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Machine learning prediction of mechanical properties of concrete: Critical review

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HIGHLIGHTS

- Empirical models for concrete mechanical strength are inaccurate and cannot accommodate new input parameters.
- Machine learning models are more accurate, flexible and can be retrained with updated databases.
- Advantages and shortcomings of ML models identified model performance is compared.
- Recommendations for selecting suitable model are made based on review.
- Knowledge gaps and needed future research are identified.

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ABSTRACT

Accurate prediction of the mechanical properties of concrete has been a concern since these properties are often required by design codes. The emergence of new concrete mixtures and applications has motivated researchers to pursue reliable models for predicting mechanical strength. Empirical and statistical models, such as linear and nonlinear regression, have been widely used. However, these models require laborious experimental work to develop, and can provide inaccurate results when the relationships between concrete properties and mixture composition and curing conditions are complex. To overcome such drawbacks, several Machine Learning (ML) models have been proposed as an alternative approach for predicting the mechanical strength of concrete. The present study examines ML models for forecasting the mechanical properties of concrete, including artificial neural networks, support vector machine, decision trees, and evolutionary algorithms. The application of each model and its performance are critically discussed and analyzed, thus identifying practical recommendations, current knowledge gaps, and needed future research.

1. Introduction

Rapid developments of novel concrete types stimulated by the ever-challenging requirements of the construction industry has motivated further research to develop new predictive models that can estimate concrete properties. Predicting the mechanical properties of concrete has been an important research task that could better satisfy the requirements of various design codes and standards. Conventional models for forecasting mechanical, rheological, durability, and other properties of concrete consisted essentially of empirical relationships developed from statistical analysis of experimental data, where linear and nonlinear regression models have been established [1,2]. In such models, analytical equations are generated through regression analysis to determine the unknown coefficients affecting the relationship between concrete strength and other variables. Those equations are generally expressed by the following form:

$$y = f(b_i, x_i)$$

where y is the value of mechanical strength, f is a linear or nonlinear function, b_i and x_i represent the regression coefficients and concrete attributes, respectively [3,4]. In the open literature, various regression models have been suggested to estimate mechanical properties of concrete, including compressive strength, tensile strength, shear strength and elastic modulus [5–10].

Even though these models have proven to be effective in some cases and tend to save time and cost for future applications, their development is associated with multiple drawbacks. Costly and time-consuming trial batches required to establish empirical models is among their major shortcomings. In addition, conventional models perform poorly in dealing with complex materials [4],

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which makes them unreliable for estimating properties of several types of concrete. For instance, Chou et *al.* [11] stated that some properties of high-performance concrete (HPC) cannot be easily modelled due to the intricate relationship between mechanical strength and mixture constituents. Furthermore, most of the current empirical equations provided in design codes and standards incorporate a fixed number and type of parameters, making their applicability to assess the strength of novel concrete types with additional new features questionable since the effects of the new mixture constituents are ignored.

To compensate for the drawbacks of conventional linear and nonlinear regression models, ML techniques have been recently introduced as a strong contender for predicting concrete mechanical strength. Using such prediction tools can save costly and time-consuming trial batches and associated experimental work required to achieve desired concrete strength [12]. ML approaches can generally be classified into two major types: supervised learning and unsupervised learning [13]. The former has been more commonly adopted for estimating the mechanical properties of concrete. In supervised learning, ML models consist of computer algorithms capable of generating patterns and hypotheses through a provided dataset to forecast future values [13–17].

Although these models have been proposed to achieve the same goal, i.e. prediction of mechanical strength of concrete, their structure and process can differ significantly. As shown in Fig. 1, the most common ML techniques used for estimating concrete strength can generally be grouped into four major types: artificial neural networks (ANN), support vector machines (SVM), decision trees, and evolutionary algorithms (EA). Generally, the size of the dataset and number of input parameters can affect the selection of the most suitable model. Also, the performance of each model is evaluated via various statistical metrics comparing actual and predicted values.

The aim of the present paper is to critically review and compare the different ML techniques used for forecasting the mechanical properties of concrete materials and structures. A comprehensive survey of literature was carried out. The main ML techniques used to predict the mechanical strength of concrete were identified. References relevant to each technique were classified and used in the analysis. Redundant information was not considered. ML techniques with insufficient details or of rare occurrence were discounted, and focus was on the common and successful techniques that can benefit the critical review, while keeping the paper within acceptable length. The subsequent sections of this paper are organized as follows: Section 2 provides a review of the different ML algorithms used to predict concrete strength, including compressive strength, tensile strength, shear strength, and elastic modulus. In Section 3, the performance of each model is critically analyzed and compared to other models. Section 4 identifies current knowledge gaps and presents practical recommendations that emanate from the current review. Finally, conclusions from this study are presented in Section 5.

2. Prediction of mechanical properties of concrete

ML models have been extensively used as an effective tool for forecasting mechanical properties of concrete. Those models are typically applied to an extensive dataset, which is generally divided into training (TR), validation (VAL), and testing (TS) subsets. The training set is used for model training. Validation data provides unbiased evaluation of the model fit on training data and prevents model overfitting by stopping the training process when the error increases. The model is finally applied on the testing data to assess its predictive performance. The most commonly employed ML methods can be categorized into four major types, namely ANN, SVM, decision trees, and EA. The evaluation, process and the application of these models are discussed below.

2.1. Evaluation of machine learning models

Performance assessment of ML algorithms has been carried out using several statistical methods that describe the model fitting. Table 1 entails potential statistical metrics employed for evaluating ML models with their corresponding mathematical expressions. These methods indicate how well the predicted values fit with actual data. Moreover, they can be adopted in sensitivity analysis, pointing out the weight of each input variable in the prediction process [18–21]. Not only can statistical metrics assess the performance of ML techniques, they may also be used as reference for comparing the effectiveness of several algorithms.

2.2. Artificial neural network

Artificial neural network is a nonlinear model inspired by the basic framework of the human brain [22–25]. In ANN models,

Table 1
Statistical metrics.

Statistical parameter	Formula
Correlation coefficient(R)	$R = \frac{n\sum_{i=1}^{n} y'_i y_i - (\sum_{i=1}^{n} y'_i)(\sum_{i=1}^{n} y_i)}{\sqrt{n(\sum_{i=1}^{n} {y'_i}^2) - (\sum_{i=1}^{n} y'_i)^2}\sqrt{n(\sum_{i=1}^{n} y_i^2) - (\sum_{i=1}^{n} y_i)^2}}$
Coefficient of determination(R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n} (y'_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$
Mean square error(MSE)	$MSE = \frac{\sum_{i=1}^{n} (y'_i - y_i)^2}{n}$
Root mean square error($RMSE$)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y'_i - y_i)^2}{n}}$
Mean absolute error(MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n} \lvert y'_i - y_i \rvert$
Mean absolute percentage error($MAPE$)	$MAPE(\%) = \frac{1}{n}\sum_{i=1}^{n} \left\lvert \frac{y'_i - y_i}{y_i} \right\rvert \times 100$
Mean(μ)	$\mu = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{y'_i}$
Standard deviation(σ)	$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(\frac{y_i}{y'_i} - \mu\right)^2}$
Coefficient of variation(COV)	$COV(\%) = \frac{\sigma}{\mu} \times 100$

Note : y' = predictedvalue, y = actualvalue, and$n$ = numberofdatasamples.

