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Machine learning for structural engineering: A state-of-the-art review

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ABSTRACT

Machine learning (ML) has become the most successful branch of artificial intelligence (AI). It provides a unique opportunity to make structural engineering more predictable due to its ability in handling complex nonlinear structural systems under extreme actions. Currently, there is a boom in implementing ML in structural engineering, especially over the last five years thanks to recent advances in ML techniques and computational capabilities as well as the availability of large datasets. This paper provides an ambitious and comprehensive review on the growing applications of ML algorithms for structural engineering. An overview of ML techniques for structural engineering is presented with a particular focus on basic ML concepts, ML libraries, open-source Python codes, and structural engineering datasets. The review covers a wide range of structural engineering applications of ML including: (1) structural analysis and design, (2) structural health monitoring and damage detection, (3) fire resistance of structures; (4) resistance of structural members under various actions, and (5) mechanical properties and mix design of concrete. Both isolated members and whole systems made from steel, concrete and composite materials are explored. Findings from the reviewed literature, challenges and future commendations are highlighted and discussed. With available databases and ML codes provided, this review paper serves as a useful reference for structural engineering practitioners and researchers who are not familiar with ML but wish to enter this field of research.

1. Introduction

Machine learning (ML) is a class of artificial intelligence (AI) that focuses on teaching computers how to make predictions from available datasets and algorithms. Most importantly, it provides computer systems the ability to learn and improve themselves rather than being explicitly programmed. Although ML was born in 1943 and first coined in 1959, it actually started to flourish in the 1990 s, and has become the most successful subfield of AI. ML has also become one of the technology buzzwords of our age since it plays a pivotal role in many real-world applications such as image and speech recognition, traffic alerts, self-driving cars, medical diagnosis, etc.

In general, ML can be classified into three main categories based on the learning process: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is the most basic type of ML whose algorithm is trained from a labelled dataset. This method is suitable for regression and classification problems, and it has been widely used in structural engineering for damage detection (classification problems) and strength predictions (regression problems). On the contrary, the algorithm used in unsupervised learning is trained from an unlabelled dataset. Meanwhile, in the reinforcement learning method, the algorithm is trained through a trial-and-error process. A significant number of ML algorithms have been adopted in structural engineering applications, e.g., neural networks (NN), decision tree (DT), regression analysis (RA), support vector machine (SVM), random forest (RF), boosting algorithm (BA), etc. Surrogate model, also known as meta-model, is a special case of supervised ML which has been widely used in the field of engineering design to reduce computational time of complex black-box ML models with relaxed accuracy. It is an interpretable model which is trained to approximate the predictions of a black-box ML model. In other words, surrogate models are simple analytical models which mimic the behaviour of complex ML models.

Structural engineering involves the structural analysis and design of load-bearing structures. For complex structural systems under extreme actions that exhibit highly nonlinear behaviour, the use of structural analysis and design methods requires a time-consuming calibration process, and they are somehow too complicated for practical implementation. In this case, ML can provide a promising alternative to save time and effort. One of the first structural engineering applications of ML was carried out by Adeli and Yeh [1] in 1989 using artificial neural network (ANN) to design steel beams [2]. Since then, the ANN algorithm has been successfully used in many pioneering works in structural engineering including structural analysis and design [3], structural

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Nomenclature

ANN	Artificial neural network
AdaBoost	Adaptive boosting
ANFIS	Adaptive neuro-fuzzy inference system
BA	Boosting algorithm
CART	Classification and regression tree
CatBoost	Categorial gradient boosting
CFS	Cold-formed steel
CFST	Concrete-filled steel tubes
CHS	Circular hollow section
CNN	Convolutional neural network
DT	Decision tree
EFB	Exclusive feature bundling
FFNN	Feed-forward neural network
FRC	Fibre reinforced concrete
GBM	Gradient boosting method
GOSS	Gradient-based one-side sampling
GPC	Geopolymer concrete
HPC	High performance concrete
HSC	High strength concrete
kNN	k-nearest neighbour
LRFD	Load resistance factor design
LSTM	long short term memory
LWC	Lightweight concrete
LightGBM	Light gradient boosting machine
MAE	Mean absolute error
MLP	Multilayer perceptron
MSE	Mean squared error
MVS	Minimal variance sampling
NB	Naïve Bayes
NEES	Network for earthquake engineering simulation
NN	Neural network
NSC	Normal strength concrete
PEER	Pacific earthquake engineering research
PHL	Plastic hinge length
RA	Regression analysis
RA1	Linear regression
RA2	Multivariate regression
RA3	Polynomial regression
RA4	Lasso regression
RA5	Ridge regression
RA6	Logistic regression
RAC	Recycled aggregate concrete
RBF	Radial basis function
RBFNN	Radial basis function neural network
RC	Reinforced concrete
RF	Random forest
RHS	Rectangular hollow section
RNN	Recurrent neural network
SCC	Self-compacting concrete
SHM	Structural health monitoring
SHS	Square hollow section
SVC	Support vector clustering
SVM	Support vector machine
SVR	Support vector regression
UHPC	Ultra-high performance concrete
XGBoost	Extreme gradient boosting

damage detection [4], structural health monitoring (SHM) [5], structural optimisation [6-8], strength and resistance predictions [9,10], and structural reliability [11]. However, the use of ML in structural engineering is still in its infancy at that time [12] due to the limitations of ML algorithms and computing power. This is evidenced by the fact that only a few relevant articles were published each year in the early stage of structural engineering applications (see Fig. 12a in Section 3).

Another reason that hinders the application of ML in structural engineering at its early stage is a lack of experimental databases to ensure the validation of ML models. However, in recent years, the research community has taken the necessary steps towards overcoming this barrier by establishing database platforms (e.g., DataCenterHub, DesignSafe, Mendeley Data, etc.) to collect data from structural engineering tests. DataCenterHub is a massive repository platform with over 250 datasets from nearly 50,000 experiments [13]. DesignSafe is extended from the network for earthquake engineering simulation (NEEShub), a cyberinfrastructure platform to share data and tools for earthquake engineering [14,15] and disaster risk management [16,17]. Some notable databases for structural engineering include NEEShub datasets for earthquake engineering that can be accessed from DataCenterHub [18] and image databases for crack damage detection (e.g., Structural ImageNet [19] with over 10,000 images, PEER Hub ImageNet [20] developed by the Pacific earthquake engineering research (PEER) centre with over 36,000 images, bridge crack library [21] with over 11,000 images, etc.). Detailed databases used in structural engineering are given in Section 2.5.

In addition to the establishment of the database platforms for structural engineering, there have also been recent advances in ML techniques. BA methods (see Section 2.2.6), especially extreme gradient boosting (XGBoost) [22] and categorical gradient boosting (CatBoost) [23], offer extremely powerful tools to solve the problems with large datasets in a fast and accurate manner. Convolutional neural network (CNN) [24] is considered as one of the state-of-the-art ML algorithms for image-based crack detection [20] due to its ability in rapidly detecting crack damage in structures. Recently, Google team has made a new breakthrough when creating a new ML method called AutoML-Zero [25] that can evolve itself without human intervention. In addition, the availability of open-source ML libraries with hands-on ML algorithms and ready-to-run packages (e.g., TensorFlow and Keras developed by Google and PyTorch by developed by Facebook) has facilitated the development of ML-based models for structural engineering applications.

With the rapid development of ML algorithms and computational power combined with the availability of databases collected recently, the research community has witnessed a boom in the use of ML in the structural engineering domain, especially over the last five years with a clear exponential growth in the number of publications each year (see Fig. 12a in Section 3). However, practical applications of ML in structural engineering are still very limited. One of the real-world applications of ML is to improve design of buildings through generative design, where the industry (e.g., Arup) has developed ML-powered tools to generate design alternatives that meets requirements of the end-users. Although a number of review articles published recently have touched on this topic, they just focused on a certain area of structural engineering (e.g., structural design and performance assessment [26], reliability and safety [27,28], earthquake engineering [29,30], structural design for fire [31], SHM and crack detection [32–39], concrete property [40,41], concrete mix design [42], capacity prediction of concrete structures [43], and design and inspection of bridges [44]). A comprehensive review on all areas of structural engineering is lacking.

This paper is therefore aims to present a comprehensive review on all applications of ML techniques to structural engineering. The present review is considered as the most ambitious and comprehensive work when covering a wide range of structural engineering applications (i.e., structural analysis and design, SHM and damage detection, behaviour and capacity of structural members and systems, fire resistance of structures, and property and mix design of concrete) and ML algorithms (i.e., NN, SVM, DT, RF, BA, and RA). The review looks at both isolated structural members (e.g., beam, column, slab/panel, wall, and joint) and whole structural systems (e.g., truss, frame, building, and bridge) made from different materials (e.g., concrete, steel, cold-form steel (CFS), fibre reinforced polymer (FRP) composite, and steel–concrete composite). The review also considers different behaviours of structures under shear, flexural, torsional, axial, bond, and buckling actions. It should be noted that evolutional algorithms (EA) including genetic algorithm and gene expression programming are types of ML, and thus the author initially intended to cover them in this paper. However, there is a very large number of publications (about 125 references) on the application of EA to structural engineering found in the literature, and thus the inclusion of this topic will make the manuscript too lengthy. In addition, there is already one review article published recently on this topic [45]. For this reason, this topic is not covered in the manuscript.

2. ML in a nutshell

This section provides the concepts and hands-on tools to implement ML methods. It covers a wide range of ML algorithms which are widely used in the structural engineering domain. In addition, available Python libraries, open-source codes and datasets for ML are also provided for the readers to practise and execute their ML models.

2.1. Overview of ML

ML is the process of teaching a computer system (i.e., ML model) how to make an accurate prediction when feeding the new data. Fig. 1 illustrates a typical workflow of ML used in predictive modelling. By using a learning algorithm and initial data, the computer system is trained to be able to learn and improve until its performance is met. Therefore, the accuracy of a ML model strongly depends on the characteristics of initial data and the performance of the learning algorithm. There are three main steps to build a ML model: preparing database, learning, and evaluating the model.

- **Step 1**: Initial data used to build a ML model is usually presented in the form of input and corresponding output variables which are characterised in ML terminology by *feature* (input variable) and *label* (output variable). When predicting the behaviour of a structure, for example, its geometric dimension and material properties are categorized as features, whilst its ultimate strength and deflection are used as labels. Some ML algorithms require all input data to be scaled in the range [0,1] for having a better performance [46]. To test the performance of ML models, initial data is randomly split into training and testing datasets with the large portion being used for training purpose.
- **Step 2**: The aim of this learning step is to train a selected ML algorithm. A large number of ML algorithms have been developed in the literature for specific applications (a detailed explanation of each algorithm given in Section 2.2). It is therefore important to compare different algorithms to find out the best one for particular problems. The selected algorithms are then trained using the training dataset obtained from Step 1.
- **Step 3**: Once a ML model is completely trained, its performance is evaluated using the testing dataset. A *loss function* is used as a performance indicator to measure how far a predicted value is from its actual value. Typical loss functions for regression problems are the mean absolute error (MAE) and mean squared error (MSE). Loss functions play a critical role in evaluation ML models, and thus choosing the right loss function also dictates how well the model will be.

2.2. ML algorithms

Nowadays, plenty of ML algorithms have been developed in the literature as shown in Fig. 2. Each algorithm with its strength and weakness is designed for a certain types of learning methods and problems. However, this section only looks at the algorithms that are commonly used in structural engineering. In each algorithm, its concept is clearly explained which is found helpful in practice for structural engineering people without ML background.

2.2.1. Regression techniques

RA is a predictive modelling technique which was first developed in statistics to study the relationship between independent variables (predictors) and dependent variables (targets). This method was then applied in ML under the supervised learning algorithm to predict the output values based on the values of the input variables. There are different types of regression models developed in ML based on (i) the number of variables, (ii) the type of variables, and (iii) the shape of the regression line. RA models commonly used in structural engineering include:

2.2.1.1. Linear regression (RA1). This is the simplest regression model in ML where the output variable and the input variable(s) are best fitted in a straight line (linear function). The coefficients of the linear equation are determined by minimising the cost function (e.g., MSE and MAE) defined as the difference (error) between the predicted value and the actual value. If a single input variable is used, the model is called the simple linear regression. In the case of more than one input variable, it is called the multiple linear regression.

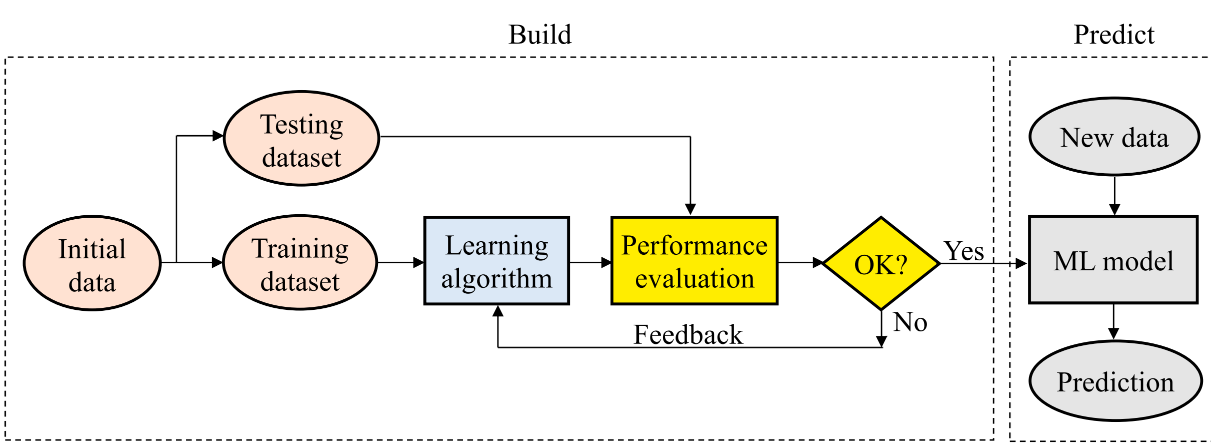


Fig. 1. Typical workflow of ML.

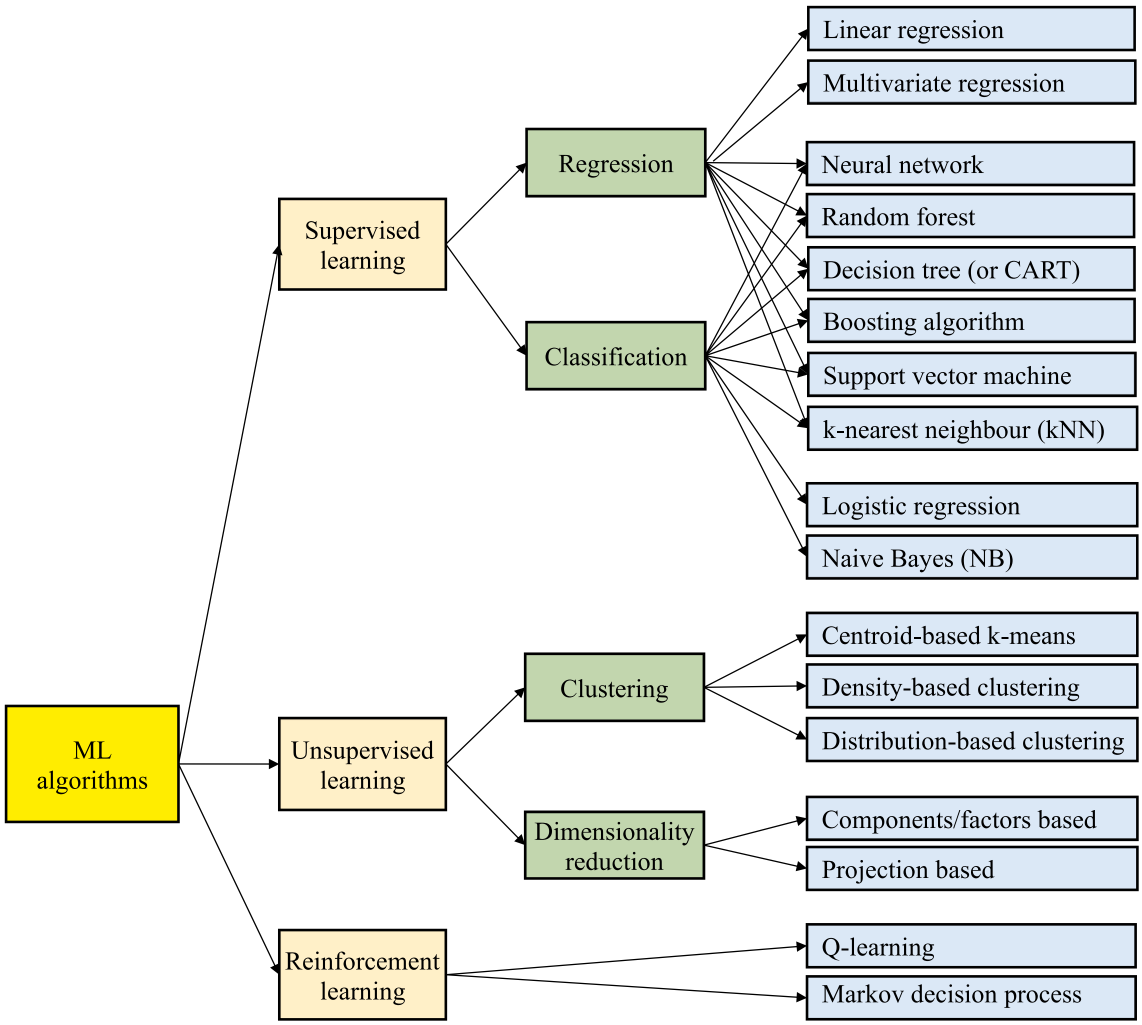


Fig. 2. ML algorithms grouped by learning type.

2.2.1.2. Multivariate regression (RA2). Multivariate regression is an extension of the multiple linear regression when dealing with the problem that has more than one output variable. The word "multivariate" refers to more than one output variable, whilst the word "multiple" refers to more than one input variable. The merit of this method is that it helps to understand the correlation between input and output variables. This method is also widely used in ML for regression problems.

2.2.1.3. Polynomial regression (RA3). The difference between RA3 model and RA1 model is the shape of the regression line. The best fit line in RA3 is a curved line (polynomial function) with the power of input variables more than one. Overfitting might occur in this model if the input variables are fitted by a higher degree polynomial to obtain a lower error. Therefore, it is useful to plot the model to make sure reasonable results are obtained.

2.2.1.4. Lasso regression (RA4). Least absolute shrinkage and selection operator (LASSO) regression is a regularized version of RA1 which is used when the input variables are highly correlated. In this case, the use of linear regression technique might result in overfitting. Therefore, RA4 is proposed to reduce overfitting by adding a regularisation term in the cost function during the training. This keeps the model weight as small as possible [47]. The regularisation term used in RA4 is L1-norm (absolute value of the weight).

2.2.1.5. Ridge regression (RA5). Similar to RA4, RA5 is also a regularized version of RA1. However, the regularisation term used in RA5 is L2-norm (squared value of the weight) instead of L1-term used in the case of RA4. The aim of the RA5 technique is to try to eliminate the weight of the least important features [47].

2.2.1.6. Logistic regression (RA6). This regression technique was developed for classification problems when the output variable is binary or discrete in nature (e.g., True/False, 1/0, Yes/No, etc.). In RA6, the relationship between the input and output variables is expressed by a logistic function also known as sigmoid function. This method is based on the concept of probability. It means that RA6 outputs a binary value of 0 (when the estimated probability is less than 50%) or 1 (when the estimated probability is greater than 50%) rather than a numerical value.

2.2.2. *Neural network and its variants*

Artificial neural network (ANN) is developed to mimic how biological neurons work. The first ANN was invented by Rosenblatt [48] in 1958 called *perceptron* for pattern recognition problems. Thanks to improving in computing power, ANN has become one of the most popular ML algorithms nowadays with various variants such as feed-forward neural network (FFNN) [49] improved by multilayer perceptron (MLP), radial basis function neural network (RBFNN) [50], CNN [24], recurrent neural network (RNN) [51] improved by long short term memory (LSTM) [52], and adaptive neuro-fuzzy inference system (ANFIS) [53]. FFNN is the first and simplest type of ANN in which the information transfers only in one direction (forward) from input nodes to output nodes, whilst MLP is an improved version of FFNN with multiple layers of computing units including one input layer, one or more hidden layers and one output layer as shown in Fig. 3a. RBFNN is an ANN in which a radial basis function (RBF) is used as activation function. CNN is specifically developed for image recognition (see Ref. [36] for a critical review on the use of CNN in image-based crack detection), whilst RNN is designed to interpret temporal or sequential information. ANFIS is a combination of the learning ability of an adaptive neural network and reasoning capabilities of a fuzzy inference system. A detailed historical review of ANN and its variants can be found in Schmidhuber [54].

2.2.2.1. ANN. An ANN structured like the human brain consists of artificial neurons also known as units or nodes. These nodes are fully interconnected and arranged in three different layers as shown in Fig. 3a. The input layer receives the input data x, whilst the output layer represents the predicted results *y* of the network. Sandwiching between the input and output layers is one or more hidden layers of computing units (Fig. 3b) which performs the main mathematical computations on the input data. When an ANN is designed with two or more hidden layers, it is called multilayer perceptron or deep learning (DL), a specific subfield of ML based on NNs [54,55].

The behaviour of each neuron unit is defined by the weights w assigned to it. When the data x_i is fed to the input layer, they are multiplied by corresponding weights w_i. Then, a transfer function is used to calculate the weighted sum of the input plus a bias b, which is gradually adjusted to minimise the difference between the predicted and actual outputs. The value of the transfer function is then passed through an activation function f to check if the node should transmit data to the output layer or not. When an ANN is trained, random values of weights are assigned to all nodes. Once the activation function passes the predicted value y to the output layer, an error function is used to calculate the difference between the predicted and actual outputs. Based on the result, the ANN model adjusts the weights of all its nodes to minimise the error. Such training process known as back-propagation [56] is iterated until the convergence condition is satisfied.

There are a number of hyper parameters that need to be optimised when training an ANN model because they control the learning and training process of the network. They include the architectural choices of an ANN (i.e., the number of hidden layers used, the number of nodes per hidden layers, and the type of activation functions) and the training variables (i.e., leaning rate, the number of epochs, momentum, and batch size). Increasing the number of hidden layers and hidden nodes can increase the accuracy of the network, but it causes computational cost. The activation function is used to account for the nonlinearity of models. The learning rate defines how quickly the ANN model updates its parameters. The use of a high learning rate will speed up the learning, but it may fail to converge. Epoch controls the number of iterations for the training dataset, while momentum is used to choose the direction of the next step from the previous step which can help to prevent oscillations. Such hyper parameters are tuned during the testing and validation stages.

2.2.2.2. CNN. This algorithm was first introduced in the 1980 s by Yann LeCun, a French computer science researcher who built one of the early versions of CNN architectures for handwritten digital recognition called LeNet [24]. The basic idea of CNN is to create a network in which each layer can convert information from the previous layers into more complex information and transform to the next layers. As shown in Fig. 4, a CNN is built based on two basic blocks: the feature learning block and the classification block. The feature learning which is composed of a number of alternate layers of convolution and pooling is used to extract and learn the feature from the input image. The extracted or learned feature is then classified through the classification block. Different CNN architectures have also been developed to improve the performance of CNN in various applications. Notable among them are LeNet, AlexNet, VGG, and ResNet. A comprehensive review on the evolution of CNN architectures can be found in Refs. [57,58].

