Journal of Building Engineering 63 (2023) 105444

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: www.elsevier.com/locate/jobe

Predictive models for concrete properties using machine learning and deep learning approaches: A review

Mohammad Mohtasham Moein [a], Ashkan Saradar [b,*], Komeil Rahmati [c], Seyed Hosein Ghasemzadeh Mousavinejad [b], James Bristow [d], Vartenie Aramali [e], Moses Karakouzian [f]

[a] Department of Civil Engineering, Allameh Mohaddes Nouri University, Mazandaran, Nour, Iran
[b] Department of Civil Engineering, University of Guilan, Rasht, Iran
[c] Department of Engineering, Islamic Azad University, Some Sara Branch, Some Sara, Iran
[d] Universal Engineering Sciences, Las Vegas, NV, USA
[e] California State University, Northridge, Los Angeles, USA
[f] Department of Civil and Environmental Engineering and Construction, University of Nevada, Las Vegas, USA

A R T I C L E I N F O

Keywords:
Machine learning
Deep learning
Artificial neural network
Mechanical properties

A B S T R A C T

Concrete is one of the most widely used materials in various civil engineering applications. Its global production rate is increasing to meet demand. Mechanical properties of concrete are among important parameters in designing and evaluating its performance. Over the past few decades, machine learning has been used to model real-world problems. Machine learning, as a branch of artificial intelligence, is gaining popularity in many scientific fields such as robotics, statistics, bioinformatics, computer science, and construction materials. Machine learning has many advantages over statistical and experimental models, such as optimal accuracy, high-performance speed, responsiveness in complex environments, and economic cost-effectiveness. Recently, more researchers are looking into deep learning, which is a group of machine learning algorithms, as a powerful method in matters of diagnosis and classification. Hence, this paper provides a review of successful ML and DL model applications to predict concrete mechanical properties. Several modeling algorithms were reviewed highlighting their applications, performance, current knowledge gaps, and suggestions for future research. This paper will assist construction material engineers and researchers in selecting suitable and accurate techniques that fit their applications.

1. Introduction

Concrete is the most widely used building material worldwide. With population growth and urbanization, the demand for concrete is expected to reach 18 billion by 2050 [1–3]. In order to improve the design of concrete structures, it is necessary to gain a better understanding of concrete performance, relying on accurate evaluation of its mechanical properties. Among the various properties of concrete, compressive strength has been considered a direct indicator of performance. It is directly related to the safety and

* Corresponding author.
E-mail addresses: m.mohtasham.moein@gmail.com (M. Mohtasham Moein), ashkan.saradar@gmail.com (A. Saradar), rahmati.komeil@yahoo.com (K. Rahmati), h.mosavi@guilan.ac.ir (S.H. Ghasemzadeh Mousavinejad), jbristow@universalengineering.com (J. Bristow), vartenie.aramali@csun.edu (V. Aramali), mkar@unlv.nevada.edu (M. Karakouzian).

https://doi.org/10.1016/j.jobe.2022.105444
Received 10 August 2022; Received in revised form 5 October 2022; Accepted 18 October 2022
Available online 26 October 2022

performance of the structure throughout its life cycle [1,4,5].

Concrete is a complex system of combinations of different components (coarse and fine aggregates, water, cement, and additional mixtures) that are randomly distributed throughout the concrete matrix [6–9]. This heterogeneous feature makes it difficult to accurately predict certain mechanical properties, especially compressive strength [10–12]. The most direct way to evaluate the compressive strength of concrete is through physical tests performed on specimens cured to the desired age [13,14]. Such a method for evaluating the compressive strength needs time while being affected by other factors related to specimen fabrications and test operators. Moreover, the test tends to damage the specimens. Empirical regression methods were therefore proposed to predict compressive strength [15–17], but the disadvantage of this method is the non-linear relationship between the concrete mixture and the concrete's compressive strength. This prevents an accurate regression expression. Numerical simulation is another method that can predict the behavior of concrete. However, a good prediction of concrete behavior is not easy to achieve due to the non-linearity and randomness [18–20].

In recent years, with the advances in the field of artificial intelligence, the trend of using machine learning methods, as well as deep learning (a branch of machine learning), to predict the mechanical properties of concrete has received much attention. Compared to traditional regression methods, it has special algorithms that can learn from data and display more accurate results as output data [21–23]. Machine learning is used in structural engineering in various fields seismic performance evaluation [24], tensile strength modeling [25] and compressive strength [26], structural system identification [27], and vibration control [28], to name a few.

This article reviews the successful application of the machine and deep learning methods to predict the mechanical properties of concrete. We investigate the prediction accuracy of different algorithms used in the field of civil engineering on concrete properties was investigated and compared them to evaluate the performance of each algorithm.

2. Artificial intelligence, machine learning, and deep learning

2.1. Artificial intelligence

Nowadays, artificial intelligence, defined as the "study and design of intelligent agents," significantly influences the world. These intelligent agents are systems that have the ability to understand the environment and take steps to maximize their chances of achieving success [29,30]. For example, smartphones and self-driving cars are among the advancements that have arisen due to upgrades in artificial intelligence [31].

With the advent of computers in the 50's, huge changes took place in this field. Although it is difficult to pinpoint the origin of artificial intelligence, a turing point in this field can be attributed to Alan Turing's paper entitled, "Computing Machinery and Intelligence" [32,33]. Today, due to the upgrade and improvement of computing power and the dramatic increase of Big Data, this field has expanded substantially [33].

Early artificial intelligence applications targeted problems based on rules that are intellectually simple for the computer but challenging for humans. In order to solve such problems, a list of encrypted expressions "if and else" was introduced to the computer [34]. Many machines equipped with artificial intelligence have used this knowledge-based approach to go beyond human ability in abstract fields [35]. AI-based systems, however, were not without flaws and, in many cases, did not perform well. They struggled to perform everyday tasks, such as recognizing objects or understanding speech, that seem simple to a normal human [36]. As a result, modern artificial intelligence systems have struggled to find alternative ways of teaching intuition to computers [37]. Machine learning was brought to artificial intelligence systems to overcome the aforementioned challenges [36,38].

Machine learning began to flourish as a branch of artificial intelligence in the 1990s (Fig. 1). Instead of using symbolic approaches, it utilizes methods and models derived from statistics and probability theory [39,40]. In fact, machine learning algorithms allow machines to acquire the knowledge they need to perform a particular task by analyzing a sufficient number of data samples [38,41]. Before using the algorithm, it is necessary to perform a step called feature extraction, in which the attributes that represent the most specific information are extracted. The next step of the process, the sample data, is based on a specific ML training method to train the system to communicate the features and separate the patterns [33,36,42].

Deep Learning methods were introduced to solve the problems of the hand-crafted features in complex ML programs [36]. In-depth learning is inspired by advances in neuroscience and is consistent with interpretation information processing and communication patterns in the nervous system. Layers used in deep learning include the hidden layers of an artificial neural network and a set of

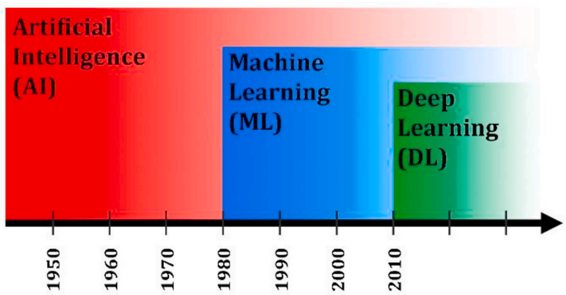

Fig. 1. Knowledge-based relationship between AI, ML, DL.

complex formulas [43,44]. Fig. 2 compares system performance in three fields: AI, ML, and DL.

2.2. Machine learning

The use of computer-aided modeling to predict the mechanical properties of building materials is growing [45]. Machine learning is a major branch of artificial intelligence that deals with the design and development of algorithms capable of identifying complex patterns of experimental data without considering a predetermined equation as a model and making intelligent decisions [46,47]. In general, the goal of machine learning is to build computer systems that learn from experience and can adapt to their environments. Important examples of machine learning include data mining (such as searching for information on the web) and implementing difficult software systems, such as automatic driving. Machine learning-based models can make predictions and describe knowledge acquisition from data [48,49]. Machine learning's scope and potential are much broader than AI and encompass many disciplines, including information theory, probability, statistics, psychology and neurobiology, computational control complexity, theory, and philosophy [50]. Researchers evaluate machine learning algorithms by solution accuracy, solution quality, and performance speed [51].

Generally, the development of an ML model involves a small number of design choices: (i) the type of learning experience, (ii) learning goal performance, (iii) displaying target performance; and (iv) an algorithm for learning the objective performance of instructional examples. Moreover, ML is divided into supervised learning, unsupervised, semi-supervised, and reinforced depending on the training resources [52,53]. Supervised and unsupervised learning are the most common types of machine learning in several applications, including engineering [51]. In supervised learning, there is a set of learning examples, which for each input, output value, or function is also specified. The learning system aims to obtain a hypothesis that guesses the function or relationship between input and output. But in unsupervised learning, there is a set of learning examples in which only the amount of inputs is known, and no information about the correct output is available. Unsupervised learning is used to group inputs or predict the next value based on the current situation [46,51,54,55]. The common types of supervised and unsupervised algorithms used in machine learning are shown in Fig. 3.

The tasks of machine learning systems can be summarized as follows [46,51,54–56]: 1) *Classification:* the goal of this step is to identify the category to which the input belongs, 2) *Regression:* The output format at this stage is considered as the difference with the classification stage. This step aims to model the relationships between the inputs and numerical outputs, 3) *Prediction:* The goal is to predict future values over a determined period of time. This step is a special type of regression, 4) *Clustering:* to extract similar points between two or more data sets. Clustering is performed according to an unsupervised method, instead of the tasks defined for the three previous steps (classification, regression, and prediction), which are performed based on supervised methods. Before starting data analysis by machine learning algorithms, one of the most important things is data normalization. Data normalization is one of the most common activities in machine learning. Among the advantages of data normalization, we can mention the improvement of gradient descent performance on normalized data compared to non-normalized data [57–61].

2.3. Deep learning

Deep Learning (Deep Neural Learning or Deep Neural Network) methods were introduced to solve the problems of hand-crafted features in complex ML programs [33,36]. DL is a subset of ML artificial intelligence, which operates with networks that can learn unsupervised, unstructured data. DL is a special type of ML method that can extract the optimal input directly from raw data without user intervention. Thus, DL algorithms can support both the relationships of features to the desired output and the feature extraction process [36,62–64]. Finally, the DL system, with proper training, can find the direct mapping from primary or raw inputs to the target outputs without extracting features. It can also find the abstract (i.e., high level) features as a hierarchy that explains simple (i.e., low level) learned features. This capability allows DL algorithms to break complex tasks into simple problems and solve them [33,36,41,

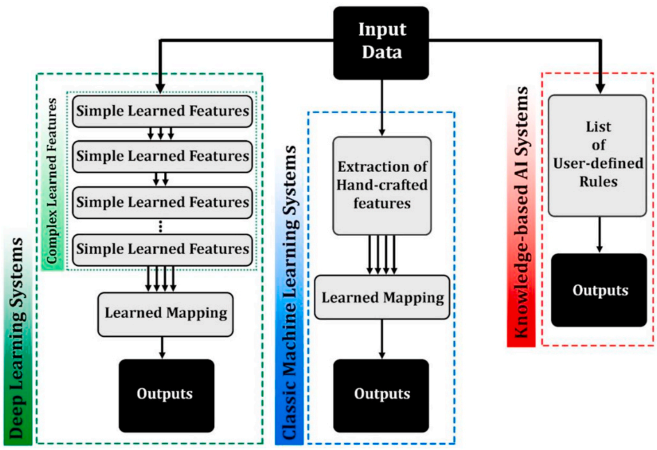

Fig. 2. Comparison of performance between AI, ML, DL.

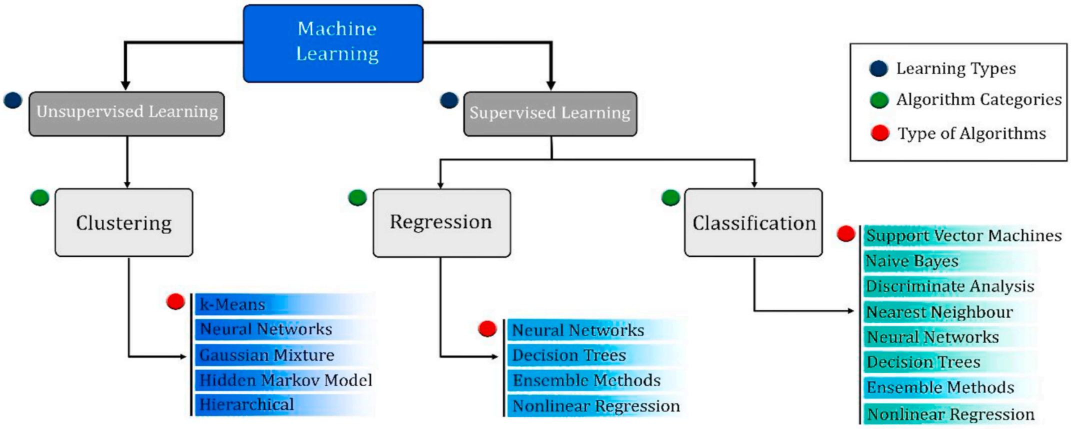

Fig. 3. Variety of commonly used machine learning algorithms.

65].

2.4. ML/Support vector machine (SVM)

A support vector machine (SVM) is one of the supervised learning methods used for both classification and information regression [66]. Fig. 4 shows the network structure of the SVM.

The SVM is a two-class classifier that separates classes by a linear boundary. The samples closest to the decision boundary are called support vectors. These vectors determine the equation of the decision boundary. This method is applied due to the structural risk minimization principle, which is applied by maximizing the distance between two transient hyperplanes from the support vectors of both classes. In order to be easy to understand and to express the theory of support vector, the simplest possible case for the classification of two classes of inseparable mode is started linearly [67,68]. Based on this principle, SVM has two salient features that lead to fruitful predictions a) excellent generalizability and b) compatibility with scattered and low data [69]. SVMs have been successfully implemented for a variety of purposes, such as error detection [70], image retrieval [71], and text recognition [72].

2.4.1. SVM development process (linear and non-linear)

Fig. 5 shows the segmentation of data by the SVM. This method aims to maximize the margin, which indicates the distance from the hyperplane to the nearest point of each class to achieve better classification performance in the test data [73].

The original SVM algorithm was invented by Vepnik in 1963 and was generalized to a nonlinear model in 1995 by Vepnik and Kurtz [73]. This method is one of the relatively newer methods that, in recent years, has shown good efficiency in predicting the mechanical properties of concrete. Fig. 6 shows the transfer of data from two-dimensional to three-dimensional space. In most cases, the data presented to the model for classification are not linearly separable. In such cases, the backup vector machine uses a nonlinear imager to transfer the data to a higher-dimensional space. With this new dimension, this method searches for a hyperplane that separates data. With a nonlinear viewfinder suitable for transferring data to a high-dimensional space, the backup vector machine can always separate two data groups.

Different kernel functions can be used to determine the output of nonlinear space. The most commonly used kernel functions are polynomial, sigmoid, radial, exponential, and linear functions. Table 1 shows a summary of kernels and their equations [67,74].

In general, the SVM method [67,74]: 1) 1) significantly more accurate and stronger, 2) less prone to overfitting compared to other models, 3) ability to model complex nonlinear decision boundaries, 4) implementation capacity in pattern recognition, classification, and regression.

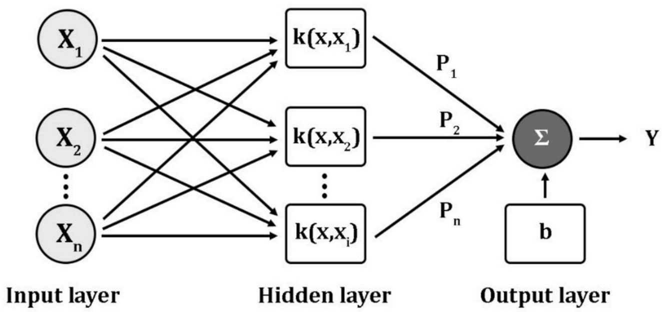

Fig. 4. Network of support vector machine [67].

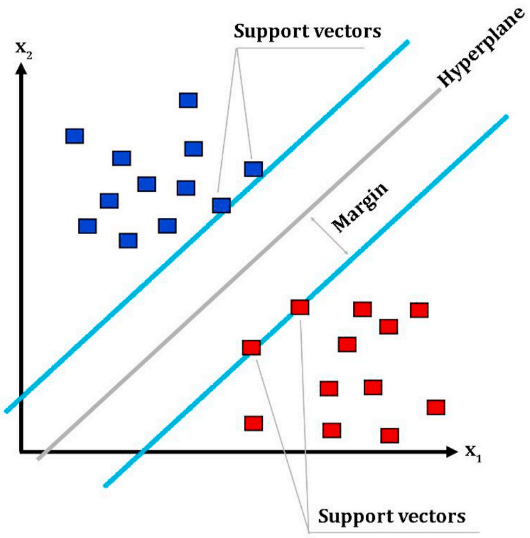

Fig. 5. Support vector machine classifier.

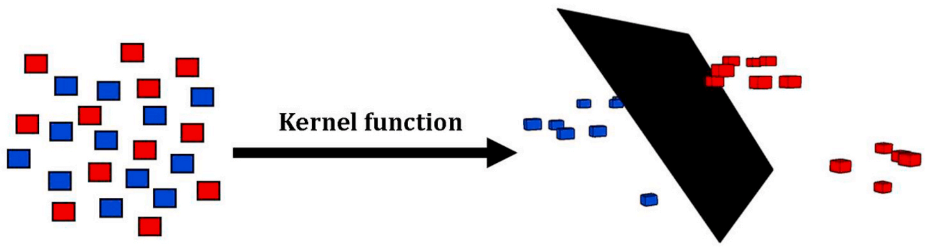

Fig. .6. Transfer data to a higher space on the support vector machine.

Table 1
Types of kernels for support vector machines.

Kernel	Equation
Linear	$K(x,y) = x.y$
Sigmoid	$K(x.y) = \tanh(ax.y + b)$
Polynomial	$K(x,y) = (1 + x.y)^d$
KMOD	$K(x,y) = a\left[\exp\left(y/_{\|x-y\|^2+\sigma^2}\right) - 1\right]$
RBF	$K(x,y) = \exp(-a\|x-y\|^2)$
Exponential RBF	$K(x,y) = \exp(-a\|x-y\|)$

In recent years, SVM modeling approaches have been widely considered in various fields when studying the mechanical properties of concrete. Therefore, researchers have used independent, hybrid, and complex models to achieve their goals. For instance, utilizing SVM for regression analysis, the model is generally called support vector regression (SVR) [75]. LSSVM was introduced as the least square support vector machine by Suykens and Vandewalle [76], which shows an extension of the standard SVM. On the other hand, the researchers examined a combination of SVM methods with unique optimization methods such as firefly algorithm (FFA), genetic algorithm (GA), network search, cuckoo optimization algorithm (COA), and particle swarm optimization (PSO). Combined methods increase efficiency, accuracy, and computational speed in machine learning technologies [67,75].

2.4.2. Studies based on SVM

In recent years, SVM whom to express the mechanical properties of concrete. Table 2 shows the studies performed on the stand-alone and hybrid SVM models. Jalal et al. [77] investigated the mechanical properties of concrete containing recycled rubber and predicted the compressive strength of concrete through SVM. Their study used three different kernels (linear, polynomial, and gaussian), optimization hyperparameters, and optimization algorithms. They concluded that SVM, with standardized data and Gaussian kernel function and L1QP optimization algorithm, produced more accurate predictions than other SVM and regression models. Deng et al. [44] considered recycled aggregates and replacement percentages as input. The model predicted the compressive

Table 2
A summary of studies based on SVM.

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
Waste tire rubberized concrete	SMO; L1QP; ISDA	Cement; silica fume; zeolitel; rubber	Compressive strength	R^2	159	78	–	22	[77]
Recycled aggregate concrete	SVM	Recycled coarse aggregate; aggregate replacement ratio; recycled fine	Compressive strength	RE	74	68	–	32	[44]
Recycled aggregate concrete	LSSVM	Recycled clay masonry; stress state (θ/P_a, τ/P_a)	Resilient modulus	R^2; RMSE; MAE; E	128	75	–	15	[78]
Concrete containing coarse recycled concrete aggregates	LSSVR	Recycled aggregate replacement ratio; aggregate to cement ratio; bulk density and water absorption of recycled concrete aggregate; water-to-cement ratio	Compressive strength Elastic modulus Tensile strength	RMSE; MAE; MAPE	650 421 346	80		20	[87]
Reinforced concrete	A combination of SFA and LS-SVR algorithms (SFA-LS-SVR)	Ratio of effective depth to breadth of beam; concrete compressive strength; yield strength of horizontal reinforcement; yield strength of vertical web reinforcement; ratio of shear span to effective depth; ratio of effective span to effective depth; main reinforcement ratio; horizontal shear reinforcement ratio; vertical shear reinforcement ratio; shear strength of RC deep beam	Shear strength	R; RMSE; MAE; MAPE	214	10-fold cross validation			[79]
Steel fiber-reinforced concrete	A combination of FFA and SVR algorithms (SVR-FFA)	Concrete strength; longitudinal steel strength; shear span to depth ratio; the effective depth of the beam; beam width; maximum aggregate size; longitudinal steel ratio; steel fiber; volume fraction; fiber length; the equivalent fiber diameter	Shear strength	SI; RMSE MAE; MAPE; RMSRE; MRE; BIAS	139	70	–	30	[80]
Steel Fiber-Unconfined Reinforced Concrete	RSM-SVR	Concrete strength; longitudinal steel strength; shear span to depth ratio; the effective depth of the beam; beam width; maximum aggregate size; longitudinal steel ratio; steel fiber volume fraction; fiber length; equivalent fiber diameter	Shear strength	MAE; RMSE	139	75	–	25	[88]
Fiber reinforced polymer confined concrete	SVR	Diameter of concrete cylinder; height-to-diameter ratio of concrete cylinder; unconfined	Strength prediction of FRP confined concrete	R; RMSE; MAPE	238	70	–	30	[89]

(continued on next page)

Table 2 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
		compressive strength of concrete cylinder; thickness of FRP jacket; ultimate tensile strength of FRP in hoop direction							
FRP reinforced concrete slabs	A combination of FFA and LS-SVR algorithms	Types of column section; section area of column; effective flexural depth of slab; compressive strength of concrete; young's modulus of the FRP slab; reinforcement ratio	Shear strength	R^2; MAPE; RMSE	82	88	–	12	[90]
Carbon Fiber-Reinforced Lightweight Concrete	SVM	The amount of cement; the amount of silica fumes; the amount of carbon fiber; the amount of aggregates; temperature	Compressive strength Flexural strength	R^2	144	72	–	28	[91]
Structural Lightweight Aggregate Concrete	SVM	Water/Cement ratio; quantity of cement; volume of aggregate; density of aggregate	Compressive strength Elastic modulus	RMSE; MAPE	180	10-fold cross validation			[92]
Concrete containing three alternative materials such as fly ash, Haydite lightweight aggregate, and portland limestone cement	SVM	Cement type; curing age; water; cementitious material; fly ash; Sand; pea gravel; haydite lightweight aggregate; micro-Air	Compressive strength	R; RMSE; MAE	144	10-fold cross validation			[93]
Lightweight foamed concrete	LSSVR	Cement; oven-dry density; water/binder ratio; foamed volume water	Compressive strength	R; RMSE MAE; RRMSE; RMAE	91	–	–	–	[94]
Geopolymer concrete	GA- SVM; PSOA- SVM; ACOA- SVM; ABCOA- SVM; ICOA- SVM	Fly ash; slag; coarse aggregate; fine aggregate; water; superplasticizer; sodium silicate; sodium hydroxide (NaOH); potassium hydroxide (KOH); oven curing temperature; oven curing time; age of ambient temperature curing	Compressive strength	R^2; MAE; RMSE; RRSE; RAE; MAPE	1347	–	–	–	[81]
Geopolymer concrete	SVR; RVM; KRR – SVM; GPR-SVM	Two different distribution of RHBA and FA; curing time; temperature	Compressive strength	R; ME; MAE; RMSE	–	70	–	30	[82]
High-performance concrete	SVM	Cement; BFS; fly ash; water; superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	R^2; RMSE; MAPE	1030	10-fold cross validation			[74]
High-performance concrete	Evolutionary Fuzzy SVM Inference Model for Time	Cement; BFS; fly ash; water; superplasticizer	Compressive strength	R; R^2; RMSE; MAE	1030	90	–	10	[83]

(*continued on next page*)

Table 2 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
	Series Data (EFSIMT)	; coarse aggregate; fine aggregate; age of testing							
High-performance concrete	SVM FA-LSSVR	Cement; fine aggregate; small coarse aggregate; medium coarse aggregate; water; superplasticizer; concrete age	Compressive strength	R^2; RMSE; MAPE	239	10-fold cross validation			[95]
High-performance concrete	ECSO-SVM	Water; cement; BFS; fly ash; superplasticizer; coarse; aggregate; fine aggregate; curing age	Compressive strength	IA; MAE MAPE; SRL; ESR	1761	70	–	30	[96]
High strength concrete	SVM	Compressive strength of concrete	Elastic modulus	RMSE; MAPE	159	78	–	22	[84]
High strength concrete; Ultra-high strength concrete	SVR	Area; notch depth; water–cement ratio; compressive strength; split tensile strength; modulus of elasticity	Fracture characteristics Failure load	R	87	70	–	30	[85]
Self-Compacting Concrete	LSSVM; RVM	Cement; fly ash; water/powder superplasticizer dosage; sand; coarse aggregate	Compressive strength	RMSE; MAE	80	70	–	30	[86]
Alkali-activated slag-fly Ash concrete	SVM	Water/solid ratio; Alkaline activator/ binder ratio; Na-Silicate/NaOH ratio; Fly ash/slag ratio; NaOH molarity	Compressive strength	RMSE; MAE; R^2	1030	70	–	30	[97]

strength of concrete containing recycled aggregates through the SVM with high accuracy and efficiency. Also, Kaloop et al. [78] used LSSVM to predict the resilient modulus of concrete containing two types of recycled aggregates (combined and separate) and concluded the optimal capability of LSSVM. Chou et al. [79] used the combined model to predict the shear strength of deep reinforced concrete beams. They reported the significant generalizability of the SFA LS-SVR model to predict shear strength. Al Musawi et al. [80] investigated the shear strength prediction of SFRC beams using the SVR-FFA algorithm. Parameters that include the geometric characteristics of the beam and the mechanical properties of the reinforcing components. The results showed that SVR-FFA accurately predicts the shear strength of concrete structures. Recent studies have also investigated the prediction of compressive strength of geopolymer concrete. Hence, Nazari and Sanjayan [81], using optimized SVM algorithms, reported that the imperialist competitive algorithm and genetic algorithm show high predictive power, as indicated by statistical criteria. On the other hand, Prem et al. [82] reported satisfactory results from kernel-based algorithms. Chou et al. [74] investigated the compressive strength of high-performance concrete (HPC) using SVM and considered the main concrete components and sample age as inputs. The resulting MAPE value indicates that the SVM has a high prediction accuracy. Cheng et al. [83] also concluded in their study on HPC that EFSIMT performed well in predicting compressive strength. In another study. In another study, Yan and Shi [84] investigated high-strength concrete (HSC) elastic modulus using SVM, and its satisfactory results were reported. Also, acceptable results were obtained from SVR to predict the fracture characteristics and failure load of ultra-high-strength concrete UHSC [85]. Aiyer et al. [86] predicted the compressive strength of self-compacting concrete (SCC) by LSSVM and Relevance Vector Machine (RVM) and reported the power of RVM to predict compressive strength.

