Canterbury Christ Church University

Research Space
Journal article

Machine learning applied to the design and inspection of reinforced concrete bridges: Resilient methods and emerging applications

Hassanin, H., Fan , W., Chen, Y., Li, J., Sun, Y., Feng, F. and Sareh, P.

Accepted version of:

Weiying Fan, Yao Chen, Jiaqiang Li, Yue Sun, Jian Feng, Hany Hassanin, Pooya Sareh,

Machine learning applied to the design and inspection of reinforced concrete bridges: Resilient methods and emerging applications,

Structures,

Volume 33,

2021,

Pages 3954-3963,

ISSN 2352-0124,

https://doi.org/10.1016/j.istruc.2021.06.110.

(https://www.sciencedirect.com/science/article/pii/S2352012421006214)

Abstract: Machine learning is one of the key pillars of industry 4.0 that has enabled rapid technological advancement through establishing complex connections among heterogeneous and highly complex engineering data automatically. Once the machine learning model is trained appropriately, it becomes able to effectively predict and make decisions. The technology is rapidly evolving and has found numerous applications in various branches of engineering due to its preponderance. This study is focused on exploring the recent advances of machine learning and its applications in reinforced concrete bridges. It covers a range of different machine learning techniques exploited in structural design, construction quality management, bridge engineering, and the inspection of reinforced concrete bridges. This review demonstrated that machine learning algorithms have established new research directions in bridge engineering, in particular for applications such as the form-finding of innovative long-span structures, structural reinforcement, and structural optimization.

Keywords: Machine learning; Deep learning; Reinforced concrete bridges; Strength prediction; Structural health monitoring

Machine learning applied to the design and inspection of reinforced concrete bridges: Resilient methods and emerging applications

Weiying Fan [a], Yao Chen [a], ∗, Jiaqiang Li [a], Yue Sun [a], Jian Feng [a], Hany Hassanin [b], Pooya Sareh [c]

[a] Key Laboratory of Concrete and Prestressed Concrete Structures of Ministry of Education, and National Prestress Engineering Research Center, Southeast University, Nanjing 211189, China

[b] School of Engineering, Technology, and Design, Canterbury Christ Church University, Canterbury, CT1 1QU, United Kingdom

[c] Creative Design Engineering Lab (Cdel), Department of Mechanical, Materials, and Aerospace Engineering, School of Engineering, University of Liverpool, Liverpool L69 3GH, United Kingdom

Abstract

Machine learning is one of the key pillars of industry 4.0 that has enabled rapid technological advancement through establishing complex connections among heterogeneous and highly complex engineering data automatically. Once the machine learning model is trained appropriately, it becomes able to effectively predict and make decisions. The technology is rapidly evolving and has found numerous applications in various branches of engineering due to its preponderance. This study is focused on exploring the recent advances of machine learning and its applications in reinforced concrete bridges. It covers a range of different machine learning techniques exploited in structural design, construction quality management, bridge engineering, and the inspection of rein- forced concrete bridges. This review demonstrated that machine learning algorithms have established new research directions in bridge engineering, in particular for applications such as the form-finding of innovative long-span structures, structural reinforcement, and structural optimization.

Keywords: Machine learning; Deep learning**;** Reinforced concrete bridges; Strength prediction; Structural health monitoring

1. Introduction

Artificial intelligence (AI), the science and engineering allowing ma- chines to simulate the human brain to learn and think, has attracted wide attention from researchers and practitioners in various fields [1]. Coupled with the explosion of data, the establishment of Industry 4.0, and the continuous progress of computer technology, AI has recently made remarkable accomplishments. Machine learning (ML) is a subset of artificial intelligence that has found numerous applications in various areas such as image recognition, speech recognition, traffic prediction, product recommendations, self-driving cars, spam email detection, virtual personal assistants, and smart factories. Statistical data on publications related to ML from 2015 to 2020 are represented in Fig. 1a. It can be seen from the number of publications that ML has attracted a great deal of interest from the scientific community, especially in the fields of computer science and engineering.

There are many advantages of applying ML in reinforced concrete bridges. First, ML is a powerful computational tool with superior logical ability in comparison with humans; it is capable of replacing tedious manual tasks, which results in lower processing time and economic costs. Second, the progress rate of ML has exponential growth, while its competitors such as searching and planning algorithms, probabilistic graphical models, and knowledge representation and reasoning (KR2) develop at a linear speed. Several reviews on ML for civil engineering applications have been recently published, but they are mostly focused on reviewing specific areas such as structural health monitoring (SHM) [2–5], construction industry [6], and structural engineering [7–9]. Falcone et al. [1] summarized the utilization of soft computing methods in structural and earthquake engineering, aiming to explore their capabilities and limitations in modeling, simulation, and optimization problems. Azimi et al. [2] generated a summary for SHM in deep learning (DL) techniques. It mainly introduces the application of DL from the perspective of vision- based SHM, vibration-based SHM, and transfer learning. Notably, this work has organized available data sets and DL tools for SHM. Dong and Catbas [3] concentrated on the application of two-dimensional computer vision functions, where the subject of analysis is the image and the acquisition tool is the camera. Based on the development of computer vision in structural health monitoring, it describes local damage identification (e.g. cracks, spalling, delamination, and corrosion) and global monitoring (e.g. displacement measurement, structural response, and external load input measurement). Avci et al. [4] built up a connection between conventional and ML approaches to vibration- based structural damage, while Sun [5] dealt with the big data and AI exploited for bridge SHM purposes. Based on the parametric and non- parametric classifications of vibration data, Avci et al. [4] compared the traditional, ML, and DL methods for measuring structural damage. Salehi and Burgueño [9] summarized the current and potential applications of pattern recognition, ML, and DL in structural engineering. They concluded that the vast majority of applications were concerned with SHM, concrete modeling, and damage identification.

In contrast with the literature mentioned above, this work is mainly focused on the recent applications of ML-based techniques in reinforced concrete bridges. As shown in Fig. 1b, bridge engineering has branches including survey, design, construction, maintenance, and verification of bridges. In this paper, a systematic review is provided considering different aspects of bridge engineering.

The rest of this paper is organized as follows. Section 2 introduces the basic concepts of ML and DL. Section 3 describes the application of ML in the structural design of reinforced concrete bridges. In section 4, an application of ML in the performance prediction of bridge components is presented. Section 5 reviews the application of ML methods in the inspection of reinforced concrete bridges, including overall assessment, damage recognition, and crack detection. In section 6, we present a discussion about ML methods, followed by a conclusion about this review study.

2. Machine learning and deep learning

The relationships among AI, ML, and DL could be clearly expressed by Fig. 1c. It can be concluded from the figure that AI includes ML and ML, and DL is a branch of ML.

2.1. Machine learning (ML)

The main purpose of ML is to teach machines to automatically learn from data samples [4]. ML algorithms are divided into two main categories: supervised algorithm and unsupervised algorithm. The distinction between them is whether the data sample has an artificially pre-pared output. Supervised algorithms train models with artificially labelled data, while unsupervised algorithms do not include such a feature [5]. In other words, supervised learning strives to narrow the gap between the predicted output and the artificial label for the samples. However, for unsupervised learning, the outputs are unknown and rely on the internal rules of the data to classify itself. The technology can also be classified into four groups such as regression, clustering, and dimensionality reduction. Classification and regression are supervised algorithms [5], whereas clustering and dimensionality reduction are unsupervised algorithms. In classification, the output results are discrete, whilst in regression the results are continuous. The basic steps for building a usable ML model are shown in Fig. 1d. Clarifying the problem and initially determining the influencing factors and expected goals is the guarantee for the establishment of a good model. Subsequently, it needs to go through a series of steps: collecting dataset, performing data preprocessing, building the ML model, training the model, evaluating the model, model deployment, and making predictions in sequence. Below is a detailed description of ML methods associated with classification, regression, and dimensionality reduction which have been utilized in recent research studies.

