Shear strength prediction of reinforced concrete beams using machine learning

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Review on Shear Strength Prediction of Reinforced Concrete Beams Using Machine Learning

Abstract: Recent years have witnessed a surge in the application of machine learning techniques for solving hard to solve structural engineering problems. The application of machine learning can replace the use of empirical and semi-empirical prediction models currently used in practice with highly accurate models. This paper provides a detailed discussion on the basic terminologies and concepts of commonly used machine learning algorithms for solving structural engineering problems. To provide confidence to use this method and show the potential of machine learning in accurately predicting the results of complex civil engineering problems, a comprehensive literature review on the application of machine learning in shear strength prediction is also presented. The literature review covers the application of different machine learning algorithms in predicting the shear strength of conventional concrete beams, steel fibre reinforced concrete beams, beams reinforced with FRP bars as well as high strength concrete beams. Major observations, challenges and future scope in this field are also discussed in detail. This article will be a valuable resource for individuals who are unfamiliar with machine learning yet aspire to learn more about it.

Keywords: Machine Learning, shear strength prediction, ANN, artificial neural network, shear strength.

1. Introduction

Shear failure is the most critical failure in a beam because of its brittle nature. Unlike flexure failure, the occurrence of shear failure in a beam can lead to a sudden structural collapse [1–4]. The shear capacity of concrete structural elements can be increased by adopting different methods such as adding discrete fiber into the concrete matrix, using fiber-reinforced polymer (FRP) sheets, and using high-strength concrete. [5,6,15–24,7–14] Numerous investigations have been conducted and are still on going to understand the exact underlying mechanism of shear transfer happening during the collapse of a structural element. After the formation of shear cracks in beams, the shear transfer mechanism is highly uncertain because it is influenced by numerous parameters, and the relationship between the shear strength and these parameters is nonlinear. The presence of fibers in the concrete matrix further complicates the shear transfer mechanism and makes it much harder to understand. Consequently, shear design is typically performed based on empirical and semi-empirical relations developed by different researchers and suggested by international codes [25,26]. These empirical equations were developed based on the results of experimental investigations carried out by various researchers. The shear strength prediction made by these models can vary considerably because the number of influencing parameters and the parameters considered for developing these models can be different[27,28]. Numerous efforts have been made to understand the actual shear transfer mechanism and develop an accurate relationship between the shear strength and influencing parameters.

In recent decades, machine learning (ML) has attracted attention for finding solutions to highly complex problems. A significant advantage of ML models is their ability to automatically analyze and learn associations between different parameters. This ability can help evaluate the influence of different parameters on shear strength and understand the complex relationship between them. Accordingly, new shear strength prediction models can be developed by utilizing ML for making accurate predictions. Amani and Moeini proposed shear prediction models using an artificial neural network (ANN) and the adaptive neuro-fuzzy inference system (ANFIS) [29]. A comparison between the proposed method and the relations in American Concrete Institute and Iranian Concrete Institute codes was performed for predicting the shear strength of reinforced beams. Researchers have observed that the prediction made by their ANN models with multilayer perceptrons using a backpropagation algorithm exhibited superior performance than other models. Abdalla et al. also employed an ANN with a backpropagation algorithm to predict the shear resistance of reinforced concrete beams with rectangular sections [30]. Different activation functions were utilized in their investigation. They concluded that the proposed ANN models could accurately predict the shear resistance of beams with rectangular cross-sections. In a separate study, Naderpour and Mirrashid demonstrated the potential of ANFIS in predicting the shear strength of reinforced concrete beams with stirrups [31]. Moreover, Chou et al. proposed a novel hybrid artificial intelligent model that combined a smart firefly algorithm and least squares support vector regression for predicting the shear strength of different types of reinforced concrete beams [32]. They compared the prediction efficiency of the proposed hybrid model with those of standard ML models, ensemble models, and empirical methods to demonstrate its prediction superiority. A random forest model was proposed to perform the shear design of reinforced concrete beams with and without stirrups [33]. Asteris et al. evaluated the potential of surrogate approaches, such as ANN models in predicting the shear capacity of concrete beams with transverse reinforcements [34]. They reported that such methods were highly effective in evaluating the shear strength of reinforced concrete beams.

Adhikary and Mutsuyoshi developed two shear strength prediction models for steel fiber-reinforced concrete (SFRC) beams using an ANN [35]. The first and second models considered five and four input parameters, respectively. The performance of the models was compared with the results predicted by the equations proposed by Swamy et al. and Khuntia et al. [12,36]. It was observed that both the proposed models made superior predictions compared with empirical relations. Yaseen et al. proposed a novel hybrid shear strength prediction model by combining the support vector regression (SVR) algorithm with particle swarm optimization (PSO) for SFRC beams. A comparison of the performance of the proposed model with that of another ANN-PSO hybrid model highlighted the superior prediction capacity of the SVR-PSO model. Keshtegar et al. developed a novel response surface method (RSM) coupled with a SVR hybrid model for predicting the shear resistance of SFRC beams [37]. Researchers have compared the performance of their hybrid model with the predictions made by standalone ML models, such as RSM, SVR, neural network (NN), and eight empirical relations. The newly developed models outperformed the prediction capacities of the other models. In a separate study, Tanarslan employed an ANN to predict the shear strength of concrete beams retrofitted with a side-bonded FRP [38]. Tanarslan reported good conformance with the experimental results, and the predictions were more accurate than those obtained using the theoretical guidelines. Furthermore, Nasrollahzadeh and Basiri proposed an original shear strength prediction model for concrete beams reinforced with FRP bars using a fuzzy inference system. They used the proposed ML model that outperformed the design provisions for the shear strength of FRP-reinforced concrete beams suggested by ACI 440-06 and CSA S806-02. Two ANN models with backpropagation were developed by Tanarslan et al. to predict the shear strength of reinforced concrete beams externally bonded with carbon fibre reinforced polymer (FRP) sheets [39]. Subsequently, the predictions made by their models were compared with the shear strength calculated from the American guideline (ACI 440.2R) and the Australian guideline to comprehend the effectiveness of the newly developed models. It was found that the shear strength predicted by the proposed models was far superior to that predicted by international standards.

Based on the literature, it can be stated that ML has huge potential to solve complex problems associated with practical engineering. Besides, good knowledgeability in this field will enable researchers and the engineering community to explore its possibilities and find solutions to hard-to-solve problems. As this field is rather new to civil engineers, this study has two main objectives. The first part of this work aims to help beginners understand the fundamental terminologies and concepts of machine learning to enhance researchers' confidence in exploiting the great potential of ML in their future research endeavors. The details regarding the common terminologies and the concept of ML algorithms used for solving structural engineering problems are explained in a simple manner in Sections 2 and 3. The second objective of this work is to highlight the potential of different ML algorithms in solving complex problems associated with civil engineering. To achieve this objective, a detailed literature review of different research works associated with accurately predicting the shear strength of conventional concrete beams, SFRC beams, beams reinforced with FRP bars, and high-strength concrete beams is presented in Section 4. The problem of accurately predicting the shear resistance of concrete beams is highly challenging owing to the influence of different parameters on the shear resistance and the complex nonlinear relationship between the shear strength and the influencing parameters. The details presented in this section will aid in comprehending the potential of ML to easily solve the shear prediction problem with high accuracy. This will provide confidence in utilizing this method to solve other complex engineering problems. Finally, the major challenges and future scope of this area of research are included in Section 5.

2. Terminologies in Machine Learning

This section discusses the details of the common terminologies used in this field to ensure that this work helps beginners gain knowledge in the field of ML. These details will allow beginners to easily analyze and understand the details of the studies discussed in the literature.

2.1 Algorithm / Learner: An algorithm or learner represents the program used to develop a model. The algorithm learns the patterns or interconnections between different parameters based on the provided database, and finalizes the parameters in the final model that are used for new predictions or classifications. For example, in the case of ANN different weights are assigned to each node and the accuracy of prediction is evaluated. Towards the end of training the optimum weights (parameters) are finalized.

2.2 Training: In ML, machines or programs learn the patterns or interconnections between different parameters. This is done by first analyzing a given set of data with defined connections. Training refers to the process in which a program learns based on the (known data) data provided for finalizing the different parameters in the final model. The data used for this purpose are known as training datasets.

2.3 Model: In the field of ML, a model represents the output of an algorithm. This can be used for new predictions of unknown data. The parameters in the model will already be finalized after the training stage of the learner.

2.4 Deep Learning: This is a subset of ML that typically uses complex neural networks for learning from databases and developing models. Generally, the accuracy of a model developed using a deep learning technique is directly proportional to the size of the database used for training the learner.

2.5 Feature: Features refer to independent variables provided to an algorithm. The quality of the features is crucial for developing an optimum correlation with different variables.

2.6 Regression, Classification and Clustering: There are three types of problems considered in ML. In regression-type problems, ML is used to develop a model that can correlate different variables. Generally, it is used to predict continuous parameters based on the variation in other parameters. The prediction of the shear strength of a beam based on different parameters, such as compressive strength, cross-sectional details, and span-to-depth ratio, is an example of this type of problem. Classification is another type of problem considered in ML, in which the primary objective involves classifying the given data under different labels that are already provided. Regression and classification are performed using supervised learning (explained later). Clustering is an unsupervised learning technique in which the program itself must find patterns and classify the data without the aid of any provided labels.

2.7 Hyperparameters: These are the parameters that control the learning process of an algorithm. For instance, when using ANNs (explained later), the number of hidden layers, number of neurons in each layer, etc., are considered as hyperparameters. Each ML algorithm has explicit hyperparameters that need to be carefully selected. Although these values are not part of the final model, they play an instrumental role in determining the quality of the final model. The values for hyperparameters are pre-assigned before starting the training process.

2.8 Bias and Variance: Bias is the quantitative estimate of the error made by the prediction model during training. The model will be developed by learning the relationships between different variables. While the final model makes a prediction, there can be differences between the predicted and actual values. A quantitative estimate of this error is known as a bias. A model with higher bias does not properly fit the given data. Variance represents the variation in prediction when a different training dataset is used. Generally, a model with high bias will have low variance, and a model with low bias will have high variance. It is difficult to develop a model that has both low bias and variance.

