Journal of Advanced Concrete Technology Vol. 20, 404-429, June 2022 / Copyright © 2022 Japan Concrete Institute

Review paper

Artificial Intelligence Models for Predicting Mechanical Properties of Recycled Aggregate Concrete (RAC): Critical Review

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Received 3 March 2022, accepted 2 June 2022

doi:10.3151/jact.20.404

Abstract

Recycled aggregate concrete (RAC) has attracted more interesting in the past several years because it is an economical and eco-friendly building material. But generally, the mechanical properties of RAC are poor compared to natural aggregate concrete (NAC). So, the mechanical properties of RAC need robust predictive models to be evaluated before its application. Traditional (empirical based) models, e.g., linear, and non-linear regression methods, have been extensively proposed. But these models lack flexibility in updating (i.e., limited to a finite number of variables) and can give inaccurate results. Consequently, to handle such shortcomings, several Artificial Intelligence (AI) models have been suggested as an alternative strategy for predicting the mechanical properties of RAC. In this study, state-of-the-art AI models were reviewed to predict the mechanical properties of RAC. The application of each predictive model and its training, testing, and performance are critically examined and analysed, consequently identifying present knowledge gaps, practical recommendations, and required future investigation.

1. Introduction

Concrete is the most widely used material in buildings, sidewalks, bridges, dams, and structural engineering. These wide applications of concrete, along with its versatility worldwide, have led to the high consumption of its components such as aggregate, sand, cement etc. Especially, natural aggregate (NA) as is a significant component in a concrete mixture. The NA's global consumption is estimated to be between 8 to 12 billion tonnes per year (Naderpour *et al.* 2018). This is considered a significant warning due to this shortage of NA resources (Duan *et al.* 2013a, 2013b; Gholampour *et al.* 2017). Moreover, extracting one tonne of NA results in 4600 tonnes of carbon gas emissions into the environment (Naderpour *et al.* 2018; Naderpour and Mirrashid 2010). Besides, the consumption of landfills due to disposal of construction and demolition waste (CDW) is another important problem around the world, especially in densely populated big cities. Consequently, these global concerns about economic and environmental issues of concrete production have forced stricter requirements for construction and urban development (Ranjbar *et al.* 2021).

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To conserve natural resources, much attention has been given to the use of waste materials in concrete mixtures (Golafshani and Behnood 2018b; Behnood and Golafshani 2010). The usage of recycled aggregate concrete (RAC) provides a workable solution to overcome these disadvantages associated with conventional concrete production because RAC can alleviate the regional lack of NA, stop massive amounts of CDW from being landfilled, and decrease carbon gas emissions from concrete production. Generally, 75% of CDW can be reused as RA in concrete production (Duan *et al.* 2013a; González-Fonteboa and Martínez-Abella 2008). Nevertheless, generally, the mechanical properties and workability of RAC are worse compared to natural aggregate concrete (NAC) (Arora *et al.* 2019; Aslani *et al.* 2018; Pliya *et al.* 2021). The usage of RA in the concrete mixture has been proved to decrease its mechanical strength (Topçu and Saridemir 2008; Xu *et al.* 2019b). Concrete's compressive strength (CS) decreases by 30% to 40% if the natural aggregate is substituted with 100% RCA (Behera *et al.* 2014) due to its higher porosity and water absorption and lower density and strength. Comprehensive reviews of the properties of RAC and its applications are available in previous works, for example, Safiuddin *et al.* (2013), Tam *et al.* (2018) and Wang *et al.* (2021). It is essential to consider the effects and relationships between the RAC mechanical properties and its mixture proportions before the building stage. Consequently, predicting the mechanical characteristics of RAC is an essential research work that could adequately meet the desires of different standard codes and other designs.

Numerous predictive models have been suggested in published literature (Andreu and Miren 2014; Corinaldesi 2010; Huda and Alam 2014; Limbachiya *et al.* 2012; Xiao *et al.* 2006), to predict the mechanical characteristics of RAC, based on conventional regression algorithms, including CS, tensile strength (TS), elastic modulus (EM), splitting tensile strength (STS) and shear strength (SS) These conventional methods for determining the RAC mechanical characteristics consist principally of empirical models generated from statistical processing for experimental datasets (Arisha *et al.* 2016; Chan *et al.* 2019; Choi and Yun 2012; Folino and Xargay 2014; Huang *et al.* 2012; Nour and Güneyisi 2019; Silva *et al.* 2015). For details on empirical and code-based models for forecasting the mechanical characteristics of RAC, see Gholampour *et al.* (2017) and Xu *et al.* (2019b), for example. Although these models have been used successfully and proven effective in some challenges and lead to cost and time savings for future work, their update and development are not easy and associated with many disadvantages. Their major limitations are the time-consuming and costly experimental batches to generate empirical models. Also, the conventional regression models' performance is poor in handling complex materials such as RAC, making them unreliable for forecasting the mechanical characteristics of such concrete, where these methods consider only a limited and small number of input parameters (Fazel Zarandi *et al.* 2008). Besides, the data set used to evaluate the models is almost tiny and can give inaccurate results (Zhang *et al.* 2020a).