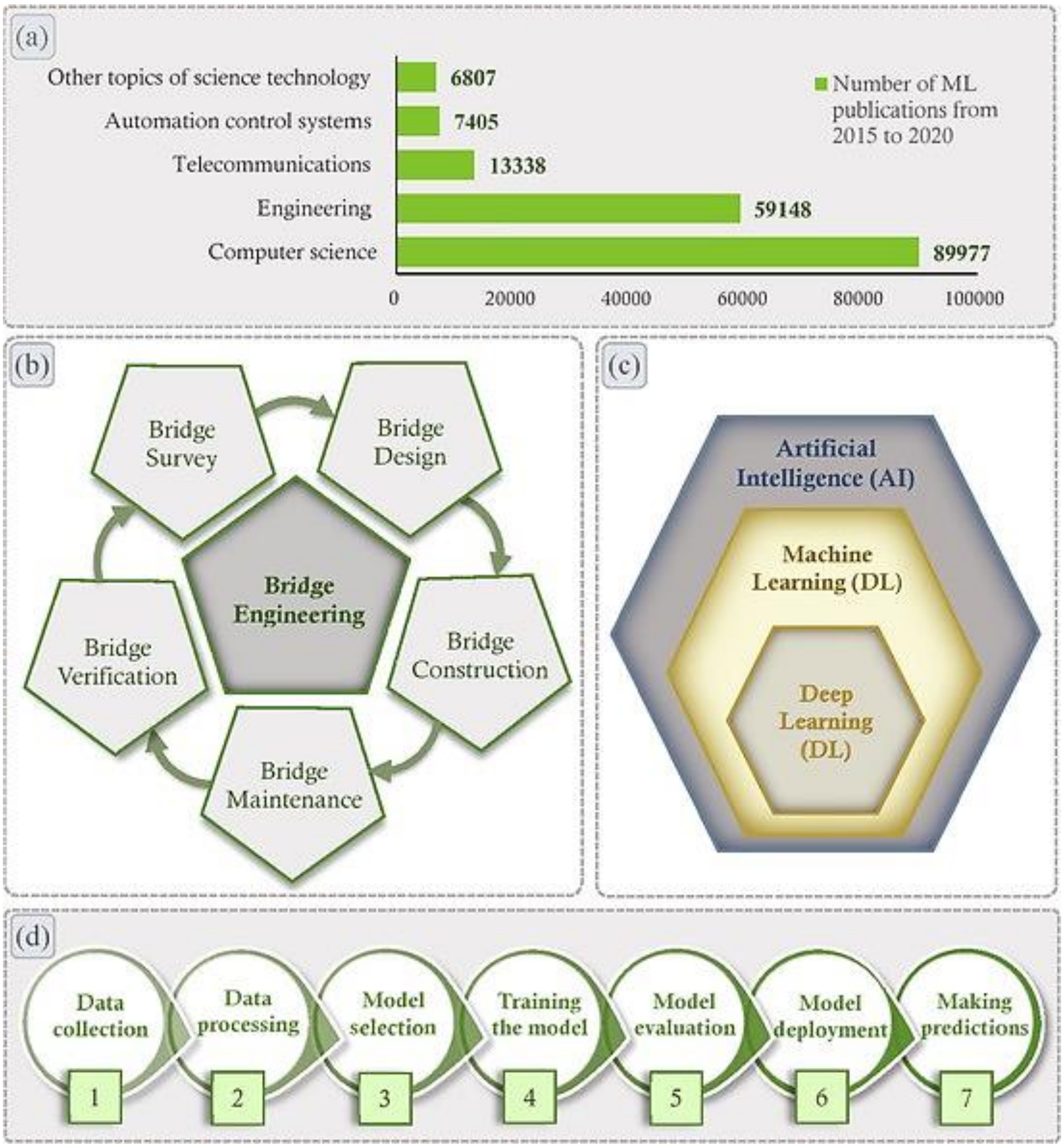

Fig. 1. (a) Number of publications on machine learning in different areas of science and technology from 2015 to 2020 according to Web of Science. (b) Different re- search areas in bridge engineering. (c) Relationships among artificial intelligence (AI), machine learning (ML), and deep learning (DL). (d) Basic steps for building a practicable machine learning model.

2.1.1. Classification

Support Vector Machine (SVM) is a typical two-category classifier [7]. The hyperplane with the maximum geometric distance is used to separate data in SVM [10]. As for establishing the hyperplane, it needs to satisfy [11]:

$$y_i(w \times x_i + b) \geq 1 \quad i = 1, \cdots, N \tag{1}$$

where xi denotes the feature vector, yi represents the class it belongs to, w is weight, N is the number of samples, and b is bias.

Artificial neural networks (ANN) are computational models inspired by human brain neurons, with basic elements including neurons, layers, and networks [1]. In accordance with the layer division, an ANN is composed of an input layer, a hidden layer, and an output layer. A network containing only an input layer and an output layer is called a single-layer neural network. The number of neurons in the input layer and the output layer is dependent on their respective data dimensions. The neurons in each layer are passed to the next layer through the weight function [12]. The neurons in this layer are connected to each neuron in the previous layer. It can be divided into a fully connected layer and a non-fully connected layer. ANN is unique in the sense that it can be optimized for both classification and regression tasks. More detailed information about ANN is presented in [8].

Random forest (RF) is composed of multiple decision tree classifiers [13]. A decision tree (DT) consists of a series of nodes, branches, and leaves [13]. The decision tree node stands for a property of the measurement, the branch indicates an evaluation output, and the leaf de- notes the type to which it belongs [13]. On the ground of identical training data, several independent decision trees could be built at the same time, and then the final classified decision could be made according to the principle of majority rule by voting.

2.1.2. Regression

A linear function can implement linear regression for carrying the relationship between the input (x) and the output (y) [14]. The situation with only one independent variable is called a simple regression, whereas that with more than one independent variable is called multiple regressions. A formula for multiple regressions is given below [15]:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{2}$$

Where β_i is a regression coefficient $(i = 1,2, \cdots, n)$, ε means an error, x_i stands for one independent variable in x, and n is the size of independent variables. X can be expressed as $[x_1, x_2, \cdots x_n]^T$.

Support Vector Regression (SVR) origins from SVM to resolve regression problems. It can be expressed by the following equation:

$$f(x) = \sum_{k=1}^{m} w_k h_k(x) + b \tag{3}$$

where $h_k(x)$ denotes a nonlinear mapping function, w_k represents the corresponding weighting vector, and b describes the deviation. The values of W and b are obtained by solving the optimization problem through the objective function.

The common evaluation indicators of regression model include R^2, R, $MAPE$ and $RMSE$. The values of R and R^2 are between 0 and 1. The closer to 1 of the values, the better the model becomes. The smaller the value of $MAPE$, $RMSE$, the closer the output predicted value to the true value. Their respective formulas are as follows:

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - p_i)^2 / \sum_{i=1}^{n}(y_i - \bar{y})^2 \quad (4)$$

$$R = \sqrt{\sum_{i=1}^{n}(p_i - \bar{p})(y_i - \bar{y}) / [\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2} \sum_{i=1}^{n}(p_i - \bar{p})^2]} \quad (5)$$

$$MAPE = (1/n) \sum_{i=1}^{n}(|p_i - y_i|/y_i) \times 100 \quad (6)$$

$$MRE = (1/n) \sum_{i=1}^{n}(|y_i - p_i|/y_i \quad (7)$$

$$MAE = (1/n) \sum_{i=1}^{n}(|y_i - p_i| \quad (8)$$

$$RMSE = \sqrt{(1/n) \times \sum_{i=1}^{n}(p_i - y_i)^2} \quad (7)$$

where p_i is the predicted value, y_i refers to the actual value, $\bar{p}$ is the average of the predicted value, $\bar{y}$ is the average of the real value, and n is the sample size.

2.1.3. Dimensionality reduction

Dimensionality reduction is the process of mapping high- dimensional space data to a low-dimensional space while maintaining its most important characteristics. After this operation, the training time of the ML model is usually shortened. Among various methods, principal component analysis (PCA) is the most commonly used algorithm for dimensionality reduction. It is usually exploited for the exploration and visualization of high-dimensional data sets. Besides, it is utilized for data compression and preprocessing. PCA can synthesize correlated high-dimensional variables into linearly independent low- dimensional variables called principal components. The principal component can retain the information of the original data as much as possible.

2.2. Deep learning

The deep learning (DL) algorithm is a multi-layer neural network. Compared with ML, DL has a stronger ability to deal with the connections between high-dimensional data; it also adds a function to extract features. In light of the function division, the classic networks in DL algorithms include multi-layer perception (MLP), convolutional neural networks (CNN), and autoencoders. The structure of a typical MLP model is illustrated in Fig. 2 [12]. Unlike ML, DL networks can perform classification or regression tasks.

CNN is a powerful image classification tool. The input layer, convolutional layer, pooling layer, fully connected layer, and output layer constitute the CNN. It obtains the features of a region, rather than merely a point, through the convolution layer. The pooling layer makes selections and operates based on the features extracted from the convolutional layer.