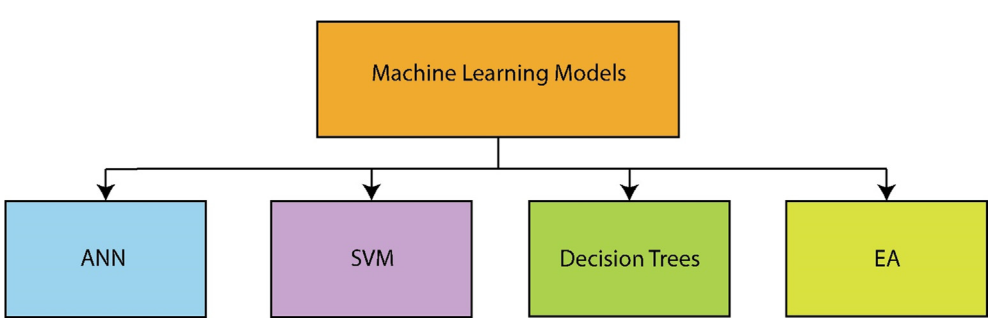

Fig. 1. Machine learning models.

information propagation is performed through links that receive the information from a processing element (neuron) to deliver it to the following neurons. Each information is affected by a weight, reflecting the significance of input variables to outputs [15]. Once a neuron receives an information, it merges it with others coming from different neurons via a combination function. Then, the combined information is transported to the following nodes. This iterative process is repeated until the algorithm precisely fits the data, indicated by the convergence of the error rate, or when the maximum iteration number has been reached [26]. The structure of ANN is generally composed of three types of layers: an input layer, hidden layer(s), and an output layer [27]. Fig. 2 illustrates the general structure of ANN. The input layer conveys input parameters for model training and testing. The hidden layer(s) is/are responsible for linking between the input layer and the output layer that delivers the result of the model. To produce the neuron output and ensure data transmission through hidden and output layers, activation functions are required [22,28]. Furthermore, ANN training is achieved via learning algorithms, which enable the model to understand the concept of the problem. Hence, the general structure of ANN changes according to the type of learning algorithm. Table 2 outlines the various ANN approaches employed for estimating concrete strength, which are discussed below.

2.2.1. Backpropagation neural network

It can be observed in Table 2 that the backpropagation (BP) approach has been widely used by researchers to train ANN [29]. BP is a local search technique that employs learning algorithms, such as gradient descent and Levenberg-Marquardt, to update the weights and biases of the ANN. Such an approach minimizes the cost function that generally expresses the error between actual and predicted strength. Backpropagation neural network (BPNN) was employed for instance to forecast the compressive strength of high-performance concrete (HPC) [30–32]. The model incorporated concrete ingredients and age of testing as input parameters. Performance assessment revealed that BPNN exhibited good forecasting ability, outperforming regression models in terms of accuracy.

Other studies investigated the ability of BPNN in estimating the compressive strength of recycled aggregate concrete (RAC) [33–37]. For example, Topçu et *al.* [33] developed a BPNN based on gradient descent algorithm in addition to fuzzy logic (FL) model to forecast the compressive strength of RAC. Both methods showed good accuracy, but BPNN slightly outperformed FL in terms of R^2, MAPE, and RMSE. Later research by Naderpour et *al.* [36] evaluated the performance of BPNN and inspected the influence of each input parameter on the compressive strength of RAC through sensitivity analysis. Their model included six input variables and eighteen hidden nodes. Results demonstrated that BPNN accurately predicted the compressive strength of RAC, and that water absorption of aggregates along with water-to-total material ratio had greatest impact on concrete strength. More recent studies examined the feasibility of forecasting the compressive strength of self-compacting concrete (SCC) via BPNN [20,38–40]. For instance, Asteris et *al.* [39] developed an ANN model trained with Levenberg–Marquardt algorithm. Their results indicated that BPNN can successfully predict the compressive strength of SCC. Sensitivity analysis revealed that viscosity-modifying admixtures incorporated within SCC had the most important effect on compressive strength.

Moreover, several researchers have explored the applicability of BPNN to estimate the tensile strength of concrete [18,33,41]. For instance, Behnood *et al.* [41] proposed a model to predict the tensile strength of steel fiber-reinforced concrete (SFRC). The model in which the compressive strength of concrete was introduced as an input parameter, predicted the tensile strength of SFRC with satisfactory accuracy, showing better results than SVM. Furthermore, the elastic modulus of concrete has been estimated via BPNN [18,42,43]. Mohammadi *et al.* [42] compared the effectiveness of BPNN and radial basis function neural network (RBFNN) in predicting the elastic modulus of RAC. The Levenberg-Marquart Learning algorithm was used in the BPNN model. Their results showed that BPNN had better predictive ability than that of RBFNN. Furthermore, multiple studies have explored BPNN forecasting of the shear capacity of reinforced concrete (RC) beams [44,45], concrete beams reinforced longitudinally with fiber reinforced polymer (FRP) bars [46–48], SFRC corbels [49], and RC beams strengthened

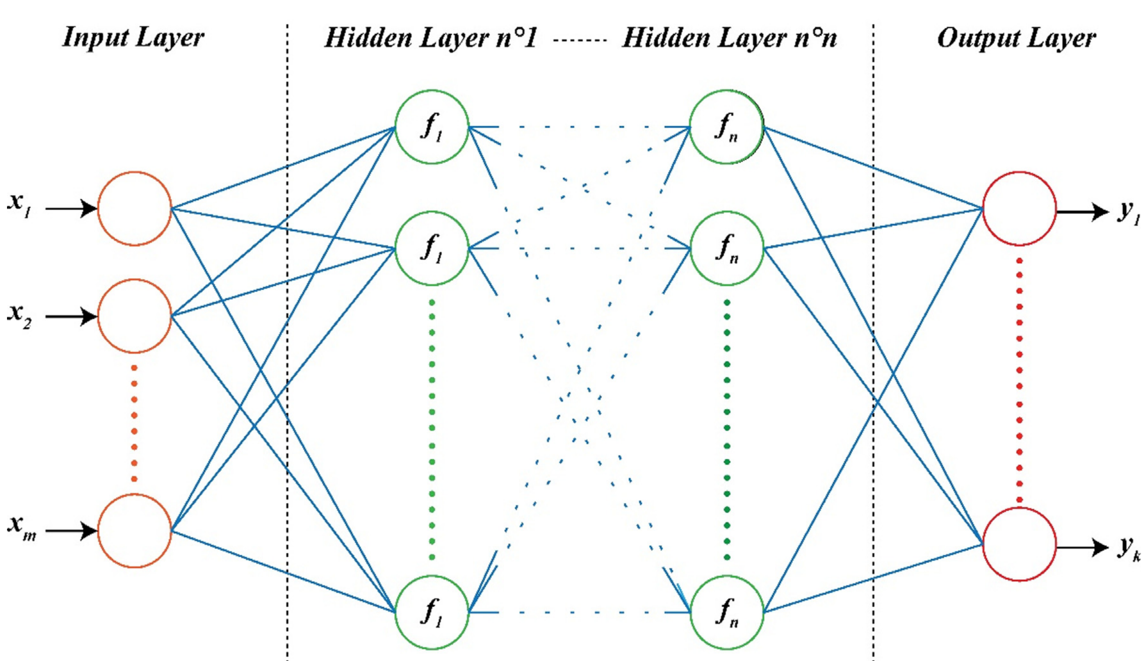

Fig. 2. Structure of ANN model with *m* input variables and *n* hidden layers.

Table 2
Summary of used ANN-based models.