CNN is considered as one of the best ML algorithms for image recognition. A detailed review on the development of CNN for the application of image classification can be found in Wang et al. [59]. In the context of SHM, CNN has been widely used to detect crack in structures based on either image classification approaches or segmentation techniques. The image classification method detects crack at the image level rather than the pixel level used in the segmentation method. Reviews on the use of CNN for structural crack detection and condition assessment were reported by Ali et al. [39] and Sony et al. [36], respectively.

2.2.2.3. RBFNN. This is a specific ANN that uses RBF as an activation function as proposed in one of the early works by Broomhead and Lowe [50]. The RBFNN has only one hidden layer called feature vector, and its output is a linear combination of RBFs of the inputs and neuron parameters (i.e., weight and bias). The merit of RBFNN over a regular NN is its fast-training ability thanks to the universal approximation of RBFs. The only concern when using RBFNN is how to properly choose the shape parameters and centres of RBF [60].

2.2.2.4. ANFIS. This algorithm combines the adaptive control technique of neuro-fuzzy systems and the learning ability of ANNs. Therefore, ANFIS can leverage the merits of both fuzzy logic and NN to

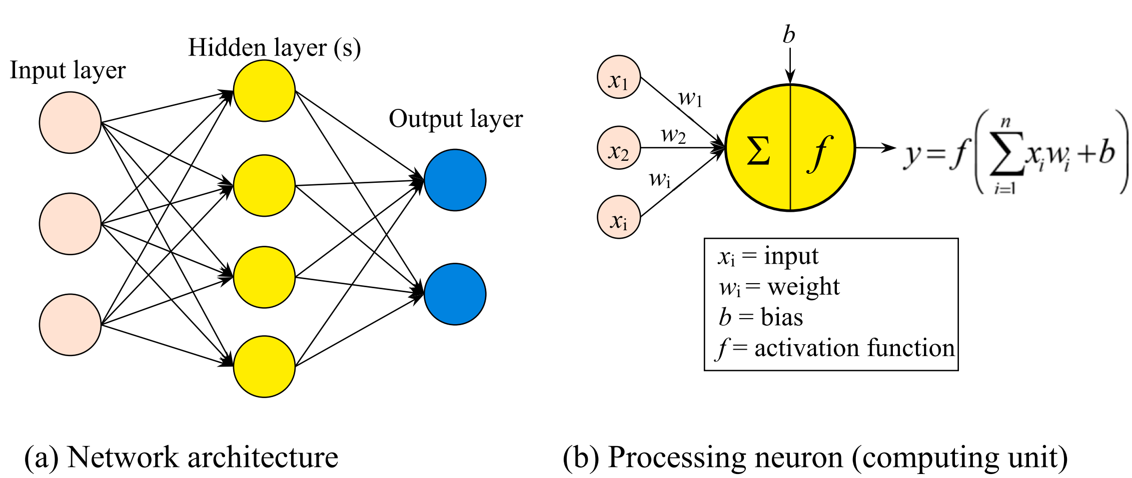


Fig. 3. Example of an ANN.

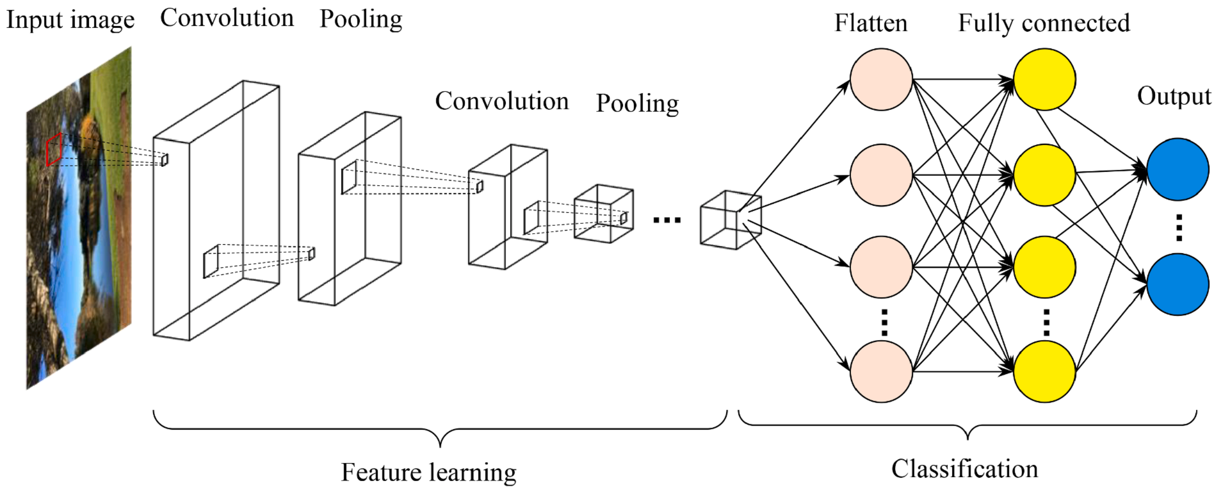


Fig. 4. Typical CNN architecture.

minimise the errors between the input data and the data predicted by the neuro-fuzzy system. A typical ANFIS architecture consists of five layers namely fuzzy layer, product layer, normalized layer, de-fuzzy layer, and overall output layer. The first layer receives the input values and determines their membership functions using premise parameters. The second layer produces the firing strength for the rules, and thus this layer is also called the "rule layer". The firing strength is then normalised in the third layer. The fourth layer receives the normalised values and consequence parameters, and then passes them to the last layer for the overall final output. The adjustable parameters (i.e., premise and consequence) are identified during the learning process to minimise the error between the actual output and desired output. Therefore, they play a vital role in deciding the performance of ANFIS.

2.2.3. Support vector machine

SVM is one of the most powerful and popular algorithms due to its accuracy and simplicity. This algorithm was first introduced for classification problems by Boser et al. [61] in 1992 using nonlinear classifiers. Cortes and Vapnik [62] later extended the SVM algorithm to cases where data are nonlinearly separable using soft margin classifiers. SVM was also expanded for regression problems [63] known as support vector regression (SVR) and clustering tasks [64] known as support vector clustering (SVC). However, the SVM technique is widely used in classification purposes.

The basic idea behind the SVM algorithm is to distinguish between groups of data features, called vectors, and then find an optimal separating hyperplane that has a maximum margin (i.e., the maximum distance between support vectors of both groups as shown in Fig. 5a). The data points located on the margins are called support vectors which influence the position and orientation of the hyperplane. In other works, SVM aims to maximise the margin by means of support vectors. SVR applies the same principle as SVM, but for regression problems. The SVR algorithm finds a function that best fits data points within a decision boundary as shown in Fig. 5b using linear regression. The best fit line is the hyperplane that has the maximum number of data points within a threshold value ε (see Fig. 5b).

In most real-world applications, data is not linearly separable, and thus it is impossible to find a separating hyperplane. In this case, a penalty parameter and kernel function are used. When the data point is on the wrong side of the margin, the penalty parameter (i.e., the slack variable ξ illustrated in Fig. 6a) is introduced to controls the trade-off between maximising the hyperplane's margins and minimising the total distance of the slack variables $\Sigma\xi_i$. This soft margin technique enables SVM to make certain mistakes to keep the hyperplane's margin sufficiently wide so that other points can still be classified correctly. Meanwhile, the kernel functions are used to map the original nonlinear separable data into a new space where the data are linearly separable as illustrated in Fig. 6b. This is called the "kernel trick". The most commonly used kernel functions are linear and nonlinear polynomial functions, RBF, and sigmoid function. Both kernel functions and penalty parameters have significant effects on the performance of SVM models. The selections of penalty parameters and kernel functions were examined and investigated by Tharwat [65].

2.2.4. Decision tree

DT also known as classification and regression tree (CART) is a tree-

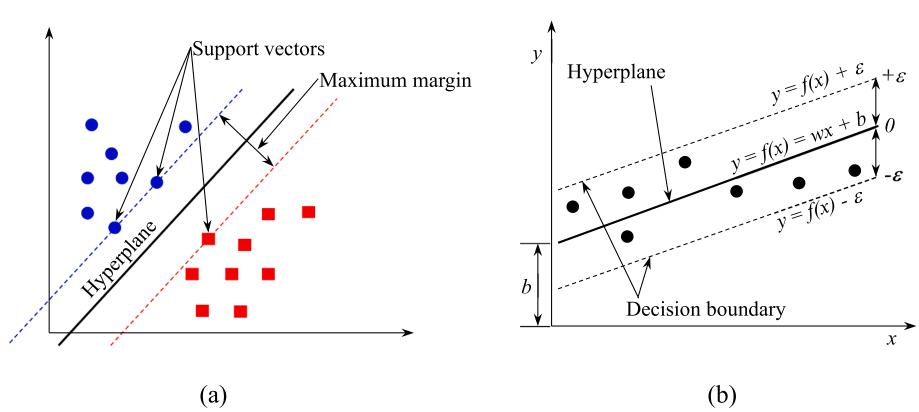


Fig. 5. Example of SVM for (a) classification and (b) regression.

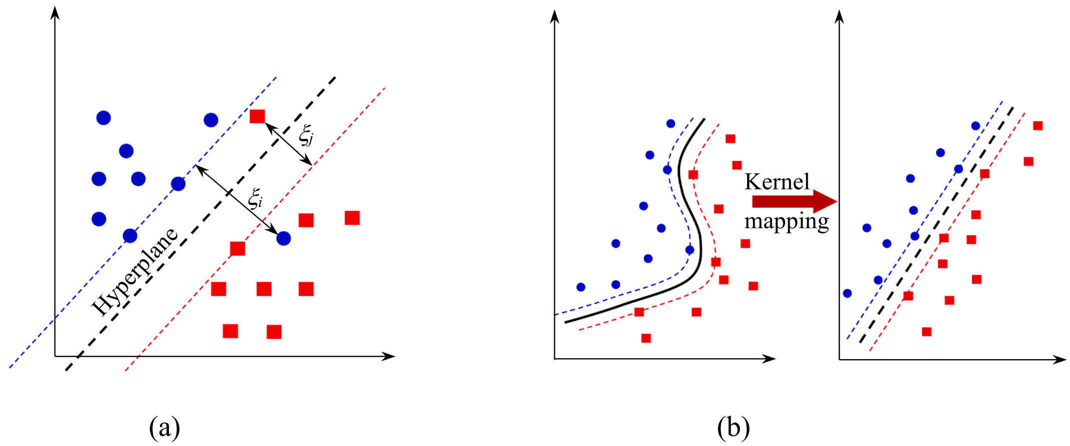


Fig. 6. Illustration of (a) penalty parameters ξ and (b) kernel functions.

based model to visualise the decision-making process. It has become one of the most popular algorithms due to its simplicity and ability to handle both numerical and categorical data. As shown in Fig. 7, a DT has four elements including a root node, two or more branches, decision nodes, and leaf (terminal) nodes. The root node is the topmost decision node of a tree representing the ultimate objective. The leaf node located at the end of the branch indicates a decision to be made, whilst the decision node represents a condition that makes a dataset split.

A tree is built by splitting the source data (root node) into many smaller subsets. The splitting condition can be based on different metrics such as the Gini index, entropy, information gain, and MSE (regression problem). The splitting process is repeated on each derived subset until it cannot find a split that reduces metrics used or it reaches the maximum depth of the tree.

Although DT offers many merits (e.g., less effort for data pre-processing due to no scaling or normalisation of data required), it is unstable and relatively inaccurate compared to other tree-based algorithms like RF and BA family. In order to reduce the risk of overfitting in DT, the model needs to be regularised to restrict the DT's freedom during training (e.g., the maximum depth of the tree, the maximum number of leaf nodes, etc.). More information about tuning regularisation hyper-parameters can be found in Géron [47].

2.2.5. *Random forest*

RF developed by Breiman [66] is an ensemble learning algorithm using DTs as the weak learners. RF builds DTs using the bagging technique (parallel training). The basic idea behind this method is to construct a forest of individual DT using a random selection of features (hence the name "Random Forest"), and then combine the outputs of each DT by taking the majority vote (classification problem) or average (regression problem) as shown in Fig. 8. Therefore, it reduces the risk of overfitting problems in the DT method.

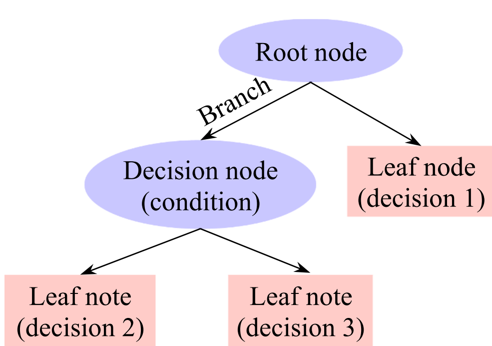


Fig. 7. Example of a DT.

RF inherits the merits of the DT method. Another advantage of RF over DT is that it works well on large databases with thousands of input variables. By using a large number of trees, RF can train faster than DT, but it is quite slow to create predictions of the trained model. RF is also a handy algorithm as its default parameters are often good enough to produce good results. However, there are also several hyperparameters in RF that can be used to make the model more accurate or faster.

2.2.6. *Boosting algorithm*

BA is an ensemble technique which combines many individual models into one predictive model that can boost the performance of the individual models [67]. The term "boosting" refers to strengthening the week learners (e.g., DT). This can be done by means of sequential approaches. BA was first introduced in 1996 by Freund and Schapire [68,69] with adaptive boosting algorithm (AdaBoost). Since then, a number of boosting approaches focusing on enhancing the speed and accuracy have been developed including gradient boosting machine (GBM) [70] also known as gradient tree boosting, extreme gradient boosting (XGBoost) [22], light gradient boosting machine (LightGBM) [71], and categorical gradient boosting (CatBoost) [23]. A comparison of various BA techniques conducted recently by Bentéjac et al. [72] indicated that CatBoost gives the most accurate results, but it is a bit slower than others. XGBoost comes second in both accuracy and speed. LightGBM is the fastest algorithm, but its accuracy is not good compared with others.

2.2.6.1. AdaBoost. This is the very first stepping-stone in the BA family. It is also one of the most popular boosting algorithms (see Ferreira and Figueiredo [73] for a detailed historical review of AdaBoost). AdaBoost is built based on DT and RF algorithms with the weak learners being the DT that has one node and two leaves called decision stumps. The idea behind AdaBoost is to improve to the performance of the weak learners using an adaptively reweighted data obtained based on the output of the previous weak learners (see Fig. 9).

The implementation procedure of AdaBoost is illustrated in Fig. 9. The first weak learner is trained using a uniform weight for all data points of the training sample. Then the second weak learner is trained using the weighted sample 1 with the weight coefficients being updated to account for the mistake from the first weak learner (i.e., increasing the weights of misclassified data points (two green points in Fig. 9) and decreasing the weights of correctly classified data points). This process is repeated until the last weak learner. Finally, the strong learner is formed by combining the decision boundaries learnt by all weak learners.

2.2.6.2. GBM. This algorithm is developed by Friedman [70] by making two modifications to the AdaBoost algorithm. The first modification is the use of DTs as the weak learners instead of decision stumps. This

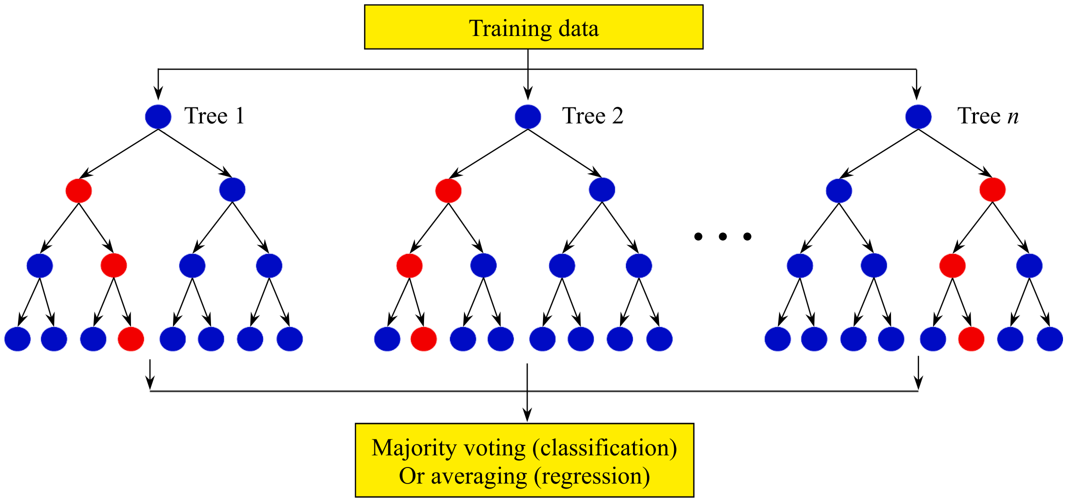


Fig. 8. Flowchart of RF (parallel training).

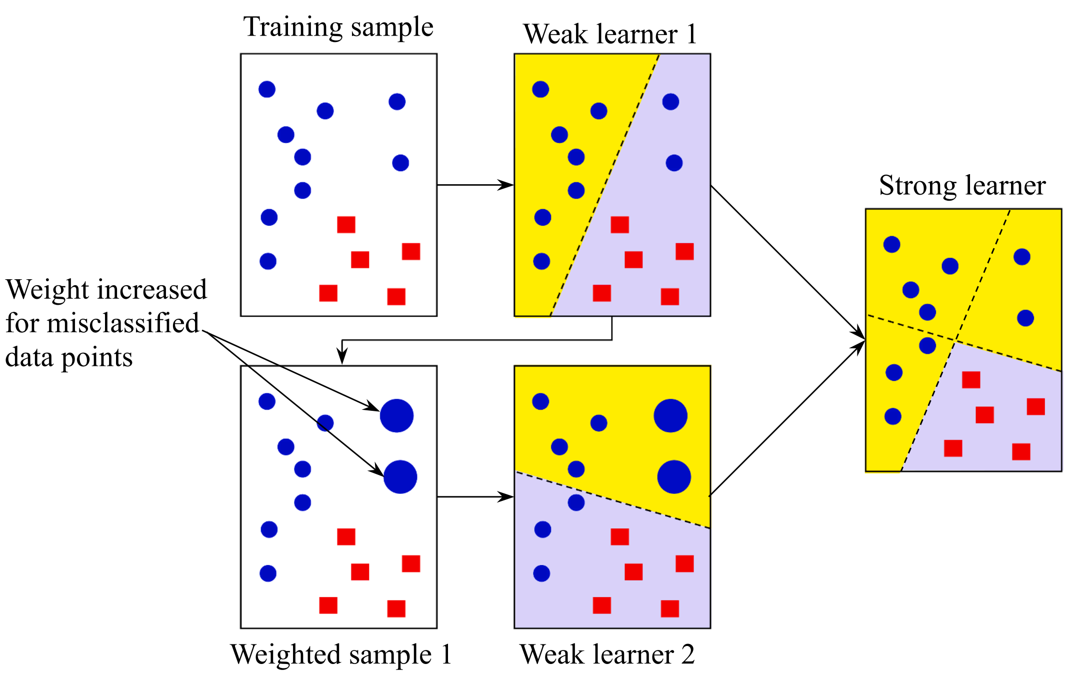


Fig. 9. Graphical representation of implementation of AdaBoost with two weak learners.

means that all trees are not necessary to be the same, and thus they can capture different outputs from the data. The second modification involves the training method. Instead of updating the weights of misclassified and correctly classified data points as in the case of AdaBoost, GBM minimises the loss function of each weak learner using the gradient descent procedure, a generic optimisation algorithm which can apply to any loss function that is differentiable. As shown in Fig. 10, the residual loss (error) of the previous tree is taken into account in training of the next tree. By combining all trees, the final model is able to capture the residual loss from the weak learners. In addition to its accuracy, GBM also offers a lot of flexibility by providing several tuning hyperparameters including number of trees, depth of trees, and learning rate to control convergence and training speed.

2.2.6.3. XGBoost. This algorithm was proposed by Chen and Guestrin [22] to improve the speed and performance of the GBM algorithm which is very slow in implementation due to its sequential model training. XGBoost implements several techniques that make it faster than GBM. For examples, randomisation technique is used to reduce overfitting and increase training speed. Compressed column-based structure is used to store data to reduce the cost of sorting which is the most time-consuming part of tree learning. Parallel and distributed computing are also implemented to enable the use of all CPU cores during training and split finding. The implementation of the parallel processing makes XGBoost extremely powerful to solve large problems with large datasets in a fast and accurate manner. It is therefore considered as one of the most efficient ML methods, and has become a favourite de-facto algorithm today.

2.2.6.4. LightGBM. This algorithm was developed by Ke et al. [71] focusing on computational efficiency with an acceptable level of accuracy (up to 20 times faster than GBM [71]). The word “Light” means this algorithm is superfast compared with other BAs even XGBoost which takes a long time to train when dealing with large amounts of data. The main difference between LightGBM and other BAs is the way the tree is

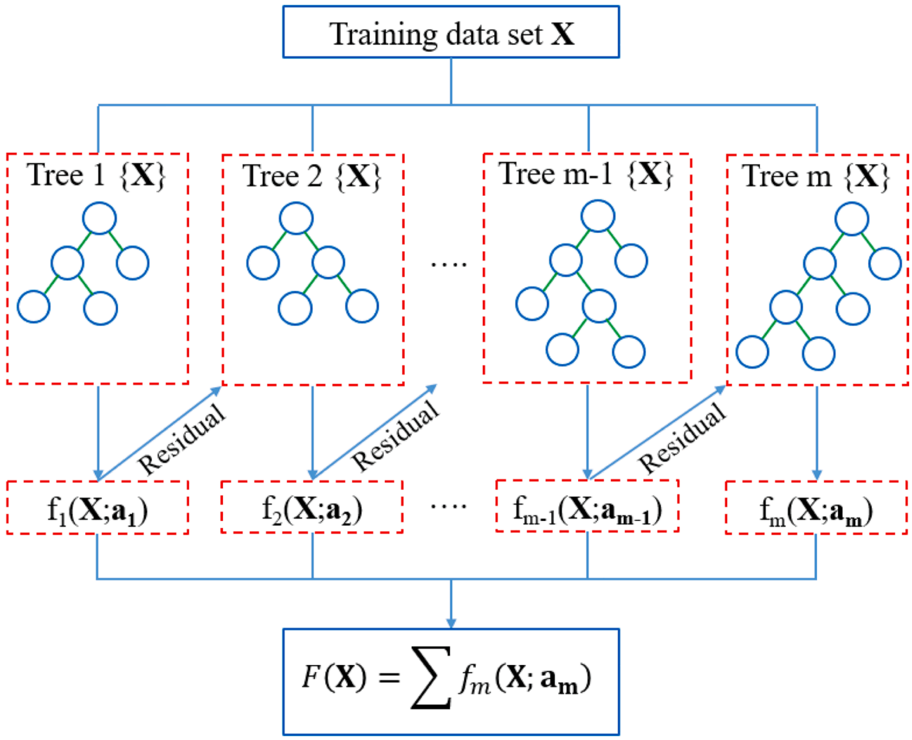


Fig. 10. Illustration of the GBM model.

expanded. LightGBM uses the leaf-wise (best-first) tree strategy to grow the leaf with large loss (see Fig. 11). Therefore, when growing on the same leaf, it can reduce more loss (i.e., better accuracy) than the level-wise (depth-first) strategy used in other BAs. Two additional important features implemented in LightGBM that make it fast are: (1) gradient-based one-side sampling (GOSS) and (2) exclusive feature bundling (EFB). GOSS is an advanced subsampling technique which can significantly reduce the number of instances by performing random sampling on the instances with small gradients only, whilst EFB is a merging technique to reduce the number of features [71]. The use of GOSS and EFB can speed up the training process because the computational time for split finding is proportional to the number of instances and features. Since LightGBM is purposely designed to be used with a large data size, it is very sensitive with small data which might cause overfitting.