2.5. *ML/decision tree*

Decision trees are one of the data mining methods that have been widely developed in the last two decades. These methods can be used to discover and extract knowledge from a database and to create predictive models [98–100]. Hence, it is a popular machine learning method that can be used to solve many real-world problems, such as sudden flood prediction [101], short-term photovoltaic power prediction [102] and spatial earthquake prediction [103]. Decision trees can generate human-understandable descriptions from relationships in a data set and can be used for categorization and prediction tasks. This decision structure can also be introduced in mathematical and computational methods that help to describe, categorize and generalize a set of data [104,105]. The strengths of decision trees are [104,106]: 1) 1) Though the algorithms that create the tree may not be simple, the results are easy to understand; 2) it has the ability to present their predictions in the form of a series of rules; 3) it does not require very complex calculations to categorize data, and 4) it indicates which context or variable has significant effects on prediction and categorization. The decision tree generally consists of root nodes, interior nodes, and terminal nodes. The root node contains all the data, and is divided into two sub-nodes on the right and left, where, in fact, each node represents an independent variable. Branches represent a specific range of variables. The set of each node, root, branch, and the inner node is called a leaf (Fig. 7) [104,107].

2.5.1. Decision tree models process

Among the types of decision tree-based models, M5P-tree, Multiple Additive Regression Trees, and Random Forests are the most widely used to predict the mechanical properties of concrete [75]. M5P is a genetic algorithm learner that is an upgraded version of the Quinlan M5 algorithm [107,108]. The M5 is a hierarchical model based on a binary decision framework [94,109]. Creating an M5 tree involves two processes. Input data is first subdivided to create a decision tree for attributes in the input-output data set. Then a model tree is created [94,110]. Fig. 8 shows a schematic view of an M5 tree.

The M5P tree model can predict numerically continuous variables from numerical trails, and the predicted results appear as multivariate linear regression models on tree leaves. The division criterion is based on selecting the standard deviation of the output values that reach the node as a measure of error. The expected reduction in standard deviation is calculated by testing each attribute (parameter) in the node using the following equation [75,108]:

$$SDR = \frac{m}{|T|} \times \beta(i) \times \left[sd(T) - \sum_{J \in (L,R)} \frac{|T_j|}{|T|} \times sd(T_j) \right] \tag{1}$$

where SDR stands for standard deviation reduction, T stands for the series of instances that reach the node, m stands for the number of instances without missing values for this attribute, ß stands for a correction factor, and TL and TR stand for the sets that result from the division on this attribute.

The Multiple Additive Regression Trees (MART) proposed by Friedman is a powerful meta-classifier and a breakthrough in data mining [111,112]. MART is the successor of regression tree-based modeling that inherits its benefits and improves prediction by eliminating drawbacks [74]. Therefore, MART increases the predictive power by using the boosting method, which uses the tree pruning tool. The mentioned process is repeated under supervised learning [112,113].

Random Forest (RF) was introduced by Bryman [114] in 2001 to develop new decision trees. Random Forest is a collective learning algorithm that uses different subsets of educational data (bagging and boosting) and has the benefits of binary splitting to predict target variables. Random Forest makes decisions from several trees and merges them to make more accurate and stable predictions [42,115, 116]. Forest construction using trees is often done by bagging. The main idea of the bagging method is that a combination of learning models enhances the model's overall results. One of the advantages of random forest is that it can be used for both classification and regression problems, which make up the majority of current machine learning systems. Instead of searching for the most important properties when splitting a node, the algorithm looks for the best properties among a random set. This leads to a lot of variety and, ultimately, a better model. Thus, in a random forest, the algorithm considers only one subset of features to split a node [42,75,113,115, 117]. Fig. 9 shows a picture of a random forest model structure.

2.5.2. Studies based on decision tree

Decision tree based methods have been considered a fast and efficient way to predict concrete's mechanical properties. Table 3 shows the studies performed on different models based on the decision tree.

The study of Behnood et al. [118] used the M5P algorithm to investigate the elastic modulus of concrete containing recycled aggregate. They report that the tree model developed by M5P provides an acceptable predictor. In another study, Gholampour et al. [87] evaluated the compressive strength, tensile strength, and elastic modulus of concrete containing recycled aggregate concrete (RAC) by the M5 model and compared it with other methods. Results indicate that the M5 can predict the mechanical properties of the RAC if accurately corrected for the impacts of critical parameters (i.e., w_{eff}/c, RCA%, a/c, ρ_{RCA}, and WA_{RCA}). Behnood and Golafshani [119] investigated concrete containing waste foundry sand and concluded it was a successful use of the M5P algorithm to produce reasonable models. In another study, Mangalathu and Jeon [120] investigated the shear strength of reinforced concrete beam-column

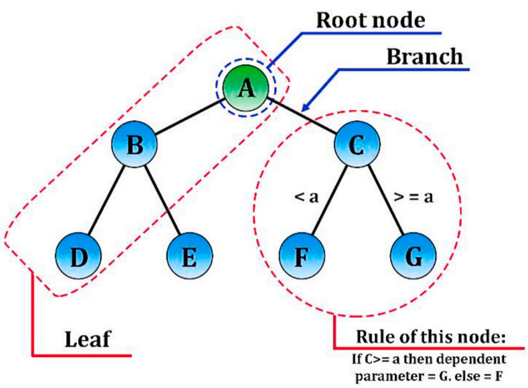

Fig. 7. Decision tree components include root node, leaf node, end node and how to interpret each tree branch.

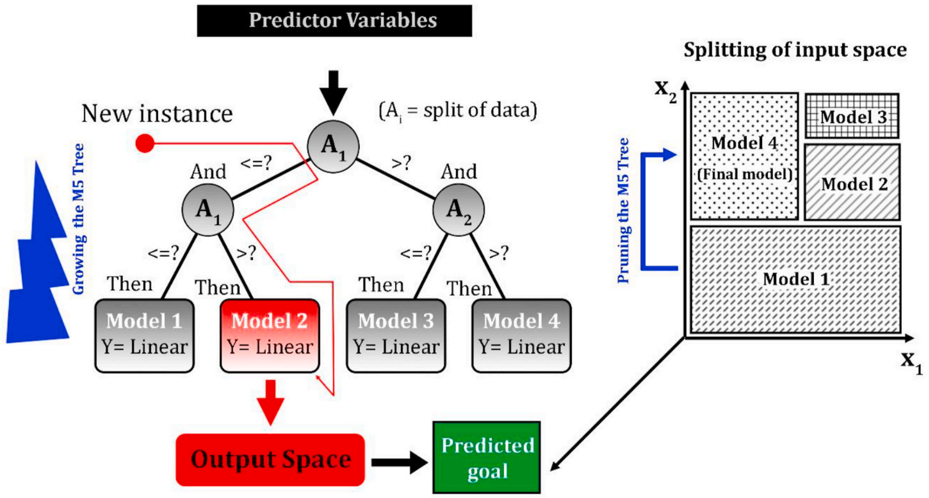

Fig. 8. A schematic view of an M5 tree.

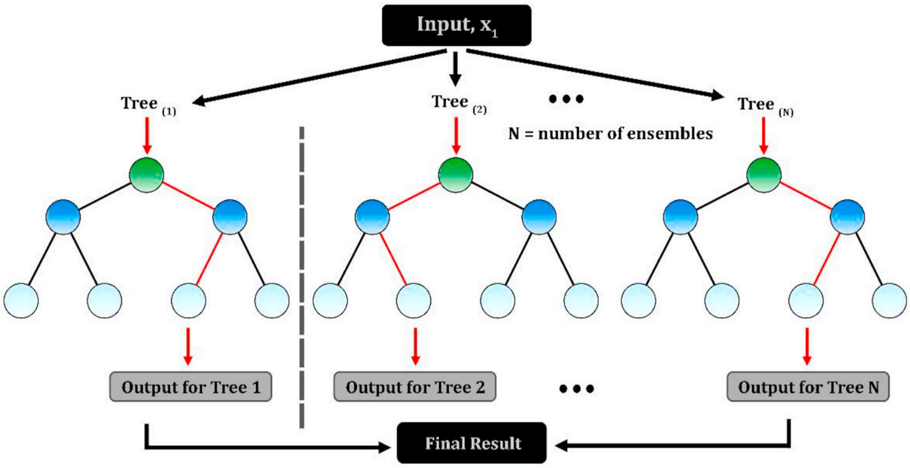

Fig. .9. Schematic view of a Random Forest model for target prediction.

joints using a Random Forest algorithm. Yaseen et al. [94] evaluated the compressive strength of lightweight foamed concrete by the M5 algorithm and reported acceptable results. Several studies have also examined high-performance concrete using the M5P algorithm. Hence, Deepa et al. [121], Behnood et al. [122], Ayaz et al. [123] used concrete constituents and curing age as input, and finally reported acceptable results using M5P to predict compressive strength. In this regard, Chou et al. [74] used another decision tree-based algorithm (MART) to investigate compressive strength and reported its effective ability to predict compressive strength with different ages of HPC. Han et al. [124] also used the RF algorithm to predict HPC concrete's compressive strength, reporting that expressing the input variables in absolute mass will enhance the model prediction performance. In another study, Zhang et al. [125] used a combination of RF algorithm and beetle antennae search (BAS) to investigate the compressive strength of lightweight self-compacting concrete and reported a high correlation coefficient of the BAS-RF model for prediction.

2.6. DL/artificial neural network

Computers have made it possible to implement computational algorithms to simulate the human brain's computational behavior in the last few decades. Many research works have been started by computer scientists, engineers, and mathematicians have contributed to the field of artificial intelligence. Artificial Neural Network is a subject in the subcategory of computational intelligence.

An artificial neural network is an idea inspired by the biological nervous system to process information and, like the brain, processes information [128]. The critical element of this idea is the new structure of the information processing system, which consists of many highly interconnected processing elements working together to solve a problem. Each neuron's output is multiplied by weight coefficients and given to the input power as a nonlinear excitation function [129,130]. Fig. 10 shows an example of a neural network.

The structure of ANNs consists of three main parts, which are [128,129,131]: 1) Input layer: which contains input parameters and

Table 3
A summary of studies based on Decision Tree.

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
Recycled aggregate concrete	M5P-tree	Compressive strength; w/c ratio; coarse aggregate to cement ratio; fine aggregate to total aggregate ratio volume fraction of recycled aggregate in RAC; Saturated surface dry specific gravity; water absorption of the mixed coarse aggregates (natural aggregate + recycled aggregate)	Elastic Modulus	R; R^2	454	80	–	20	[118]
Concretes containing coarse recycled concrete aggregates	M5	Coarse recycled concrete aggregate replacement ratio; aggregate to cement ratio; bulk density of recycled concrete aggregate; water absorption of coarse recycled concrete aggregate; water-to-cement ratio	Compressive strength Elastic modulus Tensile strength	RMSE; MAE; MAPE	650 421 346	80		20	[87]
Concretes containing waste foundry sand	M5P-Tree	Waste foundry sand to cement ratio; water to cement ratio; coarse aggregate to cement ratio; fine aggregate to total aggregate ratio; waste foundry sand to fine aggregate ratio; superplasticizer to cement ratio multiplied by 1000; age of concrete	Compressive strength Elastic modulus Tensile strength	R; $R^{2;}$ RMSE; MAE; MAPE	470	80	–	20	[119]
Pozzolan Concrete	M5P-Tree	Day; cement; silica fume; fly ash; blast furnace slag	Compressive strength Ultrasonic pulse velocity	MAE; RAE; RE	40	30-fold cross validation			[126]
Concrete containing three alternative materials as fly ash, Haydite lightweight aggregate, and portland limestone cement	M5P-tree; M5-rules; REPTree	Cement type; curing age; water; cementitious material; fly ash; sand; pea gravel; haydite lightweight aggregate; micro air	Compressive strength	R; RMSE; MAE	144	10-fold cross validation			[93]
Reinforced concrete	Random Forest	Concrete compressive strength; joint transverse reinforcement; joint shear stress; In-plane joint geometry; out-of-plane joint geometry; the ratio of beam depth to column depth; joint eccentricity parameter; the ratio of beam width to column width; column axial load ratio; beam bar bond	Shear strength	R^2; ABS; std.RMSE; std.ABS	536	70	–	30	[120]

(continued on next page)

Table 3 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
		parameter; column to beam flexural moment strength ratio; column intermediate longitudinal reinforcement factor							
Lightweight foamed concrete	M5-Tree	Cement; oven-dry density; water/binder ratio; foamed volume	Compressive strength	R; RMSE; MAE; RRMSE; RMAE	91	–	–	–	[94]
High-performance concrete	M5P-tree	Cement; BFS; fly ash; water; superplasticizer; coarse aggregate; fine aggregate; age	Compressive strength	R; RMSE; MAE	300	–	–	–	[121]
High-performance concrete	MART	Cement; BFS; fly ash; water; superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	R^2; RMSE; MAPE	1030	10-fold cross validation			[74]
High-performance concrete	The Genetic Weighted Pyramid Operation Tree (GWPOT)	Cement; fly ash; slag; water; superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	RMSE; MAE; MAPE	1030	5-fold cross validation			[127]
High-performance concrete	M5P-tree	Cement; water; fly ash; BFS; superplasticizer; coarse aggregate; fine aggregate; age of concrete	Compressive strength	RMSE; MAE; MAPE; SRL	1912	85	–	15	[122]
High-performance concrete	Random Forest	Water to binder ratio; BFS to water ratio; fly ash to water ratio; coarse aggregate to binder ratio; coarse aggregate to fine aggregate ratio	Compressive strength	R; RMSE; MAE; MAPE	1030	90	–	10	[124]
High-volume mineral-admixtures concrete	M5 M5P	Age of testing; cement; fly ash; slag content	Compressive strength	R^2; MAE	40	15-fold cross validation 20-fold cross validation			[123]
Self-Compacting Concrete	A beetle antennae search (BAS) algorithm based random forest (RF) model	Water to binder ratio; macro-synthetic polypropylene fiber; steel fiber; scoria; crumb rubber; natural fine aggregate; natural coarse aggregate	Compressive strength	RMSE; R	131	10-fold cross validation			[125]

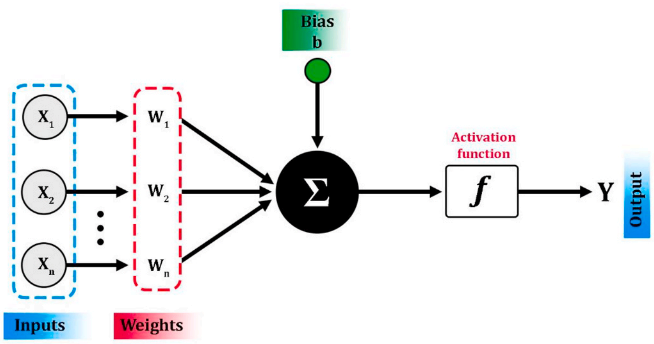

Fig. 10. The structure of the artificial neural network.

transmits them for model training and testing, 2) Hidden layer (middle): This layer is responsible for the connection between the input layer and the output layer and is the central part of the architecture of ANNs, and each hidden layer contains a set of neurons, 3) Output layer: a layer that is responsible for producing the result.

In this process, in the training phase, training information is given to the network, the network weights are adjusted so that the error between the current output and the target is minimized or the number of training times reaches a predetermined value. In modeling neural networks, selecting the number of hidden layers and the number of neurons is a vital process; if the number of hidden layers is not enough, the model will lack learning resources to solve nonlinear and complex problems. On the other hand, the training time will increase if the number of hidden layers and neurons is high. The model may work poorly in solving problems by learning behaviors other than the relationship between the parameters in the network [132–135].

The most common use of neural networks is planning to determine the probability of occurrence [136]. Neural networks have two basic learning or mapping features based on the presentation of empirical data (power and ability to generalize) and parallel structurality. These networks for problems can be prioritized by using prediction, especially complex systems that are either not possible or difficult to model. The most critical applications of neural networks can be expressed in 9 categories [137]: 1) pattern classification, identification, and recognition, 2) signal processing, 3) time series forecasting, 4) modeling and control, 5) optimization, 6) expert and fuzzy systems, 7) financial issues, insurance, security, stock market and equipment fun, 8) making industrial and medical devices, and 9) recognizing behavior in transportation models.

2.6.1. *The artificial neural network process*

The basis of learning in neural networks is repetition. One of the most widely used replication methods in neural networks is the back-propagation method of error [138]. In this method, the gradient of the error function relative to the neural network weights is calculated [139]. The after-emission algorithm extends Delta's law for perceptrons into multilayer feed neural networks [140,141]. The term backward, part of the term post-emission, is derived from the fact that the gradient is calculated backward in the lattice, with the weights' output gradient at the beginning and the input layer gradient at the end. Thus, partial derivative calculations of a single layer gradient are used for the previous layer gradient. This backward movement of the error information leads to the efficient gradient calculation in each layer relative to the state in which the layers' gradient is obtained separately [141–144]. Fig. 11 shows the structure of the back-propagation of the error algorithm.

One of the neural network models that has received much attention in recent years is the Extreme Learning Machine (ELM) model presented by Huang [145–147]. Other neural networks produce lower speeds after propagation, and in recent decades, this weakness has become a bottleneck in practical applications. Two main reasons are responsible: first, learning algorithms based on gradients are slow in training the neural network, and second, all parameters must be adjusted repeatedly in this type of learning algorithm [148]. For this reason, in industrial and practical applications, linear models are often preferred to post-diffusion neural networks due to their higher learning speed. Hence, ELM was proposed to overcome the slow structure of post-diffusion networks [148]. This neural network is a generalization of single-layer post-diffusion networks. In the case of conventional learning methods, training data must be seen before generating hidden neuron parameters. Conversely, in the ELM neural network, the input weights (i.e., the weight of the connections between the input variables and the hidden layer neurons) and the bias of the hidden layer neurons are randomly selected. Moreover, the ELM can generate these parameters before seeing the learning data [94,147,149]. Fig. 12 shows an example of the structure of the extreme learning machine algorithm.

The artificial neural network is considered as an efficient and powerful tool for solving complex problems related to engineering and science [150], but the long duration of the training, a large number of parameters, and unwanted convergence are some of its weaknesses [151,152]. Researchers have therefore resorted to combining artificial neural networks with other algorithms to overcome such problems.

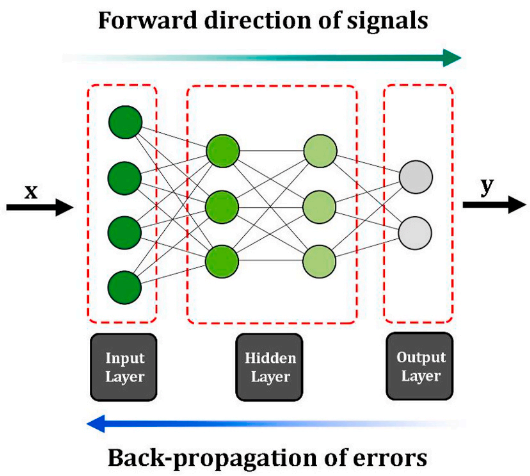

Fig. 11. A structure of the Back-propagation of errors algorithm.

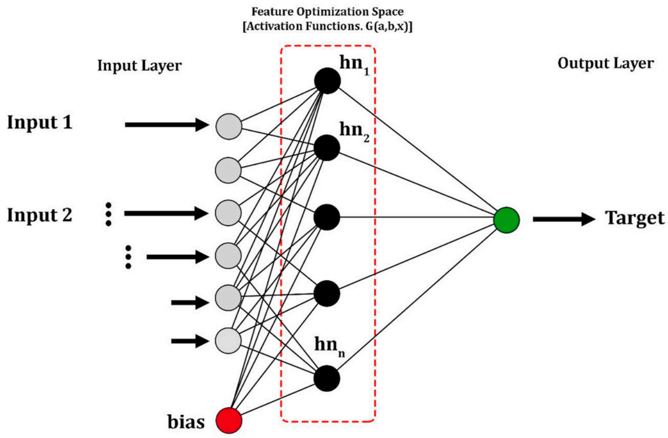

Fig. 12. A structure of the Extreme Learning Machine (ELM) algorithm.

2.6.2. Studies based on artificial neural networks

Table 4 shows the studies performed by different ANN methods to predict the mechanical properties of concrete types. Khademi et al. [153] used ANN and ANFIS to predict the 28-day compressive strength of normal concrete. Both models showed the ability to evaluate the compressive strength of different concrete mixtures. Different researchers also investigated the strength of concrete containing recycled aggregates through different ANN methods. In this regard, Dantas et al. [154] investigated the compressive strength of concrete containing construction and demolition waste usage by the BPNN method. They reported that ANN has the potential to predict 3, 7, 28, and 91-day compressive strength in both training and testing. In another study, Duan et al. [155] evaluated the compressive strength of concrete containing recycled aggregate (coarse aggregate) by 14 different inputs using the BPNN method and concluded that this method could be a suitable tool for predicting RAC compressive strength. Also, Naderpour et al. [156] evaluated the compressive strength of concrete containing construction waste (coarse-grained alternative) by the BPNN method (including 6 inputs and 18 hidden nodes) and evaluated the effect of each input parameter on the compressive strength. Their results indicate that water absorption as one of the inputs of the BPNN model has the most significant effect on compressive strength compared to other inputs. In another study, Topçu et al. [157] used fuzzy logic and BPNN methods to predict the tensile and compressive strength at 3, 7, 14, 28, 56, and 90 days of concrete containing recycled aggregate. Therefore, the comparison of R^2, RMS, and MAPE obtained for both models indicates better performance of BPNN. The study of Xu et al. [134] predicted the elastic model and the tensile strength of high-strength concrete containing recycled aggregates by the BPNN method. They concluded that BPNN could predict the mechanical properties of RAC without considering the mechanism of concrete failure and also without determining the exact functional relationship between the independent variables and the dependent variables. In Golafshani and Behnood [158] study, they investigated the elastic modulus of RCA through BPNN and RBFNN methods, and noted better BPNN performance. In another study, the results of Ababneh et al. [128] on the prediction of shear strength of RAC beams through the BPNN method yielded acceptable results.