These drawbacks of the conventional techniques and the intricate relationships of RAC's mechanical behaviour have led to an application of robust nonlinear modelling techniques. Recently, Artificial Intelligence (AI) technologies have been gained significant attention due to their impressive strengths in solving several intricate problems and successfully applied as a robust competitor for predicting RAC mechanical properties. For example, in some broader applications of AI for concrete-related problems, AI models have been used for a long time not only for CS prediction, e.g., Yeh (1998), but also for creep, e.g., Liang *et al.* (2022) and shrinkage, e.g., Hilloulin and Tran (2012) more recently. AI can accurately map relationships between inputs and outputs to foresee the RAC mechanical characteristics. Adopting such prediction mechanisms can save the time and cost of experimental effort wasted to accomplish a predictive RAC strength model (Delgado *et al.* 2020; Pham *et al.* 2020; Yaseen *et al.* 2018).

Even though these AI algorithms have been suggested to solve the same problem (i.e., estimate of RAC mechanical characteristics), the data processing and model structure can differ markedly from one algorithm to another. Generally, the quantity and quality of the datasets as well as the character of input and output features, can highly affect the choice of the most proper algorithm. Moreover, the model behaviour is assessed through different statistical indexes corresponding to the actual and predicted dataset. The most popular AI methods applied for the prediction of RAC mechanical properties can generally be categorised into four main types namely 1) Artificial Neural Networks (ANN), 2) Support Vector Machines (SVMs), 3) Decision Trees (DT), and 4) Evolutionary Algorithms (EA) as shown in **Fig. 1**. Notably, these algorithms are used in regression and classification problems.

This review paper aims to focus on the applications of AI models in predicting RAC mechanical properties, excluding the normal concrete mixtures, because the relation between the mechanical properties and mixture design of conventional concrete is somewhat simple, while that for RAC is highly nonlinear and complex. For details on the use of AI/ML in concrete in general, see, for example, ACI (2021), Behnood and Golafshani (2011) and Hu *et al.* (2021). Also, this study offers a comprehensive overview of the information about AI algorithms needed to model the mechanical properties strength of RAC. Moreover, systematic analysis and comparison of the most common AI algorithms used for predicting RAC mechanical characteristics materials and structures, besides their hyperparameters, are conducted. Eventually, the gaps and limitations of AI algorithms are identified, and recommendations about future work are also offered.

2. The basis of artificial intelligence (AI)

AI is simply a section of modern computer discipline that concentrates on developing computational algorithms that can interact or think logically to perform tasks requiring human intelligence, such as speech recognition, visual perception, reasoning, and problem-solving (Somogyi 2011). AI is the chief target, and Machine Learning (ML) and Deep Learning (DL) are some of the several techniques to reach AI. ML, which is a leading subset of AI, wherein denotes the ability of algorithms that can learn from huge data sets, also called the “Big Data”, and deliver accurate related forecasts, decisions, recommendations, and several other intelligence tasks, without requiring any explicitly extended guidance/commands (Murphy 2012). The ML approach includes a wide difference of algorithms that can generally be categorized to three major forms: 1) Supervised

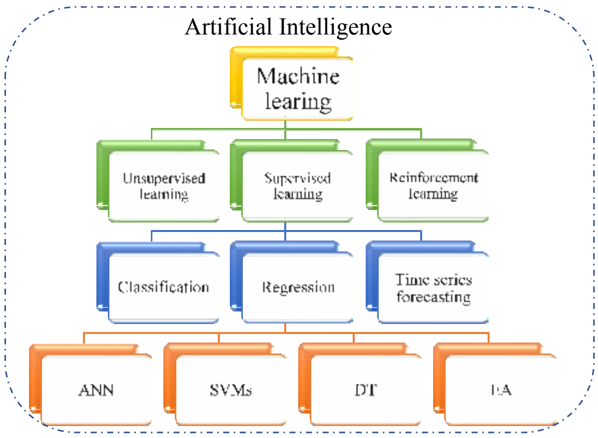

Fig. 1 AI models for predicting mechanical properties of RAC.

Learning (SL), 2) Unsupervised Learning (USL), and 3) Reinforcement Learning (RL) (Zolanvari *et al.* 2019). The former refers to the algorithms that endeavour at predicting either a discrete (classification) or continuous (regression) output (Murphy 2012). In the supervised type, the algorithm is trained practicing dataset examples by known outputs. This type is usually chosen for predicting the RAC mechanical characteristics as well as other types of concrete (Berry *et al.* 2020; Salehi and Burgueno 2018; Singh *et al.* 2016; Vu *et al.* 2021). Unlike, the goal of unsupervised type is to define the relationship within the datasets without pre-defined labels for the objective of predictive (Murphy 2012). Unsupervised type is also called nonparametric models (Murphy 2012). While reinforcement learning, this less popular type of ML, is a type of "trial and error" training that bonds the gap between unsupervised and supervised learning because it identifies similarities in datasets that provide correct answers (Elgendi 2019). DL is a subset of the ML technique that treats “big data” to build many layers of thinking that construct a functional mapping of the attributes/features to the purposes. The DL algorithms can handle more complex intelligence tasks compared to ML (e.g., self-drive cars).