2.9 Activation function: This function determines whether the considered neuron in a NN should be activated. Linear and nonlinear activation functions exist; however, linear functions are not typically preferred in NNs. The activation function considers the weighted sum of inputs and the bias to determine if the output from the considered neuron should be passed on to the next neuron. The commonly utilized activation functions are the step, sigmoid, ReLU, leaky ReLU, Tanh Function, and Softmax functions. The choice of activation function in the hidden layer has a significant effect on the efficiency of the neural network.

2.10 Cost function: This is a parameter used in ML to estimate the accuracy of the developed model in making predictions based on the predictions made and the actual value. The cost function helps improve the model and attain optimum results.

2.11 Underfitting and overfitting: Underfitting is the condition when the model fails to fit the data points. Underfitting can occur when a linear model is used for nonlinear training data, or when the model is not sufficiently trained. An underfitted model will show poor accuracy in training as well as on unknown data. Overfitting is a condition that arises because of overtraining of the model. Models such as nonlinear models have high flexibility so that they try to fit all the points in the provided data. This force fits the model to unwanted or irrelevant points. Even though an overfitted model exhibits good performance with trained data, the performance of the model with a new set of data will be poor. A proper balance between underfitting and overfitting is key to developing an efficient ML model.

2.12 Confusion Matrix: This matrix is used to evaluate the performance of a classification model. To use a confusion matrix, the actual values must already be known. Consider a case in which a model is used to predict whether the used mix combination will provide a compressive strength higher than 50 MPa. Fig 7 illustrates the confusion matrix for this model, assuming that it has made 100 predictions. Based on the correct and incorrect predictions made as given in the matrix, different parameters, such as classification accuracy, misclassification rate, precision, and recall, can be calculated.

Total Prediction = 100	Actual: Yes	Actual: No
Predicted: Yes	60	7
Predicted: No	8	25

Fig 7 Confusion Matrix

2.13 Regularization: This is a technique used to reduce the influence of overfitting and underfitting. Generally, regularization is achieved by minimizing the cost function. The application of regularization will help attain the best-fit model without overfitting and underfitting.

2.14 Ensemble learning: This is a method in which the accuracy of the prediction is enhanced by combining the predictions made by different learners. The three most commonly utilized methods for ensemble learning are bagging, stacking, and boosting. In bagging, the average value of the prediction made by different decision trees trained using separate data from the same database is considered as the final output. Stacking involves using different models to make predictions based on a common database. The final prediction is made by combining these predictions with the help of another model. In the final method, the models are sequentially added, and the error made in each model is corrected by modifying the associated weights with the samples in the following model. Finally, a strong model is developed that can make predictions with high accuracy.

3. Machine Learning

ML is a subset of artificial intelligence in which a computer or machine is programmed to make predictions based on available data. For example, ML models can be used to predict the compressive strength of concrete based on influencing parameters, such as the water-cement ratio, aggregate ratio, and age of concrete. To achieve this, an algorithm is initially developed to predict the output (compressive strength) based on influencing parameters (features). Subsequently, the model selects a crude mapping function that connects the output to features. In the example mentioned above, if the output (Compressive strength) is represented by the variable "Y" and the features water-cement ratio, aggregate ratio, and age of concrete are represented by variables "X_1," "X_2," and "X_3," respectively, the mapping function may be of the form $Y = A \times X_1 + B \times X_2 + C \times X_3$. Subsequently, the mapping function is refined using the available data highlighting the connection between the compressive strength and the effect of change in each of the influencing parameters. The process of refining the mapping function using the available data is termed as model training. During the training, the function will be optimized to match the actual relation of compressive strength and different influencing parameters provided during the training in the best possible manner. Following this stage, the performance of the developed model is tested using another set of available data that include the compressive strength corresponding to the considered influencing parameters. This process is called model testing. Different statistical parameters are used to quantitatively represent the efficiency of the final model. Following the successful completion of these two stages, if a new set of influencing parameters is fed into the developed model, it will be able to automatically predict the compressive strength of the concrete with reasonable accuracy.

Based on the training process, ML can be classified into three major categories: supervised learning, unsupervised learning, and reinforced learning. As the name suggests, in supervised learning assistance is provided to the model during the training stage. To be more precise, the data will be labelled, and this knowledge will be provided in the training data, as discussed in the above example. However, in the case of unsupervised learning, the data provided for training do not have any labels. The model must identify the patterns and differences in the data provided during the training stage.

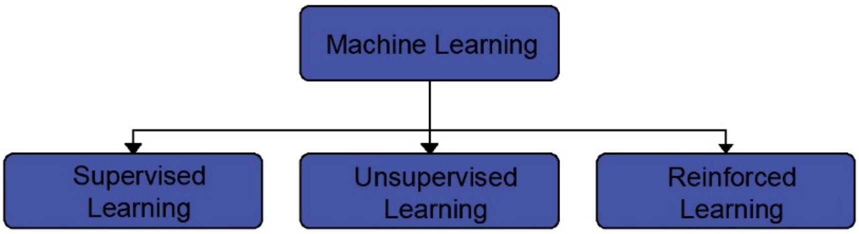

Fig 1 Classification of machine learning

An example of classifying cracks into flexure cracks, shear cracks, and flexure-shear cracks can be considered to clarify the difference between supervised and unsupervised learning. For this example, it can be assumed that the training data consist of a large number of images showing cracks in the failed beams. In the case of supervised learning, all flexure cracks, shear cracks, and flexure-shear cracks are placed in different groups, and a proper label is provided to each of the groups in the training data. Thus, the models can learn from the training data, and when a new image depicting the cracks is provided, the model can classify the crack with accuracy. Meanwhile, in the case of unsupervised learning, the same images are provided as training data but without classification or labels. In this case, the model itself has to find different patterns, locations of cracks, and geometries, and thereby categorize each crack into different groups. The cracks that are at the midspan and in the vertical direction will be placed into one group, whereas the cracks that are going at an angle of approximately 45^0 will be placed into another group. The remaining cracks may be placed into another group. In this case, all this identification and classification is performed by the model itself, and based on this, the model will train itself. Therefore, after training, when a new image depicting the crack is fed into the model, it will predict the group to which the new crack belongs. Reinforced learning is a type of training in which a model learns in a trial-and-error approach. Here, no label or relation is provided during the training. The model must learn sequentially based on the decisions. A classic example of reinforced learning is that of autonomous cars. An autonomous car should be trained in a realistic simulator before it is introduced into the real world. For each correct action taken by the model during the training, a reward is provided for the model, whereas for each wrong action, a penalty is provided. The objective of the model is to maximize the reward and train itself. Therefore, following several trials and errors, the car is self-sufficient to make decisions and drive in the real world.

3.1 Types of Machine Learning Algorithms

As ML has the potential to solve complex real-life problems, numerous research efforts have been focused on developing new and optimized ML algorithms. Consequently, many ML algorithms are already available and have been developed for different purposes. This section details on ML algorithms commonly employed for solving structural engineering-related problems. This will aid beginners in this field to understand the concept of each algorithm and use them for solving practical problems with ease.

3.1.1 Regression Models

Regression analysis is a statistical method used to make predictions based on the relationship between input parameters (independent variables) and required output parameters (dependent variable). The concept is also applicable to ML. This method is based on supervised learning, in which a labelled dataset is used for training the models, as explained in Section 3. Regression models are used when the output variable is discrete or quantitative. The primary objective of regression analysis is to determine a mathematical equation representing the best-fit line/curve for a provided training dataset. At a later stage, this relation can be used to make predictions for unknown data. Based on the number of variables involved and the type of function used to represent the dataset, regression analysis can be classified into different types, as shown in Fig 2.

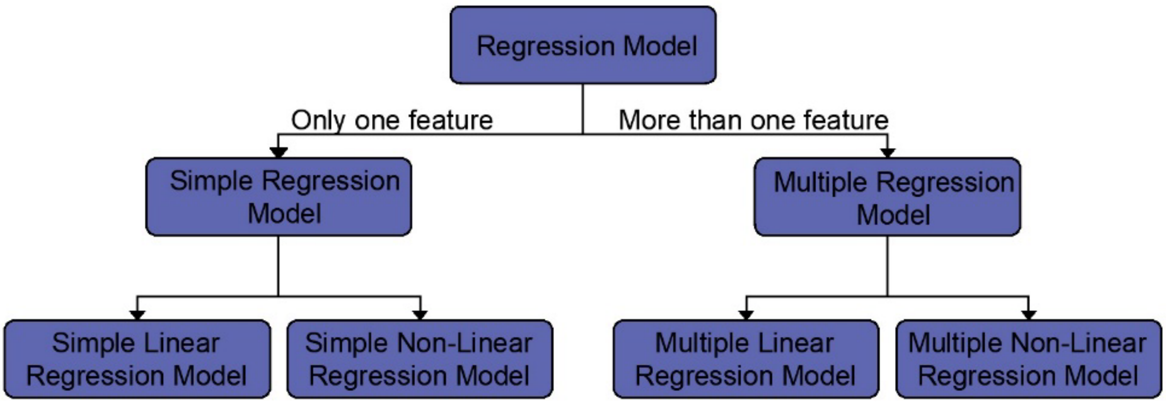

Fig 2 Classification of Regression Models

3.1.2 Linear Regression (LR)

This is the simplest form of a regression model used in ML. The objective of the linear regression model was to develop a linear relationship (a line in the case of a two-dimensional dataset) to connect the output and input parameters. If only one input parameter is considered in the model, it is called a simple linear regression; else it is called multiple linear regression. The output of the algorithm is obtained as shown in Eq 1. In this equation "Y, X, and β"

represent the dependent variable, independent variable, and the regression coefficient, respectively. The best-fit relation is obtained by reducing the value of the cost function (root mean square error).