In recent years, the use of the artificial neural networks in the case of reinforced concrete has also been considered. These include the Amani and Moeini [159] study on the shear capacity of reinforced concrete beams through ANN and ANFIS. They concluded that ANN performed better using the MLP/BP algorithm than the ANFIS model. In another study, Behnood et al. [25] considers 4 parameters as the model (water to binder ratio, concrete compressive strength, age of the specimen, and fiber reinforcing index) to predict the tensile strength of concrete reinforced with steel fibers. They used the ANN method and reported better ANN performance compared to SVM. Kumar and Barai [160] also evaluated the shear strength of steel fibrous reinforced concrete corbels without shear reinforcement and tested them under vertical loading using BPNN and concluded the high accuracy of the model. On the other hand, the study of Altun et al. [161] examined the compressive strength of lightweight reinforced concrete with steel fibers by the ANN and MLR methods, reporting better performance of the ANN model. Perera et al. [162] and Tanarslan et al. [163] also studied the shear strength of FRP-reinforced reinforced concrete beams in their study using an artificial neural network. They reported better performance of BPNN compared to the experimental equations.

Atici [164], in studying the compressive strength of concrete containing different amounts of blast furnace slag and fly ash, concluded the acceptable performance of BPNN compared with multiple regression. Nikoo et al. [165] also evaluated the compressive strength of concrete containing blast furnace slag and fly ash using a genetic algorithm to optimize the artificial neural network. Simulation results show that the ANN model has more flexibility, capability, and accuracy in predicting the compressive strength of concrete. Behnood and Golafshani [166] used a combination of artificial neural networks with multi-objective grey wolves to investigate the compressive strength of concrete containing smooth soot and concluded that the HANNMOGW model had good predictability and high accuracy. The study by Özcan et al. [167] compared artificial neural networks and fuzzy logic to predict the compressive strength of concrete containing silica fume. They reported the effectiveness of both methods and also reported the superiority of the ANN method over the FL method after comparing R^2. Yaseen et al. [94] predicted the compressive strength of lightweight foamed concrete by the extreme learning machine model and three other models (MARS, M5, and SVR). In this regard, ELM is an accurate and reliable method with better performance than the other methods approved. Dao et al. [168] used artificial

Table 4
A summary of studies based on Artificial neural network.

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
Normal concrete	BPNN; ANFIS	Cement; w/c ratio; maximum size of aggregate; gravel; sand 3/4; sand 3/8; fineness modulus of sand	Compressive strength	R^2	173	70	15	15	[153]
Concrete containing construction and demolition waste	BPNN	Cement, w/c ratio; mortar; aggregates; admixture; ratio of recycled materials; fineness modulus of fine and coarse aggregates; maximum aggregate size of fine and coarse aggregates; water absorption; age of testing	Compressive strength	R^2; AE	1178	77.8	–	22.2	[154]
Recycled aggregate concrete	BPNN	Water; cement; sand; natural coarse aggregate; recycled coarse aggregate; w/c ratio; fineness modulus of sand; water absorption of the aggregates; saturated surface-dried; density; maximum size of aggregates; impurity content and replacement ratio of recycled coarse aggregate; conversion coefficient of different concrete specimen	Compressive strength	R^2; RMSE; MAPE	168	–	–	–	[173]
Recycled aggregate concrete	BPNN	Water absorption; w/c ratio; fine aggregate; natural coarse aggregate; recycled coarse aggregate; water to total material ratio	Compressive strength	R; MSE	139	–	–	–	[174]
Recycled aggregate concrete	BPNN	Age of the specimen; cement; water; sand; aggregate; recycled aggregate; superplasticizer; silica fume	Compressive strength; Tensile strength	R^2; RMSE; MAPE	210	67	–	33	[157]
Recycled aggregate concrete	BPNN; ANFIS	Cement; natural fine aggregate; recycled fine aggregate; natural coarse aggregates 10 mm; natural coarse aggregates 20 mm; recycled coarse aggregates 10 mm; recycled coarse aggregates 20 mm; admixture; water; w/c ratio; sand to aggregate ratio; water to total materials ratio; replacement ratio of recycled aggregate to natural aggregate; aggregate/cement ratio	Compressive strength	R^2; RMSE; SSE	257	70	15	15	[175]
Recycled aggregate concrete	BPNN; Convolutional Neural Network	Recycled coarse aggregate replacement ratio; recycled fine aggregate replacement ratio; fly ash replacement ratio; w/c ratio	Compressive strength	RE	74	68	–	32	[44]
Recycled aggregate concrete	BPNN	Recycled aggregate replacement ratio; w/c ratio; aggregate to cement ratio; ratio of recycled aggregate maximum particle size to natural aggregate maximum particle size	Elastic Modulus; Tensile strength	Mean; SD; RMSE; MAPE	421	–	–	–	[134]
Recycled aggregate concrete	BPNN	Cement; water to cement ratio; total aggregate to cement ratio; fine aggregate percentage; mass substitution rate of natural aggregate by recycled aggregate; characteristic of coarse aggregate; constituents of recycled coarse aggregate; type and preparation methods of coarse aggregate; cement type; specimen size	Elastic Modulus	R^2; RMSE; MAPE	324	70	15	15	[155]
Recycled aggregate concrete	BPNN; RBFNN	w/c ratio; volume replacement of natural aggregate by recycled aggregate; coarse aggregate to cement ratio; fine aggregate to total aggregate ratio; saturated surface dry specific gravity of the	Elastic Modulus	RMSE; MAE; MAPE	400	80	–	20	[158]

(*continued on next page*)

Table 4 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
		mixed (i.e., natural and recycled) coarse aggregates; water absorption of the mixed coarse aggregates; 28-day cube compressive strength of the mixture							
Recycled aggregate concrete	BPNN	Width of beam; the effective depth of the beam; Shear span-depth ratio; replacement ratio of natural aggregate by recycled aggregate; longitudinal tension reinforcement ratio; specified concrete cylinder compressive strength	Nominal shear strength	MAE; MRE	231	–	–	–	[128]
Rubberized concrete	BPNN	Temperature; exposure duration; fiber content; w/c ratio	Compressive strength	MSE; RMSE; R; AAD; COV; SSE	324	70	15	15	[176]
Rubberized Concrete	BPNN	W/C ratio; superplasticizer; coarse aggregates; fine aggregates; crumb rubber; tire chips	Compressive strength	R; MAE; MSE	112	70	15	15	[177]
Reinforced concrete beams	BPNN; ANFIS	Concrete compressive strength; longitudinal reinforcement volume; shear span to depth ratio; transverse reinforcement; effective depth; beam width	Shear strength	R^2; RMSE; MAE	123	81	–	19	[159]
Reinforced concrete	BPNN	Cylinder concrete compressive strength; yield strength of the longitudinal and transverse reinforcing bars; shear span to effective depth ratio; cross-sectional dimensions of the beam; longitudinal and transverse reinforcement ratios	Shear strength	Mean; COV	176	80	–	20	[178]
Steel fiber-reinforced concrete	BPNN	Water to binder ratio; concrete compressive strength; age of the specimen; fiber reinforcing index	Tensile strength	R; R^2; MAPE; MAE; RMSE	980	70	15	15	[25]
Steel fibrous reinforced concrete	BPNN	Concrete cylinder compressive strength; effective depth; beam width; shear span to depth ratio; longitudinal steel ratio; fiber volume fraction; fiber aspect ratio	Shear strength	MAE; RMSE; P	730	90	–	10	[163]
Steel fiber added lightweight concrete	BPNN	The amounts of steel fiber; water; w/c ratio; cement; pumice sand; pumice gravel; superplasticizer	Compressive strength	R; MSE; MARE	126	83	–	17	[161]
Reinforced concrete beams FRP-strengthened	BPNN	Breadth of the beam; height of the beam section; ratio of the FRP transversal reinforcement; angle between the principal fiber orientation and the longitudinal axis of the member; elastic modulus of the FRP reinforcement; longitudinal steel reinforcement ratio; cross sectional area of transverse steel per length unit; yielding stress of the shear steel reinforcement; compressive strength of the concrete; shear span to depth ratio; strengthening configuration	Shear strength	Mean; Standard deviation; R; COV	98	81	–	19	[162]
RC beams strengthened in shear with FRP	BPNN	Beam width; effective height of the beam; concrete compressive strength; type of wrapping scheme; the angle between the principal fiber orientation and the longitudinal axis of the member; elastic modulus of the FRP reinforcement; rupture strain of FRP	Shear strength	R^2; RMSE	84	61	–	39	[163]

(*continued on next page*)

Table 4 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
		reinforcement; total fabric design thickness; shear span to depth ratio							
FRP-reinforced concrete	BPNN	Effective depth; width of web; shear span to depth ratio; modulus of elasticity and ratio of the FRP flexural reinforcement; compressive strength of concrete	Shear strength	Mean; Standard deviation; R^2; RMSE; COV;	106	73	–	27	[179]
Concrete Beams Reinforced by FRP Bars	BPNN	Width of web; effective depth of tensile reinforcement; shear span to depth ratio; compressive strength of concrete; FRP reinforcement ratio; modulus of elasticity of FRP	Shear strength	R; COV; MAE; MSE	177	60	20	20	[156]
Concrete members reinforced with FRP bars	BPNN	Effective depth; web width; compressive strength of concrete; shear span to depth ratio; modulus of elasticity of FRP; reinforcement ratio	Shear strength	Mean; Standard deviation; COV; MAE;	87	80	–	20	[180]
Concrete containing blast furnace slag and fly ash	BPNN	Cement; BFS; curing age; ultrasonic pulse velocity; rebound number; fly ash	Compressive strength	R; MSE	135	70	15	15	[164]
Concrete containing blast furnace slag and fly ash	A combination of ANN and GA	Cement; BFS; coarse aggregate; fine aggregate; fly ash; water; superplasticizer	Compressive strength	R^2; RMSE	180	83	–	17	[165]
Concrete containing silica fume	A combination of ANN and MOGWO	Binder; water to binder ratio; silica fume to binder ratio; coarse aggregate to total aggregate ratio; coarse aggregate to binder ratio; superplasticizer to binder ratio; maximum aggregate size; concrete age	Compressive strength	RMSE; MAE; R	1030	70	15	15	[166]
Concrete containing three alternative materials as fly ash, Haydite lightweight aggregate, and portland limestone cement	ANN	Cement type; curing age; water; cementitious material; fly ash; sand; pea gravel; haydite lightweight aggregate; micro air	Compressive strength	R; MSE; MAE	144	10-fold cross validation			[93]
Ground granulated blast furnace slag concrete	BPNN	Cement; blast furnace slag; superplasticizer; aggregates; water; age of samples	Compressive strength	R^2	225	50	–	50	[181]
Silica fume concrete	BPNN	Cement; amount of silica fume replacement; water content; amount of aggregate; plasticizer content; and age of samples	Compressive strength	MSE; MARE	240	56	21	23	[171]
Lightweight foamed concrete	ELM	Cement; oven dry density; water/binder ratio; foamed volume	Compressive strength	R; RMSE; MAE; Relative RMSE; Relative MAE	91	–	–	–	[94]
Lightweight basalt fiber reinforced concrete	ANFIS	Cement; silica fume; fly ash; and basalt fibers	Compressive strength	Regression coefficient	–	70	15	15	[182]
Geopolymer concrete	ANFIS; BPNN	Fly ash; sodium hydroxide; sodium silicate solution; water	Compressive strength	R^2; RMSE; MAE	210	70	15	15	[168]
Eco-friendly geopolymer concrete	ANN	Age of specimen; NaOH concentration; NZ content; SF content; GGBS content	Compressive strength	R; MSE	–	70	15	15	[169]
High-performance concrete	BPNN	Cement; blast furnace slag; fly ash; water; superplasticizer; coarse aggregate; fine aggregates; curing age	Compressive strength	R^2; RMSE; MAPE	300	–	–	–	[121]
High-performance concrete	BPNN	Cement; nano-silica; fine aggregate; copper slag; age of specimen; superplasticizer	Compressive strength	R; R^2; RMSE; MAPE	270	70	15	15	[132]
High-performance concrete	MFA-BPNN		Compressive strength	R; RMSE; MAE; MAPE	1133	10-fold cross validation			[170]

(*continued on next page*)

Table 4 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
		Water; cement; blast furnace slag; fly ash; superplasticizer; coarse aggregate; fine aggregate; age of testing							
High-performance concrete	MFA-BPNN	Curing age; cubic compressive strength	Tensile strength	R; RMSE; MAE; MAPE	1133	10-fold cross validation			[170]
High-performance concrete	RELM; ELM	Cement; blast furnace slag; fly ash; water; superplasticizer; coarse aggregate; fine aggregate; age of specimens	Compressive strength	R; RMSE; MAE; MAPE	1133	10-fold cross validation			[183]
High-performance concrete	ANN; BANN; GBANN; WBANN; WGBANN	Cement; blast-furnace slag; fly ash; water; superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	R^2; RMSE; MAE	1030	90,80	–	10,20	[184]
High-performance concrete	BPNN	Cement; blast-furnace slag; fly ash; water; Superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	R^2; RMSE; MAPE	1030	10-fold cross validation			[74]
High strength concrete	ELM; BPANN	Water; cement; fine aggregate; coarse aggregate; superplasticizer	Compressive strength	R; RMSE; MAE; MAPE; NSE	324	75	–	25	[147]
High strength concrete; Normal concrete	ANFIS	Compressive strength of concrete	Elastic Modulus	RMSE; MAPE	145	78,83	–	28,17	[185]
High strength concrete; Normal concrete	Grey wolf optimized ANN; Grey wolf optimized ANFIS	Coarse aggregate; sand; water; cement; BFS; fly ash; superplasticizer; age of specimens	Compressive strength	RMSE; MAE; R^2; MBE; scatter index; uncertainty with 95% confidence level	2817	70	15	15	[171]
High strength concrete	ANFIS	Tensile reinforcement ratio; concrete compressive strength; shear span to depth ratio	Shear strength	COV; R; MSE	122	80	–	20	[186]
High strength concrete	BPNN	Water to binder ratio; water content; fine aggregate ratio; fly ash replacement ratio; air-entraining agent; ratio silica fume replacement ratio and superplasticizer content	Compressive strength	R^2; RMSE; MAPE; SSE	187	90	–	10	[187]
Cellular concrete	BPNN	Cement, w/c ratio; sand to cement ratio; foam volume to cement ratio	Compressive strength	Absolute average error; Average algebraic error	99	24	23	34	[188]
Self-Compacting Concrete	BPNN	Binder; fly ash replacement percentage; water/binder ratio; fine aggregate; coarse aggregate; superplasticizer	Compressive strength	R; RE	114	80	–	20	[189]
Self-Compacting Concrete	BPNN	Cement; coarse aggregate; fine aggregate; water; limestone powder; fly ash; ground granulated BFS; silica fume; rice husk ash; superplasticizer; viscosity modifying admixtures	Compressive strength	R	169	67	16.5	16.5	[138]
Self-Compacting Concrete	BPNN	Cement; coarse aggregate; fine aggregate; water; limestone powder; fly ash; ground granulated BFS; silica fume; rice husk ash; superplasticizers; viscosity modifying admixtures	Compressive strength	R; MSE	205	67	16.5	16.5	[172]
Alkali-activated slag-fly Ash concrete	BPNN	Water/solid ratio; Alkaline activator/binder ratio; Na-Silicate/NaOH ratio; Fly ash/slag ratio; NaOH molarity	Compressive strength	RMSE; MAE; R^2	1030	70	–	30	[97]

neural networks and fuzzy logic to predict the compressive strength of geopolymer concrete containing fly ash and slag. They reported better values of MAE, RMSE, and R^2 for the fuzzy logic model compared to the artificial neural network. In addition, in another study, Shahmansouri et al. [169] predicted the compressive strength (7, 28, and 90 days) of eco-friendly geopolymer concrete by an artificial neural network. Finally, they reported the satisfactory results of the model.

The use of artificial neural networks to predict HPC and HSC resistance is another area researchers have considered. For example, Chithra et al. [132] used multiple regression analysis and artificial neural networks to predict compressive strength (1, 3, 7, 28, 56, and 90 days) high performance concrete containing nano-silica (0%, 0.5%, 1%, 1.5%, 2%, 2.5% and 3%) and copper slag. The results show that the artificial network model has a lower Root Mean Squared Error and Mean Absolute Percentage Error than the regression model and R-squared closer to one. In addition, Bui et al. [170] used a combination of an artificial neural network and a modified firefly algorithm to predict high-performance concrete tensile and compressive strength. The results showed that the MFA-ANN hybrid system has a small error in predicting the resistance and significantly reduces the computation time. Al-Shamiri et al. [147] predicted the compressive strength of high-strength concrete using the ELM model, BPNN, and considering concrete components as model inputs. They concluded the higher capacity of the ELM model to predict concrete strength. Golafshani et al. [171] used the GWO algorithm in the artificial neural network training phase and the Adaptive Neuro-Fuzzy Inference System to predict the compressive strength of normal and high-performance concrete. The results show that the combined application of GWO with both ANN and ANFIS models improves their training and generalization ability. Asteris and Kolovos [172], in their study on the compressive strength of self-compacting concrete by the BPNN model, used the Levenberg-Marquardt method to teach data and finally reported satisfactory results of BPNN use. Asteris et al. [138], in another study on self-compacting concrete by BPNN, concluded by comparing the results with experimental findings the BPNN model was capable to reliably predict.

2.7. ML/Evolutionary algorithms

One of the most cost-effective and simplest problem-solving techniques (in terms of computational load and time required to implement the algorithm) in the field of artificial intelligence is evolutionary computational methods [61,190–192]. In Computer Science and Artificial Intelligence, evolutionary computing is known as a family of algorithms for General Optimization that is inspired by biological evolution processes [190,193,194]. A subfield of artificial intelligence and soft computing that studies and implements algorithms inspired by biological evolution processes are called evolutionary computational algorithms [59,195]. Fig. 13 shows the evolutionary computing classification.

One of the important goals of evolutionary computational methods and evolutionary algorithms, in particular, is to improve the quality of poorly generated solutions to a problem. Evolutionary computing algorithms make use of evolutionary processes like mutation and others; in other words, employing operations like the mutation process, and evolutionary computing algorithms in anIterative process manipulate a large number of badly created answers until the system can solve the problem with the necessary precision [60,192,195,196]. From a technical point of view, evolutionary computational algorithms are family-based problem-solving methods based on population, trial and error, and use stochastic optimization or meta-heuristic optimization mechanisms to converge toward the global optimal solution or approximation [59,191,192]. In evolutionary calculations, a basic set of Candidate Solutions is first formed. During the evolutionary process, evolutionary computational algorithms manipulate and update the population with candidate answers to move the population to the area containing the answer (Global Optimum) [197–199]. In each iteration of evolutionary computational algorithms, also called generation, an evolutionary process will eliminate undesirable responses in the population and make very small, albeit random, changes in candidate responses. Fig. 14 shows the outline of the evolutionary algorithm.

2.7.1. Evolutionary algorithms process

In general, evolutionary algorithms are based on Charles Darwin's original evolutionary theory [200]. Although implementing evolutionary mechanisms is different, the main idea of all these changes is similar [201]. So far, various versions of evolutionary computational algorithms have been proposed. Genetic programming (GP), was invented by Kramer [60] and further developed by Koza [202]. Genetic algorithms are a family of computational models inspired by the concept of evolution. These algorithms encode potential solutions, candidate solutions, or possible hypotheses for a particular problem into a chromosome-like data structure [203–206]. The genetic algorithm preserves vital information stored in chromosome-like data structures by applying recombination operators to chromosome-like data structures [61,191,207]. Implementing a genetic algorithm usually begins with the production of a population of chromosomes (the initial population of chromosomes in genetic algorithms is usually randomly generated, and bounded up and down by the problem variables). In the next step, the generated data structures (chromosomes) are evaluated. The chromosomes that can better represent the optimal solution of the problem (target) have a better chance of reproduction than weaker solutions. In other words, more reproductive opportunities are allocated to these chromosomes [58,208,209]. Fig. 15 shows the outline of the genetic algorithm.

The artificial bee colony algorithm (ABC) is an optimization solution that simulates the behavior of a bee colony and was first proposed in 2005 by Karaboga [210] to optimize the actual parameter. In this mathematical model, an artificial bee colony has three types of bees. Worker bees work to collect food and bring it to the hive from a specific food source. Observation bees patrol among workers to determine if a food source is still worth using and finally watch as bees seek to discover new food sources [211–213]. In the ABC algorithm, a food source is defined as a state in the search space (a solution to the optimization problem), and the number of food sources is initially equal to the number of bees in the hive. The quality of food resources is determined by the value of the objective function in that position (proportionality value) [57,208,214]. Fig. 16 shows the steps of the ABCP algorithm.

Biogeography-Based Optimization (BBO) is one of the relatively new algorithms of intelligent optimization, which was introduced in 2008 by Dan Simon [215]. This algorithm is inspired by how species of organisms spread in multiple habitats. By providing a possible model for how species migrate in habitats, a mathematical model has been extracted that has eventually led to creating a new optimization model used in the BBO [208,215–217]. Fig. 17 shows the steps of the BBP algorithm.

2.7.2. Studies based on evolutionary algorithms

Table 5 shows the studies performed by evolutionary algorithms to predict the mechanical properties of concrete types. Golafshani and Behnood [208] investigated the tensile strength of concrete containing recycled aggregates using three models GP, ABCP, and BBP. They reported the models used as reliable algorithms for predicting the elastic modulus. They also concluded that the water absorption of the mixed coarse aggregate and the ratio of the fine aggregate to the total aggregate are two parameters affecting the elastic modulus of RAC. In another study, Abdollahzadeh et al. [218] evaluated the compressive strength of RAC concrete containing silica fume by gene expression programming (GEP). They reported the optimal agreement between the experimental results and the results of the GEP model. Iqbal et al. [219] studied the compressive strength, tensile strength, and elastic modulus of green concrete incorporating waste foundry sand through gene expression programming. They reported that the results obtained from RSE, MAE, RMSE, and R for all three sets of learning, validation, and testing confirm the accuracy and capability of the model. Kara [220] also reported satisfactory results using the GEP model in its study on predicting the shear strength of FRP-reinforced concrete beams. Gandomi et al. [221,222] reported the GEP model's high accuracy in predicting the shear strength of reinforced concrete beams. Also, a comparative study of the GEP model with the models derived from the ACI, EC2, CSA, and NZS regulations shows the superiority of the GEP model. In a separate study, Gandomi et al. [223] investigated the compressive strength of carbon fiber reinforced plastic confined concrete using the linear genetic programming (LGP) model. The results showed that LGP can predict compressive strength with an acceptable level of accuracy and performs better than several models presented in other studies. In another study, Beheshti et al. [224] estimated the shear strength of short rectangular reinforced concrete columns using two models of nonlinear regression and gene expression programming. Validation performed on the models showed that for the GEP model, the average errors were 15%, while for NR, ACI and EC2 models, the average errors were 50%, 45%, and 43%, respectively. Sarıdemir [225], in his study on concrete containing rice husk ash, reported the genetic programming approach model as a powerful way to predict compressive strength. The study of Shahmansouri et al. [226] predicted the compressive and electrical resistance of eco-friendly concrete containing natural zeolite. Their results indicate that, according to the values of statistical parameters (R^2, RMSE, RAE, and RRSE), the model can predict compressive and electrical resistance. Awoyera et al. [227] investigated the compressive, tensile, and flexural strength of geopolymer self-compacting concrete by GEP and ANN models. The results show that both models can predict the mechanical properties of concrete up to a confidence level of about 97%. Dao et al. [228] predicted the compressive strength of geopolymer concrete using two combined models, GAANFIS and PSOANFIS. Mousavi et al. [229] predicted high-performance concrete compressive strength using gene expression programming. In addition to reporting GEP as an effective method for predicting HPC compressive strength, they concluded that among the input parameters, three parameters of water, cement, and age of samples have the greatest impact on compressive strength. Golafshani and Ashour [230] study predicted the elastic modulus of self-compacting concrete by two models of biogeographical-based programming and artificial bee colony programming. They reported that the BBP model was slightly closer to the experimental results than the ABCP model. In addition, the sensitivity of BBP parameters shows that the prediction by the BBP model improves with increasing habitat size, colony size, and maximum tree depth.

3. Results and discussion

3.1. Comparison of ML/DL models with statistical models

Machine learning models have emerged as an important and serious competitor to classical statistical models in the last two decades. In this regard, various models such as support vector machines, decision trees, artificial neural networks, and others were developed and expanded in the machine learning suite. Statistical modeling formulates the relationship of variables in mathematical equations, while machine learning is an algorithm that can learn from data. Although machine learning is rooted in statistics, there are differences between statistical and machine learning models. Fig. 18 shows a summary of the comparison between ML/DL models and statistical models.