2.2.6.5. CatBoost. Similar to XGBoost and LightGBM, CatBoost was also developed to improve the training time of GBM, but it focuses on categorical variables. However, CatBoost also work well with other data types such as numerical and text features without requiring any data conversion in the pre-processing. Similar to the GOSS subsampling technique used in LightGBM, Prokhorenkova et al. [23] also implemented a new sampling technique called minimal variance sampling (MVS) in CatBoost to maximise the accuracy of split scoring. In the MVS technique, the weighted sampling occurs at the tree-level instead of the split-level. This leads to reducing overfitting when data is small.

2.3. Python libraries for ML

ML has become very popular nowadays, and anyone with an internet connection can use available platforms and cloud services provided by firms like Google (e.g., Kaggle.com), Facebook, and Microsoft to build their ML models. Among various ML languages, Python has emerged as the most popular programming language for coding ML models due to having a variety of available ML libraries with hundreds of ML algorithms implemented. Therefore, this paper reviews existing open-source Python libraries and platforms developed for ML models. Table 1 summarises a list of Python libraries that are commonly used in ML.

2.3.1. TensorFlow

This ML library developed by Google was first released in 2015. TensorFlow is an open-source libraries integrated a wide range of the state-of-the-art ML algorithms. It is currently hailed as the best platform for developing ML models especially with deep NNs. It is a high-level framework that contains several hands-on ML models as well as ready-to-run packages.

2.3.2. Keras

This is also an open-source library used for developing and

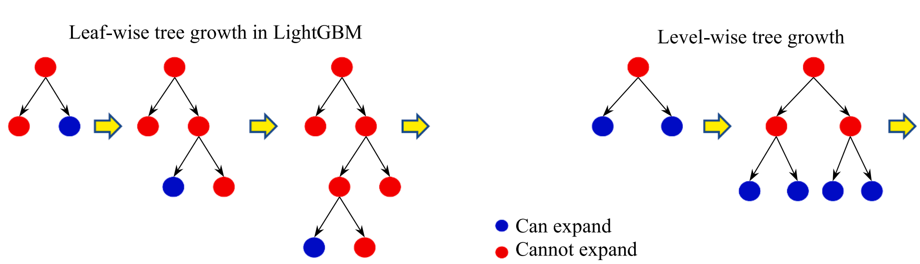


Fig. 11. Tree growth methods used in LightGBM and other BAs.

Table 1
List of commonly used Python ML libraries.

Name	Features
TensorFlow	Can run on a variety of computational platforms, and suit for very large numerical computations
Keras	Have a bunch of features to work on image and text, and ease of use with neural networks
PyTorch	Have a robust framework to build computational graphs, and ease of using and learning
Scikit-learn	Handle wide ranges of ML algorithms for statistical analysis, data mining, and data analysis
Pandas	Support for different types of data, and suit for data analysis with highly optimised performance
Spark MLlib	Make practical ML easy and scalable with the merits of speed and ease of use
Theano	Perform data-intensive computations with mathematical expressions and matrix calculations
NumPy	Process large multi-dimensional arrays and matrices, and easily integrate with most databases
SciPy	Suit for computational tasks for scientific and analytical computing
Matplotlib	Suit for data visualization with quality image plots and figures in a variety of formats

evaluating deep NNs. Keras was developed by Chollet [46] in 2015 to act as an interface for the TensorFlow library, and thus it is very easy to use. Keras can run on top of TensorFlow and Theano platforms. It contains a number of features to build NNs as well as a bunch of tools to work on images and text data.

2.3.3. PyTorch

Upon its first release in 2016 by Facebook, PyTorch has become one of the most popular DL libraries after Keras an TensorFlow [47] thanks to its ease of learning and use. It has a robust framework to build computational graphs, and provides a lot of tools and libraries for ML.

2.3.4. Scikit-learn

This library was built in 2007 based on two Python numerical and scientific libraries of NumPy and SciPy. Scikit-learn provides a wide range of functions for classification, regression, clustering, and dimensionality reduction algorithms. It has become one of the most popular ML libraries especially for data mining and data analysis.

2.3.5. Pandas

This is the most popular Python ML library for data analysis. Pandas was first released in 2008. It offers high-level data structures and options to manipulate different types of data including matrix data, tabular data, and time series data. It also provides a lot of great features for efficiently handling large datasets.

2.3.6. Spark MLlib

This ML library was developed to meet the need of handling big data size. It was built on Apache Spark (a lightning-fast engine for large-scale data processing) with the aim to make practical ML scalable and easy. Spark MLlib provides convenient tools for developing ML algorithms and applications. It is also simple and easy to use.

2.3.7. Theano

Developed by the University of Montreal as a symbolic mathematical processor, Theano is considered as a robust library for scientific computing. Similar to Spark MLlib, Theano was also designed for fast computation of large-scale computationally intensive problems. It is considered as the grandfather of DL libraries, and many DL libraries (e.g., Keras) have been built on top of it.

2.3.8. NumPy

This is a general-purpose library for array processing. NumPy stands for “Numerical Python” which is created on the top of an older library “Numeric”. It has become one of the essential and popular libraries for ML due to having a bunch of mathematical functions to handles large multi-dimensional arrays and matrices. It is particularly useful for basic algebra, random simulations, and Fourier transform.

2.3.9. SciPy

Standing for Scientific Python, this library is developed for scientific computation purposes. It is built on the top of the NumPy library. SciPy provides a range of mathematical functions for optimization, linear algebra, fast Fourier transform, and signal procession. This is the most used scientific library due to its ease of use and fast computational power.

2.3.10. Matplotlib

This is a comprehensively plotting library for visualisations in Python. It is built on the top of NumPy. Matplotlib offers a wide range of plotting functions (e.g., line plots, scatter plots, bar charts, histogram, etc.) that help to understand the common patterns and distribution of data. It is very simple and easy to use.

2.4. Open-source ML codes developed for structural engineering applications

This section reviews existing open-source ML codes developed for structural engineering examples. These code examples are found helpful for structural engineering practitioners and researchers who do not have ML background but wish to enter this field of research. Table 2 summarises a list of ML codes written mainly in Python for different structural engineering applications including shear resistance of structures [74–81], axial resistance of columns [82], compressive strength of concrete [83], failure mode of structures [84–86], and surface crack detection of structures [87–90]. Most of these open-source Python codes can be accessed from the GitHub platform with the corresponding links provided in Table 2. The databases used in these code examples can also be found in the relevant references mentioned in Table 2. More databases of different structural engineering applications are also provided in Section 2.5 for further practising purposes. Additional information about how to develop ML models using Python can be found in the following ML books [46,47,91].

Degtyarev and Naser [74] compared five BA algorithms for predicting the shear resistance of CFS channel sections with staggered web perforations. A comparison of various ML algorithms was presented in Refs. [78–81] for the shear resistance of different types of structures (e.g., reinforced concrete (RC) deep beams [78], RC slabs [79], RC walls [80], and bolted connections [81]), compressive strength of concrete [83], and failure mode of column base plate connections [84] and RC walls and columns [85,86]. Xu et al. [75] looked at the interface shear strength of cold joints used in precast structures using XGBoost. The SHapley Additive exPlanations (SHAP) technique is also used for interpreting the outcome of the XGBoost model. The XGBoost algorithm integrated with SHAP was also developed by Feng et al. [77] and Bakouregui et al. [82], but they looked at different applications (i.e., shear resistance of squat RC walls [77] and axial resistance of RC columns strengthened by FRP [82]). Fu and Feng [76] examined the residual shear resistance of corroded RC beams at various service times using GBM, whilst Refs. [87–90] dealt with the crack damage detection of concrete and masonry structures using CNN integrated with segmentation technique [87–89] and transfer learning [90].

2.5. Database for ML applications in structural engineering

Database is considered as the backbone of training ML models. It is as importance as the algorithm used [92]. In general, the more data are fed into the model, the better the model can learn and improve. Therefore, the research community has taken the necessary steps towards establishing platforms for collecting and sharing databases (e.g., DataCenterHub, DesignSafe, and Mendeley Data). A sufficient and reliable

Table 2
List of commonly used Python ML libraries.

Code link	Application	ML algorithm	Ref.
https://www.kaggle.com/vitdegtyarev/shear-strength-of-slotted-channels-using-ml	Shear strength of CFS channel sections	AdaBoost, GBM, XGBoost, LightGBM, and CatBoost	[74]
https://github.com/jgxu-njtech/XGB-SHAP-concrete-interface-shear-strength	Interface shear strength of cold joints used in precast structures	XGBoost and SHAP	[75]
https://github.com/dcfeng-87/Time-dependent-shear-strength-beam	Shear strength of corroded RC beams	GBM	[76]
https://github.com/dcfeng-87/Interpretable-ML-shear-squat-wall	Shear strength of squat RC walls	XGBoost and SHAP	[77]
https://github.com/dcfeng-87/Ensemble-learning-deep-beam	Shear strength of RC deep beams	RF, AdaBoost, GBM, and XGBoost	[78]
https://github.com/sujithmangalathu/Punching_shear_flat_slab	Punching shear of RC slabs	RA1, RA5, kNN, SVM, DT, RF, AdaBoost, and XGBoost	[79]
https://github.com/sujithmangalathu/Explainable_AL_Infrastructure_damage	Shear strength of RC walls	RA5, kNN, SVM, DT, RF, AdaBoost, and XGBoost	[80]
https://github.com/zakirsamia/Bearing-capacity-prediction-of-double-shear-bolted-connection	Shear strength of bolted connections	ANN, RA1, RA4, RA5, kNN, SVM, DT, RF, AdaBoost, XGBoost, and CatBoost	[81]
https://github.com/abdoulayesanni/Prediction-Load-Carrying-Capacity-of-FRP-RC-Columns	Axial strength of RC columns strengthened by FRC	XGBoost and SHAP	[82]
https://github.com/hoangnguyence/hpconcrete	Compressive strength of concrete	ANN, SVM, GBM, and XGBoost	[83]
https://github.com/Md-Asif-Bin-Kabir/CBP-Failure-Mode-Prediction	Failure mode prediction of column base plate connections	SVM, NB, kNN, RF, DT, XGBoost, LightGBM,AdaBoost, and CatBoost	[84]
https://github.com/sujithmangalathu/Shear-Wall-Failure-Mode	Failure mode of RC columns and shear walls	NB, DT, RF, AdaBoost, XGBoost, kNN, LightGBM, and CatBoost	[85,86]
https://github.com/OnionDoctor/FCN_for_crack_recognition	Crack detection of concrete surfaces at pixel level	CNN with segmentation technique	[87]
https://data.mendeley.com/datasets/c7cpnw32j6/1	Crack detection of concrete surfaces at pixel level	CNN with segmentation technique	[88]
https://github.com/Arenops/CrackSegNet	Concrete crack detection in tunnels	CNN with segmentation technique	[89]
https://github.com/dimitrisdais/crack_detection_CNN_masonry	Crack detection of masonry structures	CNN with transfer learning	[90]

dataset should have not only a large number of data points, but also cover a wide range of the values of input material and geometry parameters. This is especially importance in the case of experimental databases which is characterised by high variance nature caused by epistemic errors [92]. This section provides the notable datasets that have been widely used in developing ML models for structural engineering applications. A list of notable databases is summarised Table 3.

One of the early data platforms that have been developed for the earthquake engineering community is NEESHub that provides a cyber-infrastructure platform to share research data and software tools for earthquake engineering [14,15] and disaster risk management [16,17]. Examples of the NEESHub databases for the resistance of RC structures includes (i) ACI 369 circular RC column database with 172 tests, (ii) ACI 369 rectangular RC column database with 326 tests, (iii) ACI 445 punching shear of RC slab database with 519 tests, (iv) RC shear wall database with 267 tests, and (v) RC column with spiral reinforcement database with 92 tests listed in Table 3. These NEES database can be accessed from DataCenterHub [18] and DesignSafe.

Addition to the NEESHub databases, several studies have made considerable efforts to develop additional databases for RC structures. For example, Telemachos and Michael [93] compiled a dataset of 1,012 tested specimens on RC members (i.e., beams, columns, and walls) subjected primarily to cyclic loading. The database was used to develop empirical expressions to predict the lateral drift and chord-rotation of RC members under lateral loading. Nguyen et al. [94] collected an experimental database of 369 tests on squat flanged RC shear walls under a combined action of vertical and lateral loads. The database was then used to develop an ANN-based model for predicting the shear resistance of RC walls. Another database of the shear strength of squat RC shear walls was also developed recently by Feng et al. [77] by

Table 3
Notable benchmark databases used for ML applications in structural engineering.

Data size	Application	Reference
NEES experimental databases 519 tests 326 tests 267 tests 172 tests 92 tests	Strength of RC members ACI 445 punching shear of RC slabs ACI 369 rectangular RC columns RC shear walls ACI 369 circular RC columns RC columns with spiral reinforcements	[18]
1,012 tests	Deformation of RC members under seismic loading	[93]
369 tests	Shear resistance of squat flanged RC shear wall	[94]
434 tests	Shear resistance of squat flanged RC shear wall	[77]
285 tests	Shear resistance of reinforced masonry shear walls	[97]
507 tests	Shear resistance of steel fibre RC beams	[98]
185 tests	Spalling of RC columns spalling under fire	[99]
536 tests	Shear resistance of RC beam-columns joints	[100]
264 tests	RC infilled and steel frames under lateral loading	[101-103]
3,208 tests	Axial resistance of CFST columns	[104-106]
1,008 splice tests	Bond of steel bars in concrete beam	[107]
1,002 pull-out tests	Bond of FRP bars embedded in concrete	[108]
969 single-lap shear tests	Bond of FRP sheet on concrete (interfacial bond)	[109]
10,000 images (Structural ImageNet)	Image-based crack damage detection	[19]
36,413 images (PEER Hub ImageNet)	Image-based crack damage detection	[20]
11,000 images (bridge crack library)	Image-based crack damage detection of bridges	[21]

merging two datasets collected from Ning and Li [95] (182 tests) and Massone and Melo [96] (252 tests). Aguilar et al. [97] complied a database of 285 tests on the shear resistance of reinforced masonry shear walls. Recently, Rahman et al. [98] collected a large experimental database of RC beams with steel fibres. This is the most comprehensive database composed of 507 tested specimens on the shear resistance of steel fibre RC beams collected from 68 publications. In order to examine the applicability of ML methods in predicting the fire-induced spalling of RC columns, Naser [99] developed a database with 185 columns collected from fire tests. Mangalathu and Jeon [100] assembled an extensive test dataset of beam-to-column RC joints under shear action. The database was collected from 49 references consisted of 536 tested joints (294 tests on interior joints, 221 tests on exterior joints, and 21 tests on knee joints).

The test database of steel and RC frames subjected to monotonic and cyclic loadings was developed by Huang and Burton [101–103] to investigate the nonlinear force–deformation responses and hysteretic material models. The database comprised of 264 one-storey frame tests including 257 tests on one bay and 7 tests on multi bays. In terms of materials used, the dataset contained 73 steel frames and 191 RC frames incorporated with different types of masonry units. The database can also be accessed from the DesignSafe platform [101].

For CFST structures, Thai et al. [104] compiled a test database of CFST columns to examine the safety and reliability of modern design codes including the American code AISC 360-16, Eurocode 4, and Australian code AS/NZS 2327. This is the most up-to-date and comprehensive database on CFST columns with 2,308 columns (1,305 circular sections and 1,003 rectangular sections) under concentric loading and 900 columns (499 circular sections and 401 rectangular sections) under eccentric loading (i.e., beam-column member). The database which can be freely downloaded from Mendeley Data [105] was extended from their previous database [106] collected from more than 180 publications.

Regarding the bond behaviour, notable test databases were compiled by Refs. [107–109]. Hwang et al. [107] collected 1008 splice test specimens on steel rebars embedded in concrete beams. Nepomuceno et al. [108] collected a comprehensive database with a total of 1002 pull-out tests on FRP bars embedded in concrete. The interfacial bond between FRP sheets and concrete was explored by Zhou et al. [109] by collecting a large database of 969 single-lap shear tests on FRP sheets attached on concrete.

In the field of image-based crack damage detection, significant efforts have been made to develop the databases of crack pattern images. For example, Gao and Mosalam [19] proposed the concept of Structural ImageNet which was inspired by the establishment of ImageNet. The Structural ImageNet database was established by narrowing down the scope of ImageNet within structural engineering applications. With over 10,000 relevant images of structural members with both damaged and undamaged conditions, the Structural ImageNet database can be used for crack damage detection of civil engineering structures such as buildings, bridges, and other infrastructures. Gao and Mosalam [20] also extended their Structural ImageNet database to construct PEER Hub ImageNet, a more comprehensive dataset with over 36,000 images. Recently, Ye et al. [21] established an crack image database for bridge structures with over 11,000 crack images of different types of structural components of bridges collected by using multiple camera devices installed on bridges in service conditions.

3. Bibliometric survey

In this section, a bibliometric study of the current literature on the use of ML methods for structural engineering applications is presented. The literature search is limited to Scopus indexed papers collected from well recognised academic databases including Web of Science, Scopus, Science Direct, Wiley Online Library, Taylor & Francis Online, Springer Link, ASCE Library, and SAGE. The keywords used in this search include ML and soft computing related terms (e.g., artificial neural networks, regression analysis, support vector machine, decision tree, random forest, boosting algorithm, etc.) and structural engineering related terms. The papers on predicting mechanical properties of concrete are also included in the search. The search results have identified over 485 relevant publications since 1989 when Adeli and Yeh [1] published the first relevant article. The search results also indicate that, among the Scopus-indexed journals, *Engineering Structures* and *Construction and Building Materials* are the journals publishing most relevant works with 66 and 64 papers, respectively.

The yearly distribution of these relevant publications is also plotted in Fig. 12. As can be seen from Fig. 12a, the use of ML in structural engineering is not favour at the early stage. However, this topic has received much attention from the scientific community in the last five years as evidenced by an exponential growth in the number of publications. The boom of this topic can be explained by recent advances in ML algorithms and computational power as well as the availability of large datasets collected from laboratory testing or numerical modelling.

A breakdown percentage of different ML methods used in structural engineering is shown in Fig. 13. Seven groups of ML methods have been identified including NN, SVM, BA, RA, RF, DT and others (i.e., kNN and NB). It can be seen NN is the most widely used method for structural engineering with 56%. Ten most cited relevant articles also involve the use of NN in damage detection and predicting compressive strength of concrete f_c as shown in Table 4. Among NN methods, ANN has been dominantly used with 84% due to its popularity and simplicity. Similarly, RA1 has also been mostly used among six RA methods. Although XGBoost was developed recently by Chen and Guestrin [22] in 2016, it has become the most widely used method (contributing up to 40%) in the BA family, especially in recent years as shown in Fig. 12b, due to its merits in both accuracy and speed [72]. Fig. 12b also indicates that the use of BA and SVM methods in structural engineering just becomes significant in recent years.

4. ML applications

Based on the result of the bibliometric survey (Section 3), seven classes of ML methods and five different structural engineering topics have been identified as shown in Table 5. The seven groups of ML methods are (1) NN methods, (2) SVM methods, (3) BA methods, (4) RA methods (i.e., linear regression – RA1, multivariate regression – RA2, polynomial regression – RA3, LASSO regression – RA4, Ridge regression – RA5, and logistic regression – RA6), (5) RF method, (6) DT method, and (7) others. The five structural engineering topics considered are (1) member (i.e., predicting load-carrying capacity of isolated structural members), (2) material (i.e., predicting mechanical property and optimising mix design of concrete), (3) damage and SHM (i.e., crack detection and damage assessment of structures), (4) analysis and design (i.e., performing structural analysis to predict the behaviour of structures and optimising their design), and (5) fire (i.e., predicting the fire resistance of structures).

The five topics of structural engineering applications are defined to represent for distinct areas of study. These topics will cover all existing works available in the literature on ML applications in structural engineering. The member topic comprises the studies that predict the member strength (i.e., shear strength, flexural strength, axial strength, torsional strength, buckling strength, and bond strength) and member deformation (i.e., deflection, drift, and rotation). The material topic covers the works on predicting the mechanical properties (i.e., compressive strength f_c, tensile strength f_t, bending strength f_b, Young's modulus E, etc.) and optimising mix design of concrete.

Table 5 shows the number of publications on five considered topics with respect to seven groups of ML algorithms used. It can be observed that NN is the most popular ML method that has been dominantly used in all five considered topics. The applications of ML to five considered topics is also illustrated in Fig. 14. It can be seen that both member and

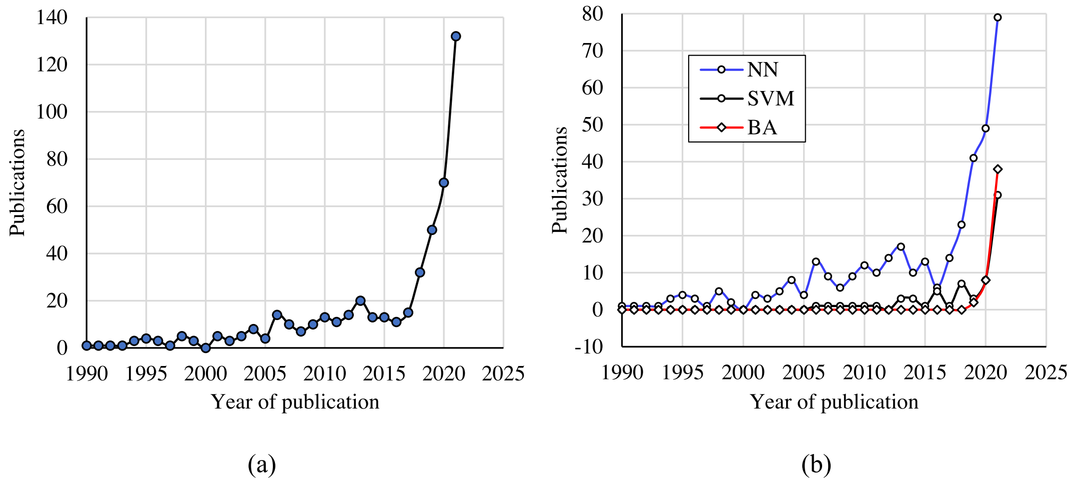


Fig. 12. Yearly distribution of articles related to ML applications in structural engineering: (a) all algorithms and (b) three mostly used algorithms.