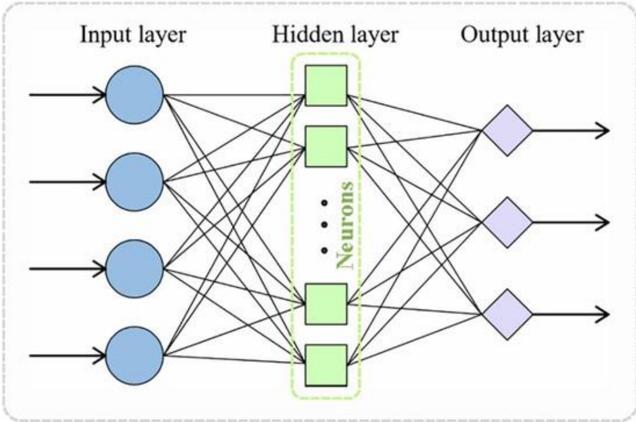

Fig. 2. Layout of a typical multi-layer perception (MLP) model.

3. Structural design of reinforced concrete bridges

In the initial stage of structural design, choosing a proper structural system is of great importance. A reasonable structural system is not only a prerequisite to ensure safety and applicability, but is also pivotal to achieve the goal of economy. It is typically decided based on the experience and judgment of structural engineers. However, people expect to explore more precise connections between bridge configuration and basic conditions in the context of the explosion of knowledge. In 2005, Freischlad and Schnellenbach-Held [16] proposed a modified fuzzy set for learning structural knowledge to inform conceptual structural de- sign. In 2017, Jootoo and Lattanzi [17] used decision tree, Bayes net- work (BN), and SVM to predict a rational type for bridges recorded by the National Bridge Inventory database. The specific process for selecting the bridge type is shown in Fig. 3. It has turned out that the prediction accuracy of a single model for all types of bridges is highly variable and unreliable.

When calculating the reinforcement ratio of components, Charalampakis and Papanikolaou [18] applied ANNs to bridge piers. Due to different cross-sectional geometries (e.g., rectangle, circle, solid, and hollow) and arrangements of the steel bars, they created various ANN net- works. It was shown that w can be produced given only some basic parameters such as normalized geometric parameters of the section, normalized axial load, and normalized bending moments. The results demonstrated that the method is both efficient and stable, implying that it may be possible in the future to solve this problem with only one net- work, which would bring great convenience to users. Only a few studies have tried to exploit ML in the structural design of concrete bridges, and the results are, in general, not satisfactory. There are few cases of using ML to calculate the reinforcement ratio of bridge components. Furthermore, intelligent algorithms have a better chance of being accepted in comparison with ML methods in learning the structural knowledge of concrete bridges.

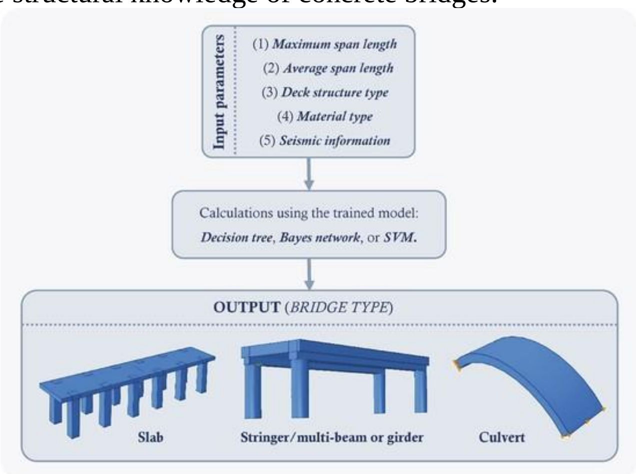

Fig. 3. Process of applying a trained model to choosing the bridge type.

4. Construction quality management of reinforced concrete bridges

Cost control, time management, and quality supervision are three key areas of project management. Similarly, ML is beneficial for quality assurance and scheduled management of reinforced concrete bridges. For example, Bilal and Oyedele [19] provided a detailed guide to the use of ML methods in the construction industry. In order to demonstrate it clearly, the study used profit rate estimation as an example, providing guidance for researchers who intend to use ML to solve practical problems. Tixier et al. [20] used RF and Stochastic Gradient Tree Boosting (SGTB) to forecast injury type, energy type, and body part. These examples demonstrate the power of ML in construction management. This section consists of three parts in relation to the quality supervision of concrete bridges: (1) strength prediction of building materials, (2) strength and failure mode prediction of bridge components, and (3) scour depth prediction of bridge piers.

4.1. Strength prediction of materials

It is well-known that concrete and steel are irreplaceable materials of civil engineering. Moreover, their quality management is closely related to engineering safety. When the strength of concrete or steel does not meet the design requirements, the structures or components will not be able to bear the set load value which may lead to local or global failure. Concretes holding various attributes are gradually developed, but the experimental study of concrete strength is still laborious. Be- cause a highly accurate prediction of concrete compressive strength (CS) needs to go through a series of complex procedures (i.e. proportioning test, specimen making, curing, and strength testing experiments), an ML approach might be a more efficient choice. Yu et al. [21] applied SVM, optimized by the enhanced cat swarm optimization, to predict the compressive strength of high-performance concrete. Chou et al. [22] reviewed some applications of ML to high-performance concrete, concluding that the performance of the ensemble model is better than the individual one. Nguyen et al. [23] proposed a DNN model with high-order neurons for foamed concrete. Sensitivity analyses revealed that density, and water-to-cement and sand-to-cement ratios, are important factors influencing CS. Moreover, the correlation coefficient of the constructed model exceeded 0.99. The ensemble of SVRs in a different input subspace was introduced to solve the correlation between the elastic modulus and compressive strength of concrete [24]. The RMS and mean absolute percentage error were less than 0.3 and 5% respectively, which were outstanding results. Naser and Uppala [25] studied the residual strength of a series of building materials after a fire with an integrated model. They first used ANN to predict the mechanical properties of the material at a specified cooling temperature. Then the GA algorithm was used to derive the expression of reduction coefficients for these properties. The results showed that the coefficient of determination for the integrated model was greater than 99.

In relation to the properties of soil and rock, Chou and Ngo [26] showed that the combination of LSSR and SVT predicted the shear strength of fiber-reinforced soil more precisely than the baseline LSSVR and experience methods. ML was also used to predict soil compaction in [27]. Asadi et al. [28] proposed three diverse functional expressions for predicting the overall rock strength obtained by the genetic algorithm. Their results revealed that approaches based on genetic algorithm and the rock classification method produced better results with the best coefficient of correlation (R2) of 0.9398. Pham et al. [29] concluded that the Backpropagation Multi-layer Perceptron (Bp-MLP) Neural Network is the most accurate model to predict soil consolidation coefficient after verifying five ML methods.

Concerning the prediction of steel properties, ML was used as a method for predicting the fatigue performance of steel [30], with an illustrative cyclic stress–strain curve given in Fig. 4.

Shiraiwa et al. [31] trained a learning model to directly predict fatigue strength from the collected data set. Wang et al. [32] proved that the ML model trained with certain data has better performance in testing the tensile proper- ties of low activation ferrite steel than the traditional model. Xiong et al. [33] employed five algorithms to predict the mechanical properties of steel and demonstrated that forest had the best performance with a correlation coefficient of 0.9725. The strength prediction of materials or components by ML is based on the fact that theory (Balshin's, Feret's, and Power's models [23]; EN1992-4 and ACI318 [34]) has been developed to a certain degree.

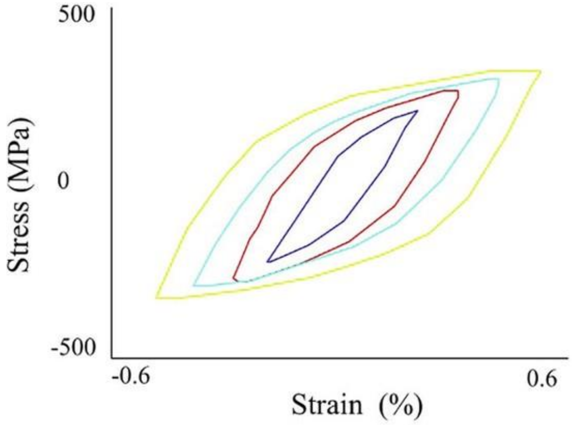

Fig. 4. An illustrative cyclic stress–strain curve for steel.