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \qquad (1)$$

3.1.3 Polynomial Regression (PR)

The most significant difference between linear regression and polynomial regression is the shape of the curve used to fit the dataset. While a straight line is used in linear regression, a curved line represented by a higher-degree polynomial is used to fit the dataset in the polynomial regression. Even though the use of a higher-degree polynomial helps to reduce the variance and obtain a better fit, it will increase the probability of overfitting. Thus, the resulting model may have a higher prediction accuracy in the testing process but will fail to accurately predict unknown data. Therefore, when using the polynomial regression model, special care must be taken to avoid overfitting. The output of the algorithm is obtained as shown in Equation 2. In this equation, "Y, X, and β" represent the dependent variable, independent variable, and the regression coefficient respectively, where the best-fit relation is obtained by reducing the value of the cost function (root mean square error).

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X^i \qquad (2)$$

3.1.4 Ridge Regression (RR) and Lasso Regression (LAR)

Ridge regression (RR) and LASSO regression are similar to linear regression in terms of their functions. The sole distinction is the addition of L1 and L2 penalties in the cost function in lasso regression and RR, respectively. These penalties are added to avoid overfitting by reducing or nullifying the coefficients β_i(weights). Overfitting is a problem that occurs when the regression model becomes overly fitted to the training data and fails to accurately generalize. Therefore, in both regression models, the weight assigned to each feature is adjusted based on their significance in the prediction. In RR, the weights of less-important features are reduced, whereas in lasso regression, they are nullified. Accordingly, these models reduce the problem of overfitting by assigning importance to the proper feature selection.

3.1.5 Decision Tree (DT)

The decision tree (DT) model is a commonly used ML algorithm that falls under the supervised learning category. It generates a tree-like model based on training data, as shown in Fig 3. DTs can be used to solve regression and classification problems. Hence, it is also known as a classification and regression tree (CART). As shown in Fig 3, the main parts of a DT include root nodes, branches, internal/decision nodes, and leaf/end nodes. The topmost node in a tree is the root node. The final node that cannot be further split is the leaf/end node. A DT is constructed by splitting different nodes starting from the root node based on certain conditions. Different metrics, such as entropy, information gain, and the Gini index, form the splitting condition at each level. The splitting process continues until the predefined depth of the tree is reached or until a split cannot be made, thereby improving the adopted metrics. Overfitting is a common problem reported by different researchers while using DT models.

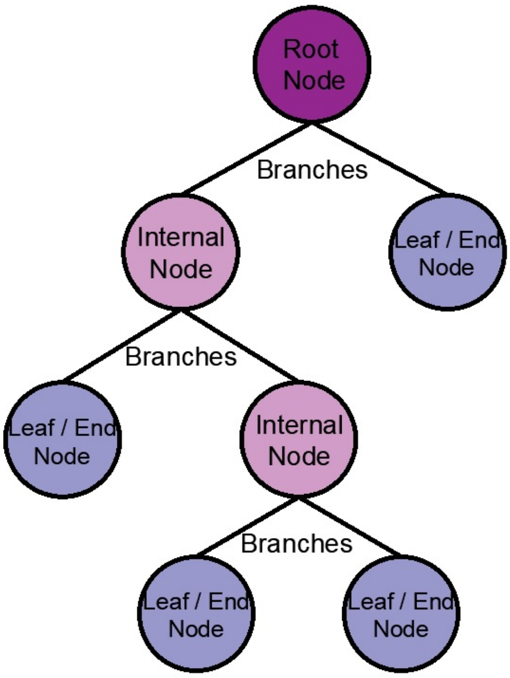

Fig 3 Decision tree with terminologies

3.1.6 Random Forest (RF)

Random forest (RF) is a powerful ML algorithm that comes under ensemble learning algorithms. The concept of RF entails constructing a group of trees (forest) by combining two or more weak learners (DT algorithms commonly used) and making an enhanced prediction by combining the decisions made by each of the weak learners. Decision trees are created using a bagging technique. This means that the weak learners are trained in parallel. Each tree is constructed by randomly selecting features from the dataset. The RF method can be used for both classification and regression problems. In a classification problem, the RF makes its final decision by voting on the predictions made by each DT. For regression problems, the final decision is made by considering the average of the predictions made by individual weak learners.

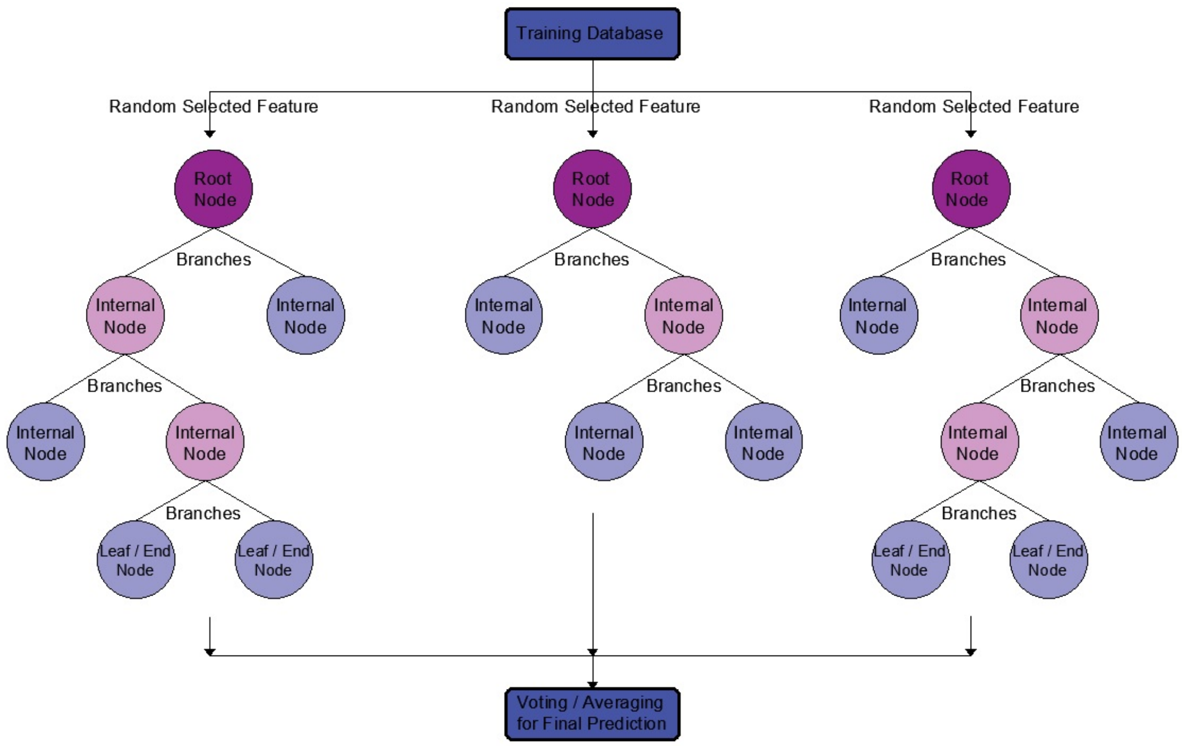

Fig 4 Random Forest Machine Learning Model

3.1.7 Artificial Neural Network (ANN)

ANNs are one of the most widely used ML techniques for solving complex problems. It primarily consists of processing elements known as nodes or neurons. They are interconnected in an optimized manner to form a network. The connections between different neurons in a NN are known as channels. Generally, an ANN can be divided into three layers: the input, hidden, and output layers, as shown in Fig 5. An ANN typically consists of one input layer, in which the data are fed, and an output layer, in which the output is obtained. All the computations required in the proposed algorithm are performed in the hidden layer. The hidden layer may contain one or more node layers. When the number of layers of nodes in the hidden layer is two or more, it is known as a multilayer perceptron or deep learning network.

In an ANN, input data are first received by the input layer. The input parameters need to be normalized before they are fed into the network. Therefore, most of the input values fed to the neurons in the input layer will be a value between 0 and 1 or -1 to 1. Each of the channels that connect one neuron to another is assigned a parameter known as weight (W_i), as depicted in Fig 5. The input value obtained in a neuron is multiplied by the weight assigned to the respective channel. The weighted sum from the input layer is then passed to the corresponding neuron in the hidden layer. Each neuron in the hidden layer is assigned a numerical value called the bias (B_i), as depicted in Fig 5. The weighted sum received from the previous layer is added to the respective bias value at each of the neurons and is then passed through a threshold function known as the activation function. Different types of activation functions are available, and the programmer can choose the best function for the problem. The results obtained from the activation function decide whether to transmit data from that neuron to the next layer. This process is repeated until it reaches the output layer, which is known as forward propagation. After obtaining the output, it is compared with the actual value in the training database, and the error is quantified using the cost function. Based on the error, details regarding the direction and magnitude of the correction required are transferred back into the network. This process is known as backpropagation (BP). Based on this data, the weights are further modified, and the process is repeated. The cycle of forward propagation and backpropagation is repeated iteratively until the values of the weights are optimized to obtain the required results. This completes the training of the NN. Then this network with fixed weights is tested using the testing database, and the performance is evaluated.