Table 6 shows the prediction of mechanical properties of different types of concrete by statistical models and ML/DL models. Therefore, the comparison of machine learning models and statistical models is performed by the following parameters, which indicate the higher potential of ML/DL models compared to statistical models:

- Coefficient of determination (R^2)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Root-Mean-Square Relative Error (MARE)

Table 6 shows the prediction statistics of ML/DL models compared to other statistical models. The comparison made in 14 groups is presented, which includes checking Compressive strength, Elastic modulus, Flexural strength, Splitting tensile strength, Shear strength. The analyzed statistical indicators include R^2, MAE, MAPE, RMSE. The size of the experimental database always plays an important role in the reliability of the models [272]. Therefore, the dataset size is also presented in Table 6.

- Xu et al. [134]: In this study, compressive strength, elastic modulus, flexural strength, splitting tensile strength, shear strength was investigated. The results indicate that the indicators for prediction by the ANN model show lower values. The indicators for

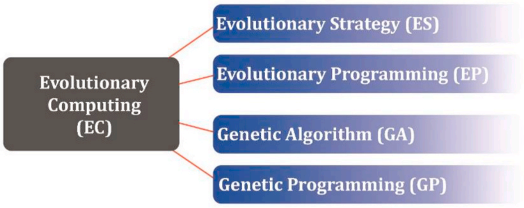

Fig. 13. A structure of evolutionary computational classification.

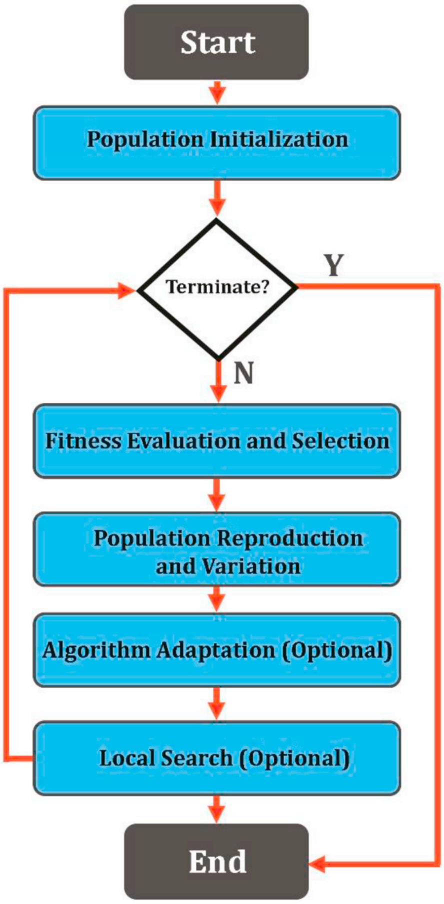

Fig. 14. Evolutionary algorithm structure.

prediction by ANN model show lower values. This can be because the ANN approach has the ability to automatically adjust the weight index for each input parameter to reduce the scatter of the target response. Such a trend has been reported by Xu et al. [134].

- Gholampour et al. [272]: Items such as elastic modulus, flexural strength were investigated in this study. They evaluated Recycled aggregate concrete by GEP model. As can be seen, the GEP model provides improved accuracy. In addition, the GEP model can be used for a larger number of data sets than other models.
- Vu & Hoang [90]: In this study, the shear strength of Steel fiber-reinforced concrete was investigated by the ANN model. The calculation results show that the equation proposed by Ospina et al. [261] is the best approach based on the formula, which includes RMSE, MAPE and R^2 of 117.51, 15.48 and 0.91, respectively. Meanwhile, the model proposed by Vu & Hoang's study [90] shows better results.
- Al-Musawi et al. [80]: In this study, steel fiber-reinforced concrete was tested for shear strength and was evaluated by SVR-FFA model. The comparison of SVR-FFA with other models of this group shows that SVR-FFA has superiority over other models and this is because of the high feasibility to understand the internal mechanism between the predictors and predictand.
- Sarveghadi et al. [233]: In this study, steel fiber-reinforced concrete was investigated and the shear strength of this concrete was evaluated by the MEP model. Many empirical models use statistical regression techniques and are developed after controlling a

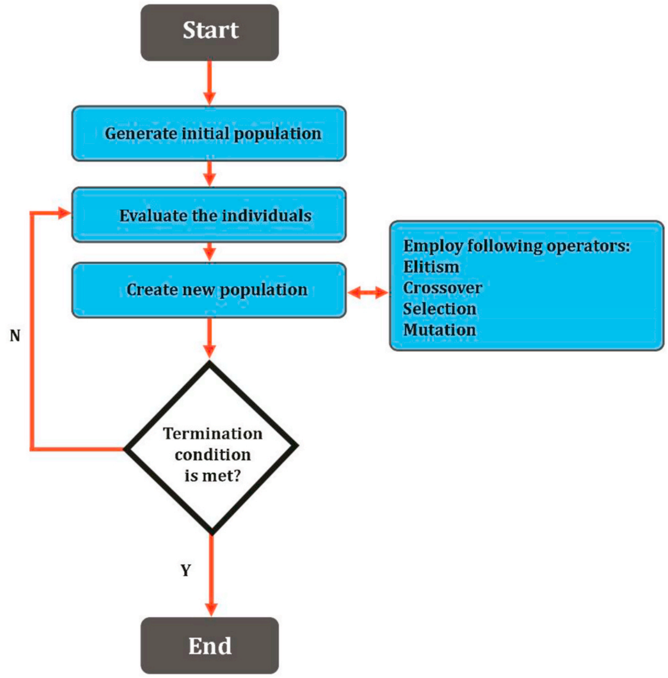

Fig. 15. Flow chart of the GP algorithm.

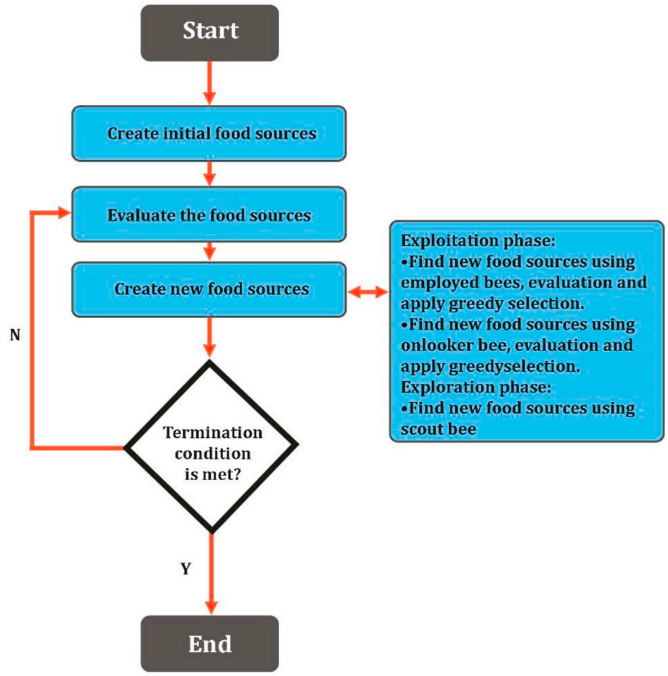

Fig. 16. Flow chart of the ABCP algorithm.

limited number of equations. Meanwhile, the MEP model was selected from many primary models. On the other hand, the MEP approach depends on the data to provide better generalization. It is worth noting that the proposed MEP models are mainly used to validate the results of laboratory tests or for cases where testing is not possible.

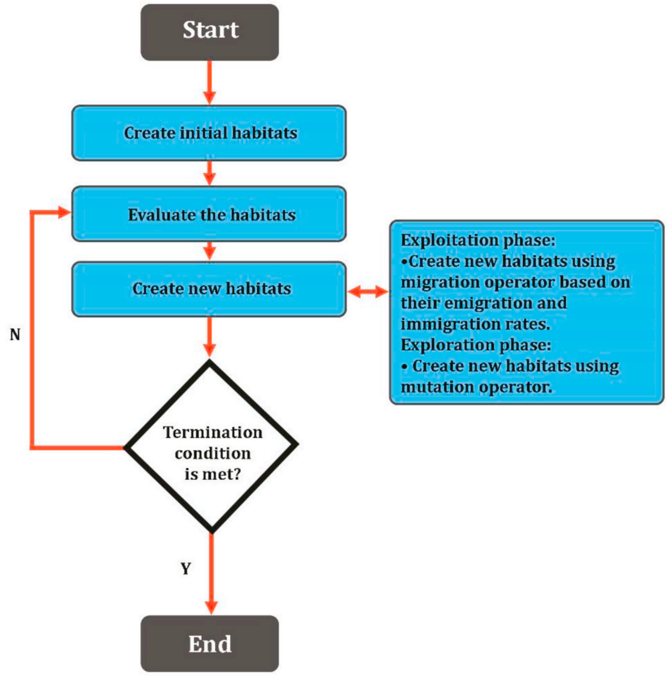

Fig. 17. Flow chart of the BBP algorithm.

- Keshtegar et al. [88]: In this study, different methods such as ANN, RSM, SVR and RSM-SVR hybrid algorithm were investigated for the shear strength of steel fiber-reinforced concrete. Comparing the results of ML/DL methods with statistical models shows that artificial intelligence has the ability to provide a more reliable platform for data prediction and analysis.

This extraordinary capability of ML/DL models stems from their ability to accurately predict the properties of concrete components and their relationship to the target strength, which is largely a non-linear relationship between them. This issue has been mentioned by other studies [75,80,90,134,233]. Fig. 19-a to **19-d** show the validation parameters and error criteria of ANN, MEP, and SVR-FFA models compared to different statistical models for predicting shear strength. ML/DL models provide a better model for predicting shear strength due to high R^2 and low error criteria (MAE and RMSE). Fig. 19-e also shows the prediction of tensile strength by the ANN model compared to the statistical models. The lower error criteria of the ANN model than other models are evident. The comparison of flexural strength prediction by the ANN model and statistical models in Fig. 19-f is also apparent. Therefore, MAE and RMSE values for the ANN model were 9.39 and 0.64, respectively, which are much lower values than the statistical models' results. A comparison of elastic modulus prediction models in Fig. 19-g shows the superiority of the ANN model compared to statistical models. Fig. 19-h also shows the prediction of compressive strength by the ANN model and other models that demonstrate a clear satisfactory performance of the ANN model.

On the other hand, according to Tables 2–5, Studies in the field of ML/DL indicate that these models use a wider range of datasets to predict target resistance than statistical models, which ultimately leads to a more accurate and efficient model. Another thing that is important in predicting the target resistance is the possibility of updating the model. In this area, statistical models do not show the possibility of a successful update due to the weakness in the optimal evaluation of the target strength of concrete in the presence of new additives. They mainly do not consider the effect of new materials on the target strength. Meanwhile, different ML/DL models can update the forecasting mechanism by controlling the concrete components, the number of input parameters, and performing pre-processing. On the other hand, ML/DL models with sensitivity analysis also provide the potential to evaluate the impact of input parameters on the target resistance. Therefore, to predict the target strength of concrete with complex structures, it is better to use ML/DL models, and contrary to expectations, limit statistical and experimental models to evaluate concrete with simple structures.

3.2. Comparison of different ML/DL models

The wide range of applications and features of different models of machine learning and deep learning has made them powerful prediction tools. In this regard, each ML/DL model follows a specific scenario to achieve its ultimate goal. Weaknesses in previous models have always been considered an incentive for researchers to create newer and more efficient models. Therefore, the strength of different ML/DL models in comparison with each other can be evaluated by statistical criteria.

Fig. 20 data size shows the compressive strength related to the studies conducted by different researchers on concrete in the ML/DL field. The data size used in different studies is very different. RMSE, as an important evaluation index that expresses the difference between the value predicted by the model or statistical estimator and the actual value, is present in most studies as a comparative parameter. Frequently lower values than the RMSE index can bring a better-fitted line and a more reasonable result. In another sense,

Table 5
A summary of studies based on Evolutionary algorithms.

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
Normal concrete	GEP	Compressive strength	Tensile strength	R^2; RMSE	251	50	25	25	[231]
Recycled aggregate concrete	GP; ABCP; BBP	Water to cement ratio; volume fraction of coarse RA in RAC; coarse aggregate to cement ratio; fine aggregate to total aggregate ratio; saturated surface dry specific gravity of the mixed coarse aggregates; water absorption of the mixed coarse aggregates; and 28-day cube compressive strength of the mixture	Elastic Modulus	MAE; RMSE; MAPE; OBJ	400	80	–	20	[208]
Recycled aggregate concrete	GEP	Age of specimens; cement; water; natural aggregates; recycled aggregates; silica fume; superplasticizer	Compressive strength	R^2; MAE; RMSE; RAE; RRSE	228	80	–	20	[218]
Green concrete incorporating waste foundry sand	GEP	Water-to-cement ratio; WFS percentage; WFS-to-cement content ratio; fineness modulus of WFS	Compressive strength Elastic modulus Split tensile strength	R; RMSE; MAE; RSE	234 85 163	–	–	–	[219]
FRP-reinforced concrete beams	GEP	Compressive strength; beam width; effective depth; shear span to depth ratio; reinforcement ratio; the ratio of modulus of elasticity of FPR to steel reinforcement	Shear strength	R; MAPE; AAE	104	54	19	27	[220]
Reinforced concrete	GEP	Beam width; effective depth; shear span to depth ratio; compressive strength; longitudinal reinforcement ratio; amount of shear reinforcement	Shear strength	R; MAE; RMSE	466	70	15	15	[222]
Reinforced concrete	GEP	Beam width; effective depth; shear span to depth ratio; compressive strength; longitudinal reinforcement ratio	Shear strength	R; MAE; RMSE	1942	70	15	15	[221]
Reinforced concrete	GEP	The axial force; the width of the cross-section; 28-day compressive strength of concrete; the ratio of shear span to the effective depth of the cross-section; the percentage of longitudinal reinforcement; the cross-sectional area; the transverse reinforcement ratio; and the yield stress of the transverse reinforcement	Shear strength	R; MAE; RMSE	83	53	22	25	[224]
Reinforced concrete	LGP	Compressive strength; mechanic arm; longitudinal reinforcement ratio; maximum size of coarse aggregate; shear span to depth ratio	Shear strength	R; MAE; RMSE	1938	70	15	15	[232]
Carbon fiber-reinforced plastic	LGP	Diameter of the concrete cylinder; thickness of the CFRP layer; ultimate tensile strength of the CFRP laminate; unconfined ultimate concrete strength	Compressive strength	R; MAPE	101	90	–	10	[223]
Steel fiber-reinforced concrete beams	MEP	Shear span to depth ratio; average fiber matrix interfacial bond stress; fiber factor; splitting tensile strength; split-cylinder strength of fiber concrete; compressive strength of concrete; longitudinal reinforcement ratio	Shear strength	R^2; MAE; RMSE	208	67	14	19	[233]
Concretes containing rice husk ash	GEP	Genes the age of specimen; portland cement 30; Portland cement 40; rice husk ash; water; superplasticizer; aggregate	Compressive strength	R^2; MAPE; RMSE	188	60	10	30	[225]
Silica fume concrete	BBP	Portland cement; silica fume; water; coarse aggregate; fine aggregate; superplasticizer; the maximum aggregate size; the concrete age	Compressive strength	R; MAE; MAPE; RMSE; OBJ	1030	75	–	15	[234]
Bagasse ash-based concrete	GEP	The water-cement ratio; bagasse ash percent replacement; quantity of fine and coarse aggregate and cement	Compressive strength	R^2; RMSE; NSE	65	–	–	–	[235]
Eco-friendly concrete containing natural zeolite	GEP	Age of specimens; water; cement; natural zeolite; coarse aggregate; fine aggregate; superplasticizer	Compressive strength Electrical resistivity	R^2; MAE; RMSE; RAE; RRSE	324 162	80	–	20	[226]

(*continued on next page*)

Table 5 (*continued*)

Concrete Type	Algorithm	Input	Output	Statistical Index	Dataset size	Training (%)	Validation (%)	Testing (%)	Ref.
Geopolymer concrete	GAANFIS	The sodium solution; the mass ratio of alkaline activation solution to fly ash; the mass ratio of sodium silicate to sodium hydroxide solution	Compressive strength	R; MAE; RMSE	210	70	30	–	[228]
Geopolymer self-compacting concrete	GEP	Fly ash; GGBS; silica fume; slump flow; T50 cm; L-box; V-funnel; J-ring; Age	Compressive strength; Split-tensile strength; Flexural strength	MAE; MSE; RMSE	105	70	15	15	[227]
High-performance concrete	Geometric Semantic Genetic Programming	Cement; fly ash; blast furnace slag; water; superplasticizer; coarse aggregate; fine aggregate; age of testing	Compressive strength	RMSE	1028	70	–	30	[236]
High-performance concrete	GEP	Water; cement; blast furnace slag; fly ash; superplasticizer; coarse aggregate; fine aggregate; age of specimens	Compressive strength	R; MAE; OBJ	1133	80	20	–	[229]
Normal strength concrete	GP; LGP	Compressive strength	Elastic Modulus	R; MAE	70	81	–	19	[237]
High-strength concrete					89	78		22	
Self-compacting concrete	ABCP; BBP	Compressive strength	Elastic Modulus	R^2; MAE; MAE; RMSE; OBJ	413	80	–	20	[230]

we calculate the sum of the errors of each point compared to the built model, and this itself is a kind of criterion for the goodness of the model built by the algorithm. Therefore, a summary of RMSE values from different studies is reported in Table 7. Also, Fig. 21 also shows a schematic picture of RMSEs of different studies. Due to the fact that many factors such as the size of the dataset, the type of data used, the method of the algorithm used in the results of the analysis, and evaluation indicators are effective, hence we see different values of RMSE.

One of the most important things in the field of machine learning is data. This is a very influential factor in choosing the type of algorithm because if the number of data is large, some algorithms will not be able to evaluate correctly and logically. Also, on the other hand, time is one of the things that are of special importance for the user of machine learning and deep learning. If the number of data is large, the time that must be spent on data analysis increases. Therefore, it is very important to choose the right algorithm according to the size of the data.

Due to its special properties, many researchers recommend an artificial neural network as a suitable model for predicting target resistance. On the other hand, ANN needs a lot of time to perform the calculations to reach its final goal, and this is due to the repetition of the trial and error tuning process. Another weakness of ANN can be related to backpropagation. The error propagation algorithm uses a descending gradient to adjust the synaptic weights. The descending gradient algorithm moves in the direction of the negative slope of the error with one step (learning rate) to reach the optimal value. The optimal value is the point where the error slope is zero. Ideally, a minimum error can be achieved by determining an appropriate learning rate. In practical projects, however, determining the learning rate is challenging because if a low learning rate is chosen, the algorithm may get stuck in local minima (because the local

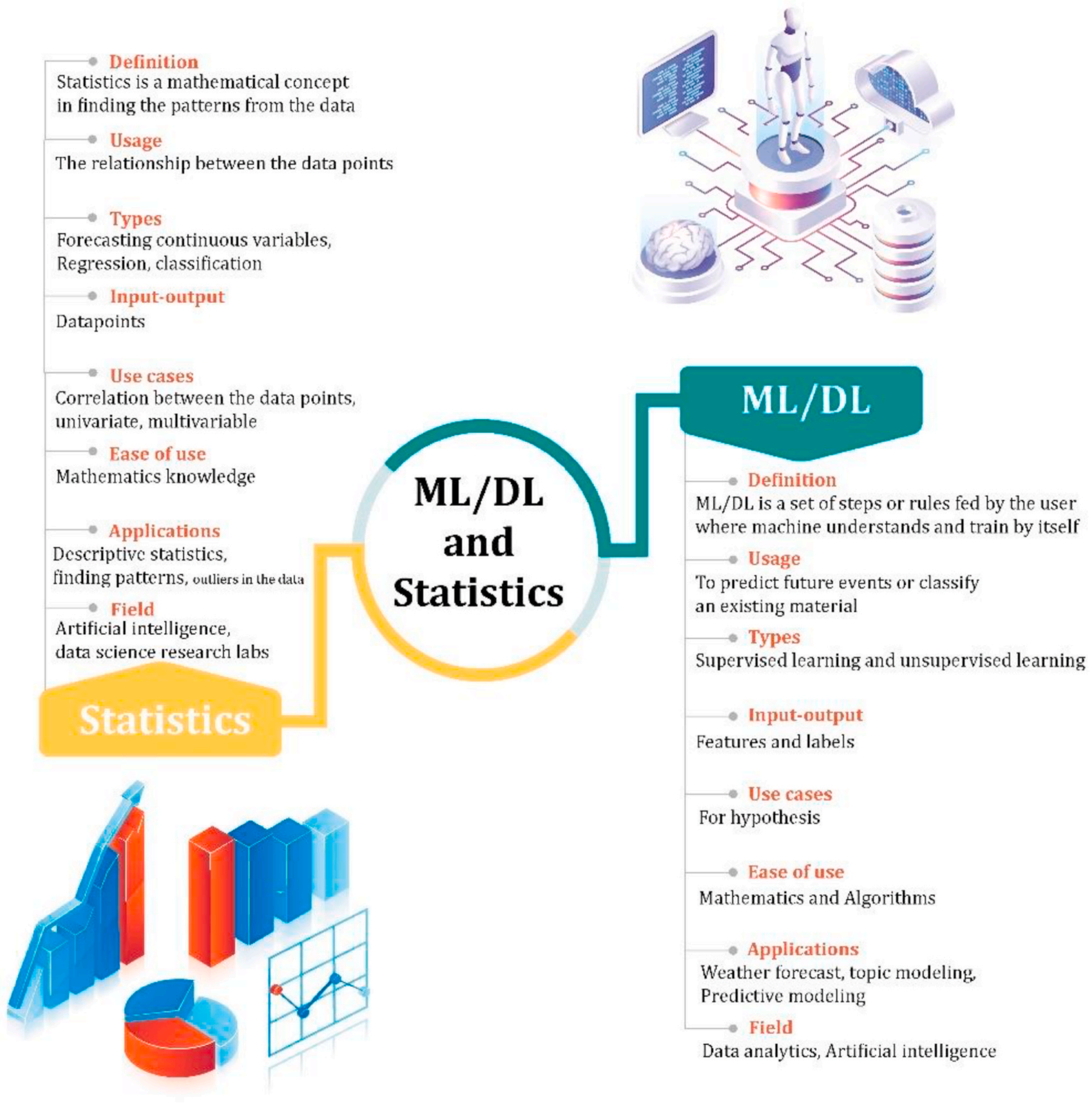

Fig. 18. A summary of comparing machine learning and deep learning models with experimental models.

Table 6
Results of ML/DL models and statistical models for predicting the mechanical properties of concrete.