3. Prediction of the mechanical characteristics of RAC

Recently, AI algorithms have been widely used as a powerful tool for predicting the mechanical characteristics of RAC. These algorithms are typically used for a large dataset, which can be divided into a training dataset (TD), validation dataset (VD), and test dataset (TSD) (Ben Chaabene *et al.* 2020). The TD is utilized for AI algorithm training. The VD gives an unbiased assessment of the appropriate algorithm of the TD and blocks overfitting via ending the data training process if the misfit errors increased. The algorithm is at last used by TD to evaluate its predictive performances. **Figure 2** shows general steps of AI model workflow for predicting the mechanical characteristics of RAC. The most popular AI algorithms, as mentioned earlier, can be categorized into four main forms, namely ANN, SVMs, DT, and EA. The evaluation of these algorithms and their application and process are discussed below. Datasets used to predict the mechanical properties of RAC by AI models have been mentioned in many published papers, e.g., Gholampour *et al.* (2017), Golafshani and Behnood (2018a) and Khan *et al.* (2022).

4. Selection of AI model inputs

Choosing the most relevant parameters or features needed to train and test different AI algorithms is key to building these algorithms successfully and enhancing their performance. In addition, the experience and intelligence of developers are needed to choose the most appropriate features to reduce the computational loads of AI algorithms. So, this points to a careful choice of data inputs that have a noticeable influence on RAC mechanical characteristics and avoidance of low-influence features, which can reduce calculation load and time. Numerous investigations have used common parameters to predict the strength of RAC. **Table 1** shows the most popular input and output variables of AI-based RAC models considered in the previous literature in general.

5. Performance validation and assessment methods of AI models

Performance evaluation of the AI algorithms was performed using various statistical approaches describing model fit. **Table 2** lists the most popular statistical in-

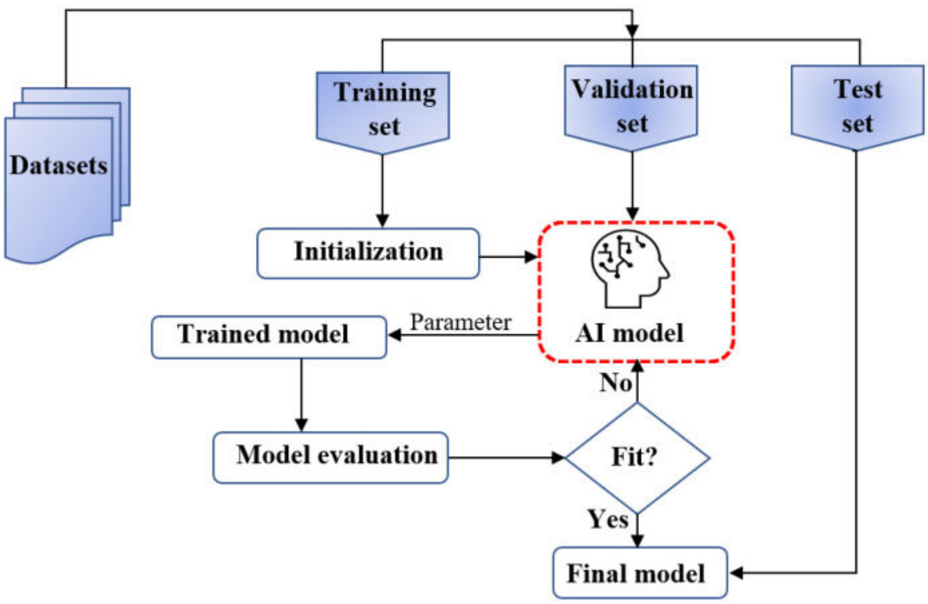

Fig. 2 General steps of AI model workflow.

Table 1 Most popular input and output variables of AI-based RAC models in general.

Variables		Description\ Abbreviation		Unit
Input	Mix design parameters	Water, cement, sand	W/C/S	%
		Water-cement ratio	WCR	%
		Ratio of dry mortar	RDM	%
		Content of total dry aggregate	CDA	%
		Natural fine aggregate	NFA	%
		Natural coarse aggregate	NCA	%
		Substitution ratio for recycled fine aggregate	PFA	%
		Substitution ratio for recycled coarse aggregate	PCA	%
		Chemical admixture rate	CDR	%
		Superplasticizer	SP	%
		Silica fume	SF	%
		Conversion coefficient for different concrete specimen	FDS	%
		Sand to aggregate ratio	SAR	%
		Water to total materials ratio	WMR	%
Input	Mix design parameters	Replacement ratio of RA to NA	RAN	%
		Aggregate/cement ratio	ACR	%
		Fly ash replacement ratio	FAR	%
		Coarse aggregate/cement ratio	CAC	%
		Fine aggregate to total aggregate ratio	FTA	%
		Size of coarse aggregate	SCA	mm
		Ratio of RA max. particle size to NA max. particle size	SRN	%
		Type and preparation methods of CA	TCA	-
		Volume fraction of RA in RAC	VRA	%
		Coarse rubber aggregate	CRA	%
		Fine rubber aggregate	FRA	%
		Moisture content of FA	MFA	%
		Particle size of FA	SFA	%
		Proportion of rubber	POR	%
		Rubber replacement percentage	RRP	%
		Particle size of rubber	PSR	mm
		Particle size of coarse natural aggregates	SCA	mm
		Re-treatment method of rubber	PMR	-
		Proportion of slag	POS	%
		Supplementary cementitious materials	SCM	%
		Specimen size	SZ	mm
		Cement type	CT	-
		Ratio of recycled mortar	RRM	%
		Ratio of recycled red ceramic	RRR	%
	Physical characteristics	Fineness modulus of sand	FMS	mm
		Fineness modulus for natural fine aggregate	FNF	mm
		Fineness modulus for natural coarse aggregate	FNC	mm
		Maximum aggregate size for natural fine aggregate	SNF	mm
		Maximum aggregate size for natural coarse aggregate	SNC	mm
		Maximum size of natural aggregates	SNA	mm
		Water absorption rate of RCA	ARC	%
		Saturated surface-dried specific gravity of RCA	SSD	kg/m^3
		Bulk density of recycled concrete aggregate	DRC	kg/m^3
		Crush index of recycled coarse aggregate	CIC	%
		Stacked porosity of recycled coarse aggregate	SPC	%
	Time	Age of the samples	AGE	Days
Output		Compressive strength	CS	MPa
		Tensile strength	TS	MPa
		Elastic modulus	EM	MPa