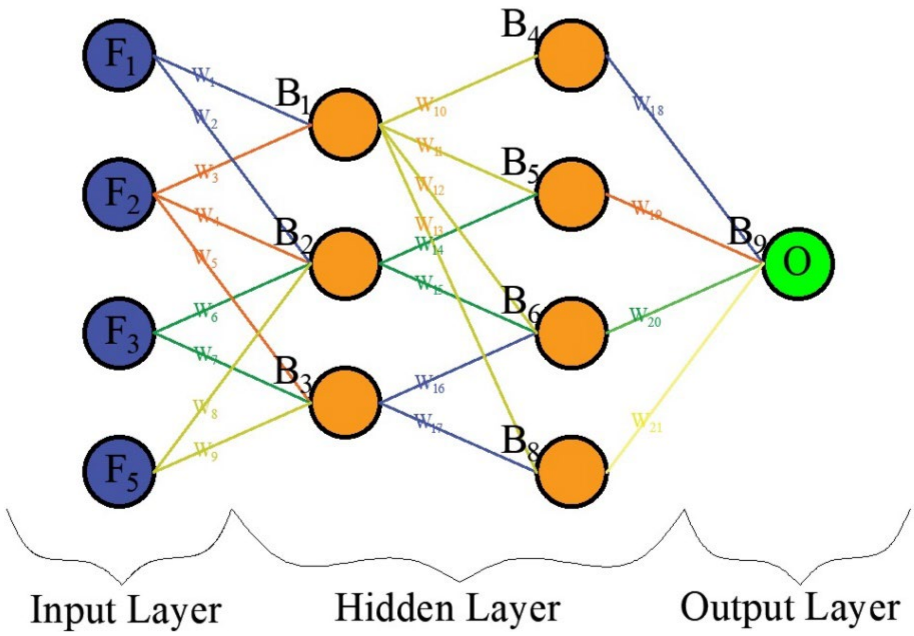

Fig 5 Typical Artificial Neural Network with two layers of nodes in the hidden layer

3.1.8 K-nearest neighbor (KNN)

The K-nearest neighbor is a simple ML algorithm that can be effectively used for classification and regression problems when the distribution of data points is highly nonlinear. In the case of the classification problem, the prediction is based on the type of “k” number of nearest points around the unknown data, as illustrated in Fig 5a. In this method, the value of “k” is a hyperparameter, and the optimum value must be determined. It should be also mentioned that the value of “k” should be always an odd number. The required number of nearest points is determined using the Euclidean or Manhattan distance. After finding the nearest points, the unknown point can be classified by analyzing the group to which the majority of the nearest point belongs. In the example presented in Fig 5, because there are four orange points near the unknown point, the new point (green point) is classified into the orange group.

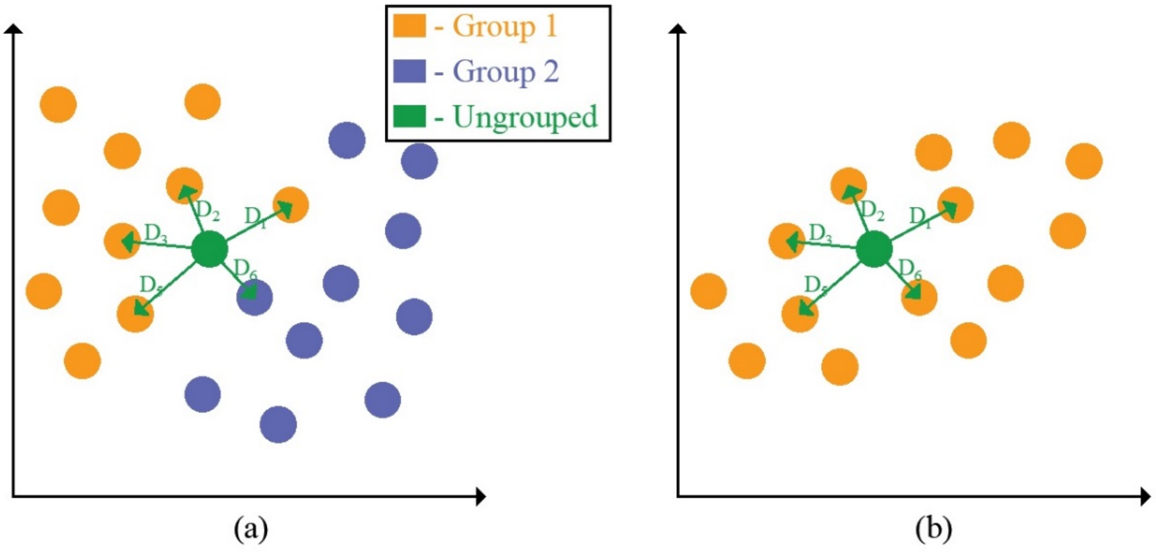

Fig 5 Concept of K-nearest neighbor

In the case of a regression problem using the Euclidean distance or Manhattan distance, “k” number of points near the unknown point will be found. Consequently, the prediction corresponding to the unknown data will be made by taking the average value corresponding to all these “k” number of neighbors as shown in Fig 5b.

3.1.9 Support vector machine (SVM)

Support vector machine (SVM) is another algorithm that was initially developed for classification problems and later extended to regression and clustering problems. When this algorithm is used for regression and clustering problems, it is referred to as SVR and support vector clustering (SVC), respectively. The fundamental concept of this method involves separating the given features using a plane (called a hyperplane or support vector classifier) with the maximum margin, as illustrated in Fig 6a. The data point located at the edge of the margin, as shown in Fig 6a, is known as the support vector. In the case of a regression problem, the idea is to determine the mathematical equation of the hyperplane that can best represent the data points, as shown in Fig 6b. Real-life problems can be complex, with a highly nonlinear distribution. Therefore, it is difficult to determine a boundary that properly classifies them. For example, the relationship between the effect of the dosage of a superplasticizer on the compressive strength is considered, as shown in Fig 6c. It is assumed that when the dose of the admixture is low or high, the compressive strength is low, whereas for values between them, the compressive strength is enhanced. It is difficult to determine a support vector classifier to solve this problem. Therefore, in the SVM, these data are first transferred to a higher dimension. As shown in Fig 6d, each piece of data is squared and plotted. Consequently, a support vector classifier that classifies the data into two groups can be provided. This transformation is called the kernel trick, and different kernel functions are available to transfer data from a lower dimension to a higher dimension. The type of kernel function used has a significant effect on the performance of the final model. The most commonly used kernel functions include linear polynomial functions, nonlinear polynomial, radial basis, and sigmoid functions.

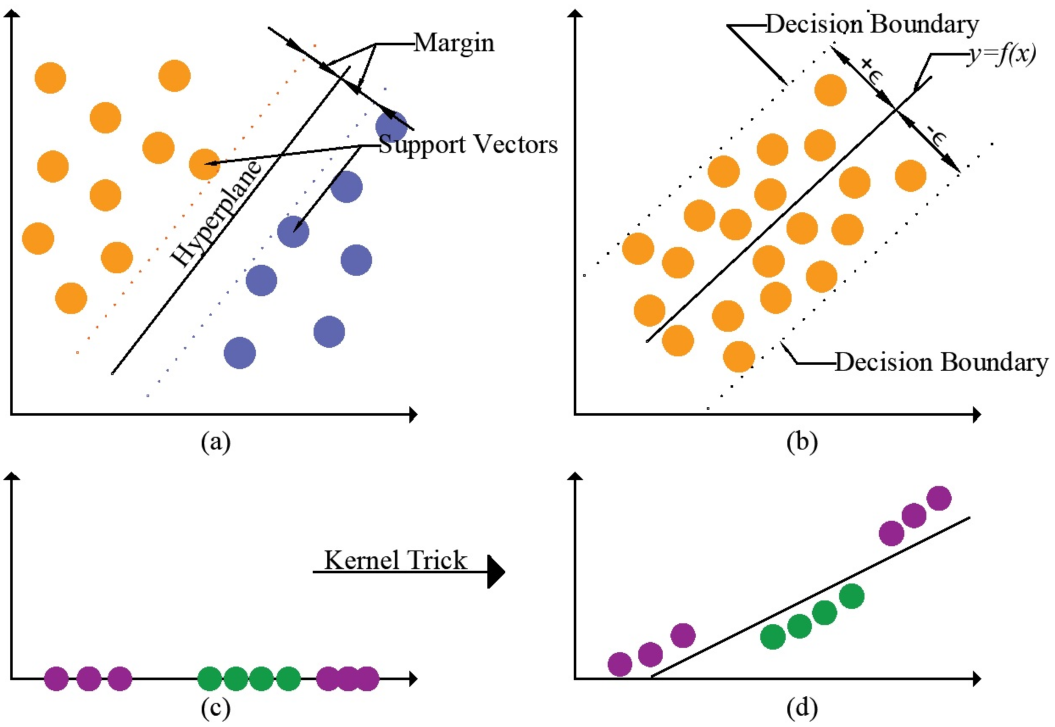

Fig 6 Support Vector Machines (SVM)

3.1.10 Extreme gradient boosting (XGBoost)

XGBoost is one of the most powerful and efficient ML algorithms available today. This method is suitable for both regression and classification problems. For the first time, Chen and Guestrin proposed this as an efficient ensemble tree model [40]. Subsequently, Friedman enhanced its efficiency using the gradient boosting algorithm [41]. In this method, the gradient boosting technique generates strong learners by sequentially adding different weak learners. The primary objective of this algorithm is to minimize the error in the current tree, in which the residual error from the previous tree has already been added. This process continues until the end of the iteration so that the remaining residual error is minimal. In XGBoost, the value of the objective function is obtained by using Eq. (3). The first part of the equation indicates the loss function and the second part represents the regularization function. This method uses several techniques, such as the randomization technique, compressed column-based structure for storage of data, parallel and distributed computing, etc., which make it more efficient and faster than other methods. With the help of the randomization technique, the problem of overfitting is addressed with great efficiency.

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{t=1}^{k} \left[\gamma k + \frac{1}{2} \times \lambda \sum_{j=1}^{k} w_j^2\right] \quad (3)$$

where L denotes the loss function for the model, w indicates the weight of the leaf, γ and λ represent the complexity of each leaf and penalty parameter, respectively.

3.1.12 Adaptive Boosting (AdaBoost)

AdaBoost is one of the oldest and most popular ML algorithms. It uses the concepts behind DT and RF algorithms. The trees considered in AdaBoost typically have only one root node and two leaves. In this algorithm, the trees with one root node and two leaves are called stumps. The method starts with a weak learner to evaluate all the data (equal weight is assigned in the first stage) and adopts a higher weight for the incorrectly predicted cases and a lower weight for the correctly predicted cases in the next iteration. Accordingly, several weak learners (stumps) can be formed during training. The influence of predictions made by each weak learner on the final output is different in the case of the AdaBoosting technique. The influence of each weak learner on the final output is determined based on the correctness of the prediction. Finally, a strong learner is developed based on the predictions made by weak learners.