Output	Model		Dataset size	R^2	MAE	MAPE	RMSE	Type of concrete
	Based on statistics	Based on ML/DL						
Compressive strength	Pereira et al. [238]		82			54.22	28.15	Recycled aggregate concrete
	Silva et al. [239]		Review of 235 papers (from 1978 to 2014)			7.81	34.66	Recycled aggregate concrete
	Gholampour et al. [240]		650			31.29	14.18	Recycled aggregate concrete
		ANN [134]	2817			15.13	7.71	Normal and high strength recycled aggregate concrete
Elastic modulus	Ravindrarajah and Tam [241]		104			17.85	5749.73	Concrete made with crushed concrete as coarse aggregate
	Bairagi et al. [134]		104			25.35	7584.52	Concrete with different proportions of natural and recycled aggregates
	Dhir 32 [242]		104			20.22	5848.93	Recycled aggregate concrete
	Kheder and AlWindawi [243]		172			17.44	6386.66	Natural and recycled aggregate concrete
	Lovato et al. [244]		204			68.51	21502.9	Recycled aggregate concrete
	Pereira et al. [238]		82			45.36	12365.1	Recycled aggregate concrete
	Gholampour et al. [240]		421			30.19	9287.91	Recycled aggregate concrete
		ANN [134]	421			11.21	4425.89	Normal and high strength recycled aggregate concrete
Elastic modulus	Xiao et al. [245]		104				6.17	Recycled aggregate concrete
	Kakizaki et al. [246]		33				4.51	Recycled aggregate concrete
	Ravindrarajah and Tam [241]		104				5.62	Concrete made with crushed concrete as coarse aggregate
	Bairagi et al. [247]		104				6.76	Concrete with different proportions of natural and recycled aggregates
	de Oliveira and Vazquez [248]		104				7.14	Recycled aggregate concrete
	Dillmann [249]		104				8.4	Recycled aggregate concrete
	Dhir [250]		104				5.15	Recycled aggregate concrete
	Tavakoli and Soroushian [251]		104				6.55	Recycled aggregate concrete made using field-demolished concrete as aggregate
	Pereira et al. [238]		82				10.54	Recycled aggregate concrete
	Wardeh et al. [252]		104				5.79	Recycled aggregate concrete
	Lovato et al. [244]		204				21.8	Recycled aggregate concrete
	Zilch and Roos [253]		84				3.1	Recycled aggregate concrete
	Kheder and Al-Windawi [243]		172				6.76	Natural and recycled aggregate concrete
	Rahal [254]		84				3.74	Concrete with recycled coarse aggregate
	Corinaldesi [254]		172				3.85	Concrete with recycled coarse aggregate
	Hoffmann et al. [255]		172				7.65	Recycled concrete and mixed rubble as aggregates
		GEP [240]	351				3.06	Recycled aggregate concrete
Flexural strength	Bairagi et al. [247]		19			11.53	0.61	Concrete with different proportions of natural and recycled aggregates
	Kheder and AlWindawi [243]		54			23.46	1.63	Natural and recycled aggregate concrete
	Silva et al. [256]		The collated data from several studies			20.45	1.29	Recycled aggregate concrete
	Gholampour et al. [240]		152			28.11	1.6	Recycled aggregate concrete
		ANN [134]	152			9.39	0.64	Normal and high strength recycled aggregate concrete
Flexural strength	Bairagi et al. [247]		19				0.73	

(continued on next page)

Table 6 (*continued*)

Output	Model		Dataset size	R^2	MAE	MAPE	RMSE	Type of concrete
	Based on statistics	Based on ML/DL						
								Concrete with different proportions of natural and recycled aggregates
	Tavakoli and Soroushian [251]		19				1.12	Recycled aggregate concrete made using field-demolished concrete as aggregate
	Kheder and Al-Windawi [243]		54				0.97	Natural and recycled aggregate concrete
		GEP [240]	118				0.52	Recycled aggregate concrete
Splitting tensile strength	Kheder and AlWindawi [243]		139			24.19	0.82	Natural and recycled aggregate concrete
	Xiao et al. [257]		109			22.75	0.75	Recycled aggregate concrete
	Lovato et al. [244]		149			78.05	2.55	Recycled aggregate concrete
	Pereira et al. [238]		58			14.65	0.72	Recycled aggregate concrete
	Silva et al. [256]		The collated data from several studies			36.66	1.14	Recycled aggregate concrete
	Gholampour et al. [240]		346			64.26	1.86	Recycled aggregate concrete
		ANN [134]	346			11.89	0.48	Normal and high strength recycled aggregate concrete
Splitting tensile strength	Xiao et al. [245]		109				0.52	Recycled aggregate concrete
	Tavakoli and Soroushian [251]		109				0.57	Recycled aggregate concrete made using field-demolished concrete as aggregate
	Pereira et al. [238]		58				0.78	Recycled aggregate concrete
	Xiao et al. [257]		109				0.67	Recycled aggregate concrete
	Lovato et al. [244]		149				2.5	Recycled aggregate concrete
	Kheder and Al-Windawi [243]		139				0.77	Natural and recycled aggregate concrete
		GEP [240]	307				0.51	Recycled aggregate concrete
Shear strength	El-Ghan-dour et al. (1999) [258]		–	0.85		28.86	188.94	FRP reinforced concrete
	El-Ghan-dour et al. (2000) [259]		–	0.9		17.07	151.27	Fiber reinforced polymers reinforced concrete flat slabs
	Matthys and Taerwe [260]		17	0.9		24.13	201.58	Concrete slabs reinforced with FRP grids
	Ospina et al. [261]		–	0.91		15.48	117.51	Steel and FRP-reinforced slab-column
		ANN [90]	82	0.96		12.86	62.29	FRP reinforced concrete slabs
Shear strength	Narayanan and Darwish [262]		49		0.670596	0.211633	0.9691	Steel fiber-reinforced concrete
	Ashour et al. [263]		18		0.773966	0.249592	1.111255	Steel fiber-reinforced concrete
	Kwak et al. [264]		139		0.523656	0.171122	0.716623	Steel fiber-reinforced concrete
	Yakoub [265]		72		1.036913	0.280306	1.673775	Steel fiber-reinforced concrete
	Khuntia et al. [266]		–		1.197633	0.359082	1.89627	Normal and high-strength fiber reinforced concrete
	Shahnewaz and Alam [266]		358		0.478787	0.157857	0.705898	Steel fiber-reinforced concrete
	Zhang et al. [267]		139		0.573344	0.211633	0.72441	Steel fiber-reinforced concrete
		SVR-FFA [80]	139		0.175995	0.249592	0.276813	Steel fiber-reinforced concrete
Shear strength	Khuntia et al. [266]		–	0.8972	1.5417		2.1557	Normal and high-strength fiber reinforced concrete
	Li et al. [268]		183	0.6169	1.1759		1.9308	Reinforced concrete
	kwak et al. (A) [264]		139	0.903	0.8038		1.6795	Steel fiber-reinforced concrete
	kwak et al. (B) [264]		139	0.889	0.9594		2.2906	Steel fiber-reinforced concrete
	Swamy et al. [269]		–	0.7458	1.5015		2.214	Steel fibre reinforced lightweight concrete
	Sharma [270]		–	0.5963	1.2135		2.0841	Steel fiber-reinforced concrete
	Narayanan and Darwish [262]		49	0.7946	1.3638		4	Steel fiber-reinforced concrete

(*continued on next page*)

Table 6 (*continued*)

Output	Model		Dataset size	R^2	MAE	MAPE	RMSE	Type of concrete
	Based on statistics	Based on ML/DL						
	Ashour et al. (A) [263]		18	0.75	1.2465		2.5579	Steel fiber-reinforced concrete
	Ashour et al. (B) [263]		18	0.8154	0.944		1.5691	Steel fiber-reinforced concrete
		MEP [233]	208	0.9063	0.5198		0.7333	Steel fiber-reinforced concrete
Shear strength	Narayanan and Darwish [262]		49		0.64		0.942	Steel fiber-reinforced concrete
	Ashour et al. [263]		18		0.737		1.079	Steel fiber-reinforced concrete
	Kwak et al. [264]		139		0.508		0.699	Steel fiber-reinforced concrete
	Yakoub [265]		72		1.033		1.693	Steel fiber-reinforced concrete
	Shama [270]		–		0.803		1.416	Steel fiber-reinforced concrete
	Khuntia et al. [266]		–		1.184		1.901	Normal and high-strength fiber reinforced concrete
	Shahnewaz and Alam [271]		358		0.461		0.688	Steel fiber-reinforced concrete
	Zhang et al. [267]		139		0.55		0.706	Steel fiber-reinforced concrete
		RSM + SVR [88]	139		0.186		0.233	Steel fiber-reinforced concrete
		RSM [88]	139		0.347		0.444	Steel fiber-reinforced concrete
		SVR [88]	139		0.622		1.04	Steel fiber-reinforced concrete
		ANN [88]	139		0.322		0.461	Steel fiber-reinforced concrete

minimum has properties similar to the original minimum, and in these areas, the error slope is zero. The algorithm mistakenly thinks that it has reached the optimal value). As a result, the network is not properly trained, or if a large learning rate is chosen, the network may fluctuate and become unstable and therefore not converged and trained.

ELM can thus be a suitable alternative to ANN because it can reduce the problem of convergence to local optima and does not require stopping criteria and learning rate [277]. Al-Shamiri et al. [147] compared the HSC compressive strength prediction by ELM and BP models and reported better ELM model results. However, they cited the number of optimal neurons in the hidden layer ELM network as a weakness. So that if the number of neurons in the hidden layer is too large, the ground for overfitting is created; as a result, the model has a very good accuracy of training data, but the generalizability of the data is not seen (testing) is incapable. Conversely, the model will have an underfitting problem if the number of optimal neurons in the hidden layer is low [278,279]. Because it is based on the empirical risk minimization (ERM) concept, the typical ELM may tend to yield an overfitting model, even if it is designed to deliver strong generalization performance at a fast learning speed [280–282]. To solve this problem, regularization is used in the ELM model [283]. Therefore, according to ridge regression theory [284], ELM is more stable and performs better generalizability [280, 283]. Al-Shamiri et al. [183] studied the performance of ELM and RELM models in predicting the compressive strength of HPC concrete. They reported better performance of RELM, an upgraded model of ELM.

To also solve the aforementioned problems, different ensemble and metaheuristic models can be used as alternative solutions. For example, Yuan et al. [204] predicted compressive strength by three algorithms ANN, GA-ANN, and ANFIS. To solve the BP-ANN problem, they used GA to optimize the weights and thresholds of BP-ANN to minimize the actual and target outputs and get the desired results. In another study, Erdal et al. [184] compared the predictive performance of ensemble models (including BANN, GBANN) and wavelet-ensemble models (including WBANN, WGBANN). Finally, they compared both groups with the standard ANN. This study showed that ensemble models show better results in predicting compressive strength and perform better than conventional ANN. Using a Discrete Wavelet Transform (DWT), they reported a significant increase in the accuracy of the ANN ensembles. The problem with ensemble models, however, can be attributed to the complexity of the model and, ultimately, the increase in computational time. Therefore, ANFIS models that use the combination of FL reasoning and ANN learning potential can provide another alternative.

Selecting membership functions and basic rules is one of the most difficult parts of creating fuzzy systems. On the other hand, implementing fuzzy logic in common hardware requires multiple time-consuming experiments. Unfortunately, the efficiency of fuzzy logic in pattern recognition is less than that of a neural network in machine learning. For this reason, it is less discussed in Data Science. In this regard, some researchers have used the combination of FL with artificial intelligence optimization techniques, such as ant

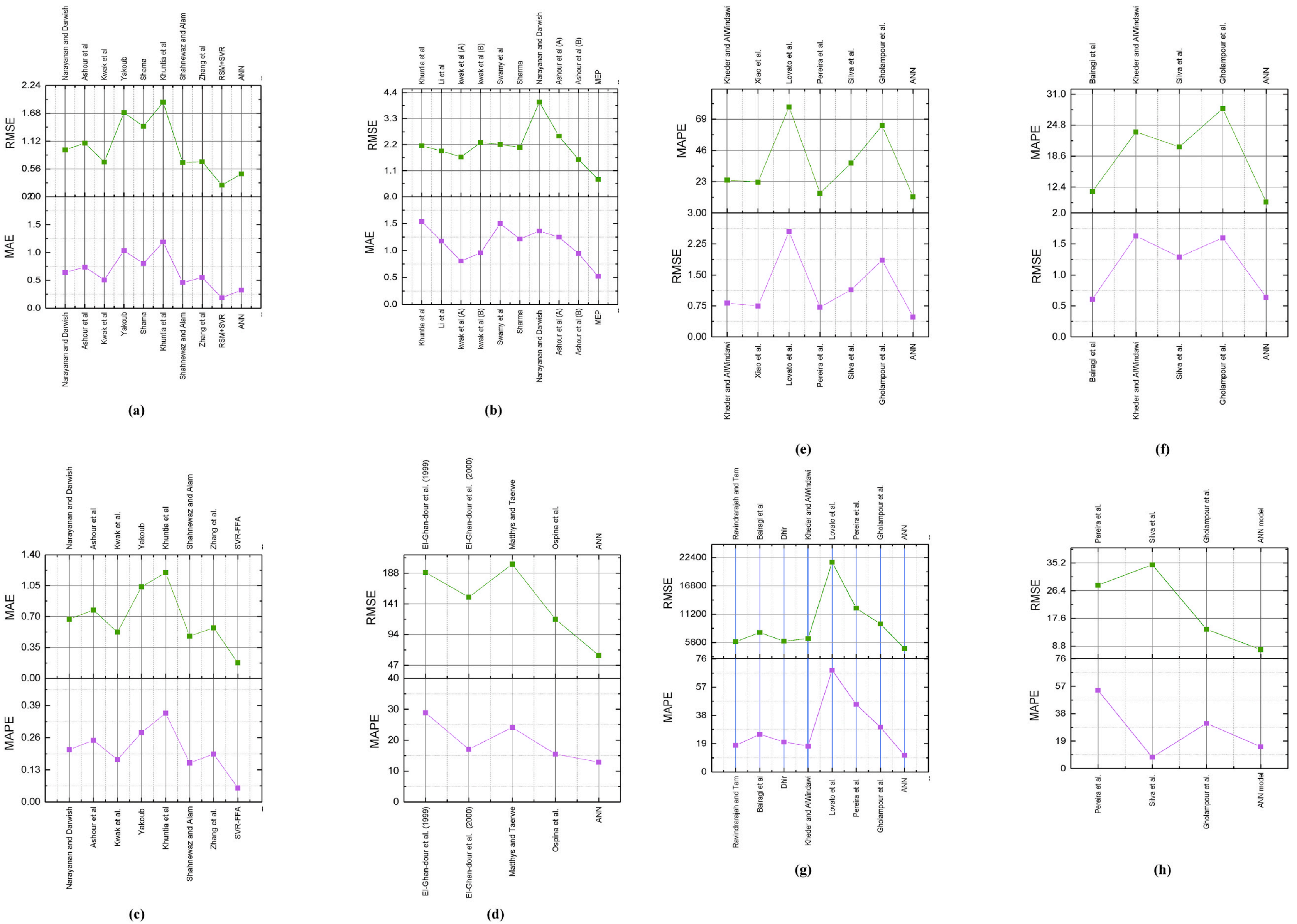

Fig. 19. Comparison of target resistance prediction by ML/DL models with statistical models: a) Shear strength (ANN), b) Shear strength (MEP), c) Shear strength (SVR-FFA), d) Shear strength (ANN), e) Tensile strength (ANN), f) Flexural strength (ANN), g) Elastic modulus (ANN), h) Compressive strength (ANN).

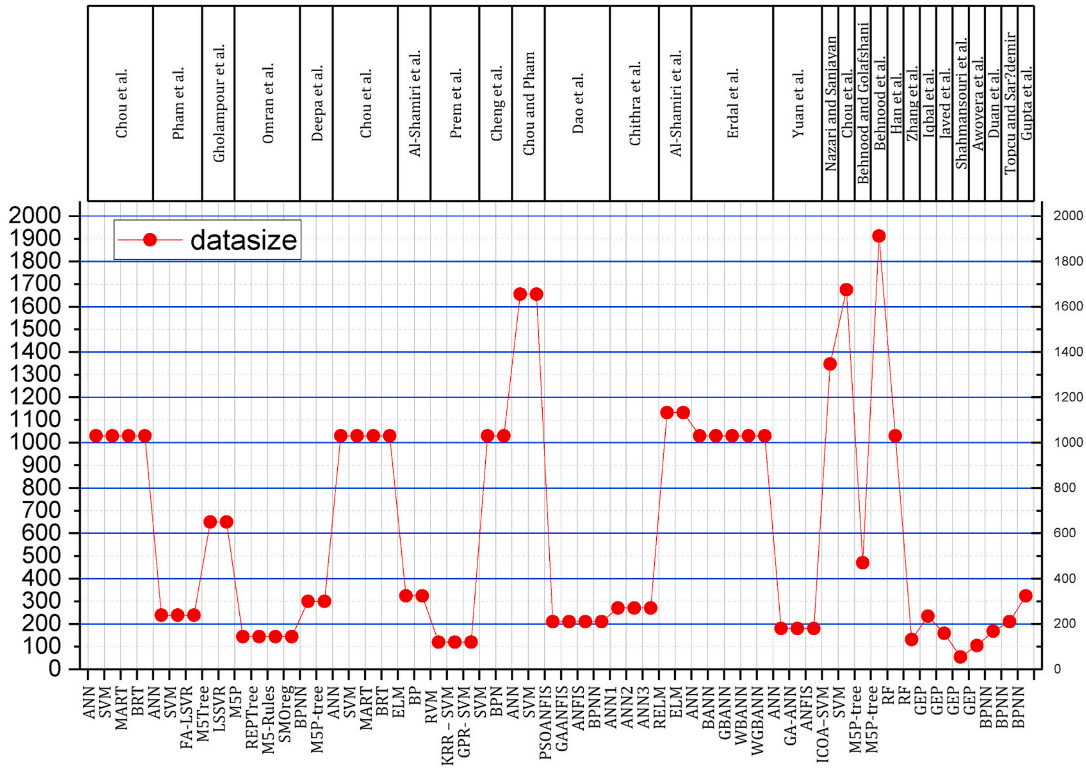

Fig. 20. Schematic representation of data size from different ML/DL models in predicting compressive strength.

colony and GA, to overcome the problems of fuzzy logic [285,286]. Therefore, optimization techniques have shown their ability to minimize time-consuming operations and the level of human intervention to optimize MFs and fuzzy rules. Dao et al. [168] predicted the compressive strength of geopolymer concrete by ANFIS and ANN models and reported better ANFIS performance according to the obtained statistical parameters. In a separate study, Dao et al. [228], In their study of two hybrid models (PSOANFIS and GAANFIS), concluded that PSOANFIS performed better. ANFIS, however, may suffer from network architecture design, fuzzy rule selection, weight and bias optimization, and the number of training samples that greatly affect model performance.

SVM has acceptable generalization and nonlinear mapping potential [89,96], but one of the weaknesses of the backup vector machine is its time-consuming approach to selecting the appropriate kernel function according to the test process. Omran et al. [93] also reported that although the advanced SMOreg data mining model has higher accuracy in forecasting than the other models in this study, the time required for building and training is significantly longer than the other models (M5P, REPTree, and M5-Rules). Therefore, this issue can be considered an important factor in choosing the right data mining model, especially when dealing with a large data set. Because ANN and SVM do not demonstrate the knowledge learned during training in a way that is comprehensible to humans, they are referred to as black-box models [127,287,288]. These models cannot provide an explicit formula for describing input and output variables, but EA or DT can be used to solve such a problem. Hence, EA and DT can describe the relationships between inputs and outputs by providing a clear mathematical formula. In addition, a review of studies in this area shows that ANN and SVM models (as combined and separate models) are more accurate than EA and DT [25,96,170]. On the other hand, the weaknesses of the DT models can be overcome by using alternative models such as MART, RF, and WSVM. Chou et al. [74] reported better performance of MART than other models (ANN, MR, SVM, BRT) in predicting compressive strength. They also noted that the ANN does not perform well in the training sector, as it requires 100 times more time in the training phase than other models. Ling and Wang [289] proposed WSVM as a modified model of SVM that can weigh all training data to allow different input points to participate in the learning decision surface. WSVM acts as a supervised learning tool to manage fuzzy input-output mapping and focus on time series data characteristics. In addition, the size of the data set used to develop the models varies from study to study. Studies that have considered fewer data samples may record accurate results. However, this model can show more errors when dealing with new data than those exposed to data from wider databases.

Table 7
RMSE value from different ML/DL models in predicting compressive strength.

Ref.	Models	RMSE	Dataset size	Ref.	Models	RMSE	Dataset size
Chou et al. [273]	ANN SVM MART BRT	5.0303 5.6192 4.9489 5.5720	1030 compressive strength	Omran et al. [93]	M5P REPTree M5-Rules SMOreg	3.8386 4.9233 4.0111 3.4967	144 compressive strength
Pham et al. [274]	ANN SVM FA-LSVR	6.74 6.07 4.86	239 compressive strength	Prem et al. [82]	RVM KRR – SVM GPR- SVM	3.29 1.02 0.96	120 compressive strength
Chithra et al. [132]	ANN1 ANN2 ANN3	2.1412 1.2315 1.0361	270 compressive strength	Yuan et al. [275]	ANN GA-ANN ANFIS	3.21 2.22 1.46	180 compressive strength
Gholampour et al. [87]	M5Tree LSSVR	8.3 7.7	650 compressive strength	Deepa et al. [121]	BPNN M5P-tree	9.9054 7.1874	300 compressive strength
Al-Shamiri et al. [147]	ELM BP	0.7998 0.9498	324 compressive strength	Cheng et al. [83]	SVM BPN	10.401 6.902	1030 compressive strength
Chou and Pham [276]	ANN SVM	6.329 6.911	1655 compressive strength	Dao et al. [228]	PSOANFIS GAANFIS	2.251 2.531	210 compressive strength
Dao et al. [168]	ANFIS BPNN	2.265 2.423	210 compressive strength	Al-Shamiri et al. [183]	RELM ELM	0.0771 0.1401	1133 compressive strength
Erdal et al. [184]	ANN	5.57	1030 compressive strength	Nazari and Sanjayan [81]	ICOA–SVM	3.8032	1347 compressive strength
	BANN	4.87		Chou et al. [45]	SVM	5.59	1675 compressive strength
	GBANN	5.24		Behnood and Golafshani [119]	M5P-tree	4.715	470 compressive strength
	WBANN	4.54		Behnood et al. [122]	M5P-tree	6.178	1912 compressive strength
	WGBANN	5.75		Han et al. [124]	RF	4.5444	1030 compressive strength
Iqbal et al. [219]	GEP	9	234 compressive strength	Zhang et al. [125]	RF	3.9021	131 compressive strength
Javed et al. [235]	GEP	4.57	159 compressive strength	Shahmansouri et al. [226]	GEP	4.238	54 compressive strength
Awoyera et al. [227]	GEP	3.33	105 compressive strength	Duan et al. [173]	BPNN	3.6804	168 compressive strength
Topcu and Sarıdemir [157]	BPNN	2.3948	210 compressive strength	Gupta et al. [176]	BPNN	0.03585 0.02865	324 compressive strength

4. Conclusions and recommendations

The present study investigated the performance of different ML/DL models to predict the mechanical properties of concrete. Among the wide range of ML/DL models, support vector machines, decision trees, evolutionary algorithms, and artificial neural networks were examined due to the popularity of these models as well as their frequent use in the field of civil engineering. Therefore, the performance of these models in various studies to evaluate the compressive strength, tensile strength, shear strength, flexural strength, and elastic modulus was evaluated. A comparison of experimental models with ML/DL methods shows that ML/DL models with better updating capability and the ability to analyze large datasets perform better. On the other hand, statistical models are not good for predicting complex structures due to their high cost and time-consuming nature. According to ML/DL methods, selecting the appropriate model for predicting the target strength of concrete should be made by considering different criteria. A review of various studies shows that the relationship between concrete components and mechanical strength is influential in choosing the forecasting model. Therefore, models that can respond in nonlinear space should be used if the relationship is nonlinear. In these cases, SVM and ANN models can be used for their acceptable performance in a non-linear environment with fewer errors. To achieve more accurate results, optimization of these models with metaheuristic algorithms can also be used. But if we need the transparency of the model and the explicit mathematical formula between input and output, we can use decision tree models and evolutionary algorithms. On the other hand, the use of ensemble models to optimize these models, although it results in higher accuracy, increases computation time and model complexity. The combined SVM and ANN models, although they increase the computation time, have accurate results in the

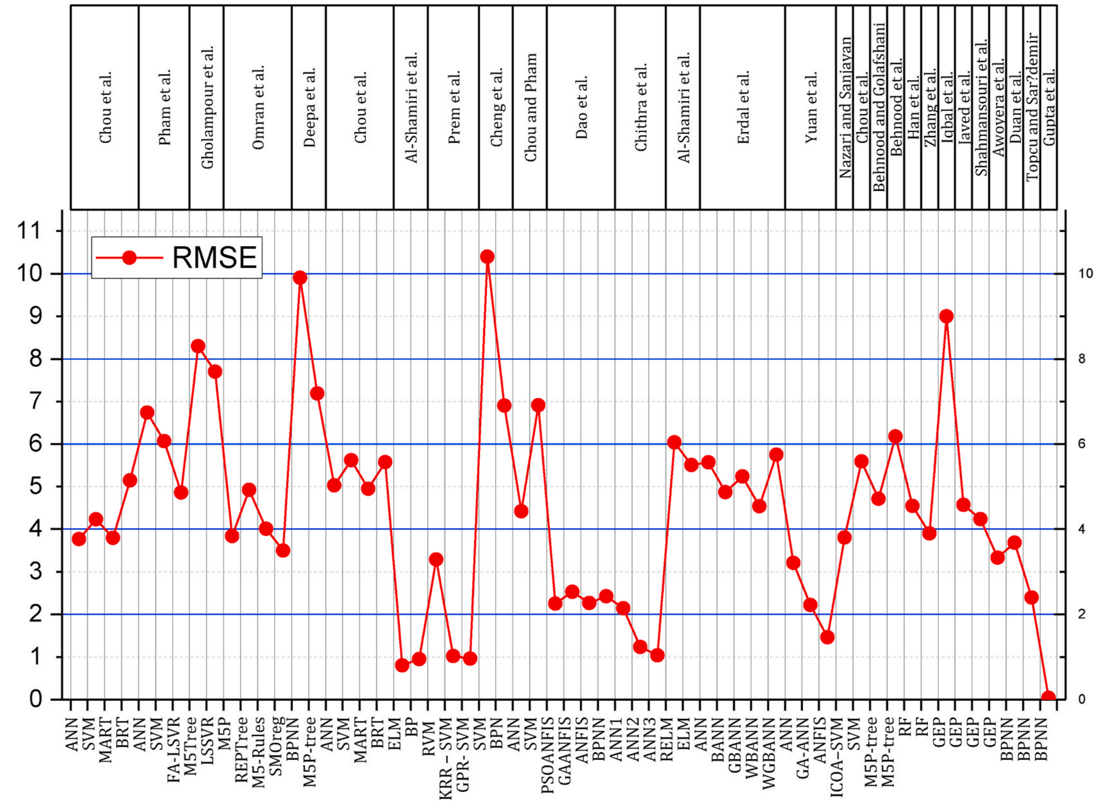

Fig. 21. Schematic representation of RMSE results from different ML/DL models in predicting compressive strength.

face of extensive data. Therefore, based on the study, the best option for predicting the strength of concrete in terms of model accuracy and model implementation is the combined use of SVM and ANN combined models.