dexes used to evaluate AI models. These indexes indicate how fit the predicted data matches the actual dataset. Besides, the indexes can be used in the analysis of models sensitivity by showing the rate of individual input variables (Azimipour *et al.* 2020; Dao *et al.* 2019a, 2019b; Douma *et al.* 2016; Saha *et al.* 2019; Siddique *et al.* 2011; Sonebi *et al.* 2016; Uysal and Tanyildizi 2012; Xu *et al.* 2019b). In addition, the statistical indexes can evaluate the performance of AI techniques and be utilized as a reference for judging the efficiency of different AI models (Ben Chaabene *et al.* 2020).

6. Artificial neural network (ANN)

ANN is one of nonlinear algorithms that simulates the basic structure of human brains (Abiodun *et al.* 2019; Aghbashlo *et al.* 2015; Marugán *et al.* 2018; Mohandes *et al.* 2019; Shrivastava *et al.* 2012). In the ANN algorithms, data generation occurs by links that collect data from one treating neuron (element) to pass on toward subsequent neurons. Each element of data is assigned a weight that reflects the importance of the data input features to the outputs (Rumelhart *et al.* 1994). When a

Table 2 Statistical indexes.

Index	Equation
Mean (m)	$m = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z_i}{z_i^{/}}\right)$
Standard deviation (σ)	$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{z_i}{z_i^{/}} - m\right)^2}$
Correlation coefficient ($\mathcal{R}$)	$\mathcal{R} = \frac{n\sum_{i=1}^{n} z_i^{/} z_i - \left(\left(\sum_{i=1}^{n} z_i^{/}\right)\left(\sum_{i=1}^{n} z_i\right)\right)}{\sqrt{n\left(\sum_{i=1}^{n}\left(z_i^{/}\right)^2\right) - \left(\sum_{i=1}^{n} z_i^{/}\right)^2}\ \sqrt{n\left(\sum_{i=1}^{n} z_i^2\right) - \left(\sum_{i=1}^{n} z_i\right)^2}}$
Root mean square error ($\mathcal{R}MSE$)	$\mathcal{R}MSE = \sqrt{\frac{\sum_{i=1}^{n}\left(z_i^{/} - z_i\right)^2}{n}}$
Mean absolute error ($\mathcal{M}$)	$\mathcal{M} = \frac{1}{n}\sum_{i=1}^{n}\left\lvert z_i^{/} - z_i\right\rvert$
Mean absolute percentage error ($\mathcal{M}_{\%}$)	$\mathcal{M}_{\%} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left\lvert z_i^{/} - z_i\right\rvert}{z_i^{/}} \times 100$

neuron in the net gets information, it fuses them with other neurons by a compound function. Then the linked information is conveyed to the subsequent nodes. After that, linked information is conveyed to subsequent neurons. This manner is repeated iteratively till the ANN model fits the datasets exactly, as symbolized via convergence indicators of misfit error rates, or while the maximum target of iterations is reached (Ahmad *et al.* 2018; Bourdeau *et al.* 2019; Li *et al.* 2020b). The framework of ANN generally consists of three classes of layers (Fadaei *et al.* 2018; Jani *et al.* 2017), as shown in **Fig. 3**. The input layer, the first one, sends the input variables to train and test the ANN model. The hidden layer(s), the second one, class manages the combining between output and input layers. The last one is the output layer that provides the product of the model. Activation functions are needed to generate the output product and guarantee datasets transfer through the other layers (Ghorbanzadeh *et al.* 2020; Kang *et al.* 2019; Khademi *et al.* 2016; Kiraz *et al.* 2018; Maleki *et al.* 2020; Naderpour *et al.* 2019; Pourtahmasb *et al.* 2015; Shariati *et al.* 2020). Moreover, ANN is trained via a learning model that enables the algorithm to realize the current task. Therefore, the general framework of the ANN