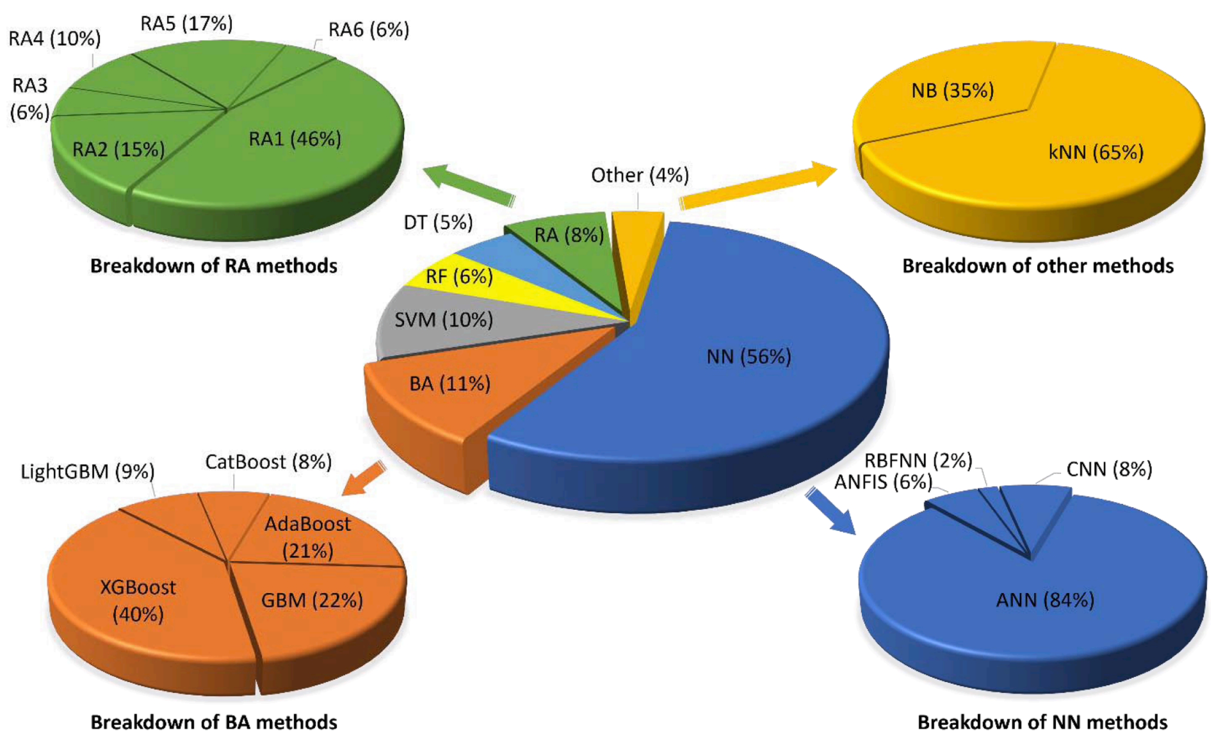


Fig. 13. ML methods used in structural engineering domain.

material topics receive the highest attention from researchers, and most of the works from these two topics focus on predicting the shear resistance of members (contributing up to 38%) and the compressive strength of concrete f_c (contributing up to 62%). The following sections provide detailed information of different ML algorithms for five structural topics mentioned above.

4.1. Prediction of structural members

4.1.1. Shear resistance

Shear resistance of structural members has received the most attention from the structural engineering community when up to 38% of the relevant publications focus on this topic as shown in Fig. 14. This might be due to the complex nature of the shear behaviour compared with other topics. A huge number of ML-based predictive models have been developed for different types of structural members including beams, slabs, shear walls, and joints as shown in Table 6. However, most papers related to this topic deal with RC beams.

For beam members, a significant numbers of ANN-based predictive models have been developed for different types of beams including RC beams [9,110–117], RC beams without stirrups [118–123], RC beams with steel fibres [124–126], RC beams strengthened by steel plates [127], RC beams strengthened by FRP strips [128–133] (Fig. 15), RC beams reinforced by FRP bars [134–136], CFS channel beams [137], and cellular steel beams [138] (Fig. 16). A comparison of ML models was also conducted for RC beams [78,139,140], RC beams with steel fibres [98], and CFS beams [74]. Both Feng et al. [78] and Rahman et al. [98] concluded that XGBoost gave the most accurate predictions for the shear resistances of RC deep beams with/without stirrups [78] and RC beams with steel fibres [98]. Among five BAs, CatBoost has the best performance in predicting the shear resistance of CFS beams based on a comparison study conducted recently by Degtyarev and Naser [74].

Table 4
List of ten most cited articles (Scopus by 11/2021) on ML for structural engineering.

Reference	Topic	Cite	Year
Cha et al. [323]	Image-based damage crack detection using CNN	1,111 (2 7 8)*	2017
Yeh [403]	Predicting f_c of concrete using ANN	645 (28)	1998
Wu et al. [4]	Vibration-based damage detection using ANN	450 (16)	1992
Cha et al. [326]	Image-based damage crack detection using CNN	396 (1 3 2)	2018
Topçu and Sarıdemir [428]	Predicting f_c of fly ash concrete using ANN	315 (24)	2008
Ni and Wang [421]	Predicting f_c of concrete using ANN	286 (14)	2000
Lee [422]	Predicting f_c of concrete using ANN	253 (14)	2003
Öztaş et al. [405]	Predicting f_c and slum of concrete using ANN	244 (16)	2006
Dung and Anh [324]	Image-based damage crack detection using CNN	246 (82)	2018
Gao and Mosalam [19]	Image-based damage crack detection using CNN	208 (69)	2018

* Citation per year

Table 5
Number of publications for different ML algorithms and applications.

Application topic	ML algorithm						
	NN	SVM	BA	RA	RF	DT	Other
Member	155	23	22	16	13	9	5
Material	114	33	16	18	11	15	2
Damage and SHM	68	15	8	4	10	8	7
Analysis and design	41	8	9	4	7	5	3
Fire	20	2	2	2	2	3	2

For RC beams, Goh [9] and Sanad and Saka [110] explored the shear resistance of RC deep beams, whilst Cladera and Marí [111] and El Chabib et al. [113] examined RC beams made from both high strength concrete (HSC) and normal strength concrete (NSC). The shear resistance of RC deep beams was examined by Mohammadhassani et al. [141] using ANFIS and by Pal and Deswal [142] and Chou et al. [143] using SVM. Meanwhile, the ANN-based predictive model developed by Caglar [116] was applied for circular RC columns. The shear resistance of one-way RC slabs under concentrated loads was also explored by Abambres and Lantsoght [117] using ANN. Recently, Fu and Feng [76] examined the residual shear strength of corroded RC beams at different service times using GBM. For RC beams without stirrups, Cladera and Marí [118] and El-Chabib et al. [121] developed ANN models to predict the shear strength of RC beams with both NSC and HSC. Elsanadedy et al. [123] investigated the shear resistance of slender beams with HSC using ANN. New empirical design equations were also suggested and compared well with existing equations from modern design codes. Zhang et al. [144] also explored the shear resistance of RC beams, but they used RF instead.

For slabs, the punching shear behaviour (see Fig. 17) has also been received significant attention. Elshafey et al. [145] and Said et al. [146] developed one of the first ANN models to predict the punching shear resistance of RC slabs without shear rebars. Gandomi and Roke [147] also looked at the punching shear of RC slabs using ANN, but they focused on investigating the parameters that overfit the ANN model. A similar work was also conducted recently by Tran and Kim [148], in which ANN-based equations were also proposed. Based on the RA1 method, Chetchotisak et al. [149] developed a new punching shear strength equation and its corresponding strength resistance factor for the practical design purpose. Recently, Nguyen et al. [150] explored the application of XGBoost to predict the punching shear strength of RC slabs. They concluded that XGBoost outperformed both ANN and RF models. A similar finding was also reported by Mangalathu et al. [79] when comparing seven ML methods including SVM, DT, RF, AdaBoost, XGBoost, kNN, and RA5. In addition, ML techniques were also employed to predict the punching shear strengths of other types of concrete slabs such as RC slabs strengthened by FRP bars [151] and RC slabs with steel fibres [152–154] as shown in Table 6.

For shear walls, Aguilar et al. [97] used ANN to develop predictive models for the shear resistance of reinforced masonry walls used in seismic regions. ANN-based predictive expressions were also developed and compared with existing empirical equations. Zhou et al. [155] explored the shear resistance of fully grouted RC masonry walls (Fig. 18a) using both ANN and ANFIS methods. Their models were compared well with existing design code equations. The shear resistance of RC walls under seismic loading as shown in (Fig. 18b) was also explored using ANN [94], SVM [156,157], RA1 [158], and XGBoost [77]. Based on 246 tests on RC walls under cyclic loading, Zeynep Tuna and Cagri [158] proposed new shear strength equations using the RA1 method. Their proposed equations also outperformed existing empirical equations and seismic design code expressions. Recently, Feng et al. [77] presented an interpretable ML model for shear resistance prediction of squat RC walls using XGBoost. An experimental database of 434 tests was also collected for training and testing purposes. By comparing with

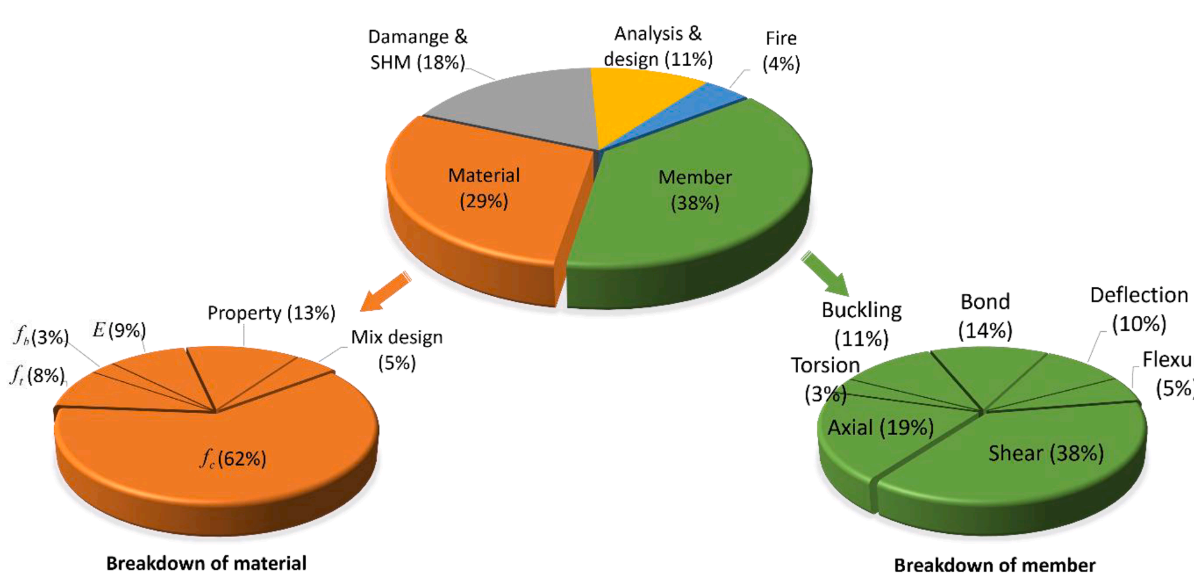


Fig. 14. ML applications in the structural engineering domain.

Table 6
Applications of ML in predicting the shear resistance of members.

Member	Type	ML algorithm	Reference
Beams	RC beams	ANN	[9,110-117]
		ANFIS	[141]
		SVM	[142,143]
		GBM	[76]
		ANN, SVM, kNN	[139]
		XGBoost, RA2	[140]
		RF, AdaBoost, GBM, XGBoost	[78]
	RC beams without stirrups	ANN	[118-123]
		RF	[144]
	RC beams with steel fibres	ANN	[124-126]
		SVM	[529,530]
		RF	[531]
		ANN, SVM, DT, RF, AdaBoost, XGBoost, CatBoost, kNN, RA1, RA4, RA5	[98]
	RC beams strengthened by steel plates	ANN	[127]
	RC beams strengthened by FRP strips	ANN	[128-132]
		ANFIS	[532]
		GBM	[133]
	Concrete beams reinforced by FRP bars	ANN	[134-136]
		SVM	[533]
	CFS beams with C-section	ANN	[137]
		AdaBoost, GBM, XGBoost, LightGBM, CatBoost	[74]
	Cellular steel beams	ANN	[138]
Slabs (punching shear)	RC slabs	ANN	[145–148]
		RA1	[149]
		XGBoost	[150]
		SVM, DT, RF, AdaBoost, XGBoost, kNN, RA5	[79]
	Slabs strengthened by FRP bars	SVM	[151]
	RC slabs with FRC	ANN, RA1	[152]
		ANN, SVM	[153]
		DT, RF	[154]
Walls	Reinforced masonry walls	ANN	[97]
		ANN, ANFIS	[155]
	RC shear walls	ANN	[94]
		SVM	[156,157]
		RA1	[158]
		XGBoost	[77,80]
	Steel plate shear wall	RBFNN	[159]
Joints	RC beam-to-column joints	ANN	[161-163]
		ANN, ANFIS	[164]
		RA1, RA2, RA6	[160]
		RA1, RA4, RA5, RF	[100]
	Bolted connections	kNN, ANN, SVM, DT, RF, RA1, RA4, RA5, AdaBoost, XGBoost, CatBoost	[81]
	Shear transfer	XGBoost	[75]
		SVM, RF	[165]

ANN, DT, RF, and GBM models, they concluded that XGBoost provided the best performance overall. A similar conclusion was also made by Mangalathu et al. [80] when comparing XGBoost with other ML methods including AdaBoost, RF, DT, SVM, RA5, and kNN. The shear resistance of steel plate shear walls (Fig. 18c) was also explored by Moradi et al. [159] using RBFNN.

For joints, Jeon et al. [160] used three regression methods (i.e., RA1, RA2, and RA6) to develop predictive models for the shear strength of RC beam-to-columns joints. The proposed models were based on a comprehensive experimental database of 516 tests on reinforced joints and 204 tests on unreinforced joints. Based on ANN, Kotsovou et al. [161] developed the shear resistance models for RC beam-to-column joints under seismic loading as shown in Fig. 19. The ANN-based model was found to be more accurate than existing mechanics-based models and design code equations. A similar work was also conducted by Alwanas et al. [162] and Park et al. [163] to predict the shear capacity of RC joints using ANN. A comparison on the performance of different ML techniques was also reported in Refs. [100,160,164]. ML was also used in predicting the shear transfer strength of RC joints [165] and the interface shear strength of cold RC joints used in precast concrete construction [75]. Recently, Zakir Sarothi et al. [81] compared the performance of 11 ML models (i.e., kNN, ANN, SVM, DT, RF, RA1, RA4, RA5, AdaBoost, XGBoost, and CatBoost) in predicting the bearing capacity of shear bolted connections based on a database of 443 tested specimens.

4.1.2. *Axial resistance*

The axial behaviour of structural members is not complex compared to the shear behaviour, and thus it is reasonably predictable using traditional mechanics-based models. However, in some cases where the structural members are made from composite forms such as concrete-filled steel tubular (CFST) columns (Fig. 20) or RC columns strengthened by FRP (Fig. 21), their axial behaviours are very complex due to composite actions. Typical failure modes of CFST columns and FRP-strengthened RC columns under axial compression are illustrated in Figs. 20 and 21, respectively. Therefore, most of the studies on axial resistance focus on such composite members (see Table 7).

The first application of ML for CFST columns was conducted by Ahmadi et al. [166] using ANN. However, their ANN model was trained by a small database with only 272 tests on short CFST columns with circular sections. One of the most comprehensive ML models were developed recently by Vu et al. [167] and Lee et al. [168] using GBM and CatBoost. Vu et al. [167] developed the GBM model for circular CFST columns under concentric load based on 1,017 tests, whilst Lee et al. [168] developed CatBoost model for both circular and rectangular CFST columns under both concentric and eccentric loads based on 3103 tests collected by Thai et al. [106]. Both GBM and CatBoost models are demonstrated to be more accurate than existing design code expressions.

A comparison of various ML algorithms in predicting the axial resistance of CFS columns was conducted by Xu et al. [169]. They compared the performance of seven ML models including ANN, ANFIS, SVM, RF, XGBoost, RA1, and RA5. It was concluded that RF gave the most accurate prediction, whilst XGBoost came second among seven ML methods considered. Their ML-based predictive models are also more accurate than the design model proposed in Eurocode.

4.1.3. *Bond strength*

Another application of ML is to predict the bond strength of reinforcing members such as steel bars and FRP sheets/bars as shown in Fig. 22. Understanding the bond behaviour and estimating the bond strength of such reinforcing members in concrete plays an important role in the design and practical application of such members. A shown in Table 8, ML applications for bond strength focus on three groups: (1) the bond between steel and concrete (i.e., steel bar embedded in concrete or structural steel encased in concrete), (2) the bond between FRP sheets/bars and concrete, and (3) the bond between FRP sheets and steel plates. It is also observed from Table 8 that ANN was dominantly used for bond strength prediction, and most of relevant works were devoted to the bond strength of steel bars embedded concrete.

Different ANN models have been developed to predict the bond strength of steel bars in concrete. The first ML-based bond strength

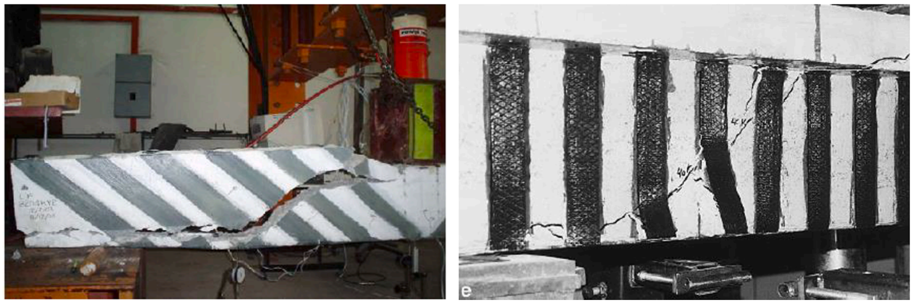


Fig. 15. Shear failure of RC beams strengthened by FRP strips [129].

Fig. 16. Web-post buckling of steel cellular beams under shear action [563].

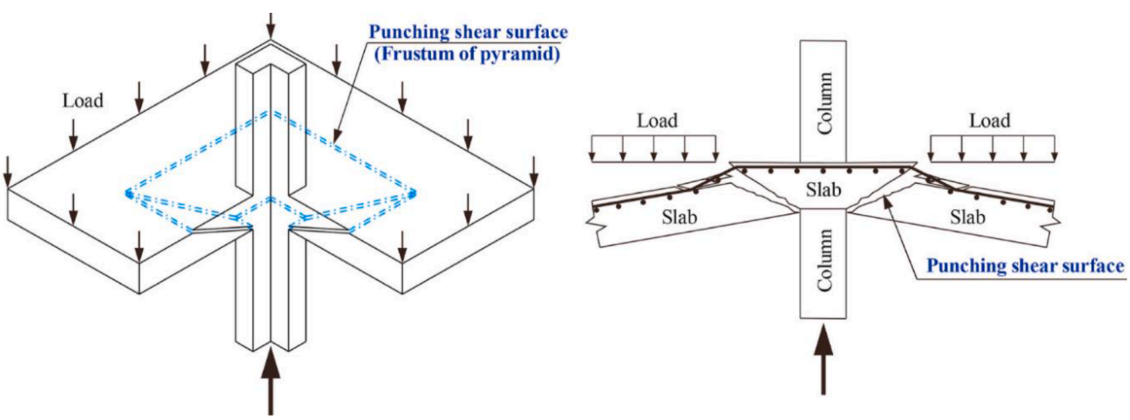
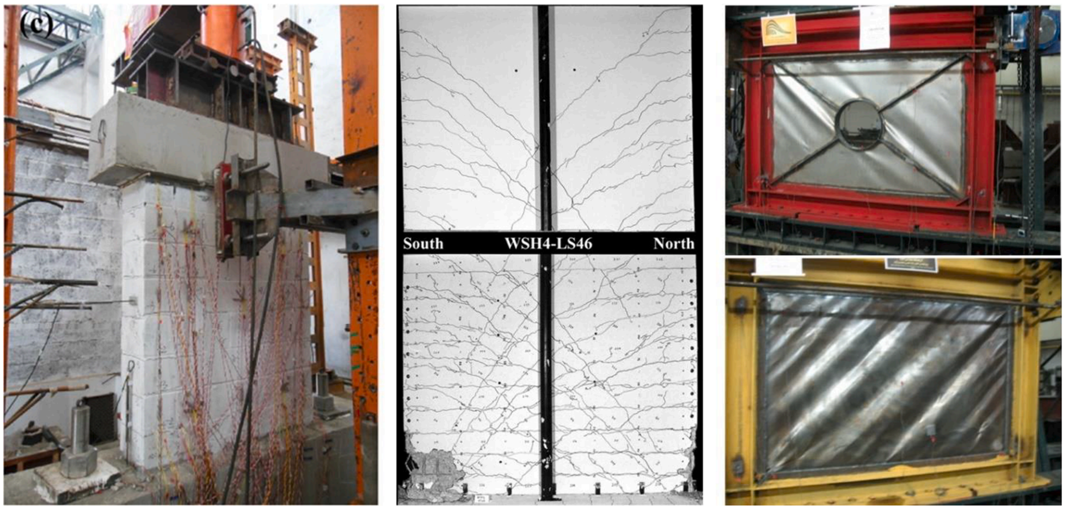


Fig. 17. Shear failure RC slabs [79].

model was developed by Dahou et al. [170] using ANN to predict the pull-out load of a steel bar embedded in concrete. Their ANN model was trained using a database of 112 pull-out tests. A similar ANN model was also developed by Makni et al. [171] using 117 pull-out tests. Golafshani et al. [172] examined the bond strength of steel bars embedded in concrete using 179 splice beam tests, whilst the ANN-based bond models developed by Ahmad et al. [173] for different types of steel bars were based on 138 pull-out tests and 108 splice tests. Hwang et al. [107] adopted a large database with 1,008 splice tests to develop their ANN model for bond strength of steel bars in concrete. Recently, Amini Pishro et al. [174] employed both ANN and RA1 to develop the bond stress models for steel bars embedded in ultra-high performance concrete (UHPC). ML techniques are also used to predict the bond strength of steel bars under corrosion. For example, Shirkhani et al. [175] and Wang et al. [176] adopted ANN to predict the bond strength of corroded bars, whilst Hoang et al. [177] used SVM with a dataset of 218 tests. The post-fire bond strength of steel bars embedded in steel fibre rubberised concrete under fire as shown in Fig. 23 was explored by Nematzadeh et al. [178] using ANN and a database of 108 pull-out test results. Wang et al. [179] developed an ANN model for bond strength of a steel I-beam encased in RC concrete columns using 191 push-out tests.

FRP composites in the forms of FRP sheets and rebars have been increasingly used in retrofitting of RC structures such as buildings and bridges due to their high strength-to-weight ratios. In such applications, the bond behaviour of FRP and concrete plays a critical role, and thus several ML-based predictive models have been developed for this purpose. For example, the interfacial bond models between FRP sheets and concrete substrates as shown in Fig. 22b were developed in Refs. [109,180–183] using the ANN model with different sizes of the test datasets (e.g., 969 test results in [109], 150 tests in [180], 203 tests in [181], 440 pull-out tests in [182], and 656 tests in [183]). Based on a dataset of 150 experimental results, Naderpour et al. [184] and Zhang and Wang [185] developed their bond models using ANFIS and SVM, respectively. Chen et al. [186] developed the GBM model for the interfacial bond using a database of 520 tests. A comparison of three ML models including ANN, SVM, and RA1 in predicting the interfacial bond between FRP sheets and concrete was also performed by Su et al. [187] using 255 tests. They concluded that the SVM model has the best performance among three models considered.

The bond strength of FRP rebars embedded in concrete was



(a) (b) (c)

Fig. 18. Shear failure of (a) masonry wall [155], (b) RC wall [564], and (c) steel plate wall [159].