In terms of concrete science, limited studies have been conducted in the field of identifying the capabilities of geopolymer concrete, engineered cementitious composite, self-healing concrete, nano-containing concrete, and self-compacting concrete, which researchers can examine in future studies.

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.

Data availability

No data was used for the research described in the article.

Nomenclature

AAD	Average Absolute Deviation
AAE	Average Absolute Error
ABCP	Artificial Bee Colony Programming
ABS	Absolute error
a/c	Aggregate-to-cement ratio
ACI, EC2, CSA, NR, NZS	Building codes
AI	Artificial Intelligence
ß	A correction factor
BANN	Bagged Artificial Neural Networks
BAS	Beetle Antennae Search
BBP	Biogeography-Based Programming
BPNN	Back-Propagation Neural Network

COA	Cuckoo Optimization Algorithm
COV	coefficient of variation
DL	Deep Learning
E	Adjusted coefficient of efficiency
EA	Evolutionary Algorithms
EFSIMT	Evolutionary Fuzzy Support Vector Machine Inference Model for Time Series Data
ELM	Extreme Learning Machine
FFA	Firefly Algorithm
FL	Fuzzy Logic
GA	Genetic Algorithm
GAANFIS	A genetic algorithm (GA)-based adaptive network-based fuzzy inference system (GAANFIS)
GBANN	Gradient Boosted Artificial Neural Networks
GP	Genetic Programming
GWO	Grey Wolf Optimizer
HANNMOGW	Hybrid Artificial Neural Network with Multi-Objective Grey Wolves
L1QP	L1 soft-margin minimization by quadratic programming
LGP	Linear Genetic Programming
LSSVM	Least Squares support Vector Machines
m	The number of instances that do not have missing values for this attribute
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MART	Multiple Additive Regression Trees
ME	Mean Error
MEP	Multi-Expression Programming
MFA	Modified Firefly Algorithm
ML	Machine Learning
MOGWO	Multi-Objective Grey Wolves Optimization
MRE	Mean Relative Error
MSE	Mean Square Error
NSE	Nash–Sutcliffe efficiency
P	Pearson coefficient of correlation
PSO	Particle Swarm Optimization
PSOANFIS	A particle swarm optimization (PSO)-based adaptive network-based fuzzy inference system (PSOANFIS)
ρ_{RCA}	Bulk density of recycled concrete aggregate
R	Coefficient of correlation
R^2	Coefficient of determination
RAE	Relative Absolute Error
RAC	Recycled Aggregate Concrete
RBFNN	Radial Basis Function Neural Network
RCA%	Coarse recycled concrete aggregate replacement ratio
RE	Relative Error
RELM	Regularized Extreme Learning Machine
RF	Random Forest
RMSE	Root Mean Square Error
RMSRE	Root-Mean-Square Relative Error
RRMSE	Relative RMSE
RRSE	Root Relative Squared Error
RSE	Relative Squared Error
RVM	Relevance Vector Machine
SDR	Standard Deviation Reduction
SI	Scatter Index
SRL	Slope of Regression Line
SSE	Sum of Squared Errors
std.ABS	The standard error of the mean value of the ABS
std.MSE	The standard error of the mean value of the MSE
SVM	Support Vector Machine
SVR	Support Vector Regression
T	The series of instances that reach the node
T_L & T_R	Sets that arise from the division on this attribute
WA_{RCA}	Water absorption of coarse recycled concrete aggregate
w_{eff}/c	Effective water-to-cement ratio

References

[1] D.C. Feng, Z.T. Liu, X.D. Wang, Y. Chen, J.Q. Chang, D.F. Wei, Z.M. Jiang, Machine learning-based compressive strength prediction for concrete: an adaptive boosting approach, Construct. Build. Mater. 230 (2020), 117000, https://doi.org/10.1016/j.conbuildmat.2019.117000.
[2] F.K. Alqahtani, I. Zafar, Characterization of processed lightweight aggregate and its effect on physical properties of concrete, Construct. Build. Mater. 230 (2020), 116992, https://doi.org/10.1016/j.conbuildmat.2019.116992.
[3] A.G. Khoshkenari, P. Shafigh, M. Moghimi, H. Bin Mahmud, The role of 0-2mm fine recycled concrete aggregate on the compressive and splitting tensile strengths of recycled concrete aggregate concrete, Mater. Des. 64 (2014) 345–354, https://doi.org/10.1016/j.matdes.2014.07.048.
[4] A. Mansoori, M. Mohtasham Moein, E. Mohseni, Effect of micro silica on fiber-reinforced self-compacting composites containing ceramic waste, J. Compos. Mater. 1 (2020), https://doi.org/10.1177/0021998320944570.
[5] B. Tahmouresi, P. Nemati, M.A. Asadi, A. Saradar, M. Mohtasham Moein, Mechanical strength and microstructure of engineered cementitious composites: a new configuration for direct tensile strength, experimental and numerical analysis, Construct. Build. Mater. 269 (2021), https://doi.org/10.1016/j.conbuildmat.2020.121361.
[6] M. Nili, V. Afroughsabet, Combined effect of silica fume and steel fi bers on the impact resistance and mechanical properties of concrete, Int. J. Impact Eng. 37 (2010) 879–886, https://doi.org/10.1016/j.ijimpeng.2010.03.004.
[7] M.C. Nataraja, N. Dhang, A.P. Gupta, Statistical variations in impact resistance of steel fiber-reinforced concrete subjected to drop weight test, Cement Concr. Res. 29 (1999) 989–995, https://doi.org/10.1016/S0008-8846(99)00052-6.
[8] P.S. Song, J.C. Wu, S. Hwang, B.C. Sheu, Assessment of statistical variations in impact resistance of high-strength concrete and high-strength steel fiber-reinforced concrete, Cement Concr. Res. 35 (2005) 393–399.
[9] A. Hatami Shirkouh, A. Soliman, Rubberized alkali-activated concrete—a review, Springer Nat. Singapore, Proc. Can. Soc. Civ. Eng. Annu. Conf. (2021) 2022, https://www.springerprofessional.de/en/rubberized-alkali-activated-concrete-a-review/22835846.
[10] D. Feng, J. Li, Stochastic nonlinear behavior of reinforced concrete frames. II: numerical simulation, J. Struct. Eng. (United States). 142 (2016), https://doi.org/10.1061/(ASCE)ST.1943-541X.0001443.
[11] D. Feng, X. Ren, J. Li, Stochastic damage hysteretic model for concrete based on micromechanical approach, Int. J. Non Lin. Mech. 83 (2016), https://doi.org/10.1016/j.ijnonlinmec.2016.03.012.
[12] P. Chopra, R.K. Sharma, M. Kumar, T. Chopra, Comparison of machine learning techniques for the prediction of compressive strength of concrete, Adv. Civ. Eng. (2018), https://doi.org/10.1155/2018/5481705, 2018.
[13] P.H. Bischoff, S.H. Perry, Compressive behaviour of concrete at high strain rates, Mater. Struct. 24 (1991) 425–450, https://doi.org/10.1007/BF02472016.
[14] H. sheng Shi, B. wan Xu, X. chen Zhou, Influence of mineral admixtures on compressive strength, gas permeability and carbonation of high performance concrete, Construct. Build. Mater. 23 (2009), https://doi.org/10.1016/j.conbuildmat.2008.08.021.
[15] M.F.M. Zain, S.M. Abd, Multiple regression model for compressive strength prediction of high performance concrete, J. Appl. Sci. 9 (2009), https://doi.org/10.3923/jas.2009.155.160.
[16] B.H. Bharatkumar, R. Narayanan, B.K. Raghuprasad, D.S. Ramachandramurthy, Mix proportioning of high performance concrete, Cem. Concr. Compos. 23 (2001), https://doi.org/10.1016/S0958-9465(00)00071-8.
[17] S. Bhanja, B. Sengupta, Investigations on the compressive strength of silica fume concrete using statistical methods, Cement Concr. Res. 32 (2002), https://doi.org/10.1016/S0008-8846(02)00787-1.
[18] J. Oliver, A.E. Huespe, E. Samaniego, E.W.V. Chaves, Continuum approach to the numerical simulation of material failure in concrete, Int. J. Numer. Anal. Methods GeoMech. 28 (2004), https://doi.org/10.1002/nag.365.
[19] D.C. Feng, S.C. Xie, W.N. Deng, Z.D. Ding, Probabilistic failure analysis of reinforced concrete beam-column sub-assemblage under column removal scenario, Eng. Fail. Anal. 100 (2019), https://doi.org/10.1016/j.engfailanal.2019.02.004.
[20] D.C. Feng, Z. Wang, G. Wu, Progressive collapse performance analysis of precast reinforced concrete structures, Struct. Des. Tall Special Build. 28 (2019), https://doi.org/10.1002/tal.1588.
[21] P. Lu, S. Chen, Y. Zheng, Artificial intelligence in civil engineering, 2012, Math. Probl Eng. (2012) 1–23, https://doi.org/10.1155/2012/145974.
[22] C. Ley, S.P.A. Bordas, What makes data science different? A discussion involving Statistics2.0 and computational sciences, Int. J. Data Sci. Anal. 6 (2018), https://doi.org/10.1007/s41060-017-0090-x.
[23] H. Salehi, R. Burgueño, Emerging artificial intelligence methods in structural engineering, Eng. Struct. 171 (2018), https://doi.org/10.1016/j.engstruct.2018.05.084.
[24] Q. Liu, P. Sun, X. Fu, J. Zhang, H. Yang, H. Gao, Y. Li, Comparative analysis of BP neural network and RBF neural network in seismic performance evaluation of pier columns, Mech. Syst. Signal Process. 141 (2020), https://doi.org/10.1016/j.ymssp.2020.106707.
[25] A. Behnood, K.P. Verian, M. Modiri Gharehveran, Evaluation of the splitting tensile strength in plain and steel fiber-reinforced concrete based on the compressive strength, Construct. Build. Mater. 98 (2015), https://doi.org/10.1016/j.conbuildmat.2015.08.124.
[26] D. Dutta, S.V. Barai, Prediction of compressive strength of concrete: machine learning approaches, in: Lect, Notes Civ. Eng., 2019, https://doi.org/10.1007/978-981-13-0362-3_40.
[27] X. Jiang, S. Mahadevan, H. Adeli, Bayesian wavelet packet denoising for structural system identification, Struct. Control Health Monit. 14 (2007), https://doi.org/10.1002/stc.161.
[28] O. Abdeljaber, O. Avci, D.J. Inman, Active vibration control of flexible cantilever plates using piezoelectric materials and artificial neural networks, J. Sound Vib. 363 (2016), https://doi.org/10.1016/j.jsv.2015.10.029.
[29] S. Russel, P. Norvig, Artificial Intelligence—A Modern Approach, third ed., 2012, https://doi.org/10.1017/S0269888900007724.
[30] D.L. Poole, A. Mackworth, R.G. Goebel, Computational intelligence and knowledge, Comput. Intell. A Log. Approach. (1998).
[31] A. Kaplan, M. Haenlein, Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence, Bus. Horiz. 62 (2019), https://doi.org/10.1016/j.bushor.2018.08.004.
[32] A.M. Turing, Computing machinery and intelligence, in: Mach. Intell. Perspect. Comput. Model, 2012, https://doi.org/10.7551/mitpress/6928.003.0012.
[33] M. Haenlein, A. Kaplan, A brief history of artificial intelligence: on the past, present, and future of artificial intelligence, Calif. Manag. Rev. 61 (2019) 5–14, https://doi.org/10.1177/0008125619864925.
[34] L. Deng, D. Yu, Deep learning: methods and applications, found, Trends Signal Process 7 (2013), https://doi.org/10.1561/2000000039.
[35] J.E. (James E. Tomayko, Behind deep blue: building the computer that defeated the world chess champion (review), Technol. Cult. 44 (2003), https://doi.org/10.1353/tech.2003.0140.
[36] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, D.J. Inman, A review of vibration-based damage detection in civil structures: from traditional methods to Machine Learning and Deep Learning applications, Mech. Syst. Signal Process. 147 (2021), 107077, https://doi.org/10.1016/j.ymssp.2020.107077.
[37] Z. Ghahramani, Probabilistic machine learning and artificial intelligence, Nature 521 (2015), https://doi.org/10.1038/nature14541.
[38] A.C. Müller, S. Guido, Introduction to Machine Learning with Python: a Guide for Data Scientists, 2016, https://doi.org/10.1017/CBO9781107415324.004.
[39] C. Rosental, Certifying knowledge: the sociology of a logical theorem in artificial intelligence, Am. Socio. Rev. 68 (2003), https://doi.org/10.2307/1519742.
[40] P. Langley, The changing science of machine learning, Mach. Learn. 82 (2011) 275–279, https://doi.org/10.1007/s10994-011-5242-y.
[41] T.G. Dietterich, Ensemble methods in machine learning, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) (2000), https://doi.org/10.1007/3-540-45014-9_1.
[42] A. Marani, M.L. Nehdi, Machine learning prediction of compressive strength for phase change materials integrated cementitious composites, Construct. Build. Mater. 265 (2020), 120286, https://doi.org/10.1016/j.conbuildmat.2020.120286.

[43] J.P. Huelsenbeck, F. Ronquist, R. Nielsen, J.P. Bollback, Bayesian inference of phylogeny and its impact on evolutionary biology, Science (80-.) (2001) 294, https://doi.org/10.1126/science.1065889.
[44] F. Deng, Y. He, S. Zhou, Y. Yu, H. Cheng, X. Wu, Compressive strength prediction of recycled concrete based on deep learning, Construct. Build. Mater. 175 (2018) 562–569, https://doi.org/10.1016/j.conbuildmat.2018.04.169.
[45] J.S. Chou, C.F. Tsai, A.D. Pham, Y.H. Lu, Machine learning in concrete strength simulations: multi-nation data analytics, Construct. Build. Mater. 73 (2014) 771–780, https://doi.org/10.1016/j.conbuildmat.2014.09.054.
[46] R. Bekkerman, M. Bilenko, J. Langford, Scaling up machine learning: Introduction, in: Scaling up Mach. Learn. Parallel Distrib. Approaches, 2011, https://doi.org/10.1017/CBO9781139042918.002.
[47] M. Kanevski, A. Pozdnoukhov, V. Timonin, Machine Learning for Spatial Environmental Data: Theory, Applications and Software, 2009, https://doi.org/10.1201/9781439808085.
[48] K.P. Murphy, Machine Learning - A Probabilistic Perspective - Table-Of-Contents, MIT Press, 2012, https://doi.org/10.1038/217994a0.
[49] S. Marsland, Machine Learning: an Algorithmic Perspective, 2014, https://doi.org/10.1201/b17476.
[50] T. Mitchell, Chapther 06, Mach. Learn, 1997, https://doi.org/10.1007/s10994-009-5101-2.
[51] W.Z. Taffese, E. Sistonen, Machine learning for durability and service-life assessment of reinforced concrete structures: recent advances and future directions, Autom. ConStruct. 77 (2017) 1–14, https://doi.org/10.1016/j.autcon.2017.01.016.
[52] S. Parsons, Introduction to machine learning, MIT Press, in: Second Editon by Ethem Alpaydin, 25, 2010, p. 584, https://doi.org/10.1017/s0269888910000056. $55.00. ISBN 978-0-262-01243-0, Knowl. Eng. Rev..
[53] M. Ivanović, M. Radovanović, Modern machine learning techniques and their applications, in: Electron. Commun. Networks IV - Proc, CECNet2014, 4th Int. Conf. Electron. Commun. Networks, 2015, https://doi.org/10.1201/b18592-153.
[54] W.Z. Taffese, E. Sistonen, J. Puttonen, CaPrM, Carbonation prediction model for reinforced concrete using machine learning methods, Construct. Build. Mater. 100 (2015) 70–82, https://doi.org/10.1016/j.conbuildmat.2015.09.058.
[55] L. Rokach, O. Maimon, in: second ed.Data Mining with Decision Trees Theory and Applications, 2012. 66 .עלון הנוטע.
[56] S. da Silva, M. Dias Júnior, V. Lopes Junior, M.J. Brennan, Structural damage detection by fuzzy clustering, Mech. Syst. Signal Process. 22 (2008), https://doi.org/10.1016/j.ymssp.2008.01.004.
[57] X. Wang, X. Xie, T.C.E. Cheng, A modified artificial bee colony algorithm for order acceptance in two-machine flow shops, Int. J. Prod. Econ. 141 (2013), https://doi.org/10.1016/j.ijpe.2012.06.003.
[58] A.A. Shahmansouri, H. Akbarzadeh Bengar, S. Ghanbari, Compressive strength prediction of eco-efficient GGBS-based geopolymer concrete using GEP method, J. Build. Eng. 31 (2020), https://doi.org/10.1016/j.jobe.2020.101326.
[59] A.A. Freitas, A review of evolutionary algorithms for data mining, in: Soft Comput. Knowl. Discov, . Data Min., 2008, https://doi.org/10.1007/978-0-387-69935-6_4.
[60] M. Baioletti, G. Di Bari, A. Milani, V. Poggioni, Differential evolution for neural networks optimization, Mathematics 8 (2020), https://doi.org/10.3390/math8010069.
[61] P.A. Vikhar, Evolutionary algorithms: a critical review and its future prospects, Proc. - Int. Conf. Glob. Trends Signal Process. Inf. Comput. Commun. ICGTSPICC (2017) 261–265, https://doi.org/10.1109/ICGTSPICC.2016.7955308, 2016.
[62] L. Deng, D. Yu, Deep Learning, (n.d.) 3–4.
[63] Y. Bengio, Learning deep architectures for AI, Found. Trends Mach. Learn. 2 (2009), https://doi.org/10.1561/2200000006.
[64] J. Schmidhuber, Deep Learning in neural networks: an overview, Neural Network. 61 (2015), https://doi.org/10.1016/j.neunet.2014.09.003.
[65] I. Goodfellow, Y. Bengio, A. Courville, Deep Learning - whole book, Nature 521 (2016) 800, https://doi.org/10.1038/nmeth.3707.
[66] W.C. Hong, P.F. Pai, Potential assessment of the support vector regression technique in rainfall forecasting, Water Resour. Manag. 21 (2007), https://doi.org/10.1007/s11269-006-9026-2.
[67] A. Zendehboudi, M.A. Baseer, R. Saidur, Application of support vector machine models for forecasting solar and wind energy resources: a review, J. Clean. Prod. 199 (2018) 272–285, https://doi.org/10.1016/j.jclepro.2018.07.164.
[68] M. Martínez-Rojas, N. Marin, M. Amparo Vila, The role of information technologies to address data handling in construction project management, J. Comput. Civ. Eng. 30 (2012) 1–11, https://doi.org/10.1061/(ASCE)CP.1943-5487.
[69] M. Behzad, K. Asghari, E.A. Coppola, Comparative study of SVMs and ANNs in aquifer water level prediction, J. Comput. Civ. Eng. 24 (2010), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000043.
[70] Y. Tian, M. Fu, F. Wu, Steel plates fault diagnosis on the basis of support vector machines, Neurocomputing 151 (2015), https://doi.org/10.1016/j.neucom.2014.09.036.
[71] D. Tao, X. Tang, X. Wu, Asymmetric bagging and random subspace for support vector machines-based relevance feedback in image retrieval, IEEE Trans. Pattern Anal. Mach. Intell. 28 (2006), https://doi.org/10.1109/TPAMI.2006.134.
[72] K.I. Kim, K. Jung, S.H. Park, H.J. Kim, Support vector machine-based text detection in digital video, Pattern Recogn. 34 (2001), https://doi.org/10.1016/S0031-3203(00)00095-9.
[73] M.A. DeRousseau, J.R. Kasprzyk, W.V. Srubar, Computational design optimization of concrete mixtures: a review, Cement Concr. Res. 109 (2018), https://doi.org/10.1016/j.cemconres.2018.04.007.
[74] J.S. Chou, C.K. Chiu, M. Farfoura, I. Al-Taharwa, Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data-mining techniques, J. Comput. Civ. Eng. 25 (2011), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000088.
[75] W. Ben Chaabene, M. Flah, M.L. Nehdi, Machine learning prediction of mechanical properties of concrete: critical review, Construct. Build. Mater. 260 (2020), 119889, https://doi.org/10.1016/j.conbuildmat.2020.119889.
[76] J.A.K. Suykens, J. Vandewalle, Least squares support vector machine classifiers, Neural Process. Lett. 9 (1999), https://doi.org/10.1023/A:1018628609742.
[77] M. Jalal, P. Arabali, Z. Grasley, J.W. Bullard, H. Jalal, Behavior assessment, regression analysis and support vector machine (SVM) modeling of waste tire rubberized concrete, J. Clean. Prod. 273 (2020), 122960, https://doi.org/10.1016/j.jclepro.2020.122960.
[78] M.R. Kaloop, A.R. Gabr, S.M. El-Badawy, A. Arisha, S. Shwally, J.W. Hu, Predicting resilient modulus of recycled concrete and clay masonry blends for pavement applications using soft computing techniques, Front. Struct. Civ. Eng. 13 (2019) 1379–1392, https://doi.org/10.1007/s11709-019-0562-2.
[79] J.S. Chou, N.T. Ngo, A.D. Pham, Shear strength prediction in reinforced concrete deep beams using nature-inspired metaheuristic support vector regression, J. Comput. Civ. Eng. 30 (2016) 1–9, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000466.
[80] A.A. Al-Musawi, A.A.H. Alwanas, S.Q. Salih, Z.H. Ali, M.T. Tran, Z.M. Yaseen, Shear strength of SFRCB without stirrups simulation: implementation of hybrid artificial intelligence model, Eng. Comput. 36 (2020), https://doi.org/10.1007/s00366-018-0681-8.
[81] A. Nazari, J.G. Sanjayan, Modelling of compressive strength of geopolymer paste, mortar and concrete by optimized support vector machine, Ceram. Int. 41 (2015) 12164–12177, https://doi.org/10.1016/j.ceramint.2015.06.037.
[82] P.R. Prem, A. Thirumalaiselvi, M. Verma, Applied linear and nonlinear statistical models for evaluating strength of Geopolymer concrete, Comput. Concr. 24 (2019) 7–17, https://doi.org/10.12989/cac.2019.24.1.007.
[83] M.Y. Cheng, J.S. Chou, A.F.V. Roy, Y.W. Wu, High-performance concrete compressive strength prediction using time-weighted evolutionary fuzzy support vector machines inference model, Autom. ConStruct. 28 (2012) 106–115, https://doi.org/10.1016/j.autcon.2012.07.004.
[84] K. Yan, C. Shi, Prediction of elastic modulus of normal and high strength concrete by support vector machine, Construct. Build. Mater. 24 (2010) 1479–1485, https://doi.org/10.1016/j.conbuildmat.2010.01.006.
[85] P. Yuvaraj, A. Ramachandra Murthy, N.R. Iyer, S.K. Sekar, P. Samui, Support vector regression based models to predict fracture characteristics of high strength and ultra high strength concrete beams, Eng. Fract. Mech. 98 (2013) 29–43, https://doi.org/10.1016/j.engfracmech.2012.11.014.
[86] B.G. Aiyer, D. Kim, N. Karingattikkal, P. Samui, P.R. Rao, Prediction of compressive strength of self-compacting concrete using least square support vector machine and relevance vector machine, KSCE J. Civ. Eng. 18 (2014) 1753–1758, https://doi.org/10.1007/s12205-014-0524-0.

[87] A. Gholampour, I. Mansouri, O. Kisi, T. Ozbakkaloglu, Evaluation of mechanical properties of concretes containing coarse recycled concrete aggregates using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression (LSSVR) models, Neural Comput. Appl. 32 (2020) 295–308, https://doi.org/10.1007/s00521-018-3630-y.

[88] B. Keshtegar, M. Bagheri, Z.M. Yaseen, Shear strength of steel fiber-unconfined reinforced concrete beam simulation: application of novel intelligent model, Compos. Struct. 212 (2019) 230–242, https://doi.org/10.1016/j.compstruct.2019.01.004.

[89] R.A. Mozumder, B. Roy, A.I. Laskar, Support vector regression approach to predict the strength of FRP confined concrete, Arabian J. Sci. Eng. 42 (2017) 1129–1146, https://doi.org/10.1007/s13369-016-2340-y.

[90] D.T. Vu, N.D. Hoang, Punching shear capacity estimation of FRP-reinforced concrete slabs using a hybrid machine learning approach, Struct. Infrastruct. Eng. 12 (2016) 1153–1161, https://doi.org/10.1080/15732479.2015.1086386.