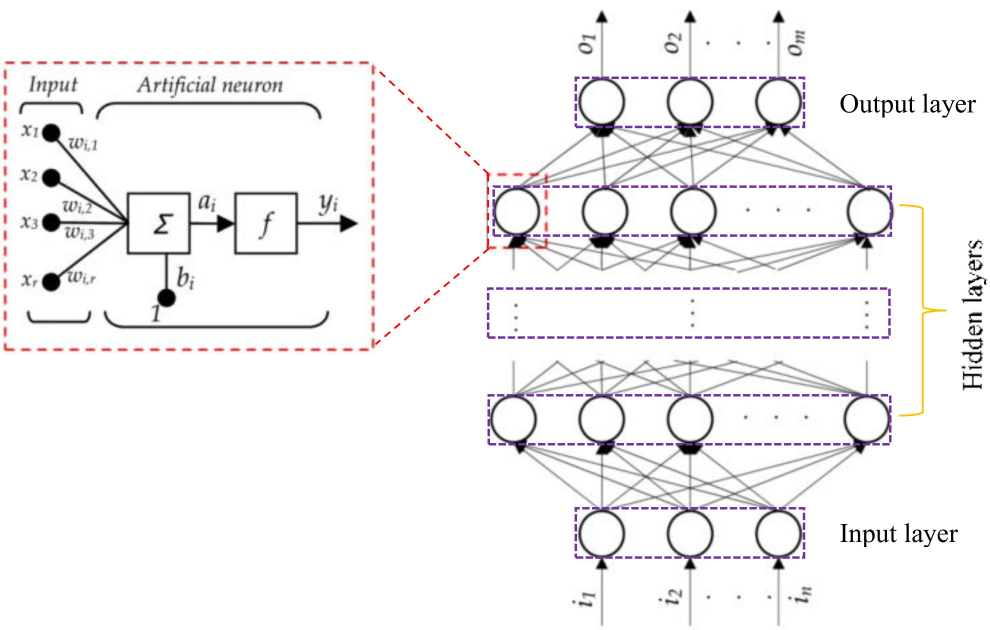

Fig. 3 Schematic layout of the BNN architecture of multilayers.

Table 3 Outline of applied ANN-based RAC models.

Method	Size of datasets	TD, %	VD, %	TSD, %	Input parameters*	Output of model	Statistical index*	Reference
BNN	1178	77.8	N/A	22.2	WCR, CEM, RDM, CDA, PFA, PCA, CDR, RRM, RRC, RRR, FNF, FNC, SNF, SNC, WAR, AGE	CS	$\mathcal{R}$, $\mathcal{M}$	Dantas *et al.* (2013)
BNN	210	67	N/A	33	AGE, W/C/S, CDA, SP, SF, RA	CS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Topçu and Saridemir (2008)
BNN	168	N/A	N/A	N/A	W/C/S, WCR, NCA, RFA, RCA, FMS, WAR, SSD, SNA, PCA, FDS	CS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Duan *et al.* (2013a)
BNN, ANFIS	257	70	15	15	W/C/S, NFA, NCA (10, 20 mm), RFA, RCA (10, 20 mm), WCR, PCA, WMR, RAN, ACR	CS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Khademi *et al.* (2016)
BNN	139	N/A	N/A	N/A	WAR, WCR, NFA, NCA, RCA, WMR	CS	$\mathcal{R}$, $\mathcal{M}$	Naderpour *et al.* (2018)
BNN, CNN	74	68	N/A	32	WCR, PCA, PFA, FAR	CS	$\mathcal{RMSE}$	Deng *et al.* (2018)
BNN	257	70	15	15	CEM, RFA, W/C/S, NFA, NCA (10, 20 mm), RFA, RCA (10, 20 mm), WCR, PCA, WMR, RAN, ACR	CS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Deshpande *et al.* (2014)
BNN	421	N/A	N/A	N/A	RAN, WCR, ACR, SRN	EM	m, σ, $\mathcal{RMSE}$, $\mathcal{M}$	Xu *et al.* (2019b)
BNN, RBFNN	400	80	N/A	20	WCR, RAN, CAC, FTA, CS, WAR	EM	$\mathcal{RMSE}$, $\mathcal{M}$, $\mathcal{M}_{\%}$	Golafshani and Behnood (2018a)
BNN	324	70	15	15	WCR, ACR, PFA, PCA, RAN, SCA, TCA, CT, SZ	EM	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Duan *et al.* (2013b)
BNN	346	N/A	N/A	N/A	RAN, WCR, ACR, SRN	TS	m, σ, $\mathcal{RMSE}$, $\mathcal{M}$	Xu *et al.* (2019b)
BNN	210	67	N/A	33	AGE, C/W/S, NA, RA, SP, SF	TS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Topçu and Saridemir (2008)
BNN	353	70	15	15	RRP, PSR, FRA, MFA, SFA, POR, PMR, C, CT, SCA, WCR, W, PCA, SF, FAR	CS, EM, FS, STS	$\mathcal{R}^2$, $\mathcal{RMSE}$, $\mathcal{M}$	Huang *et al.* (2012)
BNN	88	70	N/A	30	C, W, S, NCA, RCA, WCR, PCA, PFA	CS	$\mathcal{R}^2$, $\mathcal{RMSE}$, $\mathcal{M}$	Bui *et al.* (2018)
BNN	121	70	15	15	WCR, NFA, NCA, PFA, PCA, ARC	CS	$\mathcal{R}^2$, $\mathcal{RMSE}$	Catherina Vasanthalin and Chella Kavitha (2021)
ICA-ANN	209	80	N/A	20	RFA, RCA, WCR, WMR, ARC, NCA	CS	$\mathcal{R}$, σ, $\mathcal{RMSE}$, $\mathcal{M}$	Duan *et al.* (2020)
ICA-ANFIS	209	80	N/A	20	RFA, RCA, WCR, WMR, ARC, NCA	CS	$\mathcal{R}$, σ, $\mathcal{RMSE}$, $\mathcal{M}$	Duan *et al.* (2020)