Fig. 19. Shear failure of RC beam-to-column joints [565].

(a) (b) (c)

Fig. 20. Failure of CFST columns: (a) short column with local buckling [566], (b) intermedia column with local and global buckling [567], and (c) long column with global buckling [567].

examined in Refs. [188–191] using ANN. Basaran et al. [192] compared the performance five ML methods including ANN, SVM, DT, RA1, and RA2 using a database of 874 tests. They also compared their derived ML-based models with the bond equations from design codes and found that the design equation from ACI 440.1R-15 gave the best result. Chen et al. [193] used both RF and GBM to develop bond models for FRP sheets stick to steel plates. By comparing with three other ML models including ANN, SVM, and DT, they concluded that the GBM model gives the best

(a) (b)

Fig. 21. FRP-strengthened RC columns under (a) concentric load [568] and (b) eccentric load [569].

Table 7
Applications of ML in predicting the axial strength of members.

Member	Type	ML algorithm	Reference
CFST columns	CFST columns with circular sections	ANN	[166,524,534-540]
		ANFIS	[536]
		SVM	[541]
		RF	[539]
		DT	[538]
		GBM	[167,538]
		CatBoost	[168]
		RA2	[536]
	CFST columns with rectangular sections	ANN	[524,542-547]
		ANFIS	[548]
		RBFNN	[549]
		CatBoost	[168]
	CFST columns with elliptical sections	ANN	[550]
		ANFIS	[551,552]
	CFST columns with CFS	ANN	[525]
	CFST columns strengthened by FRP	ANN	[553]
Concrete columns	RC columns	ANN	[554]
	RC columns strengthened by FRP	ANN	[555-558]
	RC columns reinforced by FRP bars	XGBoost	[82]
Steel columns	Steel columns with single angle sections	ANN	[559]
	Steel tube columns strengthened by FRP	ANN	[560]
	CFS columns	RF, XGBoost	[561]
		ANN, ANFIS, SVM, RF, XGBoost, RA1, RA5	[169]
Walls	Masonry walls	ANN	[562]

accuracy for the considered problem.

4.1.4. Buckling strength

Structural members made from CFS and thin-walled sections under compression usually buckle and fail before reaching the yield stress due to its slender nature of their cross-section. The strengths of such members are therefore governed by the instability associated with local buckling, distortional buckling (see Fig. 24), and lateral-torsional buckling (see Fig. 25). In this case, the derivations of empirical or closed-form solutions using experiments or physics-based models are time consuming and very complex. Therefore, the use of ML-based models is an alternative approach to overcome the limitations of physics-based models. A list of ML applications for predicting the buckling resistance of members under different buckling modes is presented in Table 9. It is observed that most of ML applications in this area focus on local buckling and distortional buckling modes due to their complexity. In addition, ANN is the only method used in this topic due to its ease of use and higher interpretability.

The first ML-based predictive model for buckling strength of members was developed by Mukherjee et al. [194] in 1996 to predict the global buckling curve of columns. Sheidaii and Bahraminejad [195] also examined the global buckling of columns, but they focused on the post-buckling behaviour and equilibrium paths. The global buckling of columns under various boundary conditions and tapered I-sections was investigated by Kumar and Yadav [196] and Nguyen et al. [197], respectively.

Pala [198] and Pala and Caglar [199] developed ANN models to predict the distortional buckling stress of CFS channel sections. Tohidi and Sharifi [200] also used ANN to predict the moment capacity of steel I-beams due to inelastic distortional buckling. Their equation was demonstrated to be more accurate than the existing design equations in American code AISC 360-16, Australian code AS 4100, and Eurocode 3. A similar work was also carried out recently by Hosseinpour et al. [201] for castellated steel beams. Dias and Silvestre [202] employed the ANN method to derive equations for the distortional buckling of elliptical tubes.

The local buckling of steel plates under axial compression was investigated by Refs. [203-206] using ANN. Pu and Mesbahi [203] considered both elastic and inelastic local buckling of plates using a database of 143 tests, whilst Sonmez and Komur [204] only examined the elastic buckling of perforated steel plates under linearly varying compression. Sadovský and Guedes Soares [205] included initial imperfections, whilst Sun et al. [206] considered the effect of hat-stiffeners. The local buckling of thin cylindrical shells under axial compression was considered by Tahir and Mandal [207]. Guzelbey et al. [208] developed an ANN model to examine the buckling strength of CFS sheetings due to web crippling. The web crippling strength was also examined by Fang et al. [209], but they looked at CFS channel sections using 17,281 numerical data points generated by ABAQUS. Fang et al. [210,211] also used ANN to develop design equations for the strength of CFS channel sections under axial compression. Their ANN-based equations are able to capture all local buckling, distortional buckling, and global buckling modes of CFS channel sections in short, intermediate, and long columns. To cover a wide range of geometric parameters, comprehensive numerical databases of 10,500 columns without stiffeners and web holes [211] and 50,000 columns with stiffeners and web holes [210] were developed in ABAQUS considering the effects of both residual stresses and initial geometric imperfections. Gholizadeh et al. [212] looked at the shear strength of castellated steel beams considering local buckling of the web post. Recently, Kaveh et al. [213] looked at the buckling strength of laminated composite cylinders subjected to bending

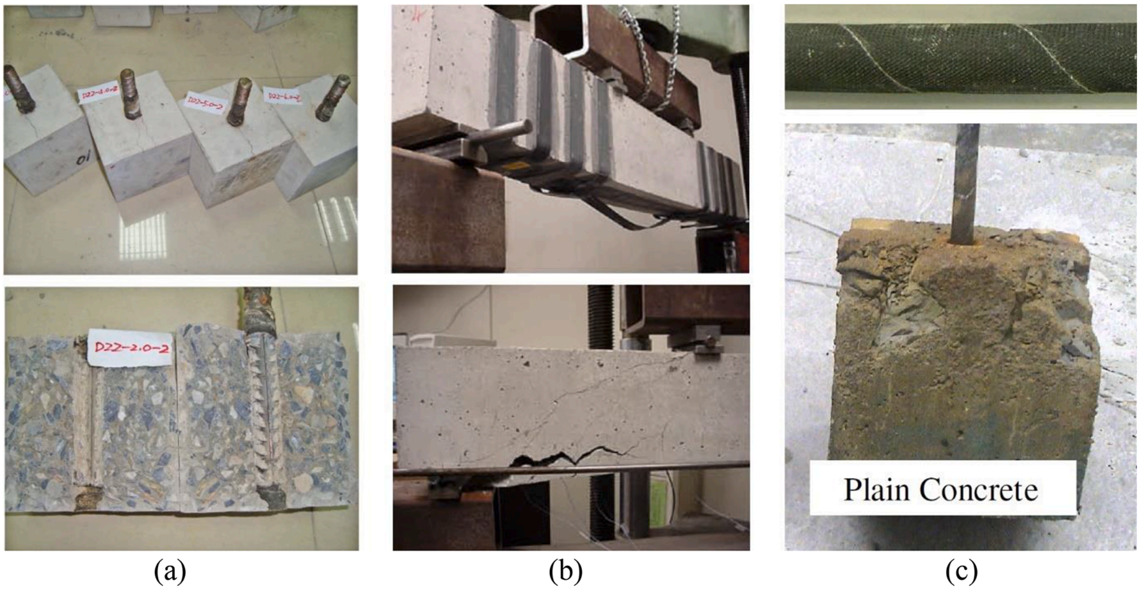


Fig. 22. Bond of (a) steel bar embedded in concrete [570], (b) FRP sheet attached to concrete [571], and (c) FRP bar embedded in concrete [572].

Table 8
Applications of ML in predicting the bond strength and behaviour.

Material	Structure	ML algorithm	Reference
Steel-concrete	Steel bars embedded in concrete	ANN	[107,170–173]
	Steel bars embedded in UHPC	ANN	[174]
	Corroded steel bars embedded in concrete	ANN	[175,176]
		SVM	[177]
	Steel bars embedded in concrete exposed to fire	ANN	[178]
	Steel beams encased in concrete	ANN	[179]
FRP-concrete	FRP sheets and concrete substrates	ANN	[109,180-183]
		ANFIS	[184]
		SVM	[185]
		GBM	[186]
		ANN, SVM, RA1	[187]
	FRP bars embedded in concrete beams	ANN	[188-191]
		ANN, SVM, DT, RA1, RA2	[192]
FRP-steel	FRP sheets stick to steel plates	RF, GBM	[193]

moments using different ML methods including ANN, RA1, DT and RF.

The lateral-torsional buckling of simply supported cellular I-beams under transverse loads was examined in Refs. [214-216] using the ANN method. Sharifi et al. [215] developed an empirical equation to predict the lateral-torsional buckling strength of simply supported beams under point loads using an experimental database of 99 tests. Meanwhile, the ANN-based predictive model developed by Abambres et al. [214] is applicable for simply supported beams under uniform loads using a numerical database of 3,645 beams generated by ABAQUS. Recently, Ferreira et al. [216] developed a numerical database of 768 beams to build an ANN-based predictive equation for lateral-torsional buckling design including post-buckling and distortional buckling of the web.

4.1.5. Flexural and torsional resistances

The flexural and torsional behaviours of RC beams have been well understood. Their resistance is also predictable using design equations derived from physics-based models since they are not complex compared with the shear behaviour. Therefore, the use of ML methods in predicting the flexural and torsional resistance of RC members is not significant compared with that in predicting the shear strength. As shown in the breakdown of members in Fig. 14, the use of ML methods for flexure and torsion contributes only 5% and 3%, respectively, compared with 38% in the case of shear. Table 10 lists all relevant works on the use of ML for flexural and shear resistances of structural members. It can be seen that the ANN method has been dominantly used in this topic.

The first ML application in this topic was conducted by Shahin and Elchalakani [217] using ANN and a dataset of 104 tests on bending of

Fig. 23. Bond post-fire bond behaviour of steel bar in steel fibre concrete [178].

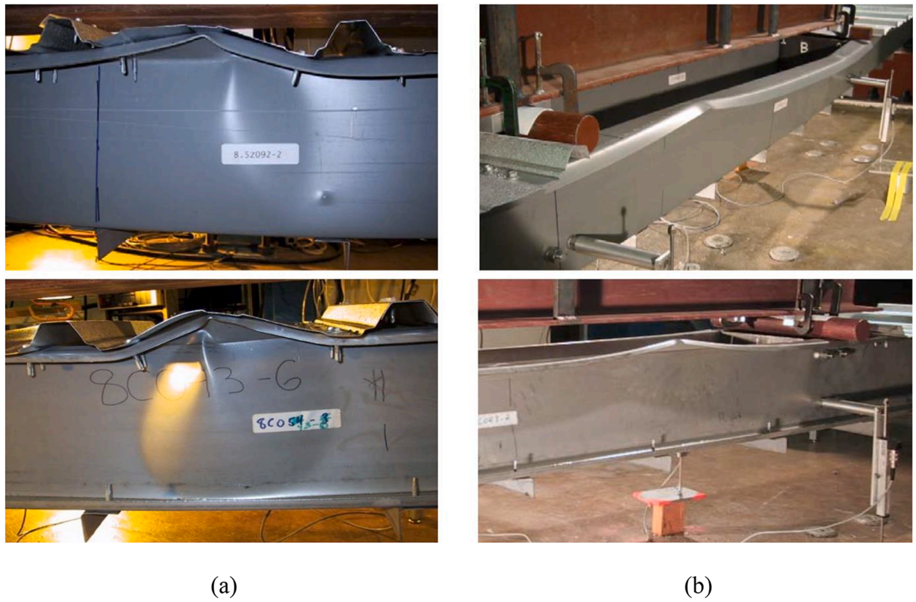


Fig. 24. Buckling of CFS beams: (a) local buckling and (b) distortional buckling [573].

Fig. 25. Lateral-torsional buckling of Marcy Bridge [578].

steel beams with circular hollow sections (CHS). Their proposed equations were also compared well with design equations from American code, Eurocode 3, and Australian code. D'Aniello et al. [218] also examined the bending resistance of steel beams using ANN. However, their model was applied to simply supported and cantilever beams under point loads.

Kotsovou et al. [219] adopted ANN to predict the bending moment resistance of RC beams using 296 beam tests and 196 column tests. Recently, Naser [220] compared three different ML methods including ANN, XGBoost, and LightGBM in predicting the moment resistance of RC beams strengthened by FRP sheets. The comparison results indicated that XGBoost has the best performance. The bending strength of CFST beams was investigated by Hanoon et al. [221] and Basarir et al. [222] using ANN and ANFIS, respectively. Koçer et al. [223] and Naderpour and Mirrashid [224] employed ML methods to predict the moment capacity of RC beams under a combined action of axial force and bending moment. Koçer et al. [223] used the ANN technique with 79 test results, whilst Naderpour and Mirrashid [224] used both ANN and ANFIS methods with an experimental database of 202 specimens. Recently, Congro et al. [225] and Gopinath and Kumar [226] developed ANN-based models to predict the moment resistance of fibre RC slabs under point loads and masonry panels strengthened by textile reinforced mortar, respectively.

The first application of ML in predicting the torsional resistance of

Table 9
Applications of ML in predicting the buckling strength of members.

Buckling mode	Member	ML algorithm	Reference
Local buckling	Steel plates	ANN	[203–205]
	Steel panels with hat-stiffeners	ANN	[206]
	Thin cylindrical shells	ANN	[207]
	Web crippling of CFS sheeting	ANN	[208]
	Web crippling of CFS C-section	ANN	[209]
	CFS beams with C-sections	ANN	[210,211]
	Castellated steel beams	ANN	[212]
	Composite cylinders	ANN, RA1, DT, RF	[213]
Distortional buckling	CFS beams with C-sections	ANN	[198,199]
	Steel beams with I-shaped section	ANN	[200]
	Castellated steel beams	ANN	[201]
	Elliptical tubes	ANN	[202]
Global buckling	Slender columns	ANN	[194,195]
	Beam-columns with various end conditions	ANN	[196]
	Steel columns with tapered I-section	ANN	[197]
Lateral-torsional buckling	Cellular I-beams	ANN	[214–216]

RC beams was carried out by Tang [227] in 2006 using the RBFNN method. Since then, a significant work [228–231] has been done to predict the torsional strength of RC beams using ANN. For instance, Arslan [228] collected 76 experimental results to developed ANN-based equations which were more accurate than current design equations in predicting the torsional resistance of RC beams. Huang [229] developed ANN-based torsional resistance equations and compared them with ACI 318 code. The ANN-based models developed by Ilkhani et al. [230] were based on 112 tests on RC beams under torsion, whilst the model developed recently by Haroon et al. [231] was based on an experimental databased of 159 tests. The torsional resistance of RC beams with steel fibres was also examined by Engin et al. [232] using ANN.

Table 10
Applications of ML in predicting the flexural and torsional strengths of members.

Behaviour	Structures	ML algorithm	Reference
Flexure	Steel beam with CHS	ANN	[217,218]
	RC beam	ANN	[219]
	RC beam strengthened by FRP	ANN, XGBoost, LightGBM	[220]
	CFST beam	ANN	[221]
		ANFIS	[222]
	RC beam-column	ANN	[223,224]
		ANFIS	[224]
	Fibre RC slab	ANN	[225]
	Masonry wall	ANN	[226]
Torsion	RC beams	ANN	[228-231]
		RBFNN	[227]
	RC beams with steel fibre	ANN	[232]

4.1.6. Serviceability

The application of ML to predict deflection, drift and rotational capacity of structures are summarised in Table 11. It can be seen that most of the works in this topic focus on predicting the deflections of RC beams and composite beams considering the long-term effect of concrete. Different ML methods were also adopted in predicting the deflections of RC beams.

The use of ML in predicting the deflection of RC beams was conducted in Refs. [233–237] using different ML techniques. Patel et al. [233] used ANN to develop their predictive model for RC beams, whilst Darain et al. [234] used ANFIS to predict the deflection of RC beams strengthened by steel and FRP bars as shown in Fig. 26. Nguyen et al. [235] employed XGBoost to predict the long-term deflection of RC beams. Bai et al. [236] compared three ML methods including ANN, ANFIS, and SVM in predicting the deflection of RC beams based on 120 experimental tests, whilst Pham et al. [237] compared four ML methods (i.e., ANN, SVM, DT, and RA1) in predicting the long-term deflection of RC beams using a test database of 181 specimens. The deflection of deep beams made from HSC was investigated by Mohammadhassani et al. [238,239] using ANFIS [238] and ANN and RA1 [239]. Beljkaš and Baša [240] examined the deflection of continuous beams strengthened by FRP bars using ANN and 11 tests on continuous beams (see Fig. 27). The lateral drift of RC columns under seismic loading was also investigated by Inel [241] using 273 tests on rectangular columns.

The deflection of composite beams is examined in Refs. [242–247] using ANN. Pendharkar et al. [242] developed an ANN model for the inelastic deflection of continuous composite beams. Gupta et al. [245] and Tadesse et al. [244] considered the deflection of multi-span composite bridge girders, whilst Sakr and Sakla [243] and Kumar et al. [246] explored the deflection of simply supported composite bridge girders. Sakr and Sakla [243] developed a comprehensive numerical dataset of 4,500 beams, whilst Kumar et al. [246] generated a numerical database with 360 beams. Wang et al. [247] explored the deflection of composite box girder bridges under construction stage.

Table 11
Applications of ML in serviceability prediction of members.

Deformation	Members	ML algorithm	Reference
Deflection	RC beams	ANN	[233]
		ANFIS	[234]
		XGBoost	[235]
		ANN, ANFIS, SVM	[236]
		ANN, SVM, DT, RA1	[237]
	Deep beams with SCC	ANFIS	[238]
		ANN, RA1	[239]
	Concrete beams reinforced by FRP bars	ANN	[240]
	Composite beams	ANN	[242]
	Composite beams with partial shear interaction	ANN	[243–246]
	Composite box-girder bridge	ANN	[247]
Drift	RC columns	ANN	[241]
Rotation capacity	Steel I-beams	ANN	[248]
	Semi-rigid steel joints	ANN	[250]
	Semi-rigid composite joints in fire	ANN	[251]
	Cold-formed hollow beams	ANN	[249]

ML techniques especially the ANN method were also used to predict rotational capacity required in serviceability design of structures. Guzelbey et al. [248] used the ANN method to develop design equations for predicting rotation capacity of wide flange beams using 81 tests on simply supported beams under point and uniform loads. D'Aniello et al. [249] also developed ANN-based equations for predicting rotational capacity of steel beams, but they focused on CFS beams with rectangular hollow sections (RHS) under point loads. Rotational capacity of semi-rigid joints was explored by Iranpour et al. [250] and Al-Jabr and Al-Alaw [251] using ANN. Iranpour et al. [250] considered single-plate shear steel joints, whilst Al-Jabr and Al-Alaw [251] looked at composite joints under fire.

4.2. Prediction of fire resistance of structures

Under fire conditions, the load-carrying capacity of structures, especially steel structures, drops rapidly due to the significant reduction in stiffness and strength of the material used. The behaviour of structures exposed to fire is extremely complex due to involving highly nonlinear behaviour (e.g., large deformation in steel structures as illustrated in Fig. 28 and spalling in concrete structures as shown in Fig. 29). In order to understand this complex behaviour, a number of experimental tests have been conducted in both isolated structural members and the whole structural systems (e.g., the Cardington fire test of a full scale eight-storey composite steel building in 1996 [252] as shown in Fig. 30). The results obtained from experimental tests have enabled the development of design guidelines for fire safety design as well as improved the understanding of the actual behaviour of structures in fire.

Fire safety is one of the critical concerns in the design of buildings. However, the current design process of buildings under fire is time-consuming, and it requires structural engineers to understand the complex behaviour of the structure exposed to high temperatures [253]. The use of ML is therefore considered as a promising and effective tool to tackle this problem. Significant research works have been devoted to leveraging ML techniques for structural fire engineering, especially in recent years as summarised in Table 12.

One of the first applications of ML techniques in fire design of structures was conducted by Al-Khaleefi et al. [254] in 2002 using ANN to predict the fire resistance of CFST columns. Their ANN-based model was also well compared with experimental results. Recently, Moradi et al. [255] also explored the use of ANN for CFST columns in fire, but their study focused on evaluating the fire resistance rating and residual strength index of CFST columns after fire. An experimental database of 266 fire tests was also collected for this purpose, and a graphic user interface (GUI) tool of the ANN-based predictive models were also developed for the implementation in practical design. Zhao [256] used 126 test results of steel columns under fire to develop an ANN-based model for predicting the resistance of columns at elevated temperatures.

The fire resistance and explosive spalling of RC columns were investigated in Refs. [99,257,258] using different ML algorithms and sizes of the test databases. Seitlllari and Naser [257] used both ANN and ANFIS with an experimental dataset of 89 fire tests on RC columns, whilst Naser et al. [258] and Naser [99] recently compared the performance of different ML methods in predicting the fire-induced spalling of RC columns using different data sizes (140 tests and 169 numerical data [258] and 185 tests [99]). They concluded that the BA methods (i.e., GBM, XGBoost, and LightGBM) gave the best performance in terms of

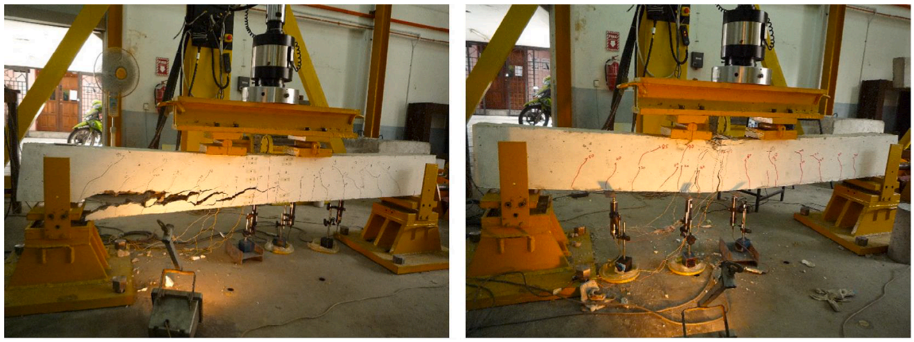


Fig. 26. Failure of RC beams strengthened by FRP and steel bars [234].

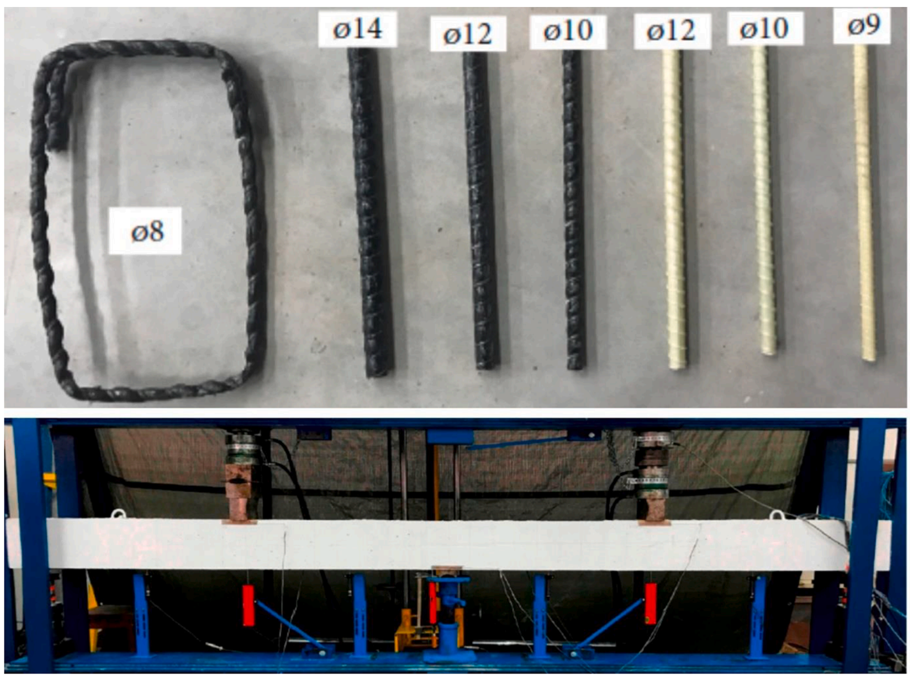


Fig. 27. Continuous concrete beams with FRP bars [240].

accuracy.