[91] H. Tanyildizi, Prediction of the strength properties of carbon fiber-reinforced lightweight concrete exposed to the high temperature using artificial neural network and support vector machine, Adv. Civ. Eng. (2018), https://doi.org/10.1155/2018/5140610, 2018.

[92] A.L. Bonifácio, J.C. Mendes, M.C.R. Farage, F.S. Barbosa, C.B. Barbosa, A.L. Beaucour, Application of support vector machine and finite element method to predict the mechanical properties of concrete, Lat. Am. J. Solid. Struct. 16 (2019) 1–11, https://doi.org/10.1590/1679-78255297.

[93] B.A. Omran, Q. Chen, R. Jin, Comparison of data mining techniques for predicting compressive strength of environmentally friendly concrete, J. Comput. Civ. Eng. 30 (2016) 1–13, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000596.

[94] Z.M. Yaseen, R.C. Deo, A. Hilal, A.M. Abd, L.C. Bueno, S. Salcedo-Sanz, M.L. Nehdi, Predicting compressive strength of lightweight foamed concrete using extreme learning machine model, Adv. Eng. Software 115 (2018) 112–125, https://doi.org/10.1016/j.advengsoft.2017.09.004.

[95] A.D. Pham, N.D. Hoang, Q.T. Nguyen, Predicting compressive strength of high-performance concrete using metaheuristic-optimized least squares support vector regression, J. Comput. Civ. Eng. 30 (2016), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000506.

[96] Y. Yu, W. Li, J. Li, T.N. Nguyen, A novel optimised self-learning method for compressive strength prediction of high performance concrete, Construct. Build. Mater. 184 (2018) 229–247, https://doi.org/10.1016/j.conbuildmat.2018.06.219.

[97] Mohammad Mohtasham, A. Soliman Moein, Predicting the compressive strength of alkali-activated concrete using various data mining methods, Springer Nat. Singapore, Springer Nature Singapore, https://www.springerprofessional.de/en/predicting-the-compressive-strength-of-alkali-activated-concrete/22835800, 2022.

[98] C.Y. Fan, P.C. Chang, J.J. Lin, J.C. Hsieh, A hybrid model combining case-based reasoning and fuzzy decision tree for medical data classification, Appl. Soft Comput. J. 11 (2011), https://doi.org/10.1016/j.asoc.2009.12.023.

[99] K.Y. Tung, I.C. Huang, S.L. Chen, C.T. Shih, Mining the Generation Xers' job attitudes by artificial neural network and decision tree - empirical evidence in Taiwan, Expert Syst. Appl. 29 (2005), https://doi.org/10.1016/j.eswa.2005.06.012.

[100] Z. Yu, F. Haghighat, B.C.M. Fung, H. Yoshino, A decision tree method for building energy demand modeling, Energy Build. 42 (2010) 1637–1646, https://doi.org/10.1016/j.enbuild.2010.04.006.

[101] K. Khosravi, B.T. Pham, K. Chapi, A. Shirzadi, H. Shahabi, I. Revhaug, I. Prakash, D. Tien Bui, A comparative assessment of decision trees algorithms for flash flood susceptibility modeling at Haraz watershed, northern Iran, Sci. Total Environ. 627 (2018), https://doi.org/10.1016/j.scitotenv.2018.01.266.

[102] J. Wang, P. Li, R. Ran, Y. Che, Y. Zhou, A short-term photovoltaic power prediction model based on the Gradient Boost Decision Tree, Appl. Sci. 8 (2018), https://doi.org/10.3390/app8050689.

[103] B. Thai Pham, D. Tien Bui, I. Prakash, Landslide susceptibility modelling using different advanced decision trees methods, Civ. Eng. Environ. Syst. 35 (2018), https://doi.org/10.1080/10286608.2019.1568418.

[104] M.A. DeRousseau, J.R. Kasprzyk, W.V. Srubar, Computational design optimization of concrete mixtures: a review, Cement Concr. Res. 109 (2018) 42–53, https://doi.org/10.1016/j.cemconres.2018.04.007.

[105] H.B. Ly, E. Monteiro, T.T. Le, V.M. Le, M. Dal, G. Regnier, B.T. Pham, Prediction and sensitivity analysis of bubble dissolution time in 3D selective laser sintering using ensemble decision trees, Materials (Basel) 12 (2019), https://doi.org/10.3390/ma12091544.

[106] R. Nisbet, G. Miner, K. Yale, Handbook of Statistical Analysis and Data Mining Applications, 2017, https://doi.org/10.1016/c2012-0-06451-4.

[107] A.S. Mohammed, Vipulanandan model for the rheological properties with ultimate shear stress of oil well cement modified with nanoclay, Egypt, J. Petrol. 27 (2018), https://doi.org/10.1016/j.ejpe.2017.05.007.

[108] A. Mohammed, S. Rafiq, P. Sihag, R. Kurda, W. Mahmood, K. Ghafor, W. Sarwar, ANN, M5P-tree and nonlinear regression approaches with statistical evaluations to predict the compressive strength of cement-based mortar modified with fly ash, J. Mater. Res. Technol. 9 (2020) 12416–12427, https://doi.org/10.1016/j.jmrt.2020.08.083.

[109] R.C. Deo, O. Kisi, V.P. Singh, Drought forecasting in eastern Australia using multivariate adaptive regression spline, least square support vector machine and M5Tree model, Atmos. Res. 184 (2017), https://doi.org/10.1016/j.atmosres.2016.10.004.

[110] A. Rahimikhoob, M. Asadi, M. Mashal, A comparison between conventional and M5 model tree methods for converting Pan evaporation to reference evapotranspiration for semi-arid region, Water Resour. Manag. 27 (2013), https://doi.org/10.1007/s11269-013-0440-y.

[111] M.O. Elish, Improved estimation of software project effort using multiple additive regression trees, Expert Syst. Appl. 36 (2009) 10774–10778, https://doi.org/10.1016/j.eswa.2009.02.013.

[112] J.H. Friedman, Stochastic gradient boosting, Comput. Stat. Data Anal. 38 (2002), https://doi.org/10.1016/S0167-9473(01)00065-2.

[113] J.C. Fu, H.Y. Huang, J.H. Jang, P.H. Huang, River stage forecasting using multiple additive regression trees, Water Resour. Manag. 33 (2019) 4491–4507, https://doi.org/10.1007/s11269-019-02357-x.

[114] B. L, Random forests, Random For 45 (2011) 5–32, https://doi.org/10.1023/A:1010933404324.

[115] S. Lu, M. Koopialipoor, P.G. Asteris, M. Bahri, D.J. Armaghani, A novel feature selection approach based on tree models for evaluating the punching shear capacity of steel fiber-reinforced concrete flat slabs, Materials (Basel) 13 (2020) 1–20, https://doi.org/10.3390/ma13173902.

[116] L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone, Classification and Regression Trees, 2017, https://doi.org/10.1201/9781315139470.

[117] Y. Pan, S. Chen, F. Qiao, S.V. Ukkusuri, K. Tang, Estimation of real-driving emissions for buses fueled with liquefied natural gas based on gradient boosted regression trees, Sci. Total Environ. 660 (2019), https://doi.org/10.1016/j.scitotenv.2019.01.054.

[118] A. Behnood, J. Olek, M.A. Glinicki, Predicting modulus elasticity of recycled aggregate concrete using M5 model tree algorithm, Construct. Build. Mater. 94 (2015) 137–147, https://doi.org/10.1016/j.conbuildmat.2015.06.055.

[119] A. Behnood, E. Mohammadi, Machine learning study of the mechanical properties of concretes containing waste foundry sand, Construct. Build. Mater. 243 (2020), 118152, https://doi.org/10.1016/j.conbuildmat.2020.118152.

[120] S. Mangalathu, J. Jeon, Classi fi cation of failure mode and prediction of shear strength for reinforced concrete beam-column joints using machine learning techniques, Eng. Struct. 160 (2018) 85–94, https://doi.org/10.1016/j.engstruct.2018.01.008.

[121] C. Deepa, K. SathiyaKumari, V.P. Sudha, Prediction of the compressive strength of high performance concrete mix using tree based modeling, Int. J. Comput. Appl. 6 (2010) 18–24, https://doi.org/10.5120/1076-1406.

[122] A. Behnood, V. Behnood, M. Modiri Gharehveran, K.E. Alyamac, Prediction of the compressive strength of normal and high-performance concretes using M5P model tree algorithm, Construct. Build. Mater. 142 (2017) 199–207, https://doi.org/10.1016/j.conbuildmat.2017.03.061.

[123] A. Fatih, M. Burhan, Modeling of compressive strength and UPV of high-volume mineral-admixtured concrete using rule-based M5 rule and tree model M5P classifiers, Yas 94 (2015) 235–240, https://doi.org/10.1016/j.conbuildmat.2015.06.029.

[124] Q. Han, C. Gui, J. Xu, G. Lacidogna, A generalized method to predict the compressive strength of high-performance concrete by improved random forest algorithm, Construct. Build. Mater. 226 (2019) 734–742, https://doi.org/10.1016/j.conbuildmat.2019.07.315.

[125] J. Zhang, G. Ma, Y. Huang, J. sun, F. Aslani, B. Nener, Modelling uniaxial compressive strength of lightweight self-compacting concrete using random forest regression, Construct. Build. Mater. 210 (2019) 713–719, https://doi.org/10.1016/j.conbuildmat.2019.03.189.

[126] A.F. Kocamaz, Y. Ayaz, M.B. Karakoç, İ. Türkmen, R. Demirboğa, Prediction of compressive strength and ultrasonic pulse velocity of admixtured concrete using tree model M5P, Struct. Concr. (2020) 1–15, https://doi.org/10.1002/suco.202000061.

[127] M.Y. Cheng, P.M. Firdausi, D. Prayogo, High-performance concrete compressive strength prediction using genetic weighted pyramid operation tree (GWPOT), Eng. Appl. Artif. Intell. 29 (2014) 104–113, https://doi.org/10.1016/j.engappai.2013.11.014.
[128] A. Ababneh, M. Alhassan, M. Abu-Haifa, Predicting the contribution of recycled aggregate concrete to the shear capacity of beams without transverse reinforcement using artificial neural networks, Case Stud. Constr. Mater. 13 (2020), e00414, https://doi.org/10.1016/j.cscm.2020.e00414.
[129] A. Ahmad, G. Kotsovou, D.M. Cotsovos, N.D. Lagaros, Assessing the accuracy of RC design code predictions through the use of artificial neural networks, Int. J. Adv. Struct. Eng. 10 (2018), https://doi.org/10.1007/s40091-018-0202-4.
[130] A. Ahmad, V. Plevris, Q.U.Z. Khan, Prediction of properties of frp-confined concrete cylinders based on artificial neural networks, Crystals 10 (2020) 1–22, https://doi.org/10.3390/cryst10090811.
[131] R. Haddad, M. Haddad, Predicting fiber-reinforced polymer-concrete bond strength using artificial neural networks: a comparative analysis study, Struct. Concr. (2020) 1–12, https://doi.org/10.1002/suco.201900298.
[132] S. Chithra, S.R.R.S. Kumar, K. Chinnaraju, F. Alfin Ashmita, A comparative study on the compressive strength prediction models for High Performance Concrete containing nano silica and copper slag using regression analysis and Artificial Neural Networks, Construct. Build. Mater. 114 (2016) 528–535, https://doi.org/10.1016/j.conbuildmat.2016.03.214.
[133] P.G. Asteris, V.G. Mokos, Concrete compressive strength using artificial neural networks, Neural Comput. Appl. 32 (2020) 11807–11826, https://doi.org/10.1007/s00521-019-04663-2.
[134] J. Xu, X. Zhao, Y. Yu, T. Xie, G. Yang, J. Xue, Parametric sensitivity analysis and modelling of mechanical properties of normal- and high-strength recycled aggregate concrete using grey theory, multiple nonlinear regression and artificial neural networks, Construct. Build. Mater. 211 (2019) 479–491, https://doi.org/10.1016/j.conbuildmat.2019.03.234.
[135] S. Haykin, Neural Networks and Learning Machines, 2008.
[136] D. Anderson, G. McNeill, ARTIFICIAL NEURAL NETWORKS TECHNOLOGY, ELIN:A011, New York, 1992.
[137] H. Adeli, Neural networks in civil engineering: 1989-2000, Comput. Civ. Infrastruct. Eng. 16 (2001), https://doi.org/10.1111/0885-9507.00219.
[138] P.G. Asteris, K.G. Kolovos, M.G. Douvika, K. Roinos, Prediction of self-compacting concrete strength using artificial neural networks, Eur. J. Environ. Civ. Eng. 20 (2016), https://doi.org/10.1080/19648189.2016.1246693 s102–s122.
[139] P.O. Awoyera, Predictive models for determination of compressive and split-tensile strengths of steel slag aggregate concrete, Mater. Res. Innovat. 22 (2018) 287–293, https://doi.org/10.1080/14328917.2017.1317394.
[140] T.F. Awolusi, O.L. Oke, O.O. Akinkurolere, A.O. Sojobi, O.G. Aluko, Performance comparison of neural network training algorithms in the modeling properties of steel fiber reinforced concrete, Heliyon 5 (2019), e01115, https://doi.org/10.1016/j.heliyon.2018.e01115.
[141] V. Chandwani, V. Agrawal, R. Nagar, Modeling slump of ready mix concrete using genetic algorithms assisted training of Artificial Neural Networks, Expert Syst. Appl. 42 (2015) 885–893, https://doi.org/10.1016/j.eswa.2014.08.048.
[142] C.A. Jeyasehar, K. Sumangala, Damage assessment of prestressed concrete beams using artificial neural network (ANN) approach, Comput. Struct. 84 (2006) 1709–1718, https://doi.org/10.1016/j.compstruc.2006.03.005.
[143] S.J. Kwon, H.W. Song, Analysis of carbonation behavior in concrete using neural network algorithm and carbonation modeling, Cement Concr. Res. 40 (2010) 119–127, https://doi.org/10.1016/j.cemconres.2009.08.022.
[144] X. Zhou, J. Zheng, K. Mao, Application of modified backpropagation algorithm to the prediction of the chloride ion concentration in cracked concrete, 2007, Proc. - Third Int. Conf. Nat. Comput. ICNC 3 (2007) 257–261, https://doi.org/10.1109/ICNC.2007.257.
[145] G. Bin Huang, Q.Y. Zhu, C.K. Siew, Extreme learning machine: theory and applications, Neurocomputing 70 (2006), https://doi.org/10.1016/j.neucom.2005.12.126.
[146] F. Kang, J. Liu, J. Li, S. Li, Concrete Dam Deformation Prediction Model for Health Monitoring Based on Extreme Learning Machine, 2017, pp. 1–11, https://doi.org/10.1002/stc.1997.
[147] A.K. Al-Shamiri, J.H. Kim, T.F. Yuan, Y.S. Yoon, Modeling the compressive strength of high-strength concrete: an extreme learning approach, Construct. Build. Mater. 208 (2019) 204–219, https://doi.org/10.1016/j.conbuildmat.2019.02.165.
[148] G. Huang, G. Bin Huang, S. Song, K. You, Trends in extreme learning machines: a review, Neural Network. 61 (2015), https://doi.org/10.1016/j.neunet.2014.10.001.
[149] M. Shariati, M.S. Mafipour, B. Ghahremani, F. Azarhomayun, M. Ahmadi, N.T. Trung, A. Shariati, A novel hybrid extreme learning machine–grey wolf optimizer (ELM-GWO) model to predict compressive strength of concrete with partial replacements for cement, Eng. Comput. (2020), https://doi.org/10.1007/s00366-020-01081-0.
[150] Z. Shao, D. Jahed Armaghani, B. Yazdani Bejarbaneh, M.A. Mu'azu, E. Tonnizam Mohamad, Estimating the Friction Angle of Black Shale Core Specimens with Hybrid-ANN Approaches, Elsevier Ltd, 2019, https://doi.org/10.1016/j.measurement.2019.06.007.
[151] M. Inthachot, V. Boonjing, S. Intakosum, Artificial neural network and genetic algorithm hybrid intelligence for predicting Thai stock price index trend, 2016, Comput. Intell. Neurosci. (2016), https://doi.org/10.1155/2016/3045254.
[152] E. Momeni, R. Nazir, D. Jahed Armaghani, H. Maizir, Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN, Meas. J. Int. Meas. Confed. 57 (2014) 122–131, https://doi.org/10.1016/j.measurement.2014.08.007.
[153] F. Khademi, M. Akbari, S. Mohammadmehdi, M. Nikoo, Multiple Linear Regression , Arti Fi Cial Neural Network , and Fuzzy Logic Prediction of 28 Days Compressive Strength of Concrete, 11, 2017, pp. 90–99, https://doi.org/10.1007/s11709-016-0363-9.
[154] A.T.A. Dantas, M. Batista Leite, K. De Jesus Nagahama, Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks, Construct. Build. Mater. 38 (2013) 717–722, https://doi.org/10.1016/j.conbuildmat.2012.09.026.
[155] Z.H. Duan, S.C. Kou, C.S. Poon, Using artificial neural networks for predicting the elastic modulus of recycled aggregate concrete, Construct. Build. Mater. 44 (2013) 524–532, https://doi.org/10.1016/j.conbuildmat.2013.02.064.
[156] H. Naderpour, O. Poursaeidi, M. Ahmadi, Shear Resistance Prediction of Concrete Beams Reinforced by FRP Bars Using Artificial Neural Networks, 2018, https://doi.org/10.1016/j.measurement.2018.05.051. Measurement.
[157] B. Topc, Prediction of Mechanical Properties of Recycled Aggregate Concretes Containing Silica Fume Using Artificial Neural Networks and Fuzzy Logic, 42, 2008, pp. 74–82, https://doi.org/10.1016/j.commatsci.2007.06.011.
[158] E.M. Golafshani, A. Behnood, Application of soft computing methods for predicting the elastic modulus of recycled aggregate concrete, J. Clean. Prod. 176 (2018) 1163–1176, https://doi.org/10.1016/j.jclepro.2017.11.186.
[159] J. Amani, R. Moeini, Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network, Sci. Iran. 19 (2012) 242–248, https://doi.org/10.1016/j.scient.2012.02.009.
[160] S. Kumar, S.V. Barai, Neural networks modeling of shear strength of SFRC corbels without stirrups, Appl. Soft Comput. J. 10 (2010) 135–148, https://doi.org/10.1016/j.asoc.2009.06.012.
[161] F. Altun, K. Aydin, in: Predicting the Compressive Strength of Steel Fiber Added Lightweight Concrete Using Neural Network, 42, 2008, pp. 259–265, https://doi.org/10.1016/j.commatsci.2007.07.011.
[162] R. Perera, M. Barchín, A. Arteaga, A. De Diego, Prediction of the ultimate strength of reinforced concrete beams FRP-strengthened in shear using neural networks, Compos. B Eng. 41 (2010) 287–298, https://doi.org/10.1016/j.compositesb.2010.03.003.
[163] H.M. Tanarslan, M. Secer, A. Kumanlioglu, An approach for estimating the capacity of RC beams strengthened in shear with FRP reinforcements using artificial neural networks, Construct. Build. Mater. 30 (2012) 556–568, https://doi.org/10.1016/j.conbuildmat.2011.12.008.
[164] U. Atici, Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network, Expert Syst. Appl. 38 (2011) 9609–9618, https://doi.org/10.1016/j.eswa.2011.01.156.
[165] M. Nikoo, F. Torabian Moghadam, Ł. Sadowski, Prediction of concrete compressive strength by evolutionary artificial neural networks, Adv. Mater. Sci. Eng. (2015), https://doi.org/10.1155/2015/849126, 2015.

[166] A. Behnood, E.M. Golafshani, Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves, J. Clean. Prod. 202 (2018) 54–64, https://doi.org/10.1016/j.jclepro.2018.08.065.
[167] F. Özcan, C.D. Atiş, O. Karahan, E. Uncuoğlu, H. Tanyildizi, Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete, Adv. Eng. Software 40 (2009) 856–863, https://doi.org/10.1016/j.advengsoft.2009.01.005.
[168] D. Van Dao, H.B. Ly, S.H. Trinh, T.T. Le, B.T. Pham, Artificial intelligence approaches for prediction of compressive strength of geopolymer concrete, Materials (Basel) 12 (2019), https://doi.org/10.3390/ma12060983.
[169] A.A. Shahmansouri, M. Yazdani, S. Ghanbari, H. Akbarzadeh Bengar, A. Jafari, H. Farrokh Ghatte, Artificial neural network model to predict the compressive strength of eco-friendly geopolymer concrete incorporating silica fume and natural zeolite, J. Clean. Prod. 279 (2021), 123697, https://doi.org/10.1016/j.jclepro.2020.123697.
[170] D. Bui, T. Nguyen, J. Chou, H. Nguyen-xuan, T. Duc, A modified firefly algorithm-artificial neural network expert system for predicting compressive and tensile strength of high-performance concrete, Construct. Build. Mater. 180 (2018) 320–333, https://doi.org/10.1016/j.conbuildmat.2018.05.201.
[171] E.M. Golafshani, A. Behnood, M. Arashpour, Predicting the compressive strength of normal and high-performance concretes using ANN and ANFIS hybridized with grey wolf optimizer, Construct. Build. Mater. 232 (2020), 117266, https://doi.org/10.1016/j.conbuildmat.2019.117266.
[172] P.G. Asteris, K.G. Kolovos, Self-Compacting Concrete Strength Prediction Using Surrogate Models Self-Compacting Concrete Strength Prediction Using Surrogate Models, 2019, https://doi.org/10.1007/s00521-017-3007-7.
[173] Z.H. Duan, S.C. Kou, C.S. Poon, Prediction of compressive strength of recycled aggregate concrete using artificial neural networks, Construct. Build. Mater. 40 (2013) 1200–1206, https://doi.org/10.1016/j.conbuildmat.2012.04.063.
[174] H. Naderpour, A. Hossein, P. Fakharian, in: Compressive Strength Prediction of Environmentally Friendly Concrete Using Arti Fi Cial Neural Networks, 16, 2018, pp. 213–219, https://doi.org/10.1016/j.jobe.2018.01.007.
[175] F. Khademi, S. Mohammadmehdi, N. Deshpande, Predicting strength of recycled aggregate concrete using artificial neural network , adaptive neuro-fuzzy inference system and multiple linear regression, Int. J. Sustain. Built Environ. (2016), https://doi.org/10.1016/j.ijsbe.2016.09.003.
[176] T. Gupta, K.A. Patel, S. Siddique, R.K. Sharma, S. Chaudhary, Prediction of mechanical properties of rubberised concrete exposed to elevated temperature using ANN, Measurement 147 (2019), 106870, https://doi.org/10.1016/j.measurement.2019.106870.
[177] R. Bachir, A. Mamoune, S. Mohammed, T. Habib, Using Artificial Neural Networks Approach to Estimate Compressive Strength for Rubberized Concrete, 2018.
[178] M.Y. Mansour, M. Dicleli, J.Y. Lee, J. Zhang, Predicting the shear strength of reinforced concrete beams using artificial neural networks, Eng. Struct. 26 (2004) 781–799, https://doi.org/10.1016/j.engstruct.2004.01.011.
[179] S. Lee, C. Lee, Prediction of shear strength of FRP-reinforced concrete flexural members without stirrups using artificial neural networks, Eng. Struct. 61 (2014) 99–112, https://doi.org/10.1016/j.engstruct.2014.01.001.
[180] R. Bashir, A. Ashour, Composites : Part B Neural network modelling for shear strength of concrete members reinforced with FRP bars, Compos. Part B. 43 (2012) 3198–3207, https://doi.org/10.1016/j.compositesb.2012.04.011.
[181] C. Bilim, C.D. Atiş, H. Tanyildizi, O. Karahan, Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network, Adv. Eng. Software 40 (2009) 334–340, https://doi.org/10.1016/j.advengsoft.2008.05.005.
[182] A. Saradar, P. Nemati, A.S. Paskiabi, M.M. Moein, H. Moez, E.H. Vishki, Prediction of mechanical properties of lightweight basalt fiber reinforced concrete containing silica fume and fly ash: experimental and numerical assessment, J. Build. Eng. 32 (2020), 101732, https://doi.org/10.1016/j.jobe.2020.101732.
[183] A.K. Al-Shamiri, T.F. Yuan, J.H. Kim, Non-tuned machine learning approach for predicting the compressive strength of high-performance concrete, Materials (Basel) 13 (2020) 1–14, https://doi.org/10.3390/ma13051023.
[184] H.I. Erdal, O. Karakurt, E. Namli, High performance concrete compressive strength forecasting using ensemble models based on discrete wavelet transform, Eng. Appl. Artif. Intell. 26 (2013) 1246–1254, https://doi.org/10.1016/j.engappai.2012.10.014.
[185] B. Ahmadi-nedushan, Prediction of elastic modulus of normal and high strength concrete using ANFIS and optimal nonlinear regression models, Construct. Build. Mater. 36 (2012) 665–673, https://doi.org/10.1016/j.conbuildmat.2012.06.002.
[186] M. Mohammadhassani, H. Nezamabadi-pour, M. Shariati, An Evolutionary Fuzzy Modelling Approach and Comparison of Different Methods for Shear Strength Prediction of High-Strength Concrete Beams without Stirrups, 2014, https://doi.org/10.12989/sss.2014.14.5.785.
[187] A. Öztaş, M. Pala, E. Özbay, E. Kanca, N. Çağlar, M.A. Bhatti, Predicting the compressive strength and slump of high strength concrete using neural network, Construct. Build. Mater. 20 (2006) 769–775, https://doi.org/10.1016/j.conbuildmat.2005.01.054.
[188] M. Nehdi, Y. Djebbar, A. Khan, Neural Network Model for Preformed-Foam Cellular Concrete, 2016.
[189] O. Belalia, D. Bakhta, B. Mohamed, G. Arezki, Prediction of properties of self-compacting concrete containing fly ash using artificial neural network, Neural Comput. Appl. (2016), https://doi.org/10.1007/s00521-016-2368-7.
[190] A. Slowik, H. Kwasnicka, Evolutionary algorithms and their applications to engineering problems, Neural Comput, Appl 32 (2020), https://doi.org/10.1007/s00521-020-04832-8.
[191] A.E. Eiben, S.K. Smit, Parameter tuning for configuring and analyzing evolutionary algorithms, Swarm Evol. Comput. 1 (2011) 19–31, https://doi.org/10.1016/j.swevo.2011.02.001.
[192] C.A.C. Coello, G.B. Lamont, D.A. Van Veldhuizen, Evolutionary Algorithms for Solving Multi-Objective Problems, 2007, https://doi.org/10.1007/978-0-387-36797-2.
[193] D.B. Fogel, Evolutionary algorithms in engineering applications [book reviews], IEEE Trans. Evol. Comput. 2 (2005), https://doi.org/10.1109/tevc.1998.728209.
[194] D. Greiner, J. Periaux, D. Quagliarella, J. Magalhaes-Mendes, B. Galván, Evolutionary algorithms and metaheuristics: applications in engineering design and optimization, Math. Probl Eng. (2018), https://doi.org/10.1155/2018/2793762, 2018.
[195] H.Q. Nguyen, H.B. Ly, V.Q. Tran, T.A. Nguyen, T.T. Le, B.T. Pham, Optimization of artificial intelligence system by evolutionary algorithm for prediction of axial capacity of rectangular concrete filled steel tubes under compression, Materials (Basel) 13 (2020), https://doi.org/10.3390/MA13051205.
[196] Y. Sun, Y. Gao, A multi-objective particle swarm optimization algorithm based on Gaussian mutation and an improved learning strategy, Mathematics 7 (2019), https://doi.org/10.3390/math7020148.
[197] S. Ostovari, H. Shayani, Effect of the number of design variables in thickness optimization of concrete barrel roof shells using evolutionary algorithms, Int. J. Space Struct. 34 (2019), https://doi.org/10.1177/0956059919893212.
[198] A. Długosz, I. Pokorska, M.A. Glinicki, R. Jaskulski, Identification of thermal properties of hardening concrete by means of evolutionary algorithms, Comput. Assist. Mech. Eng. Sci. 24 (2017).
[199] D. Veenendaal, J. Coenders, J. Vambersky, M. West, Design and optimization of fabric-formed beams and trusses: evolutionary algorithms and form-finding, Struct. Concr. 12 (2011), https://doi.org/10.1002/suco.201100020.
[200] C. Darwin, On the Origin of the Species, or, the Preservation of Favoured Races in the Struggle for Life, 1859.
[201] D. Câmara, Evolution and evolutionary algorithms, Bio-Inspired Netw (2015) 1–30, https://doi.org/10.1016/b978-1-78548-021-8.50001-6.
[202] J. Koza, Genetic Programming: on the Programming of Computers by Means of Natural Selection, 1992.
[203] M. Monjezi, H. Amini Khoshalan, M. Razifard, A neuro-genetic network for predicting uniaxial compressive strength of rocks, Geotech. Geol. Eng. 30 (2012), https://doi.org/10.1007/s10706-012-9510-9.
[204] Z. Yuan, L.N. Wang, X. Ji, Prediction of concrete compressive strength: research on hybrid models genetic based algorithms and ANFIS, Adv. Eng. Software 67 (2014), https://doi.org/10.1016/j.advengsoft.2013.09.004.
[205] B. Filipič, D. Juričić, An interactive genetic algorithm for controller parameter optimization, in: Artif. Neural Nets Genet. Algorithms, 1993, https://doi.org/10.1007/978-3-7091-7533-0_66.
[206] T. Krink, M. Løvbjerg, The lifecycle model: combining particle swarm optimisation, genetic algorithms and hillclimbers, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) (2002), https://doi.org/10.1007/3-540-45712-7_60.