4.2. Strength and failure mode prediction of bridge components

Concrete beams, plates, and columns (or piers) are crucial components in beam bridges. They are typically brittle and can easily lead to sudden structural collapse. Therefore, it is essential to predict the strength of concrete components accurately. When dealing with a large project, it is time-consuming to calculate the strengths of all the components relying on the traditional method. So far, a large number of ML models, such as the neural network, support vector regression, and mixed intelligence models have been validated to perform better than traditional calculation methods. However, given that no optimal model has been developed yet, researchers are constantly exploring possible improved models.

There are several studies on applying ML for the prediction of the shear strength of concrete beams. The EMARS model, built by Cheng and Cao [35], was able to run automatically without manual intervention and achieved accurate estimation under different parameter set- tings. The method proposed by Chou et al. requires a specific ability to optimize computer programs and set the initial scope of SFA. Chou et al.

[15] compared the reported model in [36] with other integrated artificial intelligence models, confirming the superiority of the hybrid artificial intelligence model. In order to predict the ultra-shear strength of steel fiber reinforced concrete beams, Ly et al. [37] integrated a neural network and an optimization algorithm. Table 1 lists a summary of methods employed to predict the strength of the beam. Fig. 5 [35] shows the input parameters of the beam. It can be observed that input parameters change with the alternation of materials and geometric specifications. Expectedly, single ML algorithms cannot satisfactorily undertake multiple and complex regression tasks. To overcome the drawback of using a single model, researchers gradually begin to explore the functions of hybrid and integrated models.

Table 1 Information on the shear strength of reinforced concrete beam

Element	Input parameters	Output parameters	Model	Evaluation index of test dataset
Deep beam	$\boldsymbol{a/d}$, $\boldsymbol{p_s}$, $\boldsymbol{f_c}$, $\boldsymbol{L/d}$, $\boldsymbol{f_{yh}}$, $\boldsymbol{p_h}$, $\boldsymbol{p_v}$, d/b, f_{yv}	V	EMARS [35] BPNN [35] BPFNN [35]	$R^2 = 0.973$ $MAPE = 5.670\%$ $R^2 = 0.846$ $MAPE = 8.816\%$ $R^2 = 0.954$ $MAPE = 5.566\%$ $R^2 = 0.896$ $MAPE = 14.108\%$
Beam	b_w, d, a/d, p_w, f, a_g a, b, d, f_c, p_{rt}, fry, pst, b, d, a/d, fc, p_{FPR}, fsy, E_F	V V V	Hybrid model [15]	$R = 0.977$ $MAPE = 21.386\%$ $R = 0.994$ $MAPE = 6.588\%$ $R = 0.992$ $MAPE = 13.914\%$
Steel fiber reinforced beam	$\boldsymbol{H}$, $\boldsymbol{l_{span}}$, $\boldsymbol{a}$, $\boldsymbol{p}$, $\boldsymbol{f_c}$, $\boldsymbol{F}$, $\boldsymbol{f_y}$, $\boldsymbol{a/d}$, $\boldsymbol{l_f\ /d_f}$, a_v/d, d_{aggmax}, V_f, $f_{tenfiber}$, b_w, d, a_v	Vu	NN-FFA [37] (Hybrid model)	$R = 0.965$ – $R = 0.979$
Deep beam	d/b_w, f_c, f_{yh}, f_{yv}, a/d, L/d, ρ, ρ_h, ρ_v	V	NN-RCGA [37](Hybrid model) LS-SVR + SFA [36](Hybrid model)	$R = 0.9876$ $MAPE = 4.48\%$

Note: The bold font represents the important factors, and the normal font represents factors with limited effect on the shear strength of the beam.

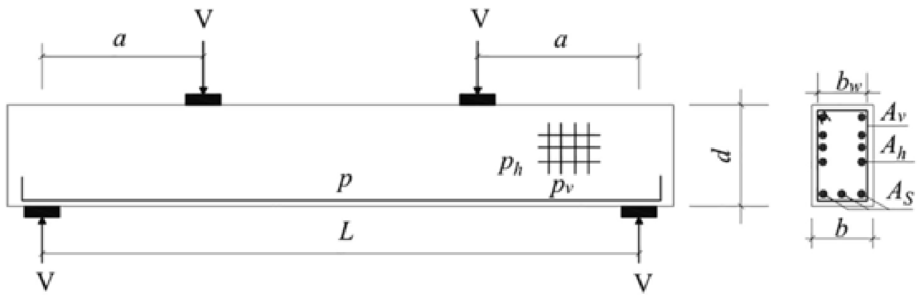

Fig. 5. Parameters of the beam.

L: Span	$f_{tenfiber}$: Tensile strength of fibers	a_g : Maximum specified size of coarse aggregate
b_w: Effective breadth of beam	p_v: Vertical web reinforcement ratio	f_{yv}: Yield strength of vertical web reinforcement
a: *shear span*	f_c: Concrete cylinder strength	EF: Young's modulus of longitudinal reinforcemen
b: Web width of the member	ρ_v:Vertical shear reinforcement ratio	f_{yh}: Yield strength of horizontal reinforcement
H: Height of cross-section	p_{FPR}: Longitudinal reinforcement ratio	$f\ ry$: Axial tensile strength of concrete in CEN
p: Reinforcement ratio	d_{aggmax}: Maximum aggregate size	ρ_h: Horizontal shear reinforcement ratio
a_v: Clear shear span	p_h: Horizontal web reinforcement ratio	fsy: Yielding strength of transverse reinforcement
V_f:Fiber volume fraction	f_y: Yield strength of reinforcement steel	p_w: Percentage of reinforcement based on web width
d: Effective depth of beams	pst: The transverse reinforcement ratio	p_s: Longitudinal reinforcement to area of concrete ratio
F:Fiber factor	l_f/d_f:Length/diameter ratio of fibers	V_u : Ultimate shear strength
V: Shear strength	p_{rt}: Cross-sectional area of the reinforcement as a proportion of the cross-sectional area of the beam	

In addition, the failure modes of structural members have been studied using ML approaches. In 2019, Mangalathu and Jeon [12] utilized ML techniques to explore the failure patterns of circular reinforced concrete columns. After verification, the recognition accuracy of ANN in the crown of learning models was as high as 91%. The failure mode of beam-column joints was explored [10]; this was a binary classification mission with an accuracy of 81%. However, the common shortcoming of such models is that environmental factors or noise are not considered. More often than not, the models' performance is compromised when the data sample in the training set is increased or decreased by an input element. In 1997, Skibniewski et al. [38] implemented the constructability analysis of precast beams based on ML. where they considered three constructability decisions (poor, good, and excellent).
As for others, Hwang et al. [39] used the neural network to modify the length and strength formulas of the tension steel lap joint. ANN was also exploited to evaluate the interface strength between concrete and corroded rebar [40]. Garcia-Sanchez et al. [41] assessed the bearing performance of critical components in a viaduct. Furthermore, SVM was employed to

investigate the uniaxial compressive strength of jet grouting columns [42].

4.3. Scour depth prediction of bridge piers

The scouring of piers affects the service life and safety of the bridge. The scour depth is a key factor influencing the bridge foundation depth in the river [43]. Although empirical formulas for calculating scour depth are proposed, the error is relatively large due to ignoring the complexity of reality. As a result, ML has been gradually recognized as an alternative strategy. It is recommended that the combination of empirical model and data-driven model be used to predict the critical scour depth of bridge piers. A new model superior to conventional models was presented by Kim et al [44]:

$$\frac{y_s}{y_1} = 0.69 \times \left(\frac{a}{y_1}\right)^{0.35} \times \left(\frac{D_{50}}{y_1}\right)^{-0.10} \times \sigma^{0.39} \times F^{0..56} \quad (10)$$

where is estimated scour depth, denotes approaching flow depth, represents pier width, is median grain size, is sediment gradation coefficient, and is Froude number. This formula was ac- quired from two field datasets. When the datasets are expanded, this formula can be optimized. Sharafi et al. [45] compared SVM models with various kernel functions, among which the polynomial kernel function model performed best. In addition to the influencing factors of Eq. (10), this work adds the ratio of pier length to flow depth. Cheng et al. [43] Developed an integrated model of Radial Basis Function Neural Network (RBFNN) and Artificial Bee Colony (ABC). ABC can automatically search for the best parameters suitable for RBFNN to ensure the superiority of the proposed model. In this work, the developed model considered single-pier bridges only. In order to improve the accuracy of predicting local scour depth for complex bridge piers, Bui et al. [46] combined two ensemble models, i.e. the reduced error pruning tree and the random subspace. The parameters of the pier influencing the local scour depth are shown in Fig. 6 [46]. It is verified that the position, thickness, and width of the pier cap are important factors affecting the local scour depth. Compared with empirical formulas and existing ML models, this method wins with a correlation coefficient of 0.95. Although the above models have the same output parameters, the input conditions are varied. Some models take the main influencing fac- tors obtained through sensitivity analysis. Models with the direct in- putting of all the variables related to scour depth are also available. In short, the choice of input parameters depends on specific issues. It can be concluded from the work of Kim et al [44] that combining intelligent algorithms is helpful for the development of fairly concise mathematical expressions.