The fire resistance of different types of RC columns was also examined in Refs. [259–261] using ANN. For example, McKinney and Ali [259] looked at the failure time and spalling classification of RC columns made from HPC using 30 tests. Hisham et al. [260] predicted the temperature variation of FRP-strengthened RC columns under fire using 1,200 numerical data generated from ANSYS. Li et al. [261] considered the fire resistance of encased composite columns using 15,200 data generated from an analytical model.

The fire resistance of RC beams was examined in Refs. [262–265] using ANN. Based on a numerical database of 90 RC beams obtained from ANSYS, Naser et al. [262] develop an ANN-based model to predict the moment resistance of RC T-beams strengthened by FRP under fire. Erdem [263] developed ANN-based models to predict the moment resistance of RC beams exposed to fire using 280 data generated from an analytical model. A similar work was also conducted by Cai et al. [264] using 480 numerical data obtained from ABAQUS. Cai et al. [265] examined the post-fire shear resistance of RC beams a numerical database of 384 data generated by ABAQUS.

The application of ML techniques to predict the moment capacity of RC slabs under fire was conducted by Erdem [266] using ANN and Bilgehan and Kurtoğlu [267] using ANFIS. Erdem [266] developed a database of 294 slabs under fire, and derived a predictive model to predict the moment resistance of RS slabs. Recently, Panev et al. [268] adopted the SVM method to predict the moment resistance of composite slim flooring systems. A comprehensive database composed of 182 configurations of a wide range of composite slabs was also developed for training and testing purposes using LSDYNA.

Fire performance of bolted endplate steel joints with semi-rigid behaviour was investigated by Al-Jabri et al. [269] using ANN. A test database of 392 fire tests was collected from 15 joint configurations. The ANN-based predictive model is capable of predicting the rotation of joints under fire with high accuracy. Another application of the ANN method in predicting the fire performance of joints was also conducted by Xu et al. [270]. However, their work focused on the axial capacity of welded T-joints with tubular members under fire.

In term of the fire performance of the whole structural system, Hozjan et al. [271] applied ANN to steel frames under fire. However, they just actually employed the ANN method to model the stress–strain model of steel at elevated temperatures based on 527 material fire tests. This stress–strain model was then incorporated into a nonlinear finite element program to predict the behaviour of structures under fire. Fu [253] developed a ML framework to predict the failure pattern and assess the progressive collapse of steel frames under fire. Three ML classifiers of kNN, ANN, and DT were employed. Xu et al. [272] use ANN to predict the temperature of tubular planar truss under fire using 120

(a) (b)

Fig. 28. Fire-induced failure of (a) hollow steel truss [272] and (b) steel joint and frame in Cardington test [574].

(a) (b)

Fig. 29. Fire-induced failure of (a) encased composite column [575] and (b) RC slab [576].

data points generated from ABAQUS using shell elements.

4.3. ML applications in SHM and damage detection

SHM is a process of monitoring the health of structures via damage detection and condition assessment. The use of ML in SHM has been increased significantly especially in recent years. In general, the damage detection techniques used in SHM can be classified into two groups: vibration-based method and image-based method [34]. Vibration-based method is a traditional SHM method in which the structural damage is detected indirectly through the change of modal parameters of structures such as natural frequency and mode shape, whilst image-based method is currently one of the most advanced SHM methods that directly detect the structural damage via crack detection from images. Although a number of reviews have touched on this topic [33–38], they just focused on either a specific damage detection method or a ML technique, and a comprehensive review on this area is still lacking. For example, the reviews reported by Refs. [33,36,37] were only focused on the use of NN techniques such as CNN [36,39] and DL [33,37]. Hsieh and Tsai Yichang [35] only reviewed the works using the image-based detection method. Both vibration-based and image-based methods were included in Refs. [34,38], but they limited to ANN and SVM methods with a focus on civil engineering structures (i.e., dam, wind turbine, stadium, and bridge) [34], and heritage buildings [38]. This section will provide a comprehensive review on both vibration-based and image-based methods using various ML techniques. Table 13 presents a breakdown of articles on SHM and damage detections of different types of structures using various ML algorithms.

4.3.1. Bridges

SHM of steel bridges was considered in Refs. [273–280] using ANN and the vibration-based detection method. Hakim and Abdul Razak [274] compared the performance of ANN and ANFIS in damage detection of steel girder bridges. Neves et al. [275] applied ANN in damage detection of the steel girder of railway bridges. Kostić and Gül [276] considered the effect of temperatures in their ANN model developed for

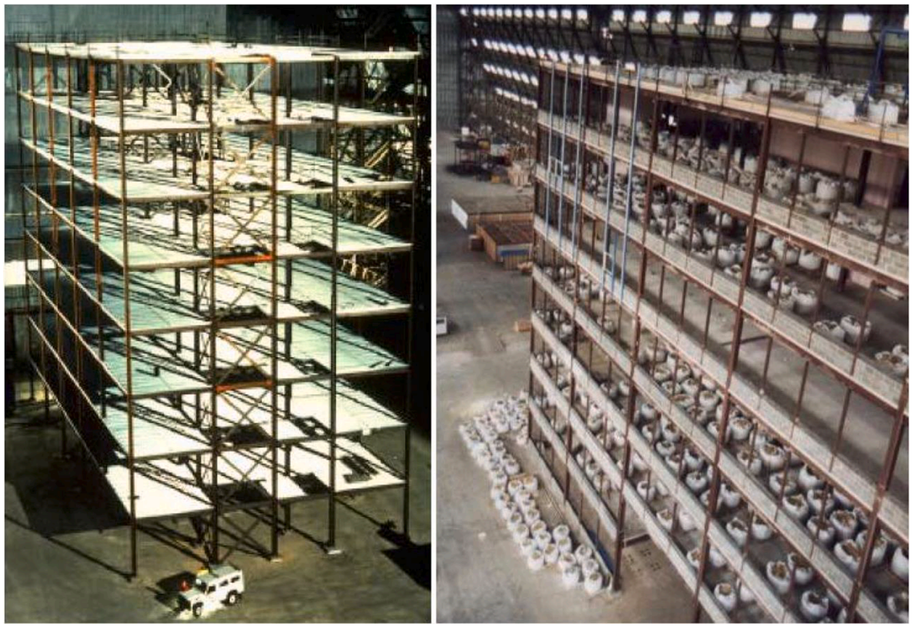


Fig. 30. Eight-storey Cardington test building under construction [252].

Table 12
Applications of ML in predicting fire responses of structures.

Structures	Types	ML algorithm	Reference
Columns	CFST columns	ANN	[254]
	Encased composite columns	ANN	[261]
	RC columns	ANN, ANFIS, RA1	[257]
		DT, RF, XGBoost, LightGBM	[258]
		ANN, SVM, DT, RF, GBM, RA6, NB	[99]
	RC columns with HSC	ANN	[259]
	RC columns strengthened by FRP	ANN	[260]
	Steel columns	ANN	[256]
Beams	RC T-beams strengthened by FRP sheets	ANN	[262]
	RC beams	ANN	[263,264]
	Shear of RC beams	ANN	[265]
Slabs	RC slabs	ANN	[266]
		ANFIS	[267]
	Steel-concrete composite floors	SVM	[268]
Joints	Semi-rigid steel joints	ANN	[269]
	T-joints with hollow steel sections	ANN	[270]
Systems	Steel frames	ANN	[253,271]
		DT, kNN	[253]
	Steel trusses	ANN	[272]

damage detection of Dowling Hall Footbridge (Fig. 31a), whilst Weinstein Jordan et al. [277] considered long-term effects in their model. Eftekhar Azam et al. [278] adopted ANN to detect damage of railway truss bridges. Tran-Ngoc et al. [279] improved the training parameters of ANN models developed for damage detection of a steel truss bridge (Fig. 31b). Nick et al. [280] used ANN to estimate damage of steel girder bridges. The use of SVM in SHM of steel girder bridges was carried out by Hasni et al. [281].

SHM of RC bridges was also examined in Refs. [282–285] using various ML techniques. For instance, Mangalathu et al. [282] proposed a process for rapid assessment of post-earthquake damage of RC bridges using four different ML methods of kNN, NB, RF, and DT. Their results also indicated that RF has the best performance among four considered ML methods. Okazaki et al. [284] also compared five different ML models including ANN, SVM, DT, RF, and RA1 in detecting crack in RC bridges. Sharma and Sen [283] incorporated the effect of temperatures on their ANN model for damage detection of RC bridges, whilst Lim and Chi [285] adopted XGBoost technique to proactively estimate the damage of RC bridges.

4.3.2. Frame and truss systems

One of the first applications of ML in structural damage detection was conducted by Wu et al. [4] using ANN to predict damage of three-storey RC frames under earthquakes. Similar ANN-based models were also developed by Refs. [5,286–291] for damage detection of multi-storey RC frames under earthquakes. Recently, Lei et al. [292] developed a CNN-based model for damage detection of RC shears frames under seismic excitation. Huang and Burton [293] compared 6 ML methods (i.e., ANN, SVM, DT, RF, AdaBoost, and RA6) in predicting the failure modes of RC frames with masonry infills. They concluded that both AdaBoost and SVM gave the best performance.

Regarding the SHM and damage detection of steel frames, a large number of studies were carried out in this area using different ML methods including ANN [294–299], RBFNN [300], CNN [301–304], SVM [305], RF [306], and kNN [307]. Szewczyk and Hajela [295] and Pillai and Krishnapillai [296] employed ANN to develop damage detection models for both frame and truss problems, whilst the ANN model developed by Chang et al. [297] was applied for three-storey frames. Kao and Hung [298] and Beheshti Aval et al. [299] used ANN to develop vibration-based damage detection models and verified with an experimental test of a five-storey steel frame [298] and a four-storey steel frame [299] as shown in Fig. 32a. Machavaram and Shankar [300] adopted the RBFNN method to develop damage detection models for both steel frames and truss structures. The CNN algorithm was used in Refs. [301–303] to develop vibration-based damage detection models for frame buildings. Their models were verified with the benchmark steel frames tested by Black and Ventura [308] for four-storey frames (see Fig. 32a) and by Wu and Samali [309] for five-storey frames (see Fig. 32b). Another CNN model was also developed recently by Kim et al. [304] for damage detection of steel frames, but their CNN model was based on the image-based detection approach.

The application of ML methods for SHM and damage detection of

Table 13
Applications of ML in SHM and damage detection.

Structures	Types	ML algorithm	Reference
Bridges	Steel girder bridges	ANN	[273-280]
		ANFIS	[274]
		SVM	[281]
	RC bridges	DT, RF, kNN, NB	[282]
		ANN	[283]
		XGBoost	[285]
		ANN, SVM, DT, RF, RA1	[284]
Frame/truss systems	RC frames under earthquakes	ANN	[4,5,286-291]
		CNN	[292]
		RBFNN	[289]
	RC frames with masonry infill	ANN, SVM, DT, RF, AdaBoost, RA6	[293]
	Steel frames	ANN	[295-299]
		RBFNN	[300]
		CNN	[301-304]
		SVM	[305]
		RF	[306]
		ANN, kNN	[307]
	Steel truss	ANN	[295,296]
		RBFNN	[300]
		SVM	[305]
		ANN, ANFIS, RBFNN, SVM, RF, RA2, kNN	[310]
Beam/ column members	Prestressed concrete beams	ANN	[311]
	Beams with various end conditions	SVM	[312]
	Steel beams	ANN	[313]
	RC beams/ columns	SVM	[314,315]
		CNN	[316]
		AdaBoost	[317]
		ANN, DT	[322]
		ANN, DT, RF, kNN, NB	[318]
	GPC beams	SVM	[319]
	Steel-concrete composite beams	ANN	[320,321]
Plate/panel members	RC slabs	ANN	[339-341]
	RC shear walls	RF	[86]
		RF, DT, AdaBoost, XGBoost, LightGBM, CatBoost, kNN, NB	[85]
	Aluminium plates	SVM	[342]
	Concrete panels	ANN	[343]
		CNN	[87-89,323-325,328,330-333,335,336]
		XGBoost	[344]
		LightGBM	[338]
	Asphalt roads	CNN	[334,337]
	Masonry walls	CNN	[90]
	Corroded steel plates and bolts	CNN	[326]
	Steel gusset plates	CNN	[327,329]
Joints	RC beam-column joints	DT	[345]
		ANN, SVM, RF, AdaBoost, GBM, XGBoost, RA6, kNN, NB	[346]
	Column base plate connections	SVM, DT, RF, AdaBoost, XGBoost, LightGBM, CatBoost, kNN, NB	[84]
	Steel beam-column joints	CNN	[347]

truss systems were conducted by Ghiasi et al. [310] using different ML techniques such as ANN, ANFIS, RBFNN, SVM, RA2, and kNN. They also provided a comprehensive comparison on the performance of different ML methods in damage detection of truss structures. Two large scale truss systems were considered. The comparison results indicated that SVM outperformed the others in terms of accuracy and model construction.

4.3.3. Beam/column members

The application of ML for damage detection of beam/column members was conducted in Refs. [311–321]. Based on the vibration-based detection method, Jeyasehar and Sumangala [311] developed an ANN-based detection model for prestressed concrete beams, whilst Shimada et al. [312] employed SVM to examine the effect of various end conditions. Hakim et al. [313] explored the damage of steel beams. Their ANN model was compared with the experimental test of an I-beam as shown in Fig. 33a. The ANN method was also employed by Tan et al. [320] and Sadeghi et al. [321] to develop vibration-based detection models for steel–concrete composite beams as shown in Fig. 33b.

Based on the image-based approach, Davoudi et al. [314,315] developed SVM-based models for crack detection of RC beams and slabs under flexure [314] and shear [315]. Their models were trained based on two datasets of 862 crack pattern images captured from 127 tested specimens [314] and 558 crack images captured from 84 shear tests of RC beams and slabs [315]. Another SVM-based model was also developed recently by Aravind et al. [319] to detect crack in geopolymer concrete (GPC) beams. The developed model was verified with the experimental test (Fig. 34a). Ye et al. [316] used CNN to develop a model called Ci-Net for crack detection of concrete beams. Their model was trained using 762 crack pattern images and verified with the experimental test of RC beams (Fig. 34b).

Damage detection of RC beam-column members was examined by Mangalathu and Jeon [318], Naderpour et al. [322], and Feng et al. [317] by means of failure mode classification. Mangalathu and Jeon [318] compared five ML models (i.e., kNN, NB, RF, DT, and ANN) in predicting the failure modes of circular RC columns. A database of 311 tested specimens on circular RC columns was considered. Naderpour et al. [322] compared ANN and DT methods in predicting the failure modes of circular and rectangular RC columns. Feng et al. [317] also developed failure mode classification models for RC columns, but they used AdaBoost and a database of 254 tests on RC columns under cyclic loading.

4.3.4. Plate/panel members

Regarding plate/panel structures, a large number of works on SHM and damage detection were conducted using the image-based approach incorporated with CNN [87–90,323–337] and LightGBM [338]. In the image-based method, CNN can detect cracks using the classification approach (detecting cracks at the image level) [90,323,326,327,329,330,332,333] and the segmentation technique (detecting cracks at the pixel level) [87–90,324,325,328,331,332,334–337]. Detailed reviews on the use of CNN for crack detection and structural condition assessment were reported by Ali et al. [39] and Sony et al. [36], respectively.

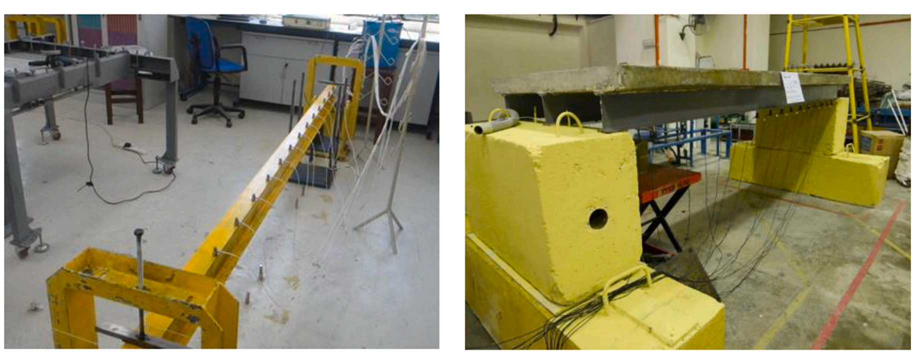
Cha et al. [323] developed a CNN model for surface crack detection of concrete structures. A database of 332 images of cracked concrete was used for training and validating purposes of the developed model which provided accuracy up to 98%. Cha et al. [326] also developed a CNN model for different types of surface damages such as concrete cracks, delamination, and corrosion in structural steel and bolts. They employed a faster region-based CNN algorithm and, thus their model can provide real-time detection. The cracks in materials other than concrete (e.g., asphalt road [334,337], masonry walls as shown in Fig. 35 [90], and steel gusset plates [327,329]) were also examined by CNN. Dorafshan et al. [332] compared the performance of various CNN models, and concluded that the CNN model with transfer learning mode provided the best results with the ability to predict the crack width up to 0.04 mm.

(a) (b)

Fig. 31. Steel bridges (a) Dowling Hall Footbridge [577] and (b) Nam O Bridge [279].

(a) (b)

Fig. 32. Benchmark frames of (a) four-storey [308] and (b) five-storey [309].



(a) (b)

Fig. 33. Model testing of (a) I-beam [313] and (b) composite beam [320].

Meanwhile, Rao et al. [330] compared the performance of 15 CNN classification-based models in detecting surface cracks of concrete structures using a large image database composed of 32,704 training patches, 2,074 validation patches, and 6,032 test patches.

Fully CNN, an extended version of CNN, was adopted by Refs. [87–89,324,325,328] for semantic segmentation on cracks of concrete at pixel level. Yang et al. [87] looked at both crack detection and measurement when developing a fully CNN model capable of reducing training time. Dung and Anh [324] used a comprehensive dataset of 40,000 images of crack concrete to train their model with the accuracy up to 90% (see Fig. 36a). Ni et al. [331] proposed a crack delineation network integrated with fully CNN to automatically delineate crack accurately and rapidly. Liu et al. [88] developed a fully CNN model that can reach high accuracy with a small training set. The fully CNN model developed by Hoskere et al. [328] can perform multi-task segmentation of both material types (i.e., steel, concrete, and asphalt) and structural damage. Ren et al. [89] and Huang et al. [336] examined concrete cracks in tunnel structures. The transfer learning technique can be used with CNN models to reduce computational cost [19,90,325,333,335,337]. For example, Li et al. [325] developed a fully CNN model to detect four types of damage in concrete structures including crack (Fig. 36b), spalling, hole, and efflorescence. A database of 2,750 images of concrete structures in

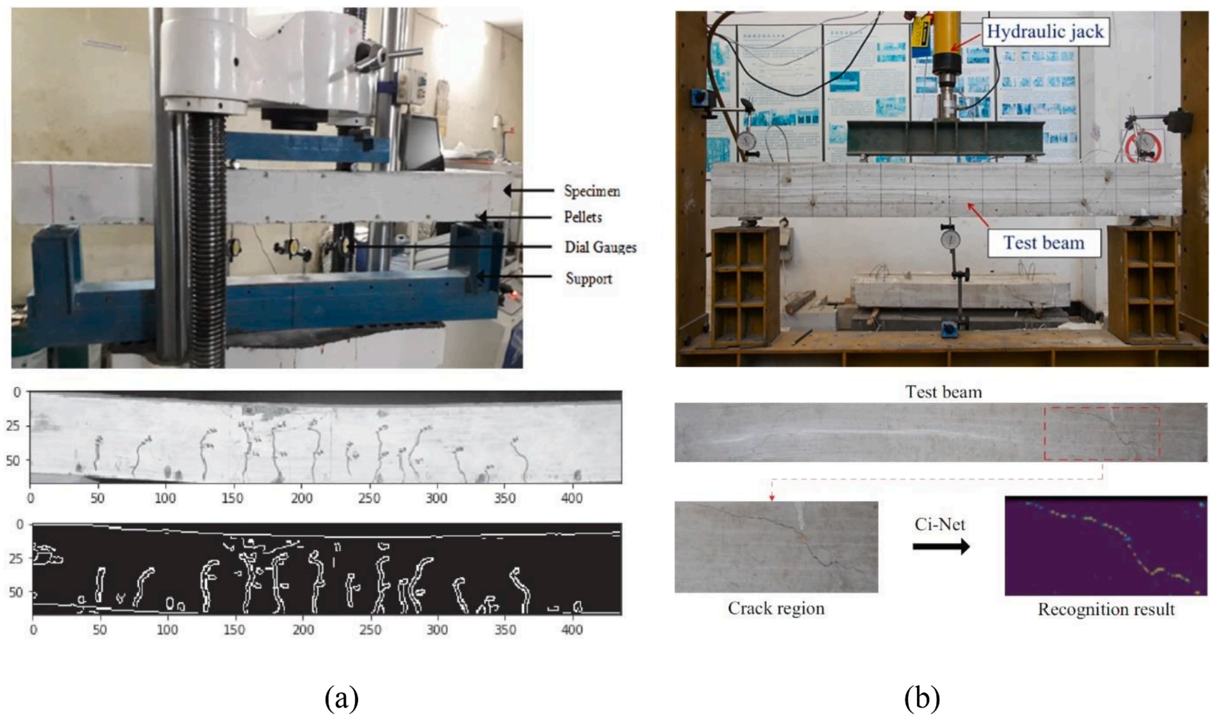


Fig. 34. Bending test of (a) GPC beam [319] and (b) RC beam [316].

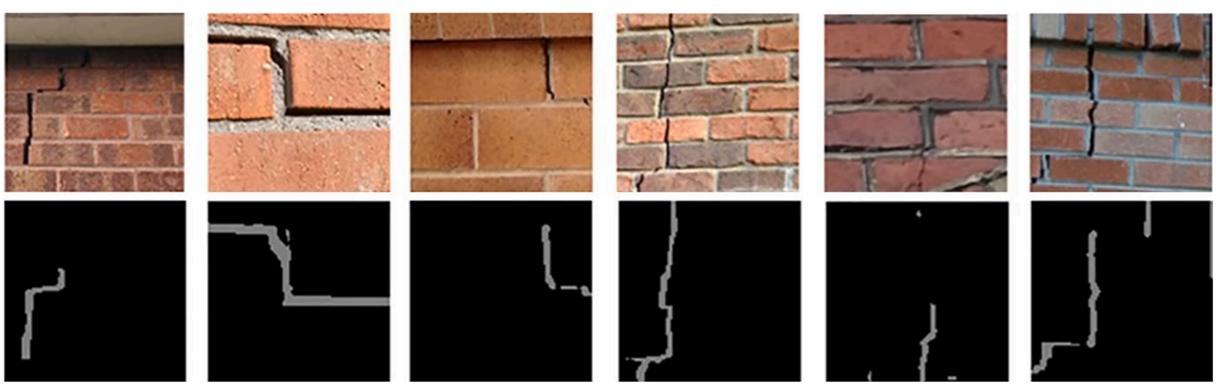


Fig. 35. Crack in masonry surfaces [90].

crack, spalling, efflorescence, and hole was also collected to build the model. Miao and Srimahachota [333] also incorporated an image processing technique to allow for raw images being detected.