[207] J. Rigelsford, Intelligent optimisation techniques: genetic algorithms, tabu search, simulated annealing and neural networks, Ind. Robot An Int. J. 27 (2000), https://doi.org/10.1108/ir.2000.04927eae.003.
[208] E.M. Golafshani, A. Behnood, Automatic regression methods for formulation of elastic modulus of recycled aggregate concrete, Appl. Soft Comput. J. 64 (2018) 377–400, https://doi.org/10.1016/j.asoc.2017.12.030.
[209] F. Aslam, F. Farooq, M.N. Amin, K. Khan, A. Waheed, A. Akbar, M.F. Javed, R. Alyousef, H. Alabdulijabbar, Applications of gene expression programming for estimating compressive strength of high-strength concrete, Adv. Civ. Eng. (2020), https://doi.org/10.1155/2020/8850535, 2020.
[210] D. Karaboga, An idea based on honey bee swarm for numerical optimization, TR06, Tech. Rep. (2005). Erciyes Univ..
[211] D. Karaboga, B. Basturk, Artificial Bee Colony (ABC) optimization algorithm for solving constrained optimization problems, in: Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), 2007, https://doi.org/10.1007/978-3-540-72950-1_77.
[212] D. Karaboga, B. Akay, A comparative study of Artificial Bee Colony algorithm, Appl. Math. Comput. 214 (2009), https://doi.org/10.1016/j.amc.2009.03.090.
[213] D. Karaboga, B. Basturk, On the performance of artificial bee colony (ABC) algorithm, Appl. Soft Comput. J. 8 (2008), https://doi.org/10.1016/j.asoc.2007.05.007.
[214] G. Zhu, S. Kwong, Gbest-guided artificial bee colony algorithm for numerical function optimization, Appl. Math. Comput. 217 (2010), https://doi.org/10.1016/j.amc.2010.08.049.
[215] D. Simon, Biogeography-based optimization, IEEE Trans. Evol. Comput. 12 (2008), https://doi.org/10.1109/TEVC.2008.919004.
[216] D. Du, D. Simon, Complex system optimization using biogeography-based optimization, Math. Probl Eng. (2013), https://doi.org/10.1155/2013/456232, 2013.
[217] H. Ma, D. Simon, P. Siarry, Z. Yang, M. Fei, Biogeography-based optimization: a 10-year review, IEEE Trans. Emerg. Top. Comput. Intell. 1 (2017), https://doi.org/10.1109/TETCI.2017.2739124.
[218] G. Abdollahzadeh, E. Jahani, Z. Kashir, Predicting of compressive strength of recycled aggregate concrete by genetic programming, Comput. Concr. 18 (2016) 155–164, https://doi.org/10.12989/cac.2016.18.2.155.
[219] M.F. Iqbal, Q. feng Liu, I. Azim, X. Zhu, J. Yang, M.F. Javed, M. Rauf, Prediction of mechanical properties of green concrete incorporating waste foundry sand based on gene expression programming, J. Hazard Mater. 384 (2020), 121322, https://doi.org/10.1016/j.jhazmat.2019.121322.
[220] I.F. Kara, Prediction of shear strength of FRP-reinforced concrete beams without stirrups based on genetic programming, Adv. Eng. Software 42 (2011) 295–304, https://doi.org/10.1016/j.advengsoft.2011.02.002.
[221] A.H. Gandomi, A.H. Alavi, S. Kazemi, M. Gandomi, Formulation of shear strength of slender RC beams using gene expression programming, part I: without shear reinforcement, Autom. ConStruct. 42 (2014) 112–121, https://doi.org/10.1016/j.autcon.2014.02.007.
[222] A.H. Gandomi, A.H. Alavi, M. Gandomi, S. Kazemi, Formulation of shear strength of slender RC beams using gene expression programming, part II: with shear reinforcement, Meas. J. Int. Meas. Confed. 95 (2017) 367–376, https://doi.org/10.1016/j.measurement.2016.10.024.
[223] A.H. Gandomi, A.H. Alavi, M.G. Sahab, New formulation for compressive strength of CFRP confined concrete cylinders using linear genetic programming, Mater. Struct. Constr. 43 (2010) 963–983, https://doi.org/10.1617/s11527-009-9559-y.
[224] S.B. Beheshti Aval, H. Ketabdari, S. Asil Gharebaghi, Estimating shear strength of short rectangular reinforced concrete columns using nonlinear regression and gene expression programming, Structures 12 (2017) 13–23, https://doi.org/10.1016/j.istruc.2017.07.002.
[225] M. Saridemir, Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash, Construct. Build. Mater. 24 (2010) 1911–1919, https://doi.org/10.1016/j.conbuildmat.2010.04.011.
[226] A.A. Shahmansouri, H. Akbarzadeh Bengar, E. Jahani, Predicting compressive strength and electrical resistivity of eco-friendly concrete containing natural zeolite via GEP algorithm, Construct. Build. Mater. 229 (2019), 116883, https://doi.org/10.1016/j.conbuildmat.2019.116883.
[227] P.O. Awoyera, M.S. Kirgiz, A. Viloria, D. Ovallos-Gazabon, Estimating strength properties of geopolymer self-compacting concrete using machine learning techniques, J. Mater. Res. Technol. 9 (2020) 9016–9028, https://doi.org/10.1016/j.jmrt.2020.06.008.
[228] D. Van Dao, S.H. Trinh, H.B. Ly, B.T. Pham, Prediction of compressive strength of geopolymer concrete using entirely steel slag aggregates: novel hybrid artificial intelligence approaches, Appl. Sci. 9 (2019) 1–16, https://doi.org/10.3390/app9061113.
[229] S.M. Mousavi, P. Aminian, A.H. Gandomi, A.H. Alavi, H. Bolandi, A new predictive model for compressive strength of HPC using gene expression programming, Adv. Eng. Software 45 (2012) 105–114, https://doi.org/10.1016/j.advengsoft.2011.09.014.
[230] E.M. Golafshani, A. Ashour, Prediction of self-compacting concrete elastic modulus using two symbolic regression techniques, Autom. ConStruct. 64 (2016) 7–19, https://doi.org/10.1016/j.autcon.2015.12.026.
[231] F. Özcan, Gene expression programming based formulations for splitting tensile strength of concrete, Construct. Build. Mater. 26 (2012) 404–410, https://doi.org/10.1016/j.conbuildmat.2011.06.039.
[232] A.H. Gandomi, A.H. Alavi, G.J. Yun, Nonlinear modeling of shear strength of SFRC beams using linear genetic programming, Struct. Eng. Mech. 38 (2011) 1–25, https://doi.org/10.12989/sem.2011.38.1.001.
[233] M. Sarveghadi, A.H. Gandomi, H. Bolandi, A.H. Alavi, Development of prediction models for shear strength of SFRCB using a machine learning approach, Neural Comput. Appl. 31 (2019) 2085–2094, https://doi.org/10.1007/s00521-015-1997-6.
[234] E.M. Golafshani, A. Behnood, Estimating the optimal mix design of silica fume concrete using biogeography-based programming, Cem. Concr. Compos. 96 (2019) 95–105, https://doi.org/10.1016/j.cemconcomp.2018.11.005.
[235] M.F. Javed, M.N. Amin, M.I. Shah, K. Khan, B. Iftikhar, F. Farooq, F. Aslam, R. Alyousef, H. Alabduljabbar, Applications of gene expression programming and regression techniques for estimating compressive strength of bagasse ash based concrete, Crystals 10 (2020) 1–17, https://doi.org/10.3390/cryst10090737.
[236] M. Castelli, L. Vanneschi, S. Silva, Prediction of high performance concrete strength using Genetic Programming with geometric semantic genetic operators, Expert Syst. Appl. 40 (2013) 6856–6862, https://doi.org/10.1016/j.eswa.2013.06.037.
[237] A.H. Gandomi, A.H. Alavi, M.G. Sahab, P. Arjmandi, Formulation of elastic modulus of concrete using linear genetic programming, J. Mech. Sci. Technol. 24 (2010) 1273–1278, https://doi.org/10.1007/s12206-010-0330-7.
[238] P. Pereira, L. Evangelista, J. De Brito, The effect of superplasticisers on the workability and compressive strength of concrete made with fine recycled concrete aggregates, Construct. Build. Mater. 28 (2012), https://doi.org/10.1016/j.conbuildmat.2011.10.050.
[239] R.V. Silva, J. De Brito, R.K. Dhir, The influence of the use of recycled aggregates on the compressive strength of concrete: a review, Eur. J. Environ. Civ. Eng. 19 (2015), https://doi.org/10.1080/19648189.2014.974831.
[240] A. Gholampour, A.H. Gandomi, T. Ozbakkaloglu, New formulations for mechanical properties of recycled aggregate concrete using gene expression programming, Construct. Build. Mater. 130 (2017), https://doi.org/10.1016/j.conbuildmat.2016.10.114.
[241] R. Sri Ravindrarajah, C. Tam, Properties of concrete made with crushed concrete as coarse aggregate, Mag. Concr. Res. 37 (1985) 29–38, https://doi.org/10.1680/macr.1985.37.130.29.
[242] R.K. Dhir, M.C. Limbachiya, T. Leelawat, Suitability of recycled concrete aggregate for use in BS 5328 designated mixes, Proc. Inst. Civ. Eng. Struct. Build. 134 (1999) 257–274, https://doi.org/10.1680/istbu.1999.31568.
[243] G.F. Kheder, S.A. Al-Windawi, Variation in mechanical properties of natural and recycled aggregate concrete as related to the strength of their binding mortar, Mater. Struct. Constr. 38 (2005), https://doi.org/10.1617/14216.
[244] P.S. Lovato, E. Possan, D.C.C.D. Molin, Â.B. Masuero, J.L.D. Ribeiro, Modeling of mechanical properties and durability of recycled aggregate concretes, Construct. Build. Mater. 26 (2012), https://doi.org/10.1016/j.conbuildmat.2011.06.043.
[245] J.Z. Xiao, J.B. Li, C. Zhang, On relationships between the mechanical properties of recycled aggregate concrete: an overview, Mater. Struct. Constr. 39 (2006), https://doi.org/10.1617/s11527-006-9093-0.
[246] Y.K.M. Harada, T. Soshiroda, S. Kubota, T. Ikeda, Strength and elastic modulus of recycled aggregate concrete, Proc. Second Int. RILEM Symp. Demolition Reuse Concr. Mason. 2 (1988) 565–574.
[247] N.K. Bairagi, K. Ravande, V.K. Pareek, Behaviour of concrete with different proportions of natural and recycled aggregates, Resour. Conserv. Recycl. 9 (1993), https://doi.org/10.1016/0921-3449(93)90036-F.

[248] M.B. De Oliveira, E. Vazquez, The influence of retained moisture in aggregates from recycling on the properties of new hardened concrete, in: Waste Manag, 1996, https://doi.org/10.1016/S0956-053X(96)00033-5.
[249] R. Dillmann, Concrete with recycled concrete aggregate, in: Sustain. Constr. Use Recycl. Concr. Aggregate-Producings Int. Symp. Held Dep. Trade Ind, . Conf. Cent., London, UK, 1988, pp. 11–12.
[250] R.K. Dhir, M.C. Limbachiya, T. Leelawat, Suitability of recycled concrete aggregate for use in BS 5328 designated mixes, Proc. Inst. Civ. Eng. Struct. Build. 134 (1999), https://doi.org/10.1680/istbu.1999.31568.
[251] M. Tavakoli, P. Soroushian, Strengths of recycled aggregate concrete made using field-demolished concrete as aggregate, ACI Mater. J. 93 (1996), https://doi.org/10.14359/9802.
[252] G. Wardeh, E. Ghorbel, H. Gomart, Mix design and properties of recycled aggregate concretes: applicability of eurocode 2, Int. J. Concr. Struct. Mater. 9 (2015) 1–20, https://doi.org/10.1007/s40069-014-0087-y.
[253] K. Zilch, F. Roos, An equation to estimate the modulus of elasticity of concrete with recycled aggregates, Civ. Eng. 76 (2001) 187–191.
[254] K. Rahal, Mechanical properties of concrete with recycled coarse aggregate, Build. Environ. 42 (2007), https://doi.org/10.1016/j.buildenv.2005.07.033.
[255] C. Hoffmann, S. Schubert, A. Leemann, M. Motavalli, Recycled concrete and mixed rubble as aggregates: influence of variations in composition on the concrete properties and their use as structural material, Construct. Build. Mater. 35 (2012), https://doi.org/10.1016/j.conbuildmat.2011.10.007.
[256] R.V. Silva, J. De Brito, R.K. Dhir, Tensile strength behaviour of recycled aggregate concrete, Construct. Build. Mater. 83 (2015), https://doi.org/10.1016/j.conbuildmat.2015.03.034.
[257] J. Xiao, P. Li, W. Qin, Study on bond-slip between recycled concrete and rebars, Tongji Daxue Xuebao/Journal Tongji Univ 34 (2006).
[258] P. El-Ghandour, A. W, K. Pilakoutas, Waldron, New approach for punching shear capacity prediction of fiber reinforced polymer reinforced concrete flat slabs, ACI Struct. J. 188 (1999) 135–144, https://doi.org/10.14359/5617.
[259] P. El-Ghandour, A. W, K. Pilakoutas, Waldron, Punching shear behavior and design of FRP RC flat slabs, TRITA-BKN Bulletin, in: Proc. Int. Work. Punching Shear Capacit. RC Slabs, Dedic. To Profr. Sven Kinnunen, 57, 2000. Stockholm.
[260] L. Peled, S. Amatthys, F. Taerwe, Lexural P Erformance of C Oncrete With Frp G Rids, ASCE J. Mater. Civ. Eng. 11 (2000) 154–161, https://doi.org/10.1061/(ASCE)1090-0268(2000)4:3(154).
[261] C.E. Ospina, S.D.B. Alexander, J.J. Roger Cheng, Punching of two-way concrete slabs with fiber-reinforced polymer reinforcing bars or grids, ACI Struct. J. 100 (2003), https://doi.org/10.14359/12800.
[262] R. Narayanan, I.Y.S. Darwish, Use of steel fibers as shear reinforcement, ACI Struct. J. 84 (1987), https://doi.org/10.14359/2654.
[263] S.A. Ashour, G.S. Hasanain, F.F. Wafa, Shear behavior of high-strength fiber reinforced concrete beams, ACI Struct. J. 89 (1992).
[264] Y.K. Kwak, M.O. Eberhard, W.S. Kim, J. Kim, Shear strength of steel fiber-reinforced concrete beams without stirrups, ACI Struct. J. 99 (2002).
[265] H.E. Yakoub, Shear stress prediction: steel fiber-reinforced concrete beams without stirrups, ACI Struct. J. 108 (2011), https://doi.org/10.14359/51682346.
[266] M. Khuntia, B. Stojadinovic, S.C. Goel, Shear strength of normal and high-strength fiber reinforced concrete beams without stirrups, ACI Struct. J. 96 (1999), https://doi.org/10.14359/620.
[267] F. Zhang, Y. Ding, J. Xu, Y. Zhang, W. Zhu, Y. Shi, Shear strength prediction for steel fiber reinforced concrete beams without stirrups, Eng. Struct. 127 (2016), https://doi.org/10.1016/j.engstruct.2016.08.012.
[268] V.C. Li, R. Ward, A.M. Hamza, Steel and synthetic fibers as shear reinforcement, ACI Mater. J. 89 (1992), https://doi.org/10.14359/1822.
[269] R.N. Swamy, R. Jones, A.T.P. Chiam, Influence of steel fibers on the shear resistance of lightweight concrete I- beams, ACI Struct. J. 90 (1993), https://doi.org/10.14359/4201.
[270] S. Ak, Shear strength of steel fiber reinforced concrete beams, ACI J 83 (1986) 624–628.
[271] M. Shahnewaz, M.S. Alam, Improved shear equations for steel fiber-reinforced concrete deep and slender beams, ACI Struct. J. 111 (2014), https://doi.org/10.14359/51686736.
[272] A. Gholampour, A.H. Gandomi, T. Ozbakkaloglu, New formulations for mechanical properties of recycled aggregate concrete using gene expression programming, Construct. Build. Mater. 130 (2017) 122–145, https://doi.org/10.1016/j.conbuildmat.2016.10.114.
[273] J.-S. Chou, C.-K. Chiu, M. Farfoura, I. Al-Taharwa, Optimizing the prediction accuracy of concrete compressive strength based on a comparison of data-mining techniques, J. Comput. Civ. Eng. 25 (2011), https://doi.org/10.1061/(asce)cp.1943-5487.0000088.
[274] A.-D. Pham, N.-D. Hoang, Q.-T. Nguyen, Predicting compressive strength of high-performance concrete using metaheuristic-optimized least squares support vector regression, J. Comput. Civ. Eng. 30 (2016), 06015002, https://doi.org/10.1061/(asce)cp.1943-5487.0000506.
[275] Z. Yuan, L.N. Wang, X. Ji, Prediction of concrete compressive strength: research on hybrid models genetic based algorithms and ANFIS, Adv. Eng. Software 67 (2014) 156–163, https://doi.org/10.1016/j.advengsoft.2013.09.004.
[276] J.S. Chou, A.D. Pham, Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength, Construct. Build. Mater. 49 (2013) 554–563, https://doi.org/10.1016/j.conbuildmat.2013.08.078.
[277] V. Christou, M.G. Tsipouras, N. Giannakeas, A.T. Tzallas, G. Brown, Hybrid extreme learning machine approach for heterogeneous neural networks, Neurocomputing 361 (2019) 137–150, https://doi.org/10.1016/j.neucom.2019.04.092.
[278] Swingler Kevin, Applying Neural Networks: A Practical Guide, 1996.
[279] S.I. Gallant, Neural Network Learning and Expert Systems, 2018, https://doi.org/10.7551/mitpress/4931.001.0001.
[280] G. Bin Huang, H. Zhou, X. Ding, R. Zhang, Extreme learning machine for regression and multiclass classification, IEEE Trans. Syst. Man Cybern. B Cybern. 42 (2012), https://doi.org/10.1109/TSMCB.2011.2168604.
[281] V.N. Vapnik, The Nature of Statistical Learning Theory, 1995, https://doi.org/10.1007/978-1-4757-2440-0.
[282] X. Luo, X. Chang, X. Ban, Regression and classification using extreme learning machine based on L1-norm and L2-norm, Neurocomputing 174 (2016), https://doi.org/10.1016/j.neucom.2015.03.112.
[283] W. Deng, Q. Zheng, L. Chen, Regularized extreme learning machine, 2009 IEEE Symp. Comput. Intell. Data Mining, CIDM 2009 - Proc (2009) 389–395, https://doi.org/10.1109/CIDM.2009.4938676.
[284] A.E. Hoerl, R.W. Kennard, ridge regression: biased estimation for nonorthogonal problems, Technometrics 12 (1970), https://doi.org/10.1080/00401706.1970.10488634.
[285] H. Ishigami, T. Fukuda, T. Shibata, F. Arai, Structure optimization of fuzzy neural network by genetic algorithm, Fuzzy Set Syst. 71 (1995), https://doi.org/10.1016/0165-0114(94)00283-D.
[286] C. Martinez, O. Castillo, O. Montiel, Comparison between ant colony and genetic algorithms for fuzzy system optimization, Stud. Comput. Intell. 154 (2008), https://doi.org/10.1007/978-3-540-70812-4_5.
[287] A.K. Yadav, S.S. Chandel, Solar radiation prediction using Artificial Neural Network techniques: a review, Renew. Sustain. Energy Rev. 33 (2014) 772–781, https://doi.org/10.1016/j.rser.2013.08.055.
[288] M.A.H. Farquad, V. Ravi, S.B. Raju, Churn prediction using comprehensible support vector machine: an analytical CRM application, Appl. Soft Comput. J. 19 (2014) 31–40, https://doi.org/10.1016/j.asoc.2014.01.031.
[289] C.F. Lin, S. De Wang, Fuzzy support vector machines, IEEE Trans. Neural Network. 13 (2002) 464–471, https://doi.org/10.1109/72.991432.