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
99	24	23	34	Cellular Concrete	BPNN	Cement, w/c ratio, sand to cement ratio, foam volume to cement ratio	Compressive strength	Absolute average error, Average algebraic error	[110]
1178	77.8	N/A	22.2	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, Absolute Error	[111]
135	70	15	15	Concrete containing FA and BFS	BPNN	Cement, BFS, curing age, ultrasonic pulse velocity, rebound number, fly ash	Compressive strength	R, MSE	[112]
180	83	N/A	17	Concrete containing FA and BFS	GA-BPNN ANFIS	Cement, BFS, coarse aggregate, fine aggregate, fly ash, water, superplasticizer	Compressive strength	RMSE, R^2	[2]
144	10-fold cross-validation			Concrete containing FA, 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, RMSE, MAE	[69]
1030	70	15	15	Concrete containing silica fume	ANN combined with multi-objective grey wolves	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	[58]
91	N/A	N/A	N/A	Foamed Concrete	ELM	Cement, oven dry density, water/binder ratio, foamed volume	Compressive strength	R, RMSE, MAE, Relative RMSE, Relative MAE	[12]
210	70	15	15	GPC	ANFIS BPNN	Fly ash, sodium hydroxide, sodium silicate solution, water	Compressive strength	R^2, RMSE, MAE	[21]
300	N/A	N/A	N/A	HPC	BPNN	Cement, BFS, fly ash, water, superplasticizer, coarse and fine aggregates, and curing age	Compressive strength	RMSE, MAE, R	[30]
1030	10- fold cross-validation method			HPC	BPNN	Cement, BFS, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	R^2, RMSE, MAPE	[31]
1030	90 80	N/A N/A	10 20	HPC	BPNN Bagged ANN Gradient boosted ANN Wavelet-bagged ANN Wavelet-gradient boosted ANN	Cement, BFS, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	R^2, RMSE, MAE	[104]
270	70	15	15	HPC	BPNN	Cement, nano silica, fine aggregate, copper slag, age of specimen, superplasticizer	Compressive strength	R, R^2, RMSE, MAPE	[32]
1133	10- fold cross-validation method			HPC	MFA-BPNN	Water, cement, BFS, fly ash, superplasticizer, coarse and fine aggregates, age of testing	Compressive strength	R, RMSE, MAE, MAPE	[59]
324	75	N/A	25	HSC	ELM BPANN	Water, cement, fine aggregate, coarse aggregate, superplasticizer	Compressive strength	RMSE, MAE, MAPE, R, Nash-Sutcliffe efficiency	[53]
173	70	15	15	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	[54]
210	67	N/A	33	RAC	BPNN	Age of the specimen, cement, water, sand, aggregate, recycled aggregate, superplasticizer and silica fume	Compressive strength	RMSE, R^2, MAPE	[33]
168	N/A	N/A	N/A	RAC	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	[34]
257	70	15	15	RAC	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, Sum of squared errors, MSE	[35]

Table 2 (*continued*)

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
139	N/A	N/A	N/A	RAC	BPNN	Water absorption, w/c ratio, fine aggregate, natural coarse aggregate, recycled coarse aggregate, water to total material ratio	Compressive strength	R, MSE	[36]
74	68	N/A	32	RAC	BPNN Convolutional Neural Network	Recycled coarse aggregate replacement ratio, recycled fine aggregate replacement ratio, fly ash replacement ratio, w/c ratio	Compressive strength	Relative error	[37]
112	70	15	15	Rubberized Concrete	BPNN	W/C ratio, superplasticizer, coarse aggregates, fine aggregates, crumb rubber, tire chips	Compressive strength	R, MAE, MSE	[113]
324	70	15	15	Rubberized concrete	BPNN	Temperature, exposure duration, fiber content, w/c ratio	Compressive strength	MSE, RMSE, R, average absolute deviation, COV, Sum of squared errors	[114]
169	67	16.5	16.5	SCC	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	[38]
114	80	N/A	20	SCC	BPNN	Binder, fly ash replacement percentage, water/binder ratio, fine aggregate, coarse aggregate, superplasticizer	Compressive strength	R, Relative error	[20]
205	67	16.5	16.5	SCC	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	[39]
126	83		17	Steel fiber added lightweight concrete	BPNN	The amounts of steel fiber, water, w/c ratio, cement, pumice sand, pumice gravel, and super plasticizer	Compressive strength	MSE, MARE, R	[115]
145	78	N/A	28	HSC	ANFIS	Compressive strength of concrete	Elastic Modulus	RMSE, MAPE	[55]
	83	N/A	17	Normal concrete					
421	N/A	N/A	N/A	RAC	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	Mean, SD, RMSE, MAPE	[18]
400	80	N/A	20	RAC	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 mixed (i.e., natural and recycled) coarse aggregates, water absorption of the mixed coarse aggregates, 28-day cube compressive strength of the mixture	Elastic Modulus	RMSE, MAE, MAPE	[42]
324	70	15	15	RAC	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	[43]
87	80	N/A	20	FRP reinforced	BPNN	Effective depth, web width, compressive strength of concrete, shear span to depth ratio, modulus of elasticity of FRP, reinforcement ratio	Shear strength	MAE, COV, σ, μ	[46]
106	73	N/A	27	FRP reinforced	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	μ, σ, COV, RMSE, R^2	[48]
177	60	20	20	FRP reinforced	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	MAE, MSE, R, COV	[47]
122	80	N/A	20	High Strength Concrete	ANFIS	Tensile reinforcement ratio, concrete compressive strength, shear span to depth ratio	Shear strength	COV, MSE, R	[56]

(*continued on next page*)

Table 2 (*continued*)

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
176	80	N/A	20	RC	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	μ, COV	[44]
123	81	N/A	19	RC	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	[45]
98	81	N/A	19	RC strengthened in shear with FRP	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	R, μ, COV, σ	[50]
84	61	N/A	39	RC 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 reinforcement, total fabric design thickness, shear span to depth ratio	Shear strength	RMSE, R^2	[51]
730	90	N/A	10	SFRC	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, Pearson's coefficient	[49]
714	10-fold cross-validation			HPC	MFA-BPNN	Curing age, cubic compressive strength	Tensile strength	R, RMSE, MAE, MAPE	[59]
346	N/A	N/A	N/A	RAC	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	Tensile strength	Mean, SD, RMSE, MAPE	[18]
210	67	N/A	33	RAC	BPNN	Age of the specimen, cement, water, sand, aggregate, recycled aggregate, superplasticizer, silica fume	Tensile strength	RMS, R^2, MAPE	[33]
980	70	15	15	SFRC	BPNN	Water to binder ratio, concrete compressive strength, age of the specimen, fiber reinforcing index	Tensile strength	R, R^2, MAPE, MAE, RMSE	[41]
187	90	N/A	10	HSC	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	RMSE, R^2, MAPE, sum of squares error	[116]
225	50	N/A	50	Ground granulated blast furnace slag concrete	BPNN	Cement, blast furnace slag, superplasticizer, aggregates, water and age of samples	Compressive strength	R^2	[117]
2817	70	15	15	Normal and high-performance concrete	Grey wolf optimized ANN Grey wolf optimized ANFIS	Coarse aggregate, sand, water, cement, BFS, fly ash, superplasticizer, age of specimens	Compressive strength	RMSE, scatter index, MAE, R^2, uncertainty with 95% confidence level, MBE	[118]
240	56	21	23	Silica fume concrete	BPNN	Cement, amount of silica fume replacement, water content, amount of aggregate, plasticizer content, and age of samples	Compressive strength	Mean absolute relative error, MSE	[119]

in shear with FRP [50,51]. Input parameters incorporated in these studies included the geometrical characteristics of beams along with the mechanical properties of concrete and reinforcing materials. Results indicated that BPNN successfully predicted the shear strength, demonstrating better accuracy than that of empirically developed equations [48].

2.2.2. Extreme learning machine

Extreme Learning Machine (ELM) in another potential approach used to train single hidden-layer feed-forward neural networks [12,52]. In the ELM approach, hidden nodes are initiated in a random process and fixed without performing an iterative tuning. The model was adopted for instance by Al-Shamiri *et al.* [53] to forecast the compressive strength of high-strength concrete (HSC). The number of hidden neurons in the model was gradually increased from 10 to 200, and the optimal obtained number was 110. Performance assessment of the model revealed the strong predictive ability of ELM, which was reflected by the value of the correlation coefficient. Earlier research by Mundher *et al.* [12] considered an ELM model to predict the compressive strength of foamed concrete. The model was benchmarked against three other ML algorithms namely M5 Tree, multivariate adaptive regression spline (MARS), and support vector regression (SVR). Performance assessment indicated that ELM had the best overall accuracy among the four models.