3.1.13 Categorical Boosting (CatBoost)

CatBoost is a recently developed, open-source algorithm. This method was developed by Yandex et al.. The key advantage of CatBoost is that it can work with different data types using a built-in preprocessor. This significantly reduces the pre-processing required by the other algorithms. This algorithm is very fast compared to other methods owing to its ability to utilize multiple cores available in both the CPU and GPU. CatBoost can be utilized for ranking, providing recommendations, forecasting problems, providing assistants, and solving regression and classification problems. Using ordered target statistics, CatBoost can automatically handle categorical features. Compared to deep learning algorithms, CatBoost can produce more accurate results even when the amount of data used for training is low.

4. Machine learning models for predicting the shear strength of concrete beams

This section provides details of research works on ML-based shear strength prediction models. With the help of ML, researchers have developed models that can precisely predict the shear strength of conventional concrete beams with stirrups, beams without stirrups, beams reinforced with FRP bars, fiber-reinforced beams, high-performance concrete beams, ultra-high-performance concrete beams, and steel beam sections. A comprehensive review of the important research works available in this field is given in the initial part of this section. In the later part of this section, some of the selected research works are explained in detail to provide a better picture of the investigation for beginners in this field. The details regarding the type of algorithm used, the database considered for developing the model, the statistical parameters used for performance evaluation, and the efficiency of the developed models are discussed in detail for each of these investigations in this part.

Sanad and Saka [42] depicted the potential of artificial neural networks in evaluating the shear strength of reinforced-concrete deep beams. They used a dataset consisting of one hundred eleven experimental data of simply supported beams carrying symmetrically applied two-point loads. Ten features were considered in their analysis which represented the geometric and material properties. The performance of their model was compared with the models proposed by ACI, strut-and-tie method and model proposed by Mau-Hsu. The proposed model was able to produce accurate shear strength prediction with a ratio of actual to the predicted value of 0.99 compared to inaccurate predictions made by other models. Cladera and Mari [43] developed new design equations for the shear design of normal and high-strength reinforced concrete beams with stirrups using ANN and a parametric study. Using the parametric investigation, the researchers highlighted the influence of different parameters on the shear strength of the concrete beam and used it to arrive at the final design expressions. Their model was having a better performance compared to the methods suggested by EC-2 or ACI. Mansour et al. [44] also utilised artificial neural networks for predicting the ultimate shear strength of RC beams with stirrups. A dataset consisting of experimental results of 176 RC beams with nine features was used for developing their model. It was observed that the proposed model was able to outperform empirical equations suggested in design standards and truss model theories. Chabib et al. [45]developed a new ANN model for predicting the shear strength of reinforced concrete beams using a dataset consisting of 656 samples. This model was used to understand the influence of transverse reinforcement on the shear resistance of concrete. It was observed that the shear resistance offered by concrete was more for beams with transverse reinforcement in comparison to beams without stirrups. But it was also observed that the effect of transverse reinforcement on shear strength was lesser for a higher percentage of transverse reinforcement. Abdalla et al. [30]evaluated the performance of ANN in predicting the shear strength of RC beams and its potential to be used as a tool for conducting parametric studies. They developed their ANN model using a dataset consisting of 164 experimental results. Back propagation neural networks with different activation functions were considered during the training and the sigmoid function was observed to be the best activation function that can produce accurate results. A comparison of performance of their model with ACI318-02 and BS8110 codes was also included in their investigation. An effort was put forward by the researchers to understand the nonlinear relationship between different features. Based on the observations' researchers also developed shear response curves and surfaces. The researchers concluded that ANN is capable of predicting the shear capacity with good accuracy and it can be used as a model for parametric studies related to shear strength.

To evaluate the effectiveness of commonly adopted models in predicting the failure load of RC beams Ahmad et al. [46]conducted a comparative study considering the experimental data and predictions obtained from the design standards, the compressive force path method and an artificial neural network. Their investigation revealed that the ANN model was able to provide close fix prediction compared to other methods. Cladera and Mari [47] developed a new ANN model for predicting the shear strength of beams without transverse reinforcement. With the help of this model, researchers conducted a parametric study to show the relationship between different influencing parameters and the shear strength. Researchers also proposed simpler expressions for calculating the shear strength with more accuracy compared to design standards. Oreta [48] developed a novel ANN model that can predict the shear strength of RC beams with reasonable accuracy and simulate the size effect on ultimate shear stress at failure. The developed model was having superior performance compared to empirical, theoretical and design code equations. The potential of ANN in establishing the relation between different parameters was also depicted by the researchers through a parametric investigation. Seleemah [49] proposed the artificial neural network (ANN) technique as an alternative to the existing shear capacity prediction methods. The performance of the researchers' model was compared with eight different codes and models available in literature. The proposed model was able to depict superior performance compared to the other models. El-Chabib [50] proposed a new ANN model for predicting the shear strength of normal and high-strength concrete beams without transverse reinforcement. To highlight the potential of ANN in shear strength prediction the results of the model were compared with the ACI method, the CSA simplified method, Response 2000, Eurocode-2, and Zsutty's method. The comparison depicted that the ANN model was able to make superior predictions compared to other methods. Jung and Kim [51] proposed an innovative idea of knowledge-based prediction of conservative shear strength for beams without transverse reinforcements using ANN models. The researchers proposed two ANN models developed using a database consisting of experimental results. The first model was similar to the ANN models available in literature but the second model was preferable when conservative predictions like in the design codes are preferred. Elsanadedy et al. [52] put forward two models for shear strength prediction of high-strength concrete beams without web reinforcements using regression and neural network methods. A large database consisting of 250 test results which cover a wide range of features was used for the training and testing of the proposed models. The ANN-based model was observed to depict a better performance compared to the regression model. The researchers proposed new empirical design models for high-strength concrete beams. They proposed the use of these models be restricted to beams having shear span to depth ratio greater than 2.5, depth less than 1000 mm, steel ratio less than 4% and compressive strength of concrete less than 100 MPa.

Adhikary and Mutsuyoshi [35] developed two ANN models for the shear strength prediction of steel fibre reinforced concrete (SFRC) beams. The main difference between the two models was the number of input features considered. The first and second model considered five and four input parameters respectively. The additional feature considered in the first model enabled it to depict a better performance. In comparison to the shear strength prediction model proposed by Swamy et al. and Khuntia et al, both the proposed models were able to depict a superior performance. Hossain et al. [53] proposed a new ANN-based model for predicting the shear strength of medium- to ultra-high-strength steel fiber-reinforced concrete beams using artificial neural network. The dataset used for training the model consisted of 173 experimental test results of SFRC beams without stirrups. The database included beams with compressive strength varying from 20 MPa to 175 MPa and various types of commonly used steel fibres. An additional database consisting of 36 experimental test results was used by the researchers for validation and testing of the developed model. Based on the results of their investigation researchers concluded that the ANN model has good potential to be employed as a design tool for predicting the shear strength of SFRC concrete beams without stirrups. Ahmadi et al. [54]developed new design equations for predicting the shear stress of SFRC beams without transverse reinforcements using Gene Expression Programming and ANN. The final model was able to efficiently connect the geometrical and material properties of the beam with the shear stress. The performance of the proposed models was evaluated using different statistical metrics and was also compared with the performance of methods suggested by the ACI code as well as different empirical models. The results show better performance for the newly proposed model for predicting the shear stress.

Perera et al. [55]developed a shear strength prediction model for RC beams strengthened in shear with the help of fibre-reinforced polymer using ANN. On comparing with other design provisions the proposed model was having good performance with high accuracy. The critical parameters that influence the shear strength of FRP strengthened beams were identified by the researchers with the help of a parametric investigation. Based on the results and observations of their investigation researchers proposed modification to the design equations suggested by ACI for the evaluation of the shear capacity of beams strengthened with FRP. Tanarslan [38] evaluated the potential of ANN in predicting the shear strength of RC beams strengthened in shear with side-bonded FRP reinforcements. In addition to the dataset collected from literature, experimental testing of ten shear deficient beams with different carbon fibre reinforced polymer (CFRP) arrangements were conducted and the results were added. Researchers depicted that the proposed model was having better performance in comparison to the available empirical models. In addition to this, a parametric investigation was also conducted to understand the critical factors that influence the parameters of the FRP contribution. Based on this research a simple equation was proposed to predict the influence of externally bonded side-bonded FRP on the resulting shear strength. Tanarslan et al. [56]showed the superiority of ANN models in predicting the shear strength of RC beams strengthened by externally bonded, wrapped and U-jacketed FRP. The geometrical properties of the beam along with the mechanical properties of the beam and strengthening material were considered as the input parameters. A dataset consisting of experimental results of 84 beams was considered for the training and testing of the ANN model. The performance of the proposed model was compared with the design standards of five different countries and was observed to be superior. Tanarslan et al. [39] proposed an innovative shear design method for RC beams retrofitted with anchored CFRP by using ANN. Two neural network models with back propagation were proposed in this investigation. Test results of 79 beams were used for training and testing the proposed models. The predictions made by the ANN models were compared with the available theoretical models and were found to be more accurate.

Abuodeh et al [57] used a resilient back-propagating neural network for predicting the shear capacity of shear deficient beams retrofitted with side-bonded and U-wrapped FRP laminates. The database considered in this investigation consisted of 120 experimental results of beams with fifteen different parameters. The recursive feature elimination and neural interpretation diagram were used by the researchers to identify the critical features for the shear prediction. The performance of models developed with the help of the feature selection as well as with all the 15 features was evaluated and compared by the researchers. It was observed that the feature selection techniques helped in improving the performance of the proposed model to a greater extent. As done by other researchers the prediction made by the proposed model was compared with the predictions made by ACI 440.R-17, fib14 and CNRDT200 also. The result indicates that the proposed model was able to make superior predictions compared to the remaining methods. Ali et al. [58] used the extreme gradient boosting method (XGBoost) for developing a shear prediction model for FRP-reinforced concrete beams without transverse reinforcements. To utilise the complete dataset K-fold cross-validation technique was implemented in this investigation. Researchers observed that the proposed model was able to make a better prediction and was more precise compared to the predictions made by other empirical relations, design codes, LASSO model as well as the model developed using random forest method. Lee and Lee [59] developed a prediction equation for the shear strength of FRP strengthened RC beams without stirrups using ANN. Using the 2^k experiment the researchers also evaluated the influence of different parameters on the shear capacity of FRP strengthened beams. The proposed model was having good performance when compared to the prediction made using existing empirical relations. Naderpour et al. [60] used ANN to develop a new model for predicting the shear strength of concrete beams reinforced with FRP bars. The geometrical and mechanical properties of the concrete section as well as the FRP bars were used as the input features during the development of the prediction model. It was observed that the proposed model was having better performance compared to the predictions made by models in ACI 440.1R-06, ISIS-M03-07, BISE, JSCE design recommendation, CNR-DT 203-06 Task Group, and Kara.