In addition to the above-mentioned image-based models, the vibration-based models were also developed for damage detecting of plate/panel structures using ANN [339–341] and SVM [342]. Bakhary et al. [339] proposed a statistical ANN model for damage detection of RC slabs that considers the uncertainties in numerical modelling and measurement noise. Bakhary et al. [340] incorporated a multi-stage substructure technique in their ANN model to enable detection of small damage in RC slabs. They also improved their ANN model to account for the uncertainties in vibration frequencies and mode shapes [341]. Xu [342] used SVM to develop an impact detection model for aluminium plates.

Damage detection by means of failure mode identification was presented by Mangalathu et al. [85,86] for RC shear walls and by Refs. [343,344] for RC panels under local impact loading. Mangalathu et al. [86] used the RF method, whilst Mangalathu et al. [85] compared the performance of eight ML methods including RF, DT, AdaBoost, XGBoost, LightGBM, CatBoost, kNN, and NB. Their models were developed based on a database of 393 experimental tests of RC shear walls. The results indicated that RF gives the highest accuracy, followed by CatBoost and XGBoost. Doan et al. [343] and Thai et al. [344] recently developed ML-based models for detecting failure modes of RC panels under impact loading using ANN [343] and XGBoost [344].

4.3.5. *Joints*

Damage detection of joints by means of failure mode identification was examined by Naderpour and Mirrashid [345] and Asif Bin Kabir et al. [84] for beam-to-column joints and Gao and Lin [346] for column base plate joints. Naderpour and Mirrashid [345] used DT with an experimental database of 411 tests on RC joints (171 tests on exterior joints and 240 tests on interior joints). Asif Bin Kabir et al. [84] and Gao and Lin [346] compared the performance of different ML techniques in predicting the failure modes of column base plate connections [84] and RC beam-to-column joints [346]. Their models were built based on experimental datasets of 189 specimens on column base plate connections [84] and 580 specimens on RC beam-to-column joints [346]. The comparison results indicated that DT outperformed for column base plate connections [84], whilst XGBoost outperformed for RC beam-to-

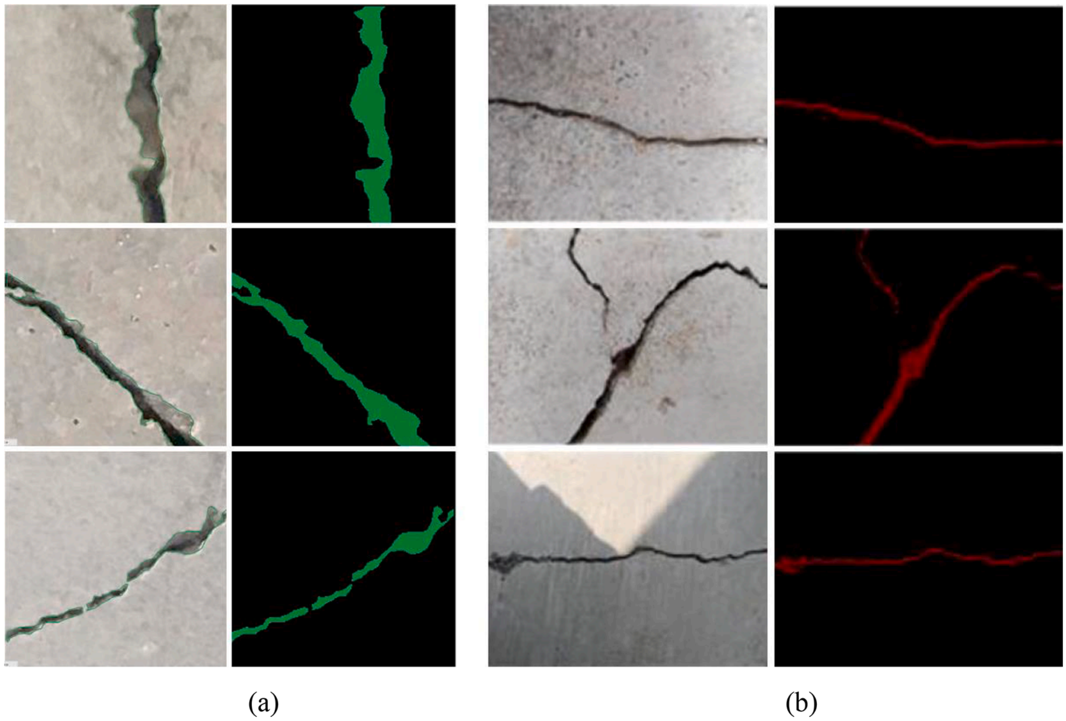


Fig. 36. Concrete crack predicted by (a) Dung and Anh [324] and (b) Li et al. [325].

column joints [346]. The structural damage of joints was also explored by Paral et al. [347] using the vibration-based detection method. They used CNN to train the data generated by SAP2000. Their model was also compared with the stiffness model given in Eurocode 3 for semi-rigid steel joints.

4.4. Structural analysis and design

The use of ML in the analysis and design of structures commenced with the first structural engineering application of ML carried out by Adeli and Yeh [1] in 1989. Since then, a significant number of papers have been published on this topic as summarised in Table 14. It is observed that the ANN method has been dominantly used in this topic.

4.4.1. Structural design

Adeli and Yeh [1] were one of the first authors who promoted the application of ML to structural engineering [2] when developing an ANN model for the design of steel beams. This ANN model was also used by Vanluchene and Sun [348] and Hadi [349] for the design of RC beams. Adeli and Park [350] later proposed another ANN-based model for the lateral-torsional buckling design of steel beams, but they used the counter-propagation algorithm. Hung and Jan [351] explored the application of ANFIS in the analysis and design of steel and RC beams. They concluded that ANFIS outperformed ANN [351].

The application of ANN to the design of CFS structures was examined by El-Kassas et al. [352,353] and Tashakori and Adeli [354]. They found that ANN can provide accurate results compared with equations from design codes [353]. Tashakori and Adeli [354] focused on the optimal design of space trusses with CFS sections. The optimal design of truss systems was also examined by Refs. [6-8] using ANN. Kaveh and Servati [355] used ANN to design large truss structures of double layer grids and evaluate their maximum deflection and weight, whilst Kaveh and Raiessi Dehkordi [356] used both ANN and RBFNN to analysed and design space dome trusses. Recently, Charalampakis and Papanikolaou [357] used ANN to design RC columns with a wide range of cross-sections. Zaker Esteghamati and Flint [358] developed five ML-based models (i.e., SVM, RF, XGBoost, RA1, and kNN) for the preliminary design of RC framed buildings.

4.4.2. Structural analysis of joints

One of the early applications of ML for structural analysis were conducted by Abdalla and Stavroulakis [359] and Stavroulakis et al. [360], in which they developed ANN models to predict moment-rotation curves of semi-rigid beam-to-column steel joints. Similar work was also conducted by Kaveh et al. [361,362]. Recently, Horton et al. [363] used ANN to predict the hysteresis behaviour of beam-to-column steel joints with reduced beam sections under cyclic loading using a dataset of 1,480 joints generated by ABAQUS. Shah et al. [364] developed both ANN and ANFIS models to predict the ultimate moments and rotations of boltless steel joints with CFS members. Cao et al. [365] explored the use of ANN in predicting the moment capacity of beam-to-column RC joints. Recently, Kim et al. [366] used both ANN and SVM methods to predict the axial resistance of tubular X-joints composed of CHS members as shown in Fig. 37. A numerical database of 4000 joints was also developed using the ABAQUS software for training and testing purposes.

4.4.3. Structural analysis of framed structures

Different ML techniques have been used for the analysis of framed structures. For example, Papadrakakis et al. [11] explored the application of ANN to the reliability analysis of steel frames, whilst Lute et al. [367] explored the use of SVM to the aerodynamic analysis of cable stayed bridges. Lagaros and Papadrakakis [368] used ANN to predict the nonlinear time-history responses of frames. Their ANN-based model compared well with numerical models. Wang et al. [369] predicted the load–deflection behaviour of CFST columns using ANN. Recently, Oh and Kim [370] adopted CNN to predict the responses of RC frames under seismic loading.

Another application of ML in structural analysis is to predict deflections and drifts of frames under gravity and lateral loads. Based on ANN, Lee et al. [371] developed an ANN model to analyse steel–concrete composite bridge girders. The obtained predictions of deflections, member forces, and ultimate loads were compared well with those predicted by numerical methods. Meanwhile, Maru and Nagpal [372] explored the application of ANN to predict the deflection of RC frames

Table 14
Applications of ML in structural analysis and design.

Type	Application	ML algorithm	Reference
Design	Steel beams	ANN	[1,350]
		ANFIS	[351]
	RC beams	ANN	[348,349]
		ANFIS	[351]
	CFS columns	ANN	[352,353]
	RC columns	ANN	[357]
	Truss systems	ANN	[6-8,354,355]
		ANN, RBFNN	[356]
	RC framed buildings	SVM, RF, XGBoost, RA1, kNN	[358]
Analysis of joints	Moment-rotation curve of steel joints	ANN	[359-362]
	Hysteresis behaviour of steel joints	ANN	[363]
	Moment and rotation of steel joints	ANN, ANFIS	[364]
	Moment of RC joints	ANN	[365]
	Axial strength of CHS steel X-joints	ANN, SVM	[366]
Analysis of frames	Reliability analysis of steel frames	ANN	[11]
	Aerodynamic analysis of cable-stayed bridges	SVM	[367]
	Time history analysis of frames	ANN	[368]
	Load-deflection behaviour of CFST columns	ANN	[369]
	Seismic responses of RC frames	CNN	[370]
	Deflection/drift prediction	ANN	[371-374]
		RF	[375]
		RF, DT, kNN, NB, RA1, RA5, AdaBoost, XGBoost	[377]
		ANN, XGBoost	[376]
	Strength predictions	ANN	[374,378-383,387]
		SVM	[384]
		XGBoost	[386]
		ANN, SVM, DT, RF, GBM	[385]
	Natural frequency of masonry infilled RC frames	ANN, DT	[389]
		SVM, DT, RF, AdaBoost, XGBoost, RA1, RA5, kNN	[388]
	Hysteresis behaviour	ANN	[390,391]
	Plastic hinge length of RC columns	AdaBoost	[392]
		SVM, DT, RF, GBM, XGBoost	[393]
	Lumped plasticity model for RC columns	RA4, RA5	[394]
Analysis of trusses	Truss under static load	ANN	[3,396,397]
		SVM	[399]
		GBM	[398]
	Time-history of truss	ANN	[395]
Analysis of plate/wall structures	Strength of RC shear walls	ANN	[400]
	RC slabs	ANN	[401]
	Deflection of RC slabs under blast load	RF	[402]

considering creep and shrinkage effects. Hosseini and Abbas [373] developed an ANN model to predict the deflection of clamped beams under impact loading by a mass. Kalman Šipoš et al. [374] examined the drift of RC frames infilled with masonry walls. Based on a numerical dataset of 621 frames under 240 ground motions, Guan et al. [375] developed a RF-based model to predict the drift of steel moment frames under earthquakes. Nguyen et al. [376] also examined the drift of steel moment frames under earthquakes, but they used ANN and XGBoost methods instead. Recently, Hwang et al. [377] compared the performance of different ML methods (i.e., RF, DT, kNN, NB, RA1, RA5, AdaBoost, and XGBoost) in predicting the drift of RC frames. They found that boosting methods (i.e., AdaBoost and XGBoost) outperformed the others.

In addition to predicting deflections and drifts of framed structures, ML methods were also used for strength predictions in Refs. [374,378–387] (see Table 14). Based on ANN, Fonseca et al. [378] examined the ultimate load of steel I-beams under patch load, whilst Hu et al. [383] predicted the buckling of I-beams prestressed by FRP bars. Truong et al. [386] also examined the strength of steel I-beams under patch load, but they used XGBoost instead of ANN. Recently, Taheri et al. [387] used ANN to predict the ultimate load-carrying capacity of upright frames made of CFS sections. Their ANN model was trained by a numerical database generated by ABAQUS. Kim et al. [385] compared five ML methods (i.e., ANN, SVM, DT, RF, and GBM) in predicting the ultimate load-carrying capacity of steel frames, and they found that GBM gave the best performance. The shear resistances of steel frames and masonry infilled RC frames under earthquakes were also investigated by Caglar et al. [379] and Kalman Šipoš et al. [374], respectively. Luo and Paal [384] also examined the shear resistance of RC columns under earthquakes, but they used the SVM method. The ANN-based models were also developed by Chaudhary et al. [381] and Patel et al. [380] to predict the inelastic moments of continuous composite beams [381] and RC beams considering crack effect [380]. Pendharkar et al. [382] improved the work in Ref. [381] by considering crack and time dependent effects.

Other applications of ML in structural analysis are to predict the natural frequency of structures [388,389] and the hysteresis behaviour of RC columns under cyclic loading [390,391]. Charalampakis et al. [389] developed both ANN and RF models to predict the natural frequency of masonry infilled RC structures. Somala et al. [388] also looked at the natural frequency of masonry infilled RC structures, but they focused on comparing the performance of eight ML methods (i.e., SVM, DT, RF, AdaBoost, XGBoost, RA1, RA5, and kNN). Their results indicated that XGBoost outperformed other ML models considered. Ning et al. [390] and Yang and Fan [391] explored the application of ANN in predicting the hysteresis loop of RC columns [390] and CHS steel columns [391] under cyclic loading, respectively.

ML techniques were also employed to improve the performance of beam-column finite elements in predicting the nonlinear inelastic responses of RC columns under static and cyclic loadings. For example, Feng et al. [392] used AdaBoost to determine the plastic hinge length (PHL) of RC columns. Their AdaBoost-based PHL model was trained based on a test database of 133 tests on RC columns, and was also compared well with existing empirical PHL models. The AdaBoost-based PHL model was then incorporated in a force-based fibre beam-column element in OpenSees software to predict monotonic and cyclic behaviours of RC columns. Wakjira et al. [393] also explored the application of ML in predicting the PHL of RC columns, but they focused on the comparison of the performance of different ML techniques including SVM, DT, RF, GBM, and XGBoost. Their results indicated that XGBoost had the best performance among five ML methods considered. Lee et al. [394] recently employed both RA4 and RA5 to predict the parameters of the lumped plasticity model for RC circular columns under cyclic using a database of 210 tests.

4.4.4. Structural analysis of truss structures

Hajela and Berke [3] conducted one of the first studies on the application of ANN to the analysis and optimal design of trusses. Chassiakos and Masri [395] explored the application of ANN in predicting the time-history response of multi degree-of-freedom systems subjected to ground motions, whilst Lee et al. [396] explored the effect of hyperparameters on the accuracy of their ANN model in analysing a

Fig. 37. CHS X-joints tested by Kim et al. [366].

plane truss. Kaveh and Iranmanesh [397] compared the performance of two ANNs, namely the back-propagation neural network and the improved counter-propagation neural network in the analysis and design of large scale space structures. Truong et al. [398] used GBM to evaluate the ultimate load-carrying capacity of truss systems based on a large numerical database generated by advanced analysis. A similar work was also conducted recently by Truong and Pham [399], but they used SVM instead of GBM.

4.4.5. Structural analysis of plate/wall structures

One of the early applications of ML for the analysis of plate/wall structures was conducted by Mo and Lin [400], in which they developed an ANN model to predict the stress–strain curves of RC shear walls under earthquakes. Hegazy et al. [401] developed different ANN-based models to predict the load–deflection curve and crack pattern of RC slabs under punching shear actions. Almustafa and Nehdi [402] use the RF technique to predict the maximum displacement of RC slabs exposed to blast loading. They also collected a test database of 150 specimens of RC slabs under fire for training and validating purposes.

4.5. Prediction of mechanical properties of concrete

Concrete is the most commonly used construction material for buildings, bridges, and other infrastructure. Different types of structural concrete have been developed for structural and civil engineering applications, e.g., NSC, HSC, high performance concrete (HPC), recycled aggregate concrete (RAC), self-compacting concrete (SCC), lightweight concrete (LWC), GPC, fibre reinforced concrete (FRC), etc. One of the issues of concrete is that its mechanical properties are strongly dependent on mix design and curing conditions. Due to the paramount importance of concrete properties in the design of RC structures, accurate prediction of these properties, especially compressive strength f_c and Young's modulus E, has become a critical concern.

Significant efforts have been made to utilise ML techniques in predicting mechanical properties of concrete. This is evidenced by the fact that this topic contributes nearly one third of the total publications on ML applications for structural engineering as shown in Fig. 14. Most of ML applications on the material topic focus on predicting the compressive strength of concrete (contributing up to 62% as shown in Fig. 14). Although a review on ML prediction of concrete properties was conducted by Ben Chaabene et al. [41], their review was limited to only four types of ML techniques (i.e., NN, SVM, DT, and EA). This section therefore provides a comprehensive review on seven groups of ML methods as shown in Fig. 13. A breakdown of publications using ML to predict mechanical properties of concrete can be found in Table 15.

4.5.1. Compressive strength

One of the early applications of ML in predicting compressive strength of concrete was conducted by Kasperkiewicz et al. [10] when using ANN to predict the compressive strength of HPC. Since then, a huge number of studies (over 110 publications) have been conducted to develop different ML models for different types of concrete as summarised in Table 15. Based on ANN, Refs. [10,403–412] explored the compressive strength of HPC [10,92,403,406,408,409,411,412] and HSC [404,405,407,410]. In addition to compressive strength, Dias and Pooliyadda [404] and Öztaş et al. [405] also examined the slump of HSC, whilst Khan [412] and Bui et al. [409] further examined the tensile strength of HPC. Prasad et al. [406] developed ANN-based predictive model for SCC. Golafshani et al. [413] compared the performance of ANN and ANFIS in predicting the compressive strength of both NSC and HSC, whilst Chou and Pham [414] and Chou et al. [415] investigated the performance of the base learners (i.e., ANN, SVM, DT, and RA1) and ensemble models (i.e., combining from more than two base learners) in predicting the compressive strength of HPC. They concluded that ensemble technique can enhance the performance of individual base learners. Recently, Nguyen et al. [83] compared the performance of four ML methods including ANN, SVM, GBM, and XGBoost. They found that the BA methods (GBM and XGBoost) outperformed ANN and SVM in predicting the compressive and tensile strengths of HPC. The compressive strength of HPC was also investigated using other ML techniques such as SVM [416,417], GBM [418], and RF [419].

Similar to HSC and HPC, there are also significant works on NSC using different ML techniques including ANN [420–435], ANFIS [436,437], RBFNN [60], CNN [438], SVM [439], AdaBoost [440], and XGBoost [441] as shown in Table 15. Moradi et al. [434] examined the compressive strength of concrete containing metakaolin. DeRousseau et al. [442] compared the performance of five ML models including RA1, RA2, DT, RF, and AdaBoost. Their results indicated that RF gave the most accurate prediction among compared models. Recently, Koya et al. [443] also compared the performance of five ML model (i.e., SVM, DT, RF, GBM, and RA2) in predicting five mechanical properties of concrete including compressive strength, tensile strength, bending strength, Young's modulus, and Poisson's ratio. It was found that SVM outperformed in most of the cases.

The potential application of ML methods to predict the compressive strength of LWC was explored by Refs. [444–452]. Again, ANN was dominantly used in this case [444–449]. In addition to the compressive strength, Yoon et al. [447] also examined the Young's modulus of LWC.

Table 15
Applications of ML in predicting mechanical properties of concrete.

Property	Application	ML algorithm	Reference
Compressive strength	HPC/HSC	ANN	[10,92,403-412]
		ANN, ANFIS	[413]
		SVM	[416,417]
		GBM	[418]
		ANN, SVM, DT, RA1	[414,415]
		RF	[419]
		ANN, SVM, GBM, XGBoost	[83]
	NSC	ANN	[420-435]
		ANFIS	[436,437]
		RBFNN	[60]
		CNN	[438]
		SVM	[439]
		AdaBoost	[440]
		XGBoost	[441]
		RA1, RA2, DT, RF, AdaBoost	[442]
		SVM, DT, RF, GBM, RA2	[443]
	LWC	ANN	[444-449]
		SVM	[450]
		RF	[451]
		ANN, SVM, DT, RA2	[452]
	FRC	ANN	[453]
		ANN, SVM	[454]
		ANN, SVM, DT, XGBoost	[455]
		ANN, SVM, DT, RF, AdaBoost, GBM, XGBoost, RA1, RA4, RA5, kNN	[456]
	GPC	ANN	[458-463,465]
		SVM	[466]
		DT	[464]
	SCC	ANN	[406,467-470]
		ANFIS	[471]
		RBFNN	[472,473]
		SVM	[474,475]
	RAC	ANN	[476-486]
		CNN	[487]
		XGBoost	[488]
		ANN, RA3	[489]
		RA2, SVM, DT	[490]
Tensile strength	HPC	ANN	[409,412]
	NSC	SVM, DT, RF, GBM, RA2	[443]
	FRC	ANN	[491]
		ANN, SVM	[454]
		ANN, SVM, DT, RA1	[492]
		ANN, SVM, DT, XGBoost	[455]
	RAC	ANN	[476,479,483,486]
		ANN, RA3	[489]
		RA2, SVM, DT	[490]
Flexural strength	FRC	ANN, SVM, DT, RF, RA1, RA4, RA5, kNN, AdaBoost, GBM, XGBoost	[456]
	GPC	ANN	[463]
	RAC	ANN	[486]
		ANN, RA3	[489]
		RA2, SVM, DT	[490]
Young's modulus	HSC and NSC	ANN	[493]
		SVM	[494,495]
	NSC	SVM, DT, RF, GBM, RA2	[443]
	LWC	ANN	[447]
		SVM	[450]
	SCC	SVM	[496]
	RAC	ANN	[476,486,497,498]
		ANN, RBFNN, SVM	[499]
		ANN, RA3	[489]
		RA2, SVM, DT	[490]
Property	Concrete slump	ANN	[404,405,470,500,501]
		SVM	[474,502]
	Stress and strain	ANN	[503,504,506,507,509,510]
		SVM	[508]
		ANN, RBFNN, ANFIS	[505]
		ANN, ANFIS, RA2, DT	[511]
	Poisson's ratio	SVM, DT, RF, GBM, RA2	[443]
	Shrinkage of concrete	ANN	[512]
	Creep of concrete	ANN, SVM	[513]
		RF, XGBoost, LightGBM	[514]
Mix design	HPC	ANN	[515]
	NSC	ANN	[516-518]
	FRC	SVM	[519]
		RF	[520]
	RAC	ANN	[521]

Bonifácio et al. [450] also explored the compressive strength and Young's modulus of LWC, but they used SVM instead of ANN. The application of RF to predict the compressive strength of LWC was carried out by Zhang et al. [451]. A comparison on the performance of ML algorithms in predicting the compressive strength of LWC was presented by Yaseen et al. [452]. They concluded that ANN outperformed SVM, DT, and RA2.