2.2.3. Hybrid ANN-based models

The idea behind hybrid approaches is to combine several algorithms so that the model performance and process can be noticeably improved. Owing to their ability in combining the advantages of more than one model, hybrid approaches have become of great interest among researchers. Thus, the performance of models like Adaptive Neuro-Fuzzy Inference System (ANFIS) has been widely examined [2,21,35,45,54–56]. ANFIS models are universal approximators that combine ANN and FL. This model uses ANN to enhance the membership capacities for decreasing the error rate in the output, while FL rules are responsible for providing expert knowledge [21,57]. FL rules are used within the algorithm as fuzzy "if-then" rules to create the specified input–output sets. ANFIS was employed for instance to predict the compressive strength of geopolymer concrete along with concrete containing blast furnace slag and fly ash [2,21]. Results disclosed that ANFIS has a strong prediction ability, outperforming the BPNN model. ANFIS was also developed to predict the shear strength of RC and HSC beams [45,56]. The model exhibited good predictions which outperformed those presented by design codes such as the American Concrete Institute and Canadian Standards Association. Another approach of optimizing ANN consisted of incorporating metaheuristic algorithms [2,58,59]. Yuan *et al.* [2] adopted the Genetic Algorithm (GA) model to optimize the weights and thresholds of BPNN. GA is a metaheuristic algorithm inspired by the natural evolution and selection concept [60,61]. Its ability in acquiring a global optimal solution while escaping local optima makes it a potential candidate for optimizing BPNN. Hybrid GA-ANN model was used to forecast the compressive strength of concrete containing slag and fly ash. Comparative study between GA-ANN and BPNN indicated that GA-ANN achieved best performance. Behnood *et al.* [58] developed a multi-objective grey wolves optimization (MOGWO) algorithm for determining the most effective ANN structure. MOGWO is based on grey wolves optimization, which is a swarm intelligence optimization method based on the hunting strategies of grey wolves swarm. The hybrid MOGWO-ANN forecasted the compressive strength of silica fume concrete with satisfactory accuracy. The maximum aggregate size was found to have significant impact on the compressive strength of concrete as indicated by sensitivity analysis. Bui *et al.* [59] employed a modified firefly algorithm (MFA) to optimize the weights and biases of an ANN model for predicting the compressive and tensile strength of HPC. The firefly algorithm (FA) is a nature inspired metaheuristics method based on the flashing characteristics and behavior of tropical fireflies [62]. Study results showed that MFA-ANN model achieved accurate predictions and short computation time.

2.3. Support vector machine

Support Vector Machine is a ML classification model that aims to find an optimal hyperplane separating two different classes. As shown in Fig. 3, the target of this method is maximizing the margin, which represents the distance from the hyperplane to the closest point of each class, to attain better classification performance on test data [15]. When the optimal hyperplane is found, the points located on its margin are called "support vectors", and the solution proposed by this algorithm is based only on those points. However, some classes cannot be separated with a linear hyperplane, as illustrated in Fig. 4. In such cases, the input space has to be mapped into a higher dimensional feature space in order to make the linear separation of classes possible [63]. Nonlinear mapping process is generally performed through nonlinear function. Then, the output of the algorithm is obtained from nonlinear space through kernel functions [64–66]. These functions can be classified into five types; polynomial, sigmoid, radial basis, exponential radial basis and linear [67]. They help determining a nonlinear decision boundary without need for computing the optimal hyperplane parameters in the feature space. Thus, the solution can be expressed as a combination of the weighted values of kernel functions at support vectors [64]. When SVM is mainly applied for regression analysis, the model is generally called support vector regression (SVR) [31,67]. It deals with regression problems as a set of linear equations, leading to faster training process and better accuracy [12,68]. Several studies have examined the predictive ability of SVM. Table 3 outlines the different SVM-based models used for estimating concrete strength. It can be observed that SVM algorithms have been employed as standalone models in some studies and optimized with metaheuristic algorithms in others.

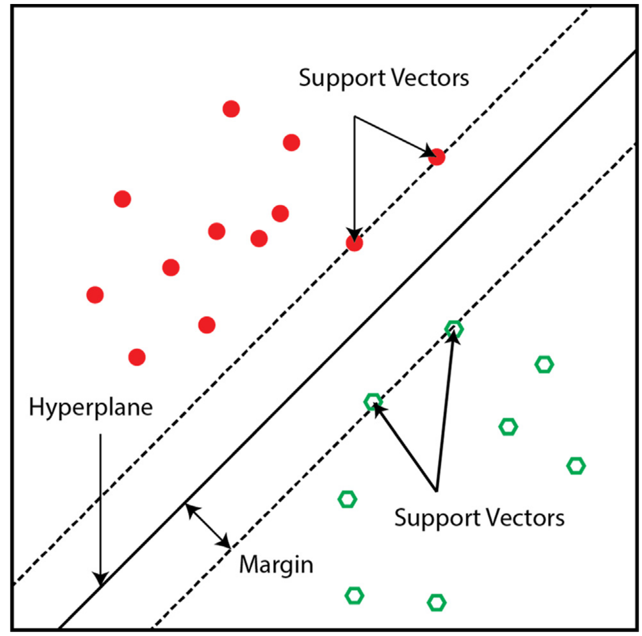

Fig. 3. Hyperplane classification.

2.3.1. Standalone SVM models

The application of individual SVM models to predict the mechanical strength of concrete has been extensively investigated. For instance, Chou *et al.* [31] used SVM to predict the compressive strength of HPC. The model was developed using a radial basis kernel function. Results indicated that SVM had high prediction accuracy based on the value of MAPE. Omran *et al.* [69] employed SVM based on sequential minimal optimization to forecast the compressive strength of concrete containing Haydite lightweight aggregate and Portland limestone cement. Deng *et al.* [37] used SVM for predicting the compressive strength of recycled aggregate concrete (RAC). Performance evaluation showed that the model achieved acceptable predictive accuracy. In another study conducted by

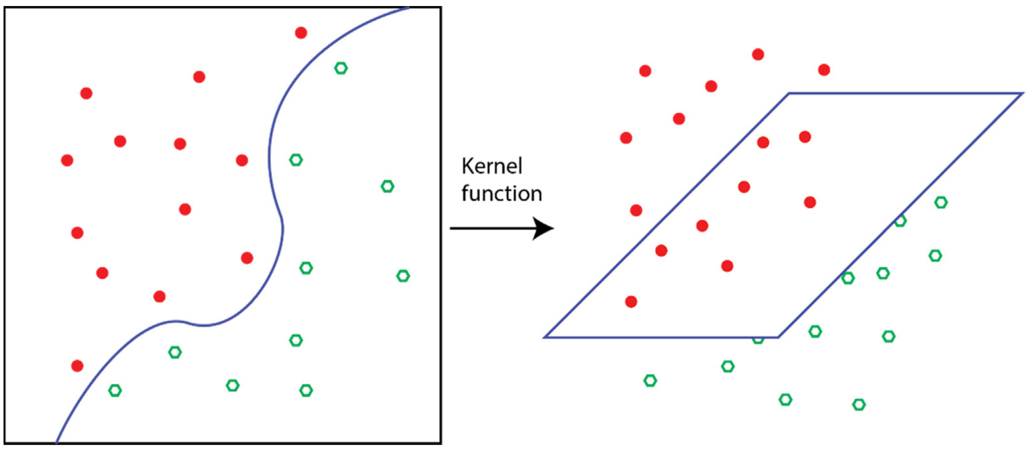

Fig. 4. Nonlinear mapping in SVM.

Behnood *et al.* [41], SVM was employed to forecast the tensile strength of SFRC and revealed better performance than that of non-linear regression analysis. The elastic modulus of HSC and RAC was also predicted via SVM [42,70] and satisfactory results were reported. The least square support vector machine (LSSVM) is another variation of SVM in which the least squares loss function is used to build the optimization problem and achieve better accuracy [71]. Several studies evaluated the performance of this model in predicting the mechanical strength of concrete. For instance, Mundher *et al.* [12] proposed the least square support vector regression (LSSVR) to predict the compressive strength of foamed concrete and this model achieved reliable accuracy.