Degtyarev [61] proposed a new ML model (ANN) for predicting the elastic shear buckling loads and the ultimate shear strengths of the channels with slotted webs. A large dataset consisting of 3512 numerical simulation results was used for training and testing the proposed model. The hyperparameters of the ANN model were optimised using a grid search in this investigation. The results of the final model were a good match with the numerical results. Limbachiya and Shamass [62] used ANN to predict the web-post buckling shear strength of cellular beams. A dataset consisting of 304 numerical results was used to train, validate and test the proposed 16 models. Among the 16 tested models the model that used geometric parameters as features were able to make the best predictions. On comparing the results with that of the existing model it was understood that the proposed ANN model was able to predict with superior accuracy. Degtyarev and Naser [63]depicted the potential of ML in accurately predicting the shear strength of CFS channels with staggered web perforations using five different boosting algorithms. They used gradient boosting regressor, XGBoost, LightGBM, CatBoost, and AdaBoost in their analysis. The dataset used for the investigation consisted of 3512 simulation results. To optimise the performance of each of the proposed models, researchers tuned the hyperparameter of each algorithm to the best possible end. The elastic buckling loads and the ultimate shear strengths predicted by the model had a good agreement with the simulation results. The CatBoost model was observed to be better than all other tested models in this investigation. Based on the results a simple Python-based template was also developed by the researcher for easily calculating the shear buckling load and ultimate shear capacity of the channels.

Mohammed and Ismail [64] reported on a new reliable soft computing model that can accurately predict the shear strength of RC beams. They considered the XGBoost and multivariable adaptive regression spline (MARS) algorithms to achieve this objective. A comparison of the predictions made by the proposed models with those predicted by SVMs and different empirical models already available in the literature is also included in this study. A detailed theoretical background of XGBoost, MARS, and SVM is provided in the initial part of their paper. Totally, 349 samples were collected from the literature for this research work [16,47,65–72]. Fourteen statistical parameters are provided for each feature in the database. In this study, the total dataset was divided into 80% and 20% for training and testing, respectively. Based on the statistical correlation between the dependent and independent parameters, nine different combinations of input parameters were selected to develop new models. The researchers employed different types of statistical metrics, such as the coefficient of determination (R2), root mean square error, mean absolute error, mean absolute percentage error, Nash–Sut–Cliffe efficiency, and modified index of agreement, to evaluate the prediction accuracy. Based on the results, the researchers observed that MARS exhibited superior performance in predicting and understanding the relationship between different parameters and shear strength. It was also noted that the predictions made by all the three models (XGBoost, MARS, and SVM) were better than those predicted by empirical relations available in the literature.

Hosein Naderpour *et al* [73] conducted an investigation to determine the optimum structure for an ANN that can accurately predict the shear strength of concrete beams with stirrups. Researchers have proposed and compared the efficiencies of three ANN configurations to achieve their objectives. These models were developed using a database comprising 194 experimental test results collected from the literature. It was ensured that all beams in the database failed in shear. Seven features were considered, namely, the strength of concrete, section width, effective depth, strength of transverse reinforcement, percentage of tensile reinforcement, strength of tensile reinforcement, and transverse reinforcement ratio. The output parameter was the shear strength of the beam. In this study, the training and testing databases were formed using 85% and 15% randomly selected data, respectively. Before feeding the data, all samples were normalized to a range between -1 and 1. The general structure of the ANN developed in this study comprised a single middle layer with a feed-forward NN using the Levenberg–Marquardt algorithm. Researchers used different numbers of neurons and activation functions in the middle layer to evaluate the performance of different ANN structures. Two of the considered ANN consisted of eight neurons in the middle layer with a tansig activation function for the first and a purelin function for the second. To check the possibility of reducing the complexity of the ANN network, a third network with only one neuron in the middle layer was also considered by the researchers. A comparison of the results obtained for the developed models with those of the experimental results and with the values proposed by the ACI code was also presented by the researchers. Researchers evaluated the performance of all models using three statistical parameters: the coefficient of determination, root mean square error, and mean square error. Based on the results, it was observed that the first model with eight neurons in the middle layer and the tansig activation function outperformed all other models during the training and testing phases. Although the ANN model with a single middle layer could not perform as well as the other two ANN models, it was able to make better predictions than the ACI code. The results of this study show that even simple ANN models with less complexity can be used to obtain better shear strength predictions for beams.

Rahman *et al* [74] conducted an investigation to develop a novel superior ML algorithm that could accurately predict the shear strength of SFRC beams with the least computational time. To obtain the best model, the researchers considered 11 different ML algorithms: linear regression, RF, RR, lasso regression, decision trees, SVMs, k-nearest neighbor, ANN, XGBoost, AdaBoost, and CatBoost. In this study, a database comprising the experimental results for 507 SFRC beams was collected from the literature and used by researchers. All SFRC beams considered had longitudinal reinforcements and no shear reinforcement to enable shear failure. Although the database comprised beams made with normal-to-high-strength concrete, the percentage of high- and ultra-high-strength concrete was lower. Approximately 66% of the beams in the database were slender, whereas the remaining 34% were deep beams. Based on the information available in the literature, the ratio of shear span to effective depth, fiber volume fraction, fiber aspect ratio, steel fiber type, longitudinal reinforcement ratio, concrete compressive strength, and fiber factor were considered as the input parameters in this study. The researchers considered 80% of the database for training and the remaining 20% for testing. A 10-fold cross-validation method was used in this study. The details of the 10-fold cross-validation accuracy of all models for training and testing data are presented using box and whisker plots in this study. In this investigation, four statistical parameters, namely, the coefficient of determination (R^2), adjusted R^2, root mean square error, and mean absolute error, were used for the performance evaluation of each model. During comparison, it was observed that the XGBoost model exhibited the best performance among the 11 models, with R^2 values of 0.998 and 0.722 for training and testing, respectively. The RF model was the second-best performer among the considered models. The rigid regression algorithm was observed to be the poorest performer among the 11 algorithms. Moreover, the researchers also compared the shear capacity predicted by their models with experimental results and equations proposed by different authors. Shear capacity models proposed by Ashour et al. [75], Khuntia et al. [76], Sharma [77], Sarveghadi et al. [78], and Alam [79] were used for this purpose. The newly developed XGBoost algorithm outperformed all the other models, as well as the models proposed in the literature. An attempt was also made to comprehend the influence of different input parameters on the shear strength prediction. Based on the investigation, it was observed that the ratio of shear span to effective depth is the most critical feature for predicting the shear capacity of SFRC beams, followed by the ratio of longitudinal reinforcement and concrete strength. The volume fraction of the fiber and the type of fiber also had a significant influence on the shear capacity of the SFRC beam.

Solhmirzaei *et al* [80] developed a computational framework using ML technique for classifying the failure type and predicting the shear strength of ultra-high-performance concrete (UHPC) in the MATLAB simulation environment. In their study, SVM, k-nearest neighbor, and ANN algorithms were used for the classification of failure types, and a model for shear strength prediction was developed using genetic programming. The database used in this study was developed based on the experimental results of UHPC beams, high-performance concrete beams, and reactive powder concrete beams available in the literature. The database also comprised beams with different cross-sectional shapes and prestressed concrete beams. Feature selection techniques were used to finalize the critical features of the prediction model. The type of concrete, shape of the cross-section, compressive strength, width of the section, effective depth, reinforcement ratio, shear span to effective depth, shear reinforcement ratio, fiber volume, aspect ratio of the fiber, and level of prestressing were considered in this investigation. The values of the minimum, maximum, mean, and standard deviation of the selected features were included in the manuscript. In this study, a k-fold cross-validation technique was employed during training to control the overfitting of the data. The scholars divided the entire database into three groups: training, validation, and testing. Seventy percent of the available data were used for training and validation, and the remaining 30% were used for testing in this study. The validation dataset was used to optimize the hyperparameters used in the model to obtain the best classification. Based on the results of validation, it was observed that the best classification percentage of 81% was obtained using the linear kernel in the case of SVM. In the case of the k-nearest neighbor, optimum classification was obtained with a value of 20 for the number of nearest neighbors. A feed-forward 2-layer ANN comprising one hidden layer with ten neurons was observed to be optimum for the ANN model. A confusion matrix and receiver operating characteristic curve were provided to illustrate the effectiveness of each of the algorithms employed in the failure classification. Based on these data, the ANN exhibited better performance for correctly classifying the failure model in comparison to the other two models. The researchers used a modified database to develop a shear strength prediction model by removing the details of beams that failed in flexure. The dataset was divided into three groups. The first and second groups represent the details of the non-prestressed beams with and without stirrups. The third dataset consisted of the prestressed beams. These groups consisted of 191, 52, and 45 datasets, respectively. A comparison of the predictions made by the newly developed model was completed with the predictions made by the models proposed by Ahmad et al.[81], Imam et al [82], Sharma [77], Narayanan and Darwish [8], Ashour et al. [75] and Kwak et al [83] and the recommendations of international codes. Upon comparison, it was observed that the proposed model could make a better prediction with a coefficient of determination (R^2 value) of 0.92. It was also observed that the UHPC and FRC models available in the literature underestimated shear capacity.