*The definition of the abbreviations is illustrated in Tables 1 and 2.

model is modified depending on the nature of the learning model. The different ANN approaches used for predicting RCA strength are shown in **Table 2**, which are discussed next sections.

6.1 Backpropagation neural network (BNN)

In **Table 3**, it can be seen that the BNN has been extensively applied in the literature for training ANN models (Liu and Zhang 2010; Xu *et al.* 2019a). The BNN is one of the local search systems which it is used for learning AI models, such as the gradient descent method (GDM) and Levenberg-Marquardt method (LMM), to renew the ANN biases and weights. This strategy is used for minimizing the loss function (or cost function), which generally denotes the misfit errors among predicted and real values of RAC strength. For example, the BNN was applied to predict the CS of RAC (Duan *et al.* 2013a, 2013b; Naderpour *et al.* 2018; Topçu and Saridemir 2008; Ababneh *et al.* 2020; Atici 2011; Chen *et al.* 2020a; Deshpande *et al.* 2014; Khademi *et al.* 2016; Paul *et al.* 2018; Xu *et al.* 2019a). For instance, Topçu and Saridemir (2008) proposed the BNN according to a GDM model plus to fuzzy logic (FL) algorithm to determine the CS of the RAC. These techniques gave a great performance, but the BNN somewhat outpaced FL on the one hand RMSE, R2, and MAPE. Also, Naderpour *et al.* (2018) assessed the BNN performance and investigated impact of each variable input in the CS of RAC model by showing the sensitivity analysis test. Their proposed approach covered 6-input parameters with 18-hidden nodes. Outcomes revealed that BNN precisely predicted the CS of RAC and that RA water-absorption, besides the water-to-total-materials ratio, gave the highest effect on the strength of RAC. The performance of the BNN model and radial-based neural network (RNN) was compared by Golafshani and Behnood (2018a) to foresee the EM of RAC. Their results revealed that the BNN model has a better predictive ability than the RNN model. Liu *et al.* (2021) studied three types of soft computing techniques, including

ANN, Gaussian process regression (GPR), and multivariate adaptive regression spline (MARS) which were applied to frost durability model of RAC mixture depending on the value of durability factors. Their findings showed that the suggested methods could foresee durability factor rates in good harmony compared to experimental outcomes. Compared with the MARS technique and the GPR technique, the ANN technique revealed the best prediction accuracy. Also, Catherina Vasanthalin and Chella Kavitha (2021) proposed the ANN and cuckoo search method (CSM) to foresee the CS of RAC. Their findings showed that both methods are a valuable tool to predict the CS of RAC, and also that the ANN model was better compared to the CSM model with a higher coefficient of regression.

6.2 Hybrid ANN-based models

Hybrid procedures aim to combine multiple AI models to significantly improve model processes and performance compared to a single algorithm. Due to their capability to merge the benefits of those combined algorithms, hybrid procedures have attracted grand interest from researchers nowadays. For example, the performance and workflow of algorithms, such as the "Adaptive-Neuro-Fuzzy-Inference-System" (ANFIS) were extensively studied (Khademi *et al.* 2016b; Pourtahmasb *et al.* 2015; Shariati *et al.* 2020; Yuan *et al.* 2014; Zhou *et al.* 2017). ANFIS algorithms are global optimizations that link FL and ANN. This algorithm utilizes ANN to extend the association abilities to reduce the rate of errors in the model outputs, whilst FL rules can give expert information (Dehghani *et al.* 2019; Roy *et al.* 2020). These rules of FL are utilized inside the model as a fuzzy system "if-then" to perform the defined input-outputs groups, as shown in **Fig. 4**. For example, ANFIS has been used to predict the CS of RCA (Khademi *et al.* 2016). The results showed a good accuracy compared to the multiple linear regression (MLR) method. Duan *et al.* (2020) implemented the Imperialist Competitive Algorithms (ICA) approach to improve the thresholds and weights of ANN and ANFIS. The ICA is one of the metaheuristic algorithms derived from the human social evolution proposed by Atashpaz-Gargari and Lucas (2007). Its ability to get a global optimum solution based on social policies and imperialist competition creates it a likely candidate to optimize ANN and ANFIS. Their hybrid ICA-ANN and ICA-ANFIS were used to compute the CS of RAC. The Genetic Algorithm (GA) was used to improve the BNN model by Yuan *et al.* (2014) to predict the CS of concrete containing fly ash and slag waste. GA is the most popular metaheuristic algorithm inspired by natural evolution that has the potential for global optimization (Kramer 2017; Kumar *et al.* 2020). Their comparative investigation between the hybrid GA-ANN and BNN model showed that the GA-ANN model provided the best performance. Also, Rezaiee-Pajand *et al.* (2021) applied the ICA method to predict RCA's TS, CT and FS. Then, the suitable number of features for evaluating each parameter is chosen by the Multi-Layer Perceptron (MLP) network. Their results revealed that the mean absolute error of the proposed techniques in predicting the TS, CT, and FS are approximately 0.48, 0.54, and 0.36, respectively.