2.3.2. Hybrid SVM-based models

The application of SVM within hybrid approaches aims to optimize the process and the performance of standalone SVM models. Several studies have used FA, for instance as an optimization approach to estimate the compressive strength and the shear strength of concrete. For example, Pham *et al.* [72] adopted the FA-LSSVR hybrid model to estimate the compressive strength of HPC. FA was mainly incorporated to evaluate the hyperparameters of LSSVM. Two experiments were conducted: the first consisted of splitting data into training and testing sets, while the second one was based on 10-fold cross-validation. Results uncovered the strong ability of FA-LSSVR in forecasting the compressive strength of concrete, which was reflected by MAPE. More recent studies investigated the prediction of the shear strength of RC and SFRC beams along with FRP reinforced slabs through FA-LSSVM algorithm [73–75]. The model comprised input parameters including geometrical characteristics of beams and slabs, as well as the mechanical properties of reinforcing components. Results showed that FA-LSSVM achieved accurate forecasting of the shear strength of concrete structures. In another study conducted by Yu *et al.* [76], an enhanced version of a swarm-based algorithm named cat swarm optimization was used to forecast the compressive strength of HPC. The enhanced cat swarm optimization (ECSO) model was employed to optimize the key parameters of SVM. The probabilistic Akaike information criterion was adopted as the objective function for the optimization problem. ECSO-SVM model exhibited high predictive ability, as evidenced by statistical metrics. Keshtegar *et al.* [77] developed a new model that hybridizes the response surface method (RSM) and SVM. The model forecasted the shear strength of SFRC beams with satisfactory results. The hybrid RSM-SVM model was also compared to other standalone intelligent models such as RSM, SVR and classical neural network in addition to eight empirical formulations. It was reported that RSM-SVR model had better accuracy compared to the other models. Cheng *et al.* [1] developed an evolutionary fuzzy SVM inference model for time series data, which combines FL, SVM, and GA to estimate the compressive strength of HPC. Results indicated that the developed model performed better than SVM and BPNN as depicted in scatter diagrams presenting actual and predicted values.

2.4. Decision tree models

Decision tree models are ML techniques in which formal rules are created through patterns in the data [15]. As outlined in Table 4, three decision tree-based models, namely M5P-tree, Multiple Additive Regression Trees (MART) and Random Forest (RF) have mostly been used to predict mechanical properties of concrete. The process and application of each model are discussed below.

2.4.1. M5P-tree

M5P is an expanded version of Quinlan's M5 algorithm, where a conventional decision tree is combined with linear regression functions at the nodes. The construction of the M5 model is performed through three main steps [78,79]. First, a tree model is built using a splitting criterion that divides the data into subsets. Then, tree pruning is performed to remove or merge unwanted subtrees in order to overcome data overfitting that appeared during tree construction. Finally, a smoothing process is performed to compensate for the sharp discontinuities occurring between adjacent linear models at the pruned tree leaves. This process is schematically represented in Fig. 5. In order to spilt the input space and generate the regression tree in this model, a measure called the standard deviation factor (SDR), which is the maximum reduction in output errors after branching, is considered [41,80]. M5 algorithm was modified to M5P to deal with enumerated attributes as well as attribute missing values. In the M5P tree algorithm, all enumerated attributes are transformed into binary variables before tree construction [81]. M5P has been used in several studies to predict the mechanical properties of concrete [30,69,80]. The application of this model included forecasting the compressive strength of HPC and foamed concrete, along with concrete fabricated with fly ash, Haydite lightweight aggregate, and Portland limestone cement [12,30,69]. The model comprised various input variables including concrete mixture ingredients, age of testing and other dimensionless ratios. It was concluded that the M5P model predicted the compressive strength accurately, as evidenced by statistical metrics.

Table 3
Summary of adopted SVM-based models.

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
1030	10- fold cross-validation			HPC	SVM	Cement, BFS, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	R^2, RMSE, MAPE	[31]
1030	90	N/A	10	HPC	Evolutionary fuzzy SVM inference model for time series data	Cement, BFS, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	R, R^2, RMSE, MAE	[1]
144	10-fold cross-validation			Concrete containing 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	[69]
239	10-fold cross-validation			HPC	FA-LSSVR	Cement, fine aggregate, small coarse aggregate, medium coarse aggregate, water, superplasticizer, concrete age	Compressive strength	RMSE, MAPE, R^2	[72]
91	N/A	N/A	N/A	Foamed concrete	LSSVR	Cement, oven dry density, water/binder ratio, foamed volume	Compressive strength	R, RMSE, MAE, Relative RMSE, Relative MAE	[12]
1761	70	N/A	30	HPC	ECSO-SVM	Water, cement, BFS, fly ash, superplasticizer, coarse, aggregate, fine aggregate, curing age	Compressive strength	Squared correlation coefficient, σ, Relative RMSE, R^2 MAPE, Index of agreement, MAE, SRL, Error to signal ratio	[76]
74	68	N/A	32	RAC	SVM	Recycled coarse aggregate replacement ratio, recycled fine aggregate replacement ratio, fly ash replacement ratio, w/c ratio	Compressive strength	Relative error	[37]
214	10-fold cross-validation			RC	Smart artificial firefly algorithm based LSSVR	Ratio of effective depth to breadth of beam, 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	R, RMSE, MAE, MAPE	[73]
82	88 10-fold cross-validation	N/A	12	FRP reinforced (slabs)	Firefly algorithm combined with LSSVM	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	RMSE, MAPE, R^2	[74]
139	70	N/A	30	SFRC	Firefly algorithm Combined with SVR	Concrete strength, longitudinal steel strength, shear span to depth ratio, effective depth of beam, beam width, maximum aggregate size, longitudinal steel ratio, steel fiber volume fraction, fiber length, the equivalent fiber diameter	Shear strength	Scatter index, MAPE, RMSE, MAE, Root mean square relative error, mean relative error, BIAS	[75]
139	75	N/A	25	SFRC	Response surface method combined with SVR	Concrete strength, longitudinal steel strength, shear span to depth ratio, effective depth of beam, beam width, maximum aggregate size, longitudinal steel ratio, steel fiber volume fraction, fiber length, equivalent fiber diameter	Shear strength	MAE, RMSE, modified agreement index, modified Nash and Sutcliffe efficiency	[77]
980	70	15	15	SFRC	SVM	Water to binder ratio, concrete compressive strength, age of the specimen, fiber reinforcing index	Tensile strength	R, R^2, MAPE, MAE, RMSE	[41]
400	80	N/A	20	RAC	SVR	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 mixed (i.e., natural and recycled) coarse aggregates, water absorption of the mixed coarse aggregates, 28-day cube compressive strength of the mixture	Elastic modulus	RMSE MAE MAPE	[42]

(continued on next page)

Table 3 (*continued*)

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
159	78 81	N/A N/A	22 19	HSC Normal concrete	SVM	Compressive strength of concrete	Elastic modulus	RMSE, MAPE	[70]
650	50	N/A	50	Concrete containing coarse recycled concrete aggregates	LSSVR	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	RMSE, MAE, MAPE	[121]
421	47	N/A	53	Concrete containing coarse recycled concrete aggregates	LSSVR	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	Elastic modulus	RMSE, MAE, MAPE	[121]
346	51	N/A	49	Concrete containing coarse recycled concrete aggregates	LSSVR	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	Tensile strength	RMSE, MAE, MAPE	[121]

2.4.2. MART

MART is a powerful metaclassifier that involves the conventional classification and regression trees (CART) enhanced with stochastic gradient boosting that tends to improve the accuracy of learning algorithms by combining and fitting a series of models with low error rates, forming an ensemble model that has better performance [82,83]. MART has been used by Chou *et al.* [31] to predict the compressive strength of HPC. The model achieved adequate predictive accuracy and outperformed both ANN and SVM in terms of R^2.