Kaveh et al. [84] proposed novel ML models for predicting the shear strength of beams without stirrups and reinforced with FRP bars using three different algorithms. They employed LASSO regression, RF, and XGBoost to develop new prediction models. A database comprising 205 FRP-reinforced beams was used in this investigation. The width of the web, effective depth of the section, shear span-to-depth ratio, compressive strength of concrete, percentage of tensile reinforcement, yield strength of the reinforcing bar, and Young's modulus were considered as the input parameters for developing the model. Based on feature importance analysis, researchers observed that the width of the web, effective depth of the cross-section, shear span to effective depth ratio, and compressive strength of concrete were more correlated with the shear strength. Statistical parameters related to the input data, such as the minimum value, maximum value, mean, and standard deviation, were included in the manuscript. k-fold cross-validation was employed to utilize the entire dataset. The performance of each model was compared using root mean square error, mean absolute error, and R-squared values. Furthermore, researchers also compared the predictions made by their models with those suggested by international codes and models available in the literature. It was observed that the predictions made by the XGBoost and RF models were superior to those of the regression and other empirical models. The results predicted for FRP-reinforced concrete beams using the relations available in the standards and the literature were conservative.

Hosein Naderpour et al [73] developed a new relationship for predicting the shear strength of beams reinforced with FRP bars using an ANN algorithm. The model was developed using a database comprising 110 experimental results for beams reinforced with FRP bars. Seventy percent of the data were considered for the training of the model. Ten percentage and twenty percentage of the data were used for validation and testing respectively. Prior to feeding the input, the data were normalized in the range of -1 to 1. The compressive strength, percentage of FRP reinforcement, Young's modulus of FRP reinforcement, shear span-to-depth ratio, web width, and effective depth were considered as the input parameters. The statistical characteristics of the features, such as minimum, maximum, range, average, and standard deviation, were also calculated and provided by the researchers. They provided an optimal ANN model with two hidden layers comprising a single node. A log-sigmoid function was used as the transfer function. To evaluate performance, different statistical parameters, such as the coefficient of variance (R2), mean absolute error, root mean square error, and mean square error, were considered. A comparison of the predictions made by the newly proposed equation was made with models proposed by researchers [85–88] and international standards like ACI 440.1R-15, BISE and ISIS-m03-01. It was observed that in training and testing, the proposed model exhibited similar performance to that of ACI and Tureyen-Frosch's equation in terms of the R^2 value. However, during validation, the proposed model outperformed all other models. Considering the results of other evaluation matrices, researchers could show that the newly developed simple ANN model could achieve better performance among the tested models. A sensitivity analysis was conducted using the finalized weights obtained after training to investigate the influence of different features on the shear strength. The depth of the cross-section was obtained as the most significant parameter based on the sensitivity analysis. The compressive strength of concrete was another parameter that had a significant effect on the shear strength. With a model developed using a very simple ANN network, researchers demonstrated the potential of NNs to make predictions comparable to those proposed by international standards and available models.

Feng et al. [89] adopted ensemble learning methods to predict the shear strength of RC deep beams with and without web reinforcement. Ensemble methods combine the decisions of multiple individual ML methods based on specific rules and generate enhanced predictions. Several investigations have demonstrated the ensemble techniques' superior generalization capability [90–92]. In their study, researchers used four different ensemble methods, namely RF, adaptive boosting (AdaBoost), gradient boosting regression tree (GBRT), and extreme gradient boosting (XGBoost), to construct prediction models. A database containing 271 sample data (80% for training and 20% for testing) with 16 different input parameters was considered by the researchers for developing the new models. Sample data were collected from different published experimental results available in the literature by the researchers [18,93–101]. To avoid the scale effect, researchers normalized the input parameters to the range 0–1. Although ML models can present accurate predictions for different complex problems, they are still considered black-box models because it is difficult to explain the physical or mechanical background of the considered problem based on them. As a solution to this problem, the researchers included feature importance and partial dependence analyses to interpret the developed model. A comparison between the prediction capacity of these four ensemble models and the performance of these models in comparison to that of empirical equations available in four different international codes (design codes of China, USA, Canada, and Europe) was also presented in their manuscript. The performance of the developed model was also compared with that of three standard ML models. ANN, SVM, and DT were the models used for this purpose. Based on a literature survey, the authors observed that most of the previous research provided only the theoretical development of methodologies along with the outcomes achieved using ML techniques. Therefore, in their study, the researchers included additional details on the implementation of the training and testing processes to help readers who are new to this field. In their work, the researchers finalized the hyperparameters for the models by combining k-fold validation with a grid search method. The use of k-fold validation will aid in overcoming the bias introduced by random sampling of the training set. Four statistical parameters (the coefficient of determination R^2, root mean squared error, mean absolute error, and mean absolute percentage error) were used to evaluate the performance of the different models. The 16 features selected in this study were the span of the beam, beam depth, effective depth, beam width, shear span, span-to-depth ratio, shear span-to-depth ratio, longitudinal reinforcement ratio, strength of longitudinal reinforcements, horizontal and vertical web reinforcement ratio, spacing and strength of transverse reinforcement, and compressive strength of concrete. The mean values of the effective span, shear span, depth, compressive strength, and shear strength are 1484.45 mm, 467.73 mm, 523.48 mm, 30.89 MPa, and 287.20 kN respectively. The researchers compared the predicted results with experimental data to assess the performance of all four models based on the testing dataset. The RF and GBRT models performed similarly, with R^2 values of 0.906 and 0.910, respectively. Better performance was displayed by both the AdaBoost model and the XGBoost model, with an R^2 value of 0.928 for the latter. Comparing the predictions with single ML models, the researchers observed that even the best individual ML model could not catch up with the worst-performing ensemble learning model. When comparing the results with models available in different international standards, researchers observed larger variations for beams with shear span-to-depth ratios of less than one. In this comparison, the models developed by the researchers outperformed those available in the standards. However, the variation in the results based on the models available in the codes can be attributed to the use of safety factors and assumptions taken from the viewpoint of practical applications. The compressive strength of concrete was observed to be the most significant factor in predicting the shear strength based on the feature importance and partial dependence analysis conducted by researchers. The other critical factors were observed to be the shear span, vertical web reinforcement spacing, horizontal web reinforcement spacing, beam width, and shear span-to-depth ratio.

Chaabene and Nehdi [102] developed a novel hybrid model to classify the failure mode and predict the shear strength of SFRC beams. The model was developed by combining atom search optimization with an ANN. An atom search optimization algorithm based on the population was first introduced by Zhao et al. [34]. It was developed on the basis of molecular dynamics. Accordingly, a global solution is obtained by iteratively updating the positions and velocities of an atomic population. The database used in this investigation consisted of the experimental results for the 573 SFRC beams. It included beams without stirrups that failed in the shear, flexure-shear, and flexure modes. From this, a database containing 484 specimens for which the failure model was either shear or flexural shear was employed to develop the shear strength prediction model. The database used for developing the classification model contained 475 specimens that failed in the shear, flexure-shear, and flexure modes. The proportion of beams that failed in flexure in the database was less (89 specimens) than that of the other failure modes. Parameters, such as the width of the beam, effective depth of the beam, longitudinal steel ratio, shear span-to-depth ratio, steel fiber volume, aspect ratio of the fiber, compressive strength of concrete, and tensile strength of the fibers were considered as features during training and testing. Researchers have used a shallow ANN consisting of one hidden layer with 10 nodes to avoid overfitting and reduce complexity. They arrived at this configuration based on a trial-and-error approach. Based on the attained accuracy, the optimum values for the number of atoms and iterations were obtained as 125 and 150, respectively. Researchers conducted the training process of their model using randomly selected specimens that constituted 75% of the database, and the remaining 25% was employed for testing. The adaptation of atom search optimization helped to optimize the NN weights and biases by minimizing the fitness function. A flow chart showing the details of developing the hybrid model proposed by the researchers is shown in Fig 7.

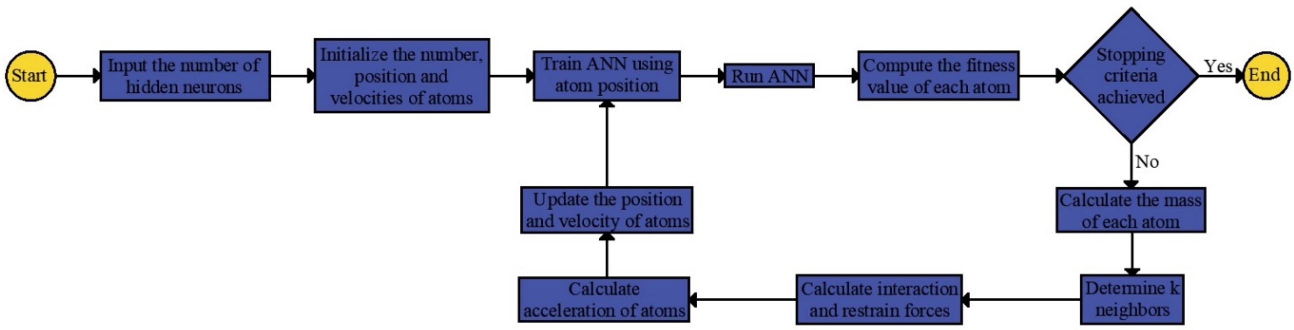

Fig 7 Flow chart of Hybrid model (ASO-ANN model)

In this study, the data were normalized using the z-score method before being fed into the algorithm. To evaluate the performance of the new ASO-ANN hybrid model, researchers compared its results with the shear strength predicted by six different empirical equations as well as with those of several hybrid and standalone ML techniques, including ANN, genetic algorithm optimized NN, particle swarm optimized NN, SVR, particle swarm optimized network, and SVR. Performance was assessed using statistical parameters, such as root mean square error, correlation coefficient, mean absolute error, and modified agreement index in their research. The performance of the proposed ASO-ANN hybrid model was observed to be superior, based on all statistical parameters. Because the developed model was a black box model, researchers conducted a sensitivity analysis with the aim of understanding the influence of the input parameters on shear strength. It was observed that the shear span-to-depth ratio and compressive strength of concrete were the most crucial factors influencing the shear strength. Although the proposed ASO-ANN model yielded superior accuracy, it should be mentioned that because of the difficulty in convergence using the adopted algorithm, this model can demand a higher computational time.