7. Support vector machines (SVMs)

SVMs are a set of supervised ML algorithms that can be used for classification tasks, regression, pattern recognition, and outlier detection problems. Developed in 1995 by Cortes and Vapnik (1995), SVMs are a powerful class of heuristic algorithms based on the statistical theory for learning (Vapnik 1999).

7.1 Support vector machine classification (SVMC)

SVMC is an ML grouping algorithm that seeks to get an ideal hyperplane (HP) separating two distinct classes (Suykens *et al.* 2002). The purpose of this system, shown in **Fig. 5**, is to maximize the gap from HP to the most adjacent point of each class, called the margin, to achieve better categorization efficiency of the test datasets (Noble 2006; Wang and Pardalos 2014). Once the ideal HP is obtained, the points lying at its edge are named "Support-Vectors" (SV), and the answer mainly suggested by this model is built only on these points. Nevertheless, some groups cannot be easily split up through a linear HP, as shown in **Fig. 6**. In cases like these, the data input must be handled to a higher-

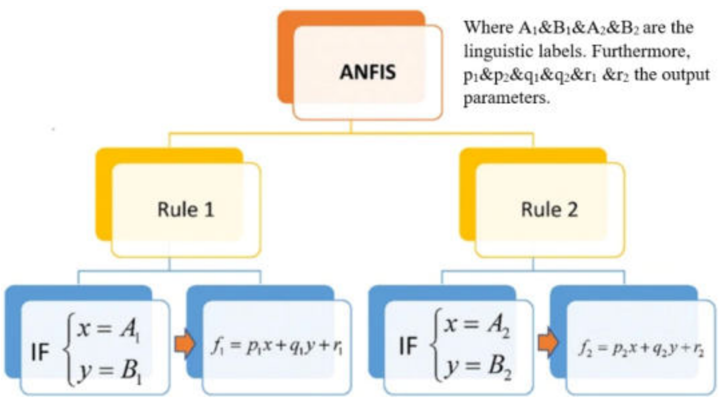

Fig. 4 The ANFIS model and its IF-THEN rules (Duan *et al.* 2020).

dimensional feature data to allow linear split of groups (Goyal *et al.* 2020; Kannan *et al.* 2018; Yu *et al.* 2020). The nonlinear mapping process is generally conducted by a nonlinear function. After that the outputs of the model are acquired from the nonlinear space by another function called kernel (Chang and Lin 2011; Cuentas *et al.* 2017; Guo and Wang 2017; Raghavendra and Deka 2014; Sheykhmousa *et al.* 2020). The kernel functions can be categorised into five categories: 1) linear, 2) polynomial, 3) radial basis, 4) sigmoid, and 5) exponential radial basis (Chen *et al.* 2017; Feizizadeh *et al.* 2017; Tharwat 2019). The functions can help in defining a nonlinear decision border without the necessary to compute the ideal HP factors in the data or feature space. So, the result can be represented as a mixture of weighted values for the kernel features at the SV (Megri and El Naqa 2016; Sharafi *et al.* 2016).

7.2 Support vector machine regression (SVMR)

SVMR is mainly used for regression analysis (Chou *et al.* 2011; Li *et al.* 2020b; Omran *et al.* 2016). It treats regression challenges as a series of linear equation systems, resulting in a quicker training procedure and greater performance (Balabin and Lomakina 2011; Quan *et al.* 2020; Wauters and Vanhoucke 2014). Numerous investigations have investigated the foretelling strength of SVMR. **Table 4** describes the various SVMs-based methods that have been applied to estimate RAC characteristics. It can be seen SVMs models have been used as stand-alone algorithms in some investigations and improved with meta-heuristic models in others.

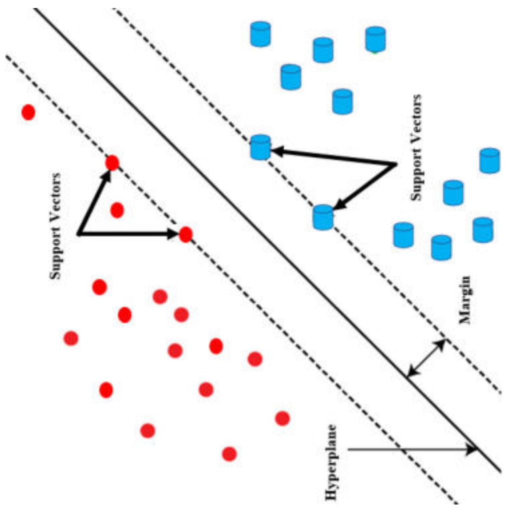

Fig. 5 SVMC-hyperplane classification.