2.4.3. Random forest

Random forest (RF) has also been adopted in multiple studies as a forecasting tool. RF combines multiple decision trees, each of which is built from a new training set based on the bagging method [84,85]. The bagging method, which is also known as bootstrap aggregation, is an ensemble training method that consists of two steps: bootstrap and aggregation. In the first step, identically distributed and independent datasets are created by randomly resampling the original set of data. During the second step, the new datasets are used for training the base predictors independently. Results are obtained by averaging the predictions of each tree predictor through the aggregation method. The RF has been used by several researchers for predicting the mechanical strength of concrete. For instance, Han *et al.* [84] employed RF to forecast the compressive strength of HPC. Earlier study by Mangalathu *et al.* [86] adopted the same model for predicting the shear strength of RC beam-column joints. Results of both studies were in good agreement, affirming the ability of RF in producing reliable predictions. Another research conducted by Zhang *et al.* [87] consisted of applying RF to estimate the uniaxial compressive strength of SCC. The RF model was enhanced with a beetle antennae search (BAS) algorithm which was developed from the behavior of the beetle that tunes to a position with a higher concentration of odor when searching nearby areas using its two antennae [88]. The authors concluded that BAS demonstrated great capacity in finding optimum hyper-parameters of RF and that the hybrid BAS-RF algorithm showed good forecasting ability.

2.5. Evolutionary algorithms

Evolutionary algorithms form a category of heuristic search methods in which the process of finding a solution in the search space is based on the mechanism of biological evolution including selection, mutation, recombination, reproduction, and recombination [89,90]. The general process of evolutionary algorithms is illustrated in Fig. 7. First, an initial population representing a set of candidate solution is randomly generated. Then, evaluation of this population is performed via the fitness function. The next generation which comprises a better set of candidates is then generated through recombination and mutation. Recombination consists of generating new candidates via a binary operator applied on the previous generation (parents). Mutation only modifies one candidate from the previous set. After both operators, i.e. recombination and mutation, are applied, a new generation is created based on the fitness function. This iterative process stops when the desired value of fitness function is achieved or when the maximum number of generations is reached.

Evolutionary algorithms have been widely adopted for predicting concrete strength. Table 5 entails some recent studies that adopted evolutionary algorithms for assessing concrete strength. Gandomi *et al.* [91,92] employed gene expression programming (GEP) to predict the shear strength of slender RC beams. Minimizing the objective function that comprises the values of statistical indexes corresponding to learning, validation and testing data has been performed to get the best GEP algorithm. The model achieved good predictive accuracy, and a comparative study revealed the superiority of GEP over design codes such as the ACI and Eurocode 2. Linear genetic programming is another evolutionary algorithm that has been used for instance in predicting the compressive strength of carbon fiber reinforced plastic (CFRP) confined concrete [93]. Four different formulations have been developed through LGP model. Results showed that the formulations can provide strong accuracy. Parametric analysis was also conducted to figure out the impact of influencing parameters. The obtained results were in good agreement with those presented from experimental studies of other researchers. Golafshani *et al.* [94] adopted three models, namely genetic programming (GP), artificial bee colony programming (ABCP), and biogeography-

Table 4
Summary of employed decision tree models.

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
300	N/A	N/A	N/A	HPC	M5P-tree	Cement, BFS, fly ash, water, superplasticizer, coarse and fine aggregates, and curing age	Compressive strength	RMSE, MAE, R	[30]
1030	10- fold cross-validation			HPC	MART Bagging regression trees	Cement, BFS, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	R^2, RMSE, MAPE	[31]
144	10- fold cross-validation			Concrete containing FA, 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	[69]
1030	5- fold cross-validation			HPC	Genetic weighted pyramid operation tree	Cement, fly ash, slag, water, superplasticizer, coarse aggregate, fine aggregate, age of testing	Compressive strength	RMSE, MAE, MAPE, Reference index	[108]
1912	85	N/A	15	Normal concrete HPC	M5P-tree	Cement, water, fly ash, BFS, superplasticizer, coarse aggregate, fine aggregate, age of concrete	Compressive strength	Slope of regression line (SRL), R, R^2, MAPE, MAE, RMSE	[80]
91	N/A	N/A	N/A	Foamed concrete	M5-Tree	Cement, oven dry density, water to binder ratio, foamed volume	Compressive strength	R, RMSE, MAE, Relative RMSE, Relative MAE	[12]
1030	90	N/A	10	HPC	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, MAE, RMSE, MAPE	[84]
131	10- fold cross-validation			SCC	Beetle antennae search based random forest	Water to binder ratio, macro-synthetic polypropylene fiber, steel fiber, scoria, crumb rubber, natural fine aggregate, natural coarse aggregate	Compressive strength	RMSE, R	[87]
536	70	N/A	30	RC	Random Forest	Concrete compressive strength, joint transverse reinforcement, joint shear stress, in-plane joint geometry, out-of-plane joint geometry, ratio of beam depth to column depth, joint eccentricity parameter, ratio of beam width to column width, column axial load ratio, beam bar bond parameter, column to beam flexural moment strength ratio, column intermediate longitudinal reinforcement factor	Shear Strength	μ, Covariance, COV, MSE, ABS, R^2	[86]
454	80	N/A	20	RAC	M5 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	[79]
470	80	N/A	20	Concrete 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, and age of concrete	Compressive strength	RMSE, MAE, MAPE, R^2, R	[120]
172	80	N/A	20	Concrete 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, and age of concrete	Elastic modulus	RMSE, MAE, MAPE, R^2, R	[120]
295	80	N/A	20	Concrete 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, and age of concrete	Tensile strength	RMSE, MAE, MAPE, R^2, R	[120]
40	15-fold cross validation 20-fold cross validation			high-volume mineral admixture concrete	M5 M5P	Age of testing, cement, fly ash, slag content	Compressive strength	R^2, MAE	[96]

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Table 4 (*continued*)

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
650	50	N/A	50	Concrete 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	RMSE, MAE, MAPE	[121]
650	50	N/A	50	Concrete 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	RMSE, MAE, MAPE	[121]
421	47	N/A	53	Concrete 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	Elastic modulus	RMSE, MAE, MAPE	[121]
346	51	N/A	49	Concrete 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	Tensile strength	RMSE, MAE, MAPE	[121]

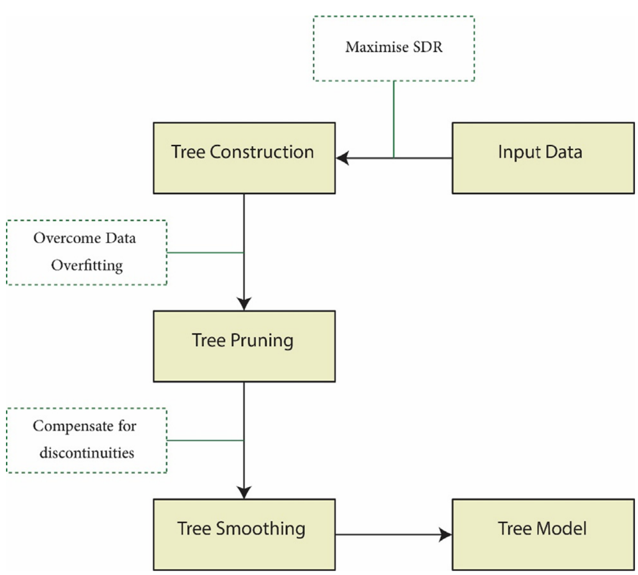

Fig. 5. M5-tree process.

based programming (BBP) to forecast the elastic modulus of RAC. The developed models achieved reliable accuracy. Also, water absorption along with fine aggregate-to-total aggregate ratio and compressive strength of concrete had significant effect on the elastic modulus of RAC.