In this study, researchers also developed a model for the classification of failure modes using four different methods: DT, k -Nearest Neighbors, SVM, and naïve Bayes. A 10-fold cross-validation method was employed in this investigation to train all models. To account for the gap arising due to the lower number of flexure-shear and flexural failure modes in the database, a novel performance metric was suggested by the researchers, as given in Eq (4).

$$\gamma = \left(\frac{1}{3}\right)\left[\frac{c_{FS}}{N_{FS}} + \frac{c_S}{N_S} + \frac{c_F}{N_F}\right] \times 100 \tag{4}$$

Where c_{FS}, c_S, c_F, N_{FS}, N_S, and N_F represent the correctly predicted and total number of specimens that failed in flexure-shear, shear, and flexure, respectively. Based on the results, it was observed that k -nearest neighbor had the best accuracy, and naïve Bayes had the lowest accuracy. Because there was an interaction between different features in the considered problem, researchers suggested the assumption of feature independence as the reason for the low accuracy of naïve Bayes.

Armaghani et al [103] investigated the development of an optimized shear prediction model using an ANN. The researchers employed a backpropagation NN to achieve their objectives. The features considered in this study were the width of the beam, effective depth, compressive strength of concrete, yield strength of tensile reinforcement, yield strength of transverse reinforcement, ratio of shear span to effective depth, tensile reinforcement ratio, transverse reinforcement ratio, and ratio of effective span of the beam to effective depth. A database containing the experimental results for 300 beams with stirrups was collected from the literature and used in this investigation. To select the optimum algorithm for training the ANN model, researchers compared the performance of different training functions, such as quasi-Newton, resilient, one-step secant, gradient descent with momentum and adaptive learning rate, and Levenberg–Marquardt backpropagation algorithms. Because the performance of the Levenberg–Marquardt backpropagation algorithm was superior to that of the remaining algorithms, the researchers used it for the remaining part of their investigation. The input and output parameters were normalized using the min-max normalization method before feeding into the program. By varying the number of features used, the researchers proposed and evaluated four different ANN structures. The first was having all the input parameters. The second structure is formulated by combining the yield strength of the tensile reinforcement and its percentage into a single feature. The number of features in the third structure was reduced by neglecting the width and the effective depth of the beam. The final structure was obtained by avoiding the compressive strength of the concrete from the input parameters. To account for the effect of compressive strength, researchers made the output in the fourth structure a dimensionless term by dividing the shear strength by the compressive strength. All four configurations were subdivided into a network with one hidden layer and a network with two hidden layers. All cases were tested with normalized and raw data to comprehend the significance of parameter normalization. In these 16 scenarios, researchers used different numbers of neurons and three different functions. Accordingly, a large number of neural networks were designed and trained by the researchers in this investigation. Sixty percent of the samples from the database were used for training the neural networks, and 20% samples were used for validation and testing respectively. Statistical parameters, such as the Pearson correlation coefficient, root mean square error, mean absolute percentage error, and variance, were used to evaluate the performance of the developed models. In addition, a novel engineering index called the a20-index was used. This index is defined as the ratio of the number of samples with an experimental value to a predicted value between 0.80 and 1.20 and that of the total number of samples. The performance of the optimum model obtained in all four categories by varying the number of features was compared with the performance of models suggested by international standards, such as the Eurocode (EC2), ACI building code, Canadian Code, New Zealand Standards, and with the model proposed by Gandomi *et al* [104]. The results reveal that all four proposed models were able to depict better performance compared to predictions made by codes and models available in the literature. The results of this investigation also highlight the superior shear strength prediction capacity of the ANN models.

Hossain et al [53] investigated the development of a new shear strength prediction model for medium-to-ultra-high-strength SFRC beams using ANNs. A database comprising 176 experimental results was used to test and validate the proposed model. An additional database comprising 36 experimental results was used to test the model. Researchers have used a backpropagation network with the Levenberg–Marquardt algorithm to develop the prediction model. The features considered in this investigation were the percentage of steel fibers, aspect ratio of steel fibers, percentage of tensile reinforcement, strength of concrete, ratio of shear span to effective depth, fiber factor, beam width, beam depth, and aggregate size. The minimum and maximum values of the different features and output parameters have been provided in the manuscript. The final architecture of the network was arrived at through a trial-and-error process. First, the researchers kept the number of features at nine and varied the number of neurons in the hidden layers from 2 to 10. After determining the optimum number of neurons in the hidden layer, the number of input parameters was varied, and the critical input parameters were selected. The performance of the network was evaluated using statistical parameters, such as the degree of agreement, mean squared error, and root mean squared error. In this study, a network architecture with nine input parameters and five neurons in the hidden layer was found to be the optimum configuration. Based on the results, researchers further concluded that the shear span to effective depth ratio is the most influential parameter, followed by the percentage of longitudinal reinforcement and the compressive strength of concrete. Researchers also presented a comparison of the performance of their model with the values predicted by empirical relations proposed by different researchers like Narayanan and Darwish [10], Ashour *et al.* [75], Sharma [77], Khuntia *et al.* [76] and Shin *et al* [105]. Based on the results of this comparison, it was observed that the proposed model was capable of making accurate predictions for medium-, high-, and ultra-high-strength SFRC beams. Notably, the empirical relations could not reasonably predict the shear strength of ultra-high-strength SFRC beams.

5. Challenges and future scope for machine learning in structural engineering

In the last few years, researchers and the engineering community have witnessed a drastic increase in the adaptation of ML for solving structural engineering problems. Although this method was able to provide accurate solutions for many complex problems in civil engineering, many challenges must be overcome for researchers and engineers to adopt it for practical engineering problems. The primary challenge for a new structural engineer in this field is the selection of an appropriate algorithm for the considered problem. Many ML algorithms have been developed and are readily available. As these algorithms were developed with the aim of solving a specific problem, the accuracy of the results for a problem will greatly depend on the correct selection of these algorithms and the context of the problem to which it is applied. Therefore, the user should be well aware of their strengths and weaknesses. Although different comparative studies are available on the use of various algorithms to solve different structural engineering problems, the conclusions arrived at by the researchers are observed to be contradictory [64,74,80,84,89,106–108]. Extensive research is required to understand and highlight the feasibility and efficiency of various algorithms in solving different structural engineering problems. The selection of the optimum number and value of the hyperparameters associated with each of these algorithms is the next challenge faced by structural engineers. Most ML algorithms have different hyperparameters. The selection of the required hyperparameters and the values provided for these parameters will strongly influence the speed and accuracy of the final model. Currently, it is difficult for beginners to determine the optimum number and value of these parameters. The authors believe that more research focused on evaluating the optimum hyperparameter for various ML algorithms applied to different structural engineering problems will be useful for beginners in this field. Another considerable challenge faced in this field is the quantity and quality of the databases available for different problems. Even though the amount of data required for training and validation using different algorithms varies, most algorithms require a large dataset to produce good models. Care should also be taken to ensure that the samples present in the dataset cover different parameters that could influence the considered output. To ensure that the final model is not biased to some parameters, it should also be ensured that the frequency of each parameter in the sample is sufficient and does not largely outnumber the other. Another challenge faced by some of the widely used algorithms like ANN is the black box problem. Even though these algorithms are able to produce accurate results, the level of dependability is still questioned by many researchers as the details of operations happening behind these algorithms are not known to the user. It is difficult to understand the contribution of different influencing parameters in reaching the final predicted values. This will give way to lack of confidence in using them in real life problems. A solution to solve this problem is to adopt physics-based models or to use feature importance study or methods like shapley additive explanations (SHAP) along with the prediction algorithms. Again, these are some of the areas where more research is needed. Even though, with the application of machine learning more accurate solutions were developed for many complex engineering problems, more research addressing the above-mentioned challenges is necessary to provide confidence for the adaptation of this method to real-life problems.

6. Summary and Conclusion

The high potential of ML to provide accurate solutions for structural engineering problems has attracted the attention of researchers and civil engineers. This is evident from the exponentially increasing number of publications by researchers who utilize ML-based methods for solving complex engineering problems. Numerous researchers have already depicted the potential of this method to provide an accurate solution for prediction and classification problems. This paper includes the details of basic terminologies associated with ML and a detailed discussion of the concept of commonly used algorithms (13 algorithms) for solving structural engineering problems. It will help beginners in this field understand the basics of ML and enable them to easily utilize its potential in their future research. A comprehensive review of the literature related to shear strength prediction of conventional concrete beams, SFRC beams, beams reinforced with FRP bars, and high-strength concrete beams is also presented to highlight the potential of ML in making accurate predictions for complex structural engineering problems. A detailed discussion on the major challenges faced in this field, as well as the scope for future research in this field, are also included in this paper. The major conclusions drawn from the current study are as follows.

- ML is a rapidly emerging field that can replace empirical and semi-empirical prediction models that are currently used in codes and standards.
- The accuracy of ML-based algorithms greatly depends on the quantity and quality of the database used for training and validation.
- The use of feature selection technique, based on the type of features and algorithm used, is highly recommended to improve the accuracy of the final model.
- As far as possible, it should be ensured that the samples in the selected dataset cover the maximum range possible.
- The dataset should contain sufficient number of samples to represent different possible variation of each feature.
- The K-fold cross-validation technique can be used to exploit the complete dataset and reduce the overfitting of the model.
- The use of separate training, validation and testing dataset will help in preventing data leakage.
- The majority of the studies utilized ANNs for developing prediction models.
- In recent years, more studies have been conducted using ensemble and hybrid models, which have resulted in enhanced performance and accuracy compared with standalone models.
- Depending on the type of algorithm used and the dataset, the hyperparameters of the learner should be optimised for enhancing the model performance.
- Most ML models are black-box systems, for which it is difficult to comprehend what is happening internally. This reduces the confidence in their use for complex engineering problems.
- There is a need to develop new ML algorithms that are easily interpretable so that they can be used safely to solve complex engineering problems with confidence.
- In the considered studies, XGBoost, Random Forest and ANN algorithms were observed to be depicting better performance for shear strength prediction.

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