and prediction accuracy but also optimizing design, guiding manufacturing and real-time health monitoring. Lastly, the findings of this whole review can be summarized as

i. The research trends on the application of ML approaches over traditional FEA to predict impact performances and damages tend to increase day by day where supervised methods with labeled data from experimentation and simulation with augmentation showed the best results for impact damage classification and characterization tasks.
ii. Different libraries and frameworks mostly Tensor Flow, PyTorch, MATLAB are deployed with Scikit-learn and Keras for the impact performance and damage prediction.
iii. In general SVM, DT, Bayesian tool are mostly applied learning approaches while neural based ANN, CNN are deployed significantly. Similarly, a decent number of hybrid approaches (mixing of ANN, KNN, DT, SVM, PCA, Ensemble) are reveled besides some unsupervised (mainly K-means, Fuzzy C Means) and alternative approaches (OA, GA, SG) deployment for predicting performance and damage. Moreover, deployed models are mostly validated by consistent cross validation, train-test-split, performance metrics, and ensemble technique.
iv. ANN is found as one of the powerful approaches for understanding and predicting the complex relationships between design, performance, and damage in FRCs because it can interpret non-linear relationships, pinpoint defects, and optimize design parameters.
v. CNN is revealed as dominant for FRCs damage identification and prediction which can replace the process of manually extracting damages from NDT images in future as it is able to extract almost all impact damages. On the other hand, memory based multilevel recurrent transfer learning offers a transformative approach to FRC analysis and design optimization.
vi. SVMs are widely deployed for FRC damage analysis and prediction but issues to be considered are - Computational efficiency, feature selection optimization, and integration with other techniques.
vii. Decision trees are applied mostly for understanding and predicting the behavior of FRCs under various loading conditions besides accurate ballistic resistance prediction, online CAI strength monitoring but they need refining in terms of factors like fiber types and micro-structural topologies.
viii. Bayesian optimization is successfully employed to unveil probabilistic relationships between design parameters, mechanical properties and precise damage prediction but incorporating with complex multi-scale models and heterogeneous material properties need further refinement.
ix. Hybrid machine learning models offer a versatile approach for FRC damage prediction and property estimation which can be further explored through damage prognosis and remaining life prediction.

x. Unsupervised approaches require more exploration to uncover deeper insights of FRCs performance and damage processes. On the other hand, application of other different alternative techniques has shown perspectives and valuable insights into impact behavior and damage detection but require careful selection of features and optimization.
xi. Most machine learning algorithms have been used to predict the mechanical performances of composites for design optimization besides some applications of impact induced damage analysis.
xii. Present studies have some challenges and limitations which exhibit the future research directions. Among them; scalability of the application of machine learning models, quality with consistency and availability of dataset, selection of hyper parameters and generalization; interpretability issue; experimental verification; prediction of overall mechanical properties; computational resources with cost and time are prominent.
xiii. Future models for predicting the impact performance and damage of FRCs can incorporate a comprehensive set of features including material properties, structural characteristics, loading conditions, environmental, sustainable and ethical factors, data-driven insights, multiscale modeling, damage mechanisms, nonlinear behavior, uncertainty quantification, integration of physics-based knowledge.

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