2.6. Selection of model inputs

Selection of the most relevant features needed for training and testing the different ML models is key to simplifying the models and improving its performance. Beside computational efforts, human intelligence and experience are needed to select the most suitable parameters for running ML models. This leads to accurate selection of the inputs that have noteworthy impact on concrete strength and avoiding parameters with low influence, which can save computation time. Several studies adopted common features for predicting concrete strength. For example, binder content, aggregates and mineral additions such as fly ash and blast furnace slag have been extensively integrated [1,30,31,38,39,59,76,84]. Aggregates are also an important parameter affecting the mechanical strength of concrete. Appropriate hardness, granular size distribution and cleanness of aggregates have a significant effect on the strength of concrete materials. Supplementary cementitious materials such as fly ash, blast furnace slag and silica fume are amongst the most commonly incorporated materials in concrete owing to the beneficial effect of their pozzolanic properties and microfiller effect on the compressive strength of concrete [95,96]. For instance, fly ash can increase the workability resulting in less mixing water needed for concrete, which in turn can improve the strength of concrete. Ultrafine silica fume particles densify the cement paste-aggregate interfacial zone, dramatically enhancing compressive strength. Moreover, the water-to-binder (w/b) ratio, curing conditions and age, and chemical admixtures have been considered as crucial input parameters for assessing concrete strength. For instance, increasing the w/b ratio decreases the proportion of hydrated products and increases the porous structure in concrete, leading to lower mechanical strength.

3. Discussion and critical analysis

ML techniques have been adopted by several researchers as a new approach to forecast the mechanical strength of concrete materials. As entailed in Table 6, statistical metrics retrieved from a non-exhaustive list of studies reflects the noteworthy advantage of ML techniques over empirical formulas for the same testing data. This can be explained by the ability of ML techniques in accurately predicting the properties of complex concrete materials, where the relationship between concrete mixture ingredients and the corresponding compressive strength is highly nonlinear. Also, it can be observed in Tables 2–5 that ML models were developed based on extensive databases, implying that the number of data examples used for developing those models is significantly higher than that of empirically developed equations. Accordingly, the applicability of empirical models is limited to few examples, leading to higher error when forecasting "unseen" data. Furthermore, a potential problem associated with empirical and statistical formulas is their inability to provide accurate estimation of the mechanical strength of concrete incorporating new admixtures, thus ignoring the effect of the new ingredients on the final output. Conversely, ML models offer the advantage of updating the predictive mechanism by controlling the number of inputs (features) and ingredients considered within the model. Moreover, the impact of each input variable on concrete strength can be determined

Table 5
Summary of used evolutionary algorithms.

Dataset size	TR (%)	VAL (%)	TS (%)	Concrete Type	Methods Used	Input Variables	Output	Statistical Index	Ref.
1942	70	15	15	RC	GEP	Beam width, effective depth, shear span to depth ratio, compressive strength, longitudinal reinforcement ratio	Shear strength	R, MAE, RMSE	[92]
466	70	15	15	RC	GEP	Beam width, effective depth, shear span to depth ratio, compressive strength, longitudinal reinforcement ratio, amount of shear reinforcement	Shear strength	R, MAE, RMSE	[91]
1938	70	15	15	RC	Linear genetic programming	Compressive strength, mechanic arm, longitudinal reinforcement ratio, maximum size of coarse aggregate, shear span to depth ratio	Shear strength	R, MAE, RMSE	[122]
208	67	14	19	SFRC	Multi expression programming (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	[123]
83	53	22	25	RC	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	[124]
1028	70	N/A	30	HPC	Geometric Semantic Genetic Programming	Cement, Fly ash, Blast furnace slag, Water, Superplasticizer, Coarse aggregate, Fine aggregate, Age of testing.	Compressive strength	RMSE	[125]
70 89	81 78	N/A N/A	19 22	Normal concrete HSC	Linear genetic programming	Compressive strength	Elastic Modulus	R, MAE	[126]
104	54	19	27	FRP-Reinforced concrete	GEP	Compressive strength, beam width, effective depth, shear span to depth ratio, longitudinal reinforcement ratio, modulus of elasticity of steel and FRP longitudinal bars	Shear strength	Average absolute error	[127]
101	90	N/A	10	CFRP confined concrete	Linear genetic programming	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	[93]
400	80	N/A	20	RAC	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	[94]

Table 6
Comparison between ML models and empirical formulas over the same testing data.

Ref.	Output	Model	Statistical metrics					
[77]	Shear strength	Kwak et al. [128] RSM-SVR	MAE	0.508 0.186	RMSE	0.699 0.233		
[123]	Shear strength	Kwak et al. [128] MEP	R	0.950 0.952	MAE	0.804 0.520	RMSE	1.680 0.733
[75]	Shear strength	Kwak et al. [128] SVR-FFA	MAE	0.524 0.176	RMSE	0.717 0.277		
[74]	Shear strength	Ospina et al. [129] ANN	R^2	0.91 0.96	RMSE	117.51 53.190	MAPE	15.48 10.48
[18]	Compressive strength	Pereira et al. [130] ANN	RMSE	28.15 7.71	MAPE	54.22 15.13		
[18]	Elastic modulus	Ravindrarajah and Tam [131] ANN	RMSE	5749.73 4425.89	MAPE	17.85 11.21		
[18]	Tensile strength	Pereira et al. [130] ANN	RMSE	0.720 0.480	MAPE	14.650 11.890		

through ML techniques via sensitivity analysis. These advantages of ML models make the application of statistical and empirical models limited to some problems in which the studied concrete has a simple structure, since conventional methods are convenient in providing explicit mathematical formulas.

In addition to the difference between statistical approaches and ML models, there are contrasts between ML algorithms in terms of process and performance. Thus, each ML technique has several advantages and drawbacks compared to other models. This can be supported by the values of statistical metrics shown in Table 7, which reveals the performance of multiple ML models over the same testing data.

As mentioned previously, several studies adopted ANN because of their inherent advantages. An explicit vector of weights and biases along with a fixed number of hidden layers and hidden neurons achieved after several trials can lead to a well-defined structure of ANN model. However, such repetitive trial and error-tuning process is time-consuming. Another major weakness of the ANN model is associated with the BP approach, where the training process is performed through a gradient descent algorithm on the error space that includes local minima [97,98]. As outlined in Fig. 6, convergence of BP to local minima and avoidance of global solutions has been a concern [2,99,100]. Using ELM as an alternative method can mitigate the problem of convergence to local

Table 7
Comparison between ML models over the same testing data.

Ref.	Dataset size	Output	Models	Statistical metrics					
[31]	1030	Compressive strength	ANN	R^2	0.909	RMSE	5.030	MAPE	10.903
			SVM		0.885		5.619		12.773
			MART		0.911		4.949		13.886
[59]	1133	Compressive strength	GEP	R	0.910	MAE	5.200		
			FA-LSSVR		0.940		3.860		
			MFA-ANN		0.950		3.410		
[21]	210	Compressive strength	ANN	R^2	0.851	MAE	1.989	RMSE	2.423
			ANFIS		0.879		1.655		2.265
[76]	1761	Compressive strength	BPNN	R^2	0.960	MAE	5.038		
			ELM		0.934		4.278		
			ANFIS		0.906		4.183		
			SVM		0.793		5.950		
			M5		0.937		4.028		
			ECSO-SVM		0.942		3.980		
[72]	239	Compressive strength	ANN	R^2	0.760	RMSE	6.740	MAPE	13.410
			SVM		0.790		6.070		12.020
			FA-LSSVR		0.870		4.860		9.810
[53]	324	Compressive strength	ELM	R	0.9965	MAE	0.6049	RMSE	0.7998
			BP		0.9949		0.7372		0.9498
[2]	180	Compressive strength	ANN	R^2	0.680	RMSE	3.21		
			GA-ANN		0.813		2.22		
			ANFIS		0.950		1.46		
[41]	980	Tensile strength	ANN	R^2	0.874	MAE	0.408	RMSE	0.526
			SVM		0.890		0.400		0.524
			M5 Tree		0.866		0.412		0.598
[77]	139	Shear strength	ANN	MAE	0.322	RMSE	0.461		
			SVR		0.622		1.040		
			RSM		0.347		0.444		
			RSM-SVR		0.186		0.233		