The application of ML to predict the compressive strength of FRC was examined by Refs. [453–456]. Based on ANN, Eredm et al. [453] developed ANN-based models to predict the compressive strength of concrete reinforced by polypropylene fibres [453]. Sultana et al. [454] employed both ANN and SVM to predict the tensile and compressive strengths of concrete reinforced by jute fibres. Guo et al. [455] compared the performance of ANN, SVM, DT, and XGBoost in predicting the tensile and compressive strengths of FRC. They concluded that the XGBoost method gave the highest accuracy among the considered ML methods for all mechanical properties. Recently, Kang et al. [456] presented a comprehensive comparison study of 11 ML models (i.e., ANN, SVM, DT, RF, AdaBoost, GBM, XGBoost, RA1, RA4, RA5, and kNN). Both compressive and flexural strengths of steel FRC were considered. The results indicated that GBM, XGBoost, RF, and DT had a good accurate prediction compared with other ML methods considered.

GPC is an ecofriendly material in which ordinary Portland cement is replaced by geopolymer cement, a sustainable product which can be made from industrial waste material containing aluminosilicate mineral such as silica fume, fly ash, granulated blast furnace slag, natural zeolite, and metakaolin when treated with alkali solutions [457]. A substantial amount of research has been dedicated to developing ML-based models to predict the mechanical properties of GPC. For example, Özcan et al. [458] and Behnood and Golafshani [459] developed ANN models to predict the compressive strength of silica fume-based GPC. Han et al. [460] and Kandiri et al. [461] also developed ANN models for predicting compressive strength of GPC made from granulated blast furnace slag concrete. Compressive strength of fly ash-based GPC was examined by Refs. [462–464] using ANN methods [462,463] and DT method [464]. Recently, Shahmansouri et al. [465] explored the compressive strength of silica fume and natural zeolite-based GPC using ANN, whilst Salami et al. [466] used SVM to examine the compressive strength of ternary-blend concrete.

SCC is a new type of HPC. One of the benefits of SCC over conventional concrete is that it has super workability, flowability, and pumpability. One of the most important characteristics of SCC is its ability in compacting itself without using external vibrators. Therefore, SCC has been widely used especially in bridges and precast construction. The application of ML to predict the compressive strength of SCC was also explored by Refs. [406,467–475]. One of the first applications of ANN in predicting the compressive strength of SCC was conducted by Prasad et al. [406]. They also developed ANN-based models for predicting the slump flow of SCC. Similar ANN-based models were also developed by Refs. [467–470]. Vakhshouri and Nejadi [471] proposed the use of ANFIS for SCC, whilst Golafshani and Pazouki [473] and Pazouki et al. [472] explored the application of RBFNN for SCC. The use of SVM for SCC was also examined by Siddique et al. [474] and Aiyer et al. [475].

ML techniques have also been used to predict the compressive strength of RAC in which aggregates are produced from recycled materials such as rubber tires and construction and demolition waste (e.g., concrete, brick, and masonry). A significant work has been dedicated to developing ML-based predictive models for RAC using ANN [476–486], CNN [487], and XGBoost [488]. Gesoğlu et al. [476] also looked at the tensile strength and Young's modulus of rubberized RAC in addition to its compressive strength. Dantas et al. [477] and Getahun et al. [480] focused on RAC made from agriculture, construction, and demolition waste, whilst Duan et al. [478] examined RAC made from various types and sources of recycled aggregates. Awoyera [479] and Chen et al. [483] developed ANN models for both compressive and tensile strengths of RAC with steel slag aggregate [479] and permeable RAC [483]. Recently, Golafshani and Behnood [486] and Xu et al. [489] explored the application of ANN and RA3 to investigate mechanical properties of RAC including compressive strength, tensile strength, flexural strength, and Young's modulus. Golafshani and Behnood [486] focused on RAC containing waste foundry sand, whilst Xu et al. [489] focused on the comparison between their ML-based models and existing code-based and empirical equations. Similar work was also conducted by Gholampour et al. [490] using different ML methods.

4.5.2. Tensile strength

ML techniques have been used to predict the tensile strength of HPC, NSC, FRC, and RAC as summarized in Table 15. The tensile strength of HPC was examined by Khan [412] and Bui et al. [409], whilst Koya et al. [443] investigated the tensile strength of NSC. It should be noted that Khan [412] and Bui et al. [409] used ANN to develop predictive models for both compressive and tensile strengths, whilst Koya et al. [443] compared the performance of five ML models (i.e., SVM, DT, RF, GBM, and RA2) for five different mechanical properties of concrete including compressive strength, tensile strength, bending strength, Young's modulus, and Poisson's ratio.

Tensile strength of FRC was studied by Ikumi et al. [491] using ANN. Their ANN model can predict accurately the tensile strength of FRC for different cracking stages. Sultana et al. [454] employed both ANN and SVM to predict the tensile strength of concrete reinforced by jute fibres. Behnood et al. [492] developed four ML models of ANN, SVM, DT, and RA1 to predict the tensile strength of FRC as a function of its compressive strength. Their ML-based models were also compared well with existing empirical equations. Guo et al. [455] compared the performance of ANN, SVM, DT, and XGBoost in predicting the tensile strength of FRC. They concluded that the XGBoost method gave the highest accuracy among the ML methods considered.

Tensile strength of RAC was examined by Refs. [476,479,483,486,489]. Gesoğlu et al. [476] developed the ANN model for the tensile strength of rubberized RAC, whilst Awoyera [479] and Chen et al. [483] developed ANN models for the tensile strength of RAC with steel slag aggregate [479] and permeable RAC [483]. Golafshani and Behnood [486] and Xu et al. [489] explored mechanical properties of RAC including compressive strength, tensile strength, flexural strength, and Young's modulus.

4.5.3. Flexural strength

Kang et al. [456] presented a comparison study on the performance of 11 ML models including ANN, SVM, DT, RF, AdaBoost, GBM, XGBoost, RA1, RA4, RA5, and kNN in predicting the flexural strength of steel FRC. They found that GBM, XGBoost, RF, and DT outperformed other ML methods considered. The flexural strength of fly ash-based GPC was examined by Barbuta et al. [463] using ANN. Golafshani and Behnood [486] and Xu et al. [489] explored the flexural strength of RAC using ANN and RA3 methods.

4.5.4. Young's modulus

Young's modulus of concrete is an important property required in the design of concrete structures. Existing empirical equations used in current design codes of RC structures are obtained from regressive analysis of experimental data. These empirical equations might not suitable or available for different types of concrete developed recently. Therefore, ML techniques can be considered as an efficient tool to predict the Young's modulus of concrete (see Table 15 for a list of publications on this topic).

The Young's modulus of NSC and HSC was examined by Demir [493] using ANN and by Yan and Shi [494] and Yazdi et al. [495] using SVM. In their ML-based models, the Young's modulus was calculated from the compressive strength of concrete. Recently, Koya et al. [443] compared the performance of five ML models of SVM, DT, RF, GBM, and RA2 in predicting the elastic modulus of NSC. They also concluded that SVM outperformed other ML models. The elastic modulus of LWC was studied by Yoon et al. [447] using ANN and Bonifácio et al. [450] using SVM, whilst the elastic modulus of SCC was explored by Cao et al. [496] using SVM.

The elastic modulus of RAC also receives much attention from the research community. Different ML-based predictive models have been developed using ANN [476,486,497,498]. Gesoğlu et al. [476] examined the modulus of rubberized concretes, whilst Golafshani and Behnood [486] examined the elastic modulus of RAC containing waste foundry sand. Duan et al. [497] developed an ANN-based model for the elastic modulus of RAC, and compared it with existing equations in design codes. Sadati et al. [498] collected an experimental database of over 480 tests to develop an ANN-based model for the elastic modulus of RAC. Golafshani and Behnood [499] examined the elastic modulus of RAC using ANN, RBFNN, and SVM methods, whilst Xu et al. [489] employed both ANN and RA3 methods for the elastic modulus of RAC.

4.5.5. Other properties

In addition to predicting the strength and elastic modulus of concrete, ML has also been employed to predict other mechanical properties of concrete such as slump, confined stress–strain, Poisson's ratio, shrinkage, and creep as summarised on Table 15. The slump of concrete was investigated in Refs. [404,405,470,500,501] using ANN and Refs. [474,502] using SVM. The ANN models developed by Dias and Pooliyadda [404] and Öztaş et al. [405] are applied for HSC, whilst the ANN model developed by Yeh [500] is used for HPC. Belalia Douma et al. [470] explored the slump of SCC using ANN. Siddique et al. [474] and Sonebi et al. [502] also developed ML-based predictive models for the slump of SCC, but they used SVM.

Another application of ML in mechanical properties of concrete is to predict the confined stress and strain of RC columns. Oreta and Kawashima [503] explored the confined stress and strain of circular concrete columns using ANN, whilst Alacalı et al. [504] used ANN to develop a predictive model for confinement coefficient in rectangular RC columns. Mansouri et al. [505] examined the confined stress and strain at the peak and residual conditions. The stress and strain of RC columns confined by FRP sheets were explored by Pham and Hadi [506] and Jiang et al. [507]

using ANN and Chen et al. [508] using SVM. Pham and Hadi [506] examined the confined stress and strain of rectangular columns, whilst Jiang et al. [507] and Chen et al. [508] examined the confined stress and strain of circular columns. Naderpour et al. [509] and Jalal and Ramezanianpour [510] also developed ANN models to predict the confined stress of FRP-strengthened concrete. Mansouri et al. [511] also examined the application of ML to FRP-strengthened concrete, but focused on the strain reduction factor and strength enhancement ratio. In addition, ML techniques were also used to predict the Poisson's ratio [443], shrinkage [512], and creep of concrete [513,514].

4.5.6. Mix design

One of the first application of ML in optimising mixture of concrete was proposed by Yeh [515] in which ANN was used to develop an optimal mixture of HPC with lowest cost for a given workability and compressive strength. Yeh [516] also implemented his ANN model in a Computer-Aided Design (CAD) platform to develop a CAD tool that optimises the mixture of NSC. Similar ANN models were also developed by Ji et al. [517] and Ziolkowski et al. [518] to develop optimal mixtures for NSC. Optimal mixtures of FRC were also proposed by Huang et al. [519] using SVM and Abellán-García and Guzmán-Guzmán [520] using RF. The FRC mixture proposed by Huang et al. [519] was optimised for compressive and flexural strengths, whilst Abellán-García and Guzmán-Guzmán [520] optimised their mixture for ductility requirements of ultra-high performance FRC for seismic retrofitting applications. Kalman Šipoš et al. [521] also used ANN to develop an optimal mix design of RAC with brick aggregates.

5. Summary, challenges, and future recommendations

5.1. Summary of the findings from the reviewed literature

A comprehensive review on the application of various ML algorithms for different areas of structural engineering presented in Sections 3 and 4 indicates the potential of ML in this field. Based on the results of this review, the following findings of ML algorithms and structural engineering applications are summarised as below:

5.1.1. Findings about ML algorithms

- For regression problems, it has been found that BA methods, especially XGBoost, have the best performance in general in predicting (i) the resistance of most structural members and systems (e.g., shear resistance of RC beams [78,98] and squat RC walls [77,80], punching shear resistance of RC slabs [79], axial resistance of RC columns reinforced by FRP bars [82] and CFST columns [167], flexural resistance of RC beams strengthened by FRP [220] and I-beams under patch load [386], compressive strength of concrete [83,455], and load-carrying capacity of truss systems [398]) and (ii) other applications (e.g., drift of RC frames [377], natural frequency of masonry infilled RC structures [388], and PHL for RC columns under seismic [393]).
- For classification problems, however, there are different ML algorithms which have been found to be best performance in identifying the failure mode for specific applications, e.g., ANN outperforming for circular RC columns [318], RF outperforming for RC shear walls [85], DT outperforming for column base plate connections [84], XGBoost giving best results for beam-to-column RC joints [346], etc. It should be noted that these findings are based on comprehensive comparison studies on a large number of ML algorithms including tree-based algorithms (i.e., DT, RF, and BA) and others (e.g., SVM, RA, ANN, kNN, NB, etc.).
- CNN has been emerged as one of the best ML algorithms for image-based crack damage detection and SHM due to the development of a wide range of CNN architectures (e.g., AlexNet, VGG, U-Net, etc.) and the availability of large databases of both crack and non-crack structural images (e.g., Structural ImageNet, PEER Hub ImageNet, bridge crack library, etc.) [36]. A comparison study conducted recently by Ali et al. [39] indicated that CNN outperformed traditional image processing techniques and other ML algorithms for both classification (i.e., cracks detected at the image level) and segmentation (i.e., cracks detected at the pixel level) approaches. In addition, the use of transfer learning training method can reduce significantly training time especially when the CNN model is trained on a large database with very deep networks [39]. Therefore, a significant amount of research works has been conducted in this area recently. A critical review on the use of CNN for structural crack detection and structural assessment can be found in Ali et al. [39] and Sony et al. [36], respectively.
- Among the ML algorithms used in structural engineering, NN has become the most widely used method (see Fig. 13) due to its popularity and ease of use. Another advantage of ANN is that it can express or interpret in terms of empirical equations to be implemented in design codes. As shown in Fig. 12b, NN is the only ML method that adopted in structural engineering since its early stage until 2006 when the SVM method was first used in structural engineering for damage detection [312]. Although the BA methods was introduced since 1996 with the AdaBoost version, they were just adopted in structural engineering in 2019 to predict the compressive strength of concrete [442] and failure modes of masonry-infilled RC frames [293]. However, this method, especially the XGBoost version, has been extensively used in various areas of structural engineering recently as evidenced by an exponential growth in the number of publications shown in Fig. 12b.
- As shown in Table 5, NN has been favourably used in all five structural engineering topics, especially in the fire and member topics where NN has been dominantly used. Among five topics considered, SVM and DT have been widely used in the material topic, whilst a large amount of BA applications is focused on the member topic.

5.1.2. Findings about ML applications in structural engineering

- Among five structural engineering topics identified, the member topic has attracted the most attention from the structural engineering community with 38% of over 485 relevant publications appearing in this topic as shown in Fig. 14. This is followed by the material topic which contributes up to 29%. Most of research works conducted in these two topics involves in predicting the shear resistance of structural members (in the member topic) and the compressive strength of concrete (in the material topic). These statistics indicate the importance of using ML as an alternative prediction tool in the areas that are too complex and time-consuming if traditional physics-based methods are utilised.
- Most of ML applications in the member topic have been devoted to predicting the shear resistance of structural members (contributing up to 38% of over 190 publications as shown in Fig. 14), especially beam structures (mainly RC beams) with 44 publications as shown in Table 6. The second most use of ML in this topic is the prediction of the axial resistance of columns and walls with 36 articles published in this area equivalent to 19% as shown in Table 7 and Fig. 14. Over two-thirds of them (25 out of 36 publications) are related to CFST columns. This is due to the complex composite action of CFST columns that makes them hard to be predicted or modelled by using traditional mechanics-based approach.
- In the material topic, compressive strength of concrete plays an important role in the design of concrete structural members. Therefore, most publications in this topic focus on predicting the compressive strength of different types of concrete (e.g., HPC, RAC, SCC, LWC, GPC, FRP, etc.) whose mechanical properties are strongly dependent on a lot of factors such as mix design and curing conditions. Due to the variation and uncertainty in compressive strength of concrete, the use of physics-based models is not reliable. Therefore,

ML techniques have emerged as a promising tool in predicting the compressive strength of concrete as well as optimising the mix design of the newly developed concrete materials.

- The damage and SHM topic has experienced an exponential growth in the use of CNN, fully CNN, and transfer learning technique in detecting crack damage in structures (see Table 13). With the availability of large image databases and recent developments in CNN architectures, detecting different types of cracks and damage and assessing the condition of different types of civil infrastructure made from various construction materials have become more accurate and efficient than traditional techniques [328]. Therefore, CNN is expected to be the future of SHM. A detailed review of recent developments in CNN for image-based crack detection and SHM can be found in Refs. [32,36,39].

5.2. Challenges

With the developments of new ML algorithms (e.g., boosting methods and CNN) outperforming other established models, the structural engineering research community has witnessed a boom in the use of ML in structural engineering in the last five years (see Fig. 12a). However, there are still several existing challenges that need to be addressed so that ML can be effectively and efficiently used in structural engineering practice. In general, the two things that mainly affect the performance of a ML-based model are the ML algorithm and database used. In the context of structural engineering, the following challenges are identified:

- The first challenge involves the selection of a right ML algorithm which is not an easy task for the structural engineering community which are unfamiliar with ML. There are a large number of ML algorithms that have been adopted in structural engineering (see Sections 2.2 and 4). Each ML algorithm might be suitable for a particular structural engineering application. Although a number of comparison and benchmarking studies have been carried out in the literature to find out suitable algorithms for different topics (see Section 5.1.1), the findings are somehow not consistent. For example, Yaseen et al. [452] confirmed in their comparison study that ANN outperformed SVM, DT, and RA2 in predicting the compressive strength of LWC, whilst Guo et al. [455] found that XGBoost outperformed ANN, SVM, and DT in predicting the tensile and compressive strengths of FRC. Whereas, Koya et al. [443] concluded that SVM outperformed DT, RF, GBM, and RA2 in predicting all mechanical properties of concrete. Therefore, non-ML background users especially structural engineers and practitioners should compare and verify their developed ML-based models before recommending them for practical design.
- Another challenge related to ML algorithms is the use of the right hyperparameters. In fact, there are several hyperparameters in each ML algorithm that can make the model more accurate and/or being trained faster. Therefore, they need to be tuned during the testing and validating stages to find the optimal values. This is also a challenge for structural engineers and practitioners who are not familiar with ML.
- Additional challenge of ML algorithms involves their “black box” nature as it is hard to understand how they work. Although some simple ML algorithms with limited number of parameters such as RA1 and DT can be easily interpreted, complex ML algorithms such as deep neural networks with multiple layers and thousands of parameters are considered as truly black boxes because their behaviour is too complex to be comprehended or explained even by ML experts [522]. Other ML algorithms that are somehow interpretable such as RF and BA also become unfamiliar to structural engineering people. In general, the complex algorithm is usually more accurate than the simple one, but they are less interpretable. Therefore, it is necessary to trade-off between accuracy and interpretability. In other words, simpler (and more interpretable) models should be used in the case there is no significant benefit gained from a complex alternative. For some applications that the use of complex models is unavoidable for more accuracy purpose, however, understanding how decisions are made by the algorithm is essential to trust the ML-based model before recommending it for practical use.
- The last challenge of ML is the quantity of training data. Each algorithm has different demands on amount of data to achieve an acceptably accurate level. Deep neural networks like CNN, for example, needs extremely large amount of data compared with other algorithms due to using multiple layers of neural networks. Training on a small or limited database tends to overfit the data, and thus leading to poor generalization. The quality of data is also crucially important to be able to generalize ML model. Therefore, the training data should cover the scope and domain of applications because ML algorithms are usually not good extrapolators.

5.3. Future research directions

Despite the recent success of ML applications across a wide range of structural engineering topics (see Section 4), additional works are still needed to promote further applications of ML for structural engineering. Although there are some promising areas in which ML can provide benefits to the structural engineering community, future efforts mainly focus on addressing the challenges identified in Section 5.2.

- *Calibrating ML algorithms and their hyper-parameters:* Determining an appropriate algorithm and its optimal hyper-parameters for a particular application is one of the most importance tasks that need to be done before recommending the ML model for practical use. This is due to the fact that each algorithm is only suitable for a particular application especially for the case of classification problems. Most of existing works did not explain how to select hyper-parameters or provide detailed optimal hyperparameters calibrated for ML algorithms used. Therefore, a comprehensive calibration framework is needed for ML algorithms to enable its practical use by structural engineering people without ML background.
- *Interpretation and explanation of ML models:* The need for transparency in ML algorithms is essential to build trust in the structural engineering community to ensure decisions made by ML models are well-grounded. Therefore, future research needs to focus on developing interpretable and explainable algorithms in structural engineering to enable the black box to be opened. Various techniques have been developed to interpretate ML models such as SHAP, feature importance, partial dependence plot, feature interaction, surrogate model, and accumulated local effect [80,220]. Among them, SHAP is the most widely used approaches in, for example, bridge damage evaluation [285], axial resistance of FRP-strengthened RC columns [82], shear resistance of RC beams [78] and squat RC walls [77], punching shear resistance of RC slabs [79], failure modes of RC walls [86] and beam-to-column RC joints [346], and PHL of RC columns [393]. Another option is to develop ML models that are inherently interpretable (i.e., interpretable at the first place) since they are faithful to what the model actually does [523].
- *Facilitating practical use in design:* Most of ML-based predictive models developed in the literature are just used as predictive tools only. In order to promote these tools for practical use in design, reliability analysis needs to be carried out to assess the safety and reliability of these models in design, as well as to determine their corresponding resistance reduction factors used in the load resistance factor design (LRFD) format. Some initial works have been done in this area for RC slabs [149], CFS structures [209-211], and CFST columns [524,525]. In addition, more efforts should be devoted to developing ML models for structural analysis to predict the load–displacement behaviour of

structures which can provide useful information about the structure such as failure modes, stiffness, and ultimate load-carrying capacity.
- *Database:* Database plays an important role in training ML models. Although the work on developing database platforms has been initiated (see Section 2.5), most of existing databases are collected from the tests or simulations of isolated structural members (e.g., beam, column, wall, and joint). The databases required for predicting the behaviour and strength of whole structural systems (e.g., truss, frame, building, and bridge) are very limited. These can be generated using finite element simulations rather than costly experimental tests.
- *Physics-informed ML*: This approach was developed for deep neural networks without requiring big data. The idea behind it is to integrate mathematical physics models with ML methods. One of the greatest merits of this method is that it yields results quickly and accurately, and thus it has emerged as a promising alternative for structural engineering. The application of this method to the structural engineering domain was conducted recently for structural analysis [526] and damage detection [527]. A review of this method can be found in Karniadakis et al. [528]. This is a promising area of future research.

6. Conclusions

ML has emerged as a promising predictive tool for a broad range of structural engineering applications, and thus it can be potential replacements for commonly used empirical models. The application of ML in structural engineering is booming evidenced by an exponential growth of the number of relevant publications in the literature in recent years. In this paper, an ambitious and comprehensive review on the applications of ML for structural engineering has been presented. The review covers a broad range of structural engineering topics (five topics) and ML algorithms (seven groups). An overview of ML algorithms along with basic concepts, open-source codes, ML libraries, and collected datasets is also provided with the aim at assisting the non-ML structural engineering community to develop their own ML models for practical applications. In addition, challenges and future opportunities for this emerging topic are also highlighted and discussed.

In a nutshell, the accuracy and reliability of ML-based prediction models strongly depends on the performance of learning algorithms and the characteristics of training databases used. That is why structural engineers and practitioners remain reluctant to adopt ML methods as structural analysis and design tools. Therefore, it should be used with caution by individuals who are familiar with ML because the structural safety is one of the primary concerns in structural analysis and design tasks. This will require structural engineers and practitioners to have background knowledge in ML to know how to develop and justify their ML-based predictive models. In the long term, basic ML related subjects should be included in curricula of civil and structural engineering courses at the university to facilitate and promote the use of ML in the structural engineering community. With the inclusion of open-source ML codes and structural engineering databases, this paper can serve as a useful reference for structural engineering practitioners and researchers to enter this field of research.

Declaration of Competing Interest

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

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