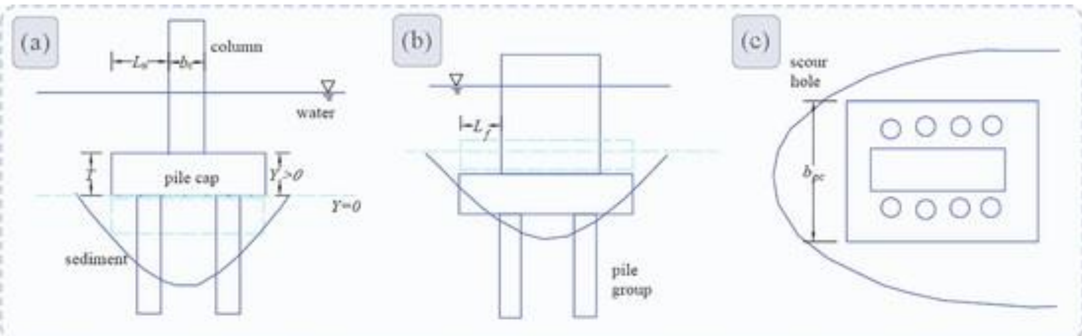

Fig. 6. Parameters used by the machine learning model for the bridge pier: (a) upstream view; (b) side view; (c) plan view.

5. Inspection of reinforced concrete bridges

Structural health monitoring (SHM) duties are composed of health track, condition assessment, and defect classification [3]. The process of SHM can prevent specific potential threats and save maintenance costs. In recent years, numerous scholars have drawn support from the computational capabilities and image processing functionalities of ML to detect the health status of engineering structures, especially bridge structures. Section 5 focuses on studies related to the overall assessment, damage recognition, and crack monitoring of concrete bridges.

5.1. Overall assessment

Besides being applied on the material and component level, ML is also successfully used in the overall assessment of concrete bridges, including safety analysis, reliability evaluation, and bearing capacity calculation.

In the context of risk and safety assessment, an ML model, a hybrid of BN and normal Cloud, was developed for risk assessment [47]. The proposed model simultaneously conveys the possibility of risk and the degree of indeterminacy in data. Obtaining the fragility curve is, generally, a complicated process, so some studies have used ML to simplify it. Liao et al. [48] used the least squares support vectors to evaluate the safety analysis of an immersive bridge in Taiwan against scouring and earthquakes. They used peak ground motion, water level, and scouring depth to predict the displacement ductility demand of the bridge. The results showed that the new model reduces the computational burden and still retains its validity. Concerning bearing capacity prediction, Alipour et al. [13] introduced a novel method through DT/RF to explore the inherent relation between bridge properties and their carrying capacity status.

Quantifying the damage possibility is the object of structural reliability analysis [49]. The failure probability ρ_f of structure [50] can be calculated by:

$$\rho_f = \int I_{g(x)\leq 0}(x) f_X(x)dx \tag{11}$$

$$I_{g(x)\leq 0}(x) = \begin{cases} 1 & g(x) \leq 0 \\ 0 & g(x) > 0 \end{cases} \tag{12}$$

where $\boldsymbol{x}$ is n-dimensional input vector, $f_X(\boldsymbol{x})$ means joint probability density function of $\boldsymbol{x}$, and $g(x)$ indicates the formula of failure domain. Under the pressure of enormous calculation and strong dependence on calculation efficiency as well as accuracy, machine learning also moves into the frontier of reliability analysis. As early as 1996, ANN combined with Monte Carlo Simulation was used for reliability analysis [51]. Subsequently, reliability analyses using ANN were reviewed in-depth [52,53]. Cheng and Lu [50] proposed the integration of various models using active learning. Owing to the large size of the candidate specimen, this algorithm needed magnanimous running time. To address this issue, Xiang et al. [49] put forward an active learning method that integrated DL and weighted sampling.

Mangalathu [54] used random forest and a strip-based method to predict the vulnerability curve of a specific bridge, which was demonstrated by a case study of a multi-span concrete bridge in California. The difference from others is that Wang et al. [55] sorts the various factors affecting the condition of the bridge firstly to eliminate the influence of noise and then evaluates the condition of the bridge, resulting in a remark- able accuracy of 99%.

Many cases concerning overall assessment for concrete bridges were reported above, but most of them treat it as a classification task. That is to say, the structural condition is roughly divided into certain categories. With the progressive advancements of ML technology, it is anticipated that specific failure probabilities or damage factors would be- come predictable in the future.

5.2. Damage recognition

Bridge damage detection is generally carried out based on dynamic data. SVM is used to monitor the damage of long-span cable-stayed bridges [56]. In order to improve its performance, three different feature extraction techniques were introduced, with the results showing that this method is superior to traditional SVM. However, Dang et al. [57] considered a DL model to avoid the trouble of feature extraction. More rigorously, Kostic et al. [58] and Chalouhi et al. [59] considered the effect of temperature on bridge damage. Unusually, static data has also been adapted to monitor the bridge. Li and Sun [60] recommended simulating the continuous deflection of a bridge based on CNN sensor monitoring. Then, the corresponding response was generated according to the deflection, and finally, the bridge damage was classified into four categories (complete, 1/2, 4/1, 3/4). The proposal was tested on a scaled model of a bridge, and the accuracy of this system reached as high as 96.9%. Karanci and Betti [61] pointed out that temperature, relative humidity, pH, and Cl- concentration are important factors affecting the corrosion of bridge cables. Liu and Zhang [62] proposed to use the CNN model to predict the condition rating of the bridge components in the next stage based on historical data. Relying on the standards of NBI, the condition rating is divided into ten categories. The study selected 24 historical data as input, including geographic region, structure configuration, and condition rating. Figueiredo et al. [63] proposed a hybrid model for the damage detection of a real bridge. The finite element model simulated the response data of the bridge under operating and vibration environments. The data used as supplementary samples to train the ML model to detect damage. This method eliminates the in- fluence of operation and environmental vibration. Li et al. [64] used the one-dimensional CNN algorithm to predict the damage state of long- span cable-stayed bridges and achieved an accuracy of 96.9%. A schematic representation of the bridge is shown in Fig. 7. The continuous deflection data, used for training the model, were obtained with the help of a scale-down bridge model, a metal pad (simulating structural deformation), and a fiber optic gyroscope. Four damage states were de- fined as follows: complete, damage at 1/4, 1/2, or 3/4 of the main span. In 2020, Assaad and El-adaway [65] compared the performance of ANN and KNN in predicting concrete bridge deck deterioration conditions. Chen et al. [66] researched the influence of conductive gussasphalt mixture on the corrosion of bridge steel plate; this work was accomplished through a powerful learning machine optimized by a genetic algorithm. Deng et al. [67] used SVM to simulate the relationship between fatigue damage and traffic load for the Nanxi suspension bridge hangers. The fatigue damage was calculated by a finite element model, and the traffic load was computed through data of Weigh-in-Motion (WIM) sensors.

For bridge structures, ML is used for crack and damage identification. The samples used for training the model are either from a real bridge structure or a dataset compiled by NBI. A vast majority of re- search studies use the NBI bridge database system established by the United States. However, geographical environments and design specifications could affect the results of such studies. It is anticipated that other countries would establish similar database systems for the intelligent monitoring of bridges in their territories.