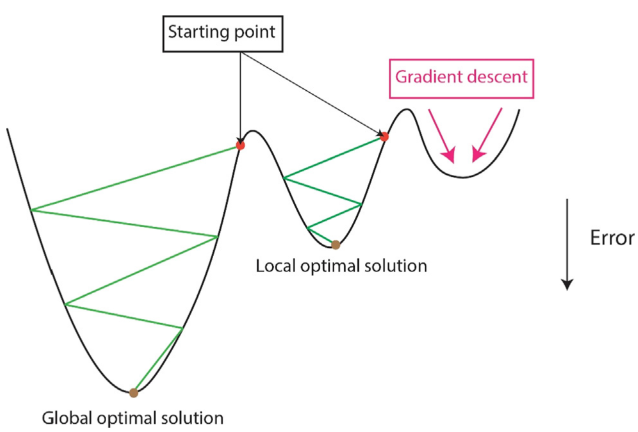

Fig. 6. BPNN searching mechanism.

optima and provide more simplicity since no learning rate and stopping criteria are required [101]. Al-shamiri *et al.* [53] compared ELM to BPNN and recorded better performance with ELM model. However, the adopted model could require more hidden neurons than the BP approach due to the random determination of the input weights and hidden biases [102,103]. An excessive number of hidden neurons used in complex models leads to overfitting, which means that the complexity of concrete properties can be overestimated by ANN [58]. To overcome the aforementioned drawbacks, various metaheuristic and ensemble models have been proposed to enhance ANN performance and process. For instance, using GA and ensemble algorithms such as bagging and gradient boosting to optimize the predictive accuracy of ANN has proven to be effective [2,104]. However, GA-ANN model adopted by Yuan *et al.* [2] tended to increase model complexity and computation time. Another alternative consists of using ANFIS models, which combine the learning abilities of ANN and the reasoning capabilities of FL [2]. Sahin *et al.* [105] reported that ANFIS could detect the nonlinear structure process with rapid learning capability. This is further supported by a comparative study conducted by Dao *et al.* [21]. However, ANFIS may suffer from issues related to fuzzy rule selection that affect its performance along with inability to generate more than one output variable [76].

Regarding SVM models, they have shown powerful nonlinear mapping and generalization abilities [76]. They also have ability of identifying and integrating support vectors during the training process, which prevents non-support vectors from affecting the performance of the model. However, this technique has multiple disadvantages, such as the time-consuming and heuristic approach of selecting the appropriate kernel function, which depends on trial and error process. In addition, the performance of the nonlinear SVR technique cannot be easily interpreted because the process

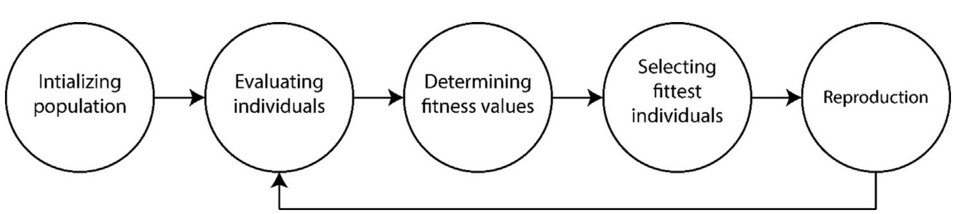

Fig. 7. General process of evolutionary algorithms.

of mapping a nonlinear input space to a high dimensional feature space can be complex [106].

The aforementioned techniques, i.e. ANN and SVM, are considered as "black-box" models due to massive node sizes and internal connections [107–109]. Thus, generating a transparent mathematical formula that describes the functional relationship between input variables and outputs through those models is difficult. To overcome this common problem, decision trees and EA can be deployed. Those models have the ability of generating explicit mathematical formulations that describe the relationships between features and corresponding outputs. However, decision trees algorithms can lead to overfitting issues. In addition, the accuracy of both decision trees and EA is typically lower than that of hybrid and standalone SVM and ANN models, as evidenced by statistical metrics retrieved from different previous studies [41,59,76]. Shortcomings of decision tree models can be mitigated through tree-based ensemble models such as RF and MART [31]. Chou *et al.* [31] for instance recorded better results from MART model than those obtained from standalone ANN and SVM. Still, ensemble models bring more complexity to the model and increase computation time.

In addition, it can be noticed that the size of the dataset used for developing the models varies from one study to another. Studies that considered fewer data examples may record accurate results. However, the model can exhibit higher error when exposed to new data compared to those developed from more extensive databases.

4. Practical recommendations and knowledge gaps

Since all ML approaches discussed above have various advantages and drawbacks, the selection of the most suitable model is based on different criteria. The nature of the relationship between concrete mixture ingredients and its mechanical strength is a major factor that influences the model choice. If this relationship is highly nonlinear and affected by several features, employing models such as ANN and SVM would be a good choice owing to their great ability in solving problems in non-linear environment with lower error. For more accurate results and better process, optimizing those models with metaheuristic algorithms is effective. However, when model transparency is required, decision trees and evolutionary algorithms can be employed because they can generate explicit mathematical formulas that better describe the physical relationship between inputs and output. Still, the accuracy of both models is lower than that of hybrid and standalone ANN and SVM models as indicated by statistical metrics shown in Table 7. Adopting ensemble models can increase the accuracy of decision trees but leads to higher computation time and model complexity.

According to the current study, hybrid ANN and SVM models have shown best ability of predicting concrete strength in terms of accuracy and process. Although they increase computation time, applying those models on extensive databases with appropriate feature selection would generate most accurate results. However, the only way to select the most suitable metaheuristic model is based on a trial and error process. Thus, no accurate method exists to select the best optimization algorithm since they can provide different results from one problem to another.

We stand at the brink of a fourth industrial revolution, where data driven intelligent systems, additive manufacturing, robotics, the internet of things, cloud computing, and other emerging technologies are fusing the digital, biological, and physical worlds. The construction field is lagging in capturing the opportunities in this rapidly changing world. Machine learning prediction of the engineering properties of construction materials and structures are a contribution towards generative intelligent design. Yet, diverse knowledge gaps still remain before structural engineers can emulate processes used in robotics, mechatronics and other advanced fields.

5. Conclusions

Several recent studies have been conducted to predict the mechanical strength of concrete, exploring the benefits of some approaches and presenting drawbacks of others. In particular, forecasting the strength of complex concrete mixtures by conventional statistical and empirical models has been a fundamental challenge since these models are generally inaccurate, and their development is costly and time-consuming. Thus, researchers have suggested ML models to overcome such drawbacks. In this study, ML models have been grouped into four major types, namely ANN, SVM, decision trees, and EA. The application of those models to predict the compressive strength, shear strength, tensile strength, and elastic modulus of concrete has been reviewed. Also, the advantages and drawbacks of the presented techniques have been critically discussed and compared. It has been realized that the performance of the models is influenced by various factors, such as the nature of the relationship between concrete mixture ingredients and its strength, the size of the training data set, and the number of features adopted in the model. The review of the performance of ML techniques along with their benefits and drawbacks presented in this study should help engineers in choosing the suitable models for predicting the mechanical strength of concrete. Owing to their ability in providing accurate estimation of concrete strength, further research shall be conducted to examine the reliability of ML models in forecasting the properties of more innovative concrete types such as self-healing concrete, geopolymer concrete, nano-modified, bio-inspired and other emerging binder systems.

Declaration of Competing Interest

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

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