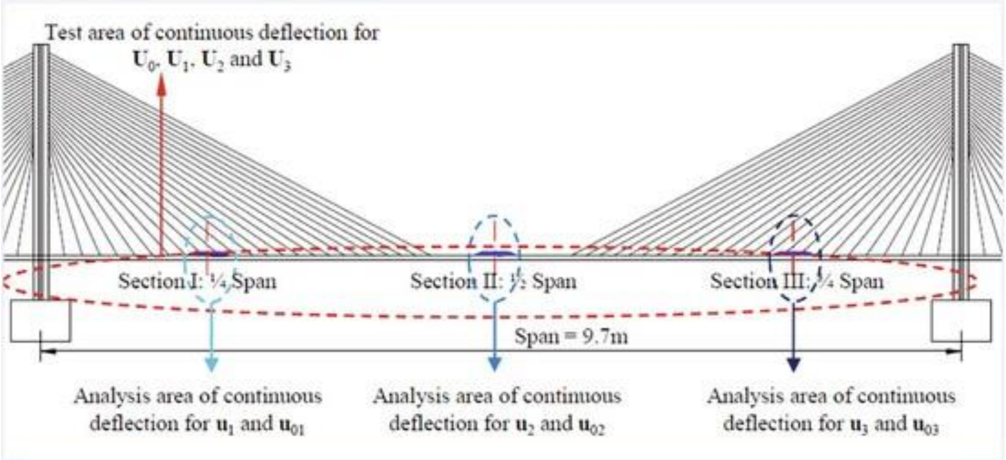

Fig. 7. Schematic representation of a long-span cable-stayed bridge.

5.3. Concrete crack detection and visualization

Cracks affect the mechanical function, endurance, serviceability [68], and durability of concrete and concrete structures [14]. Traditional crack detection is a subjective [69], time-consuming, and expensive task carried out by human inspectors [68,70]. Consequently, numerous DL utilization cases have been introduced for the crack detection of concrete structures.

With the rise and prosperity of computer vision technology, convolutional layers have played an increasingly important role in image recognition. Slonski and Tekieli [70] used R-CNN to locate multiple cracks on the concrete surface. When two cracks had a connecting part, the test result was not ideal. In order to accurately classify transverse cracks, longitudinal cracks, and crocodile cracks, Deng et al. [71] introduced deformation rules in the convolutional layer and the pooled layer of R-CNN. Wang et al. [72] provided a deeply supervised object detector identifying the initial position of a fatigue crack. Voronoi diagram was pointed out to predict crack shapes and orientations through existing cracks [13], which provided an opportunity to take preventive measures. Chen et al. [73] introduced weight share in CNN to speed up the training process of crack identification and location. However, the method cannot identify the cracks in the background with a similar colour to the cracks. Kim [68] focused on the classification and location of cracks on concrete surfaces that have noises with similar characteristics to cracks. To reduce the influence of noise, Li et al. [74] simultaneously exploited a fully convolutional network and a naive Bayes data fusion (NB-FCN) model to recognize the cracks of a concrete bridge.

The crack identification problem, on which this work focuses, be- longs to surface crack detection and identification, while there is little exploration of crack depth and crack development. The methods of automatic crack recognition are mostly based on the principle of vision, where CNN is a common tool. Difficulties in the process of crack identification include distinguishing between background and cracks (especially backgrounds with texture), identification of crack boundaries, and noise that can easily be mistaken for cracks. Therefore, many re- searchers focus on solving these difficulties to improve recognition ac- curacy. CNN can not only process image information, but also complex relationships among multi-dimensional data.

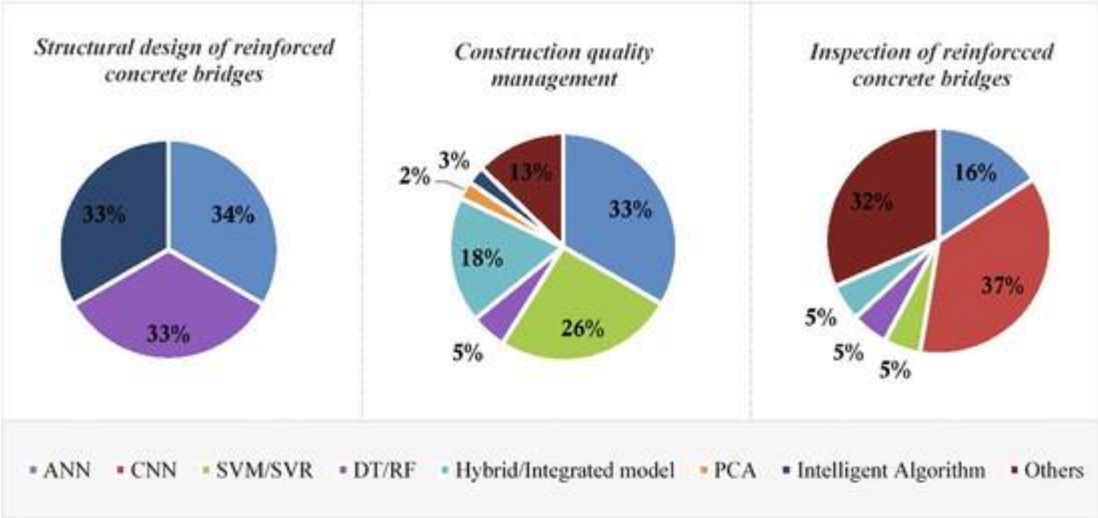

Fig. 8. Machine learning algorithms used in the investigated references.

6. Discussion

ML can fulfill simple classification or regression tasks, as well as various complex tasks. The ML model contains only one output and a one- dimensional input. Illustrated as a complex task in [20], the input of the model is 2D or 3D, and the output has multiple categories with sub-categories. Compared with DL, ML has a significant disadvantage in that it needs to look for feature values. Therefore, when the influencing factors are not clear, the sensitivity analysis task needs to be carried out first.

Among all the introduced methods, ANN can perform classification and regression tasks effectively. It can establish linear or non-linear relationships among independent and dependent variables, but its expression is implicit. There are very few researchers who use the weights, deviations, and activation functions of trained neurons to derive similar formulas because this is a time-consuming and labor-intensive task. ML algorithms such as VM, RT, RF, and SVR, have fewer hyper-parameters, making it easy to determine the optimal parameters adapted to the problem. CNN can not only process image information, but also establish a connection between high-dimensional dependent and independent variables. Fig. 8 summarizes the ML algorithms used in the references considered in this study. If there are multiple ML methods in one reference, we selected the one with the best performance. It can be seen that the ANN algorithm is commonly used in concrete bridges. In the field of inspection of concrete bridges, the CNN model is more popular. In order to improve the accuracy of the ML model, more hybrid/integrated models have been emerging. Compared with traditional methods, ML has higher accuracy and computational efficiency, which makes it of broad application prospects. For problems that are just starting to use ML techniques, the common single model above can be used. For relatively mature re- search, using hybrid or integrated models is recommended. In general, the utilization of ML algorithms for the design and inspection of con- crete bridges has not been particularly extensive and has not reached a mature point; therefore, there is still much room for development and improvement. For example, ML has the potential for symmetry recognition to improve the speed and accuracy of symmetry detection analysis [75]. De Luca et al. [76] used CNNs to predict the symmetry of a 2D black and white picture. Similarly, ML algorithms possess the latent capacity in additional research directions, such as form-finding of novel origami structures. Chen et al. [77] provided a method to compute the optimal configurations of origami structures with degree-4 vertices. In this process, the particle swarm optimization algorithm improves the accuracy and efficiency of the calculation. They respectively provide implications for the use of ML in symmetry detection and form-finding of structures in the future.

7. Conclusions

This study summarized the applications of machine learning (ML) in reinforced concrete bridges, from design to inspection. It demonstrates that ML has great computing power and image processing capability for dealing with different aspects of reinforced concrete bridges. Once an ML model is trained, the prediction efficiency is significantly high. It surpasses the speed of traditional structural damage recognition and strength prediction methods, realizing nearly real-time performance. Overall, the exploitation of ML to predict the strength of concrete and bridge members is relatively mature, whilst its use in structural design is currently limited. In crack studies, ML techniques can locate crack lo- cations, measure crack size, and make damage judgments. In order to better integrate ML into practical applications, researchers are constantly improving the structure and training methods of ML models.

Nevertheless, compared with traditional methods, ML has some limitations. Mathematical or ML models are often proposed for a particular category or a specific problem. Once the problem is slightly changed, the model will no longer be applicable. For example, the column's failure mode considers a circular section [12], but does not adopt the square section, torus section, or I-shaped section. After the cross- sectional shape is taken into consideration, it will face low accuracy and becomes an inapplicable model.

In general, the utilization of the ML algorithm in the bridge engineering domain has not reached a mature point. In addition to the ap- plications described in this article, ML can also be used in the form- finding of innovative long-span structures, structural reinforcement, and structural optimization.

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.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grants No. 51978150 and 52050410334), the Southeast University “Zhongying Young Scholars” project, and the Fundamental Research Funds for the Central Universities. The corresponding author would like to acknowledge financial support from the Alexander von Humboldt-Foundation for his academic research at Max-Planck-Institut für Eisenforschung GmbH. The authors are grateful to the editors and

anonymous reviewers for their professional comments and valuable suggestions which led to the improvement of the quality of the paper.

References:

[1] Falcone R, Lima C, Martinelli E. Soft computing techniques in structural and earthquake engineering: a literature review. Eng Struct 2020;207:110269. https://doi.org/10.1016/j.engstruct.2020.110269.

[2] Azimi M, Eslamlou AD, Pekcan G. Data-driven structural health monitoring and damage detection through deep learning: state-of-the-art review. Sensors 2020;20 (10):2778.

[3] Dong C-Z, Catbas FN. A review of computer vision-based structural health monitoring at local and global levels. Structural Health Monitoring 2021;20(2): 692–743.

[4] Avci O, Abdeljaber O, Kiranyaz S, Hussein M, Gabbouj M, Inman DJ. A review of vibration-based damage detection in civil structures: from traditional methods to machine learning and deep learning

applications. Mech Syst Sig Process 2021;147: 107077. https://doi.org/10.1016/j.ymssp.2020.107077.
[5] Sun L, Shang Z, Xia Ye., Bhowmick S, Nagarajaiah S. Review of bridge structural health monitoring aided by big data and artificial intelligence: from condition assessment to damage detection. J Struct Eng 2020;146(5):4020073. https://doi. org/10.1061/(ASCE)ST.1943-541X.0002535.
[6] Bilal M, Oyedele LO, Qadir J, Munir K, Ajayi SO, Akinade OO, et al. Big Data in the construction industry: a review of present status, opportunities, and future trends. Adv Eng Inf 2016;30(3):500–21.
[7] Cevik, A., et al., Support vector machines in structural engineering: a review. Journal of Civil Engineering and Management, 2015. 21(3): p. 261-281.
[8] Lee S, Ha J, Zokhirova M, Moon H, Lee J. Background information of deep learning for structural engineering. Arch Comput Methods Eng 2018;25(1):121–9.
[9] Salehi H, Burgueño R. Emerging artificial intelligence methods in structural engineering. Eng Struct 2018;171(15):170–89.
[10] Mangalathu S, Jeon J. Classification of failure mode and prediction of shear strength for reinforced concrete beam-column joints using machine learning techniques. Eng Struct 2018;160(1):85–94.
[11] Noori Hoshyar A, Rashidi M, Liyanapathirana R, Samali B. Algorithm development for the non-destructive testing of structural damage. Applied Sciences-Basel 2019;9 (14):2810. https://doi.org/10.3390/app9142810.
[12] Mangalathu S, Jeon J-S. Machine learning-based failure mode recognition of circular reinforced concrete bridge columns: comparative study. J Struct Eng 2019; 145(10):4019104. https://doi.org/10.1061/(ASCE)ST.1943-541X.0002402.
[13] Alipour M, Harris DK, Barnes LE, Ozbulut OE, Carroll J. Load-capacity rating of bridge populations through machine learning: application of decision trees and random forests. J Bridge Eng 2017;22(10):4017076. https://doi.org/10.1061/ (ASCE)BE.1943-5592.0001103.
[14] Bayar G, Bilir T. A novel study for the estimation of crack propagation in concrete using machine learning algorithms. Constr Build Mater 2019;215(8):670–85.
[15] Chou J-S, Pham T-P-T, Nguyen T-K, Pham A-D, Ngo N-T. Shear strength prediction of reinforced concrete beams by baseline, ensemble, and hybrid machine learning models. Soft Comput 2020;24(5):3393–411.
[16] Freischlad M, Schnellenbach-Held M. A machine learning approach for the support of preliminary structural design. Adv Eng Inf 2005;19(4):281–7.
[17] Jootoo A, Lattanzi D. Bridge type classification: supervised learning on a modified NBI data set. J Comput Civil Eng 2017;31(6):4017063. https://doi.org/10.1061/ (ASCE)CP.1943-5487.0000712.
[18] Charalampakis AE, Papanikolaou VK. Machine learning design of R/C columns. Eng Struct 2021;226:111412. https://doi.org/10.1016/j.engstruct.2020.111412.
[19] Bilal M, Oyedele L. Guidelines for applied machine learning in construction industry-a case of profit margins estimation. Adv Eng Inf 2020;43:101013.
[20] Tixier A-P, Hallowell MR, Rajagopalan B, Bowman D. Application of machine learning to construction injury prediction. Autom Constr 2016;69:102–14.
[21] Yu Y, Li W, Li J, Nguyen TN. A novel optimised self-learning method for compressive strength prediction of high performance concrete. Constr Build Mater 2018;184:229–47.
[22] Chou J-S, Tsai C-F, Pham A-D, Lu Y-H. Machine learning in concrete strength simulations: Multi-nation data analytics. Constr Build Mater 2014;73:771–80.
[23] Nguyen T, Kashani A, Ngo T, Bordas S. Deep neural network with high-order neuron for the prediction of foamed concrete strength. Comput-Aided Civ Infrastruct Eng 2019;34(4):316–32.
[24] Yazdi JS, Kalantary F, Yazdi HS. Prediction of elastic modulus of concrete using support vector committee method. J Mater Civ Eng 2013;25(1):9–20.
[25] Naser MZ, Uppala VA. Properties and material models for construction materials post exposure to elevated temperatures. Mech Mater 2020;142:103293. https://doi. org/10.1016/j.mechmat.2019.103293.
[26] Chou J-S, Ngo N-T. Engineering strength of fiber-reinforced soil estimated by swarm intelligence optimized regression system. Neural Comput Appl 2018;30(7): 2129–44.
[27] Kirts S, Panagopoulos OP, Xanthopoulos P, Nam BH. Soil-compressibility prediction models using machine learning. J Comput Civil Eng 2018;32(1):4017067. https:// doi.org/10.1061/(ASCE)CP.1943-5487.0000713.
[28] Asadi M, Eftekhari M, Bagheripour MH. Evaluating the strength of intact rocks through genetic

programming. Appl Soft Comput 2011;11(2):1932–7.
[29] Pham BT, Nguyen MD, Bui K-T, Prakash I, Chapi K, Bui DT. A novel artificial intelligence approach based on Multi-layer Perceptron Neural Network and Biogeography-based Optimization for predicting coefficient of consolidation of soil. Catena 2019;173:302–11.
[30] Miyazawa Y, Briffod F, Shiraiwa T, Enoki M. Prediction of cyclic stress-strain property of steels by crystal plasticity simulations and machine learning. Materials 2019;12(22):3668. https://doi.org/10.3390/ma12223668.
[31] Shiraiwa T, Miyazawa Y, Enoki M. Prediction of fatigue strength in steels by linear regression and neural network. Mater Trans 2018;60(2):189–98.
[32] Wang C, Shen C, Cui Q, Zhang C, Xu W. Tensile property prediction by feature engineering guided machine learning in reduced activation ferritic/martensitic steels. J Nucl Mater 2020;529:151823. https://doi.org/10.1016/j.jnucmat.2019. 151823.
[33] Xiong J, Zhang T, Shi S. Machine learning of mechanical properties of steels. Science China Technological Sciences 2020;63(7):1247–55.
[34] Olalusi OB, Spyridis P. Machine learning-based models for the concrete breakout capacity prediction of single anchors in shear. Adv Eng Softw 2020;147:102832. https://doi.org/10.1016/j.advengsoft.2020.102832.
[35] Cheng M, Cao M. Evolutionary multivariate adaptive regression splines for estimating shear strength in reinforced-concrete deep beams. Eng Appl Artif Intell 2014;28(2):86–96.
[36] Chou J, Ngo N, Pham A. Shear strength prediction in reinforced concrete deep beams using nature-inspired metaheuristic support vector regression. J Comput Civil Eng 2016;30(1):8215001.
[37] Ly H-B, Le T-T, Vu H-L, Tran VQ, Le LM, Pham BT. Computational hybrid machine learning based prediction of shear capacity for steel fiber reinforced concrete beams. Sustainability 2020;12(7):2709. https://doi.org/10.3390/su12072709.
[38] Skibniewski M, Arciszewski T, Lueprasert K. Constructability analysis: machine learning approach. J Comput Civil Eng 1997;11(1):8–16.
[39] Hwang H-J, Baek J-W, Kim J-Y, Kim C-S. Prediction of bond performance of tension lap splices using artificial neural networks. Eng Struct 2019;198:109535. https:// doi.org/10.1016/j.engstruct.2019.109535.
[40] Wang Y, Geem Z, Nagai K. Bond strength assessment of concrete-corroded rebar interface using artificial neutral network. Applied Sciences-Basel 2020;10(14):4724.
[41] Garcia-Sanchez D, Fernandez-Navamuel A, Sánchez DZ, Alvear D, Pardo D. Bearing assessment tool for longitudinal bridge performance. Journal of Civil Structural Health Monitoring 2020;10(5):1023–36.
[42] Tinoco J, Correia A, Cortez P. Support vector machines applied to uniaxial compressive strength prediction of jet grouting columns. Comput Geotech 2014;55 (1):132–40.
[43] Cheng M-Y, Cao M-T, Wu Y-W. Predicting equilibrium scour depth at bridge piers using evolutionary radial basis function neural network. J Comput Civil Eng 2015; 29(5):4014070. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000380.
[44] Kim I, Fard MY, Chattopadhyay A. Investigation of a bridge pier scour prediction model for safe design and inspection. J Bridge Eng 2015;20(6):4014088. https:// doi.org/10.1061/(ASCE)BE.1943-5592.0000677.
[45] Sharafi H, Ebtehaj I, Bonakdari H, Zaji AH. Design of a support vector machine with different kernel functions to predict scour depth around bridge piers. Nat Hazards 2016;84(3):2145–62.
[46] Tien Bui D, Shirzadi A, Amini A, Shahabi H, Al-Ansari N, Hamidi S, et al. A hybrid intelligence approach to enhance the prediction accuracy of local scour depth at complex bridge piers. Sustainability 2020;12(3):1063. https://doi.org/10.3390/ su1203106310.37473/dac/10.3390/su12031063.
[47] Chen C, Zhang L, Tiong RLK. A novel learning cloud bayesian network for risk measurement. Appl Soft Comput 2020;87:105947. https://doi.org/10.1016/j.asoc. 2019.105947.
[48] Liao K-W, Chien F-S, Ju R-J. Safety evaluation of a water-immersed bridge against multiple hazards via machine learning. Applied Sciences-Basel 2019;9(15):3116. https://doi.org/10.3390/app9153116.
[49] Xiang Z, Chen J, Bao Y, Li H. An active learning method combining deep neural network and weighted sampling for structural reliability analysis. Mech Syst Sig Process 2020;140:106684. https://doi.org/10.1016/j.ymssp.2020.106684.

[50] Cheng K, Lu Z. Structural reliability analysis based on ensemble learning of surrogate models. Struct Saf 2020;83:101905. https://doi.org/10.1016/j.strusafe. 2019.101905.
[51] Papadrakakis M, Papadopoulos V, Lagaros N. Structural reliability analysis of elastic-plastic structures using neural networks and Monte Carlo simulation. Comput Methods Appl Mech Eng 1996;136(1–2):145–63.
[52] Hurtado JE, Alvarez DA. Neural-network-based reliability analysis: a comparative study. Comput Methods Appl Mech Eng 2001;191(1–2):113–32.
[53] Chojaczyk AA, Teixeira AP, Neves LC, Cardoso JB, Guedes Soares C. Review and application of Artificial Neural Networks models in reliability analysis of steel structures. Struct Saf 2015;52:78–89.
[54] Mangalathu S, Jeon J-S. Stripe-based fragility analysis of multispan concrete bridge classes using machine learning techniques. Earthquake Eng Struct Dyn 2019;48(11):1238–55.
[55] Wang K, Ruan T, Xie F. LR-BCA: label ranking for bridge condition assessment. IEEE Access 2021;9:4038–48.
[56] Pan H, Azimi M, Yan F, Lin Z. Time-frequency-based data-driven structural diagnosis and damage detection for cable-stayed bridges. J Bridge Eng 2018;23(6): 4018033. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001199.
[57] Dang, H., et al., Deep learning-based detection of structural damage using time- series data. Structure and Infrastructure Engineering, 2020(9).
[58] Kostić B, Gül M. Vibration-based damage detection of bridges under varying temperature effects using time-series analysis and artificial neural networks. J Bridge Eng 2017;22(10):4017065. https://doi.org/10.1061/(ASCE)BE.1943-5592. 0001085.
[59] Chalouhi E, et al. Vibration-based SHM of railway bridges using machine learning: the influence of temperature on the health prediction. International Conference on Experimental Vibration Analysis for Civil Engineering Structures. San Diego, CA: Univ California San Diego; 2018. p. 200–11.
[60] Li S, Sun L. Detectability of bridge-structural damage based on fiber-optic sensing through deep-convolutional neural networks. J Bridge Eng 2020;25(4):4020012. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001531.
[61] Karanci E, Betti R. Modeling corrosion in suspension bridge main cables. I: annual corrosion rate. J Bridge Eng 2018;23(6):4018025. https://doi.org/10.1061/(ASCE) BE.1943-5592.0001233.
[62] Liu H, Zhang Y. Bridge condition rating data modeling using deep learning algorithm. Struct Infrastruct Eng 2020;16(10):1447–60.
[63] Figueiredo E, Moldovan I, Santos A, Campos P, Costa JCWA. Finite element-based machine-learning approach to detect damage in bridges under operational and environmental variations. J Bridge Eng 2019;24(7):4019061. https://doi.org/10. 1061/(ASCE)BE.1943-5592.0001432.
[64] Li S, Zuo X, Li Z, Wang H. Applying deep learning to continuous bridge deflection detected by fiber optic gyroscope for damage detection. Sensors 2020;20(3):911. https://doi.org/10.3390/s20030911.
[65] Assaad R, El-adaway IH. Bridge infrastructure asset management system: comparative computational machine learning approach for evaluating and predicting deck deterioration conditions. J Infrastruct Syst 2020;26(3):4020032. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000572.
[66] Chen Q, et al. Evaluation and prediction for effect of conductive gussasphalt mixture on corrosion of steel bridge deck. Constr Build Mater 2019;228:116837.
[67] Deng Y, Zhang M, Feng D-M, Li A-Q. Predicting fatigue damage of highway suspension bridge hangers using weigh-in-motion data and machine learning. Struct Infrastruct Eng 2021;17(2):233–48.
[68] Kim H, Ahn E, Shin M, Sim S-H. Crack and noncrack classification from concrete surface images using machine learning. Structural Health Monitoring 2019;18(3): 725–38.
[69] Chun P-j., Izumi S, Yamane T. Automatic detection method of cracks from concrete surface imagery using two-step light gradient boosting machine. Comput-Aided Civ Infrastruct Eng 2021;36(1):61–72.
[70] Slonski M, Tekieli M. 2D digital image correlation and region-based convolutional neural network in monitoring and evaluation of surface cracks in concrete structural elements. Materials 2020;13(16):166–80.
[71] Deng Lu., Chu H-H, Shi P, Wang W, Kong X. Region-based CNN method with deformable modules for visually classifying concrete cracks. Applied Sciences 2020; 10(7):2528.

https://doi.org/10.3390/app10072528.
[72] Wang SY, Zhang PZ, Zhou SY, Wei DB, Ding F, Li FK. A computer vision based machine learning approach for fatigue crack initiation sites recognition. Comput Mater Sci 2020;171:109259. https://doi.org/10.1016/j.commatsci.2019.109259.
[73] Chen K, Yadav A, Khan A, Meng Y, Zhu K. Improved crack detection and recognition based on convolutional neural network. Modelling and Simulation in Engineering 2019;2019:1–8.
[74] Li G, Liu Q, Zhao S, Qiao W, Ren X. Automatic crack recognition for concrete bridges using a fully convolutional neural network and naive Bayes data fusion based on a visual detection system. Meas Sci Technol 2020;31(7):75403. https://doi.org/10. 1088/1361-6501/ab79c8.
[75] Chen Y, Sareh P, Feng J, Sun Q. A computational method for automated detection of engineering structures with cyclic symmetries. Comput Struct 2017;191:153–64.
[76] De Luca F, Hossain MI, Kobourov S. Symmetry detection and classification in drawings of graphs. Cham: Springer International Publishing; 2019.
[77] Chen, Y., et al., Particle swarm optimization-based metaheuristic design generation of non-trivial flat-foldable origami tessellations with degree-4 vertices. Joural of Mechanical Design, 2021. 143(1): p. 011703