7.3 Standalone SVMs models

The application of single SVMs techniques to foretell the mechanical properties of RAC has been widely studied. For example, Deng *et al.* (2018) utilized SVMs to calculate the CS of RAC. The model accuracy evaluation proved that their work achieved satisfactory prediction accuracy. The EM of the RACs was also anticipated using SVMs (Golafshani and Behnood 2018a) and acceptable findings were displayed. Least-squares SVMR (LS-SVMR) is a new modification of SVMs in which the LS method is applied to make a global optimization and produce better accuracy (Debruyne *et al.* 2009; Giorgi *et al.* 2014; Mountrakis *et al.* 2011; Xu *et al.* 2013). Many investigations assessed the performance and accuracy of this technique in forecasting the mechanical properties of RAC. For example, Gholampour *et al.* (2017) applied LS-SVMR to predict the CS, EM, flexural strength (FS), and splitting tensile strength (STS) of RAC, and these models revealed better results than those of conventional non-linear regression analysis. Also, Kaloop *et al.* (2019) introduced LS-SVMR to predict the resilient modulus of RAC and the model achieved good performance.

7.4 Hybrid SVM-based models

The usage of SVMs within hybrid methodologies endeavours to improve the procedure of the standalone SVMs algorithms (Ben Chaabene *et al.* 2020). For example, numerous investigations (Li *et al.* 2021; Pham *et al.* 2016; Sun *et al.* 2019; Yu *et al.* 2018a, 2018b; Zhang *et al.* 2020a, 2020b; Zhang and Wang 2020) have applied different optimization algorithms [e.g., firefly algorithm (FA), beetle antennae search (BAS) algorithm, cat swarm optimization (CSO), and response surface method (RSM)] to predict the mechanical properties of a plain and high-performance concrete. These secondary optimization algorithms were mainly used to estimate the hyperparameters of LS-SVMs. The results revealed the strong ability of hybrid SVMs-based algorithms in forecasting the mechanical strength of RAC than standalone SVMs models, which was reflected in different

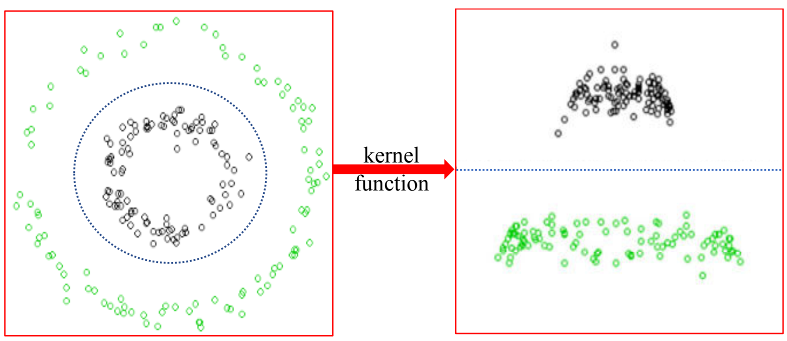

Fig. 6 Nonlinear mapping using SVMC.

Table 4 Outline of applied SVMs-based RAC models.

Method	Size of data sets	TD, %	VD, %	TSD, %	Input parameters*	Output of model	Statistical index*	Reference
SVMC	74	68	N/A	32	WCR, PCA, PFA, FAR	CS	$\mathcal{RMSE}$	Deng *et al.* (2018)
SVMR	400	80	N/A	20	WCR, RAN, CAC, FTA, CS, WAR	EM	$\mathcal{RMSE}, \mathcal{M}, \mathcal{M}_{\%}$	Golafshani and Behnood (2018a)
LS-SVMR	650	50	N/A	50	PCA, ACR, DRC, ARC, WCR	CS	$\mathcal{RMSE}, \mathcal{M}, \mathcal{M}_{\%}$	Gholampour *et al.* (2018)
	346	51	N/A	49		CT		
	421	47	N/A	53		EM		
ICA-SVMR	209	80	N/A	20	RFA, RCA, WCR, WMR, ARC, NCA	CS	$\mathcal{R}, \sigma, \mathcal{RMSE}, \mathcal{M}$	Duan *et al.* (2020)

*The definition of the abbreviations is illustrated in Tables 1 and 2.

statistical indexes. However, to the authors' knowledge, the use of hybrid SVMs-based models in RAC has not been reported in literature.

8. Decision tree analysis (DTA)

Decision tree analysis (DTA) is a set of supervised ML techniques that involves creating a tree-shaped description to map out a sequence of actions where a dataset is continually segmented according to certain parameters. DTA models are applied to deal with complex classification and regression problems (tree branches). Decision tree models comprise of nodes (which examine the weight of a particular attribute), branch/edges (which match to the examination result and link to the following leaf or node), and leaf nodes (the terminal leaves that forecast the upshot), making it a complete structure, as shown in **Fig. 7** (DeRousseau *et al.* 2018; Nunez *et al.* 2020; Omran *et al.* 2016). Compared to classical regression methods, decision tree models offer better accuracy in prediction (Deshpande *et al.* 2014). Additionally, these models explicitly describe the relationships and patterns inherent in datasets through base and regression equations, whereas other intelligent algorithms such as SVR and ANN keep them hidden (Almasi *et al.* 2017). As shown in **Table 5**, four types of DTMs, namely the "M5P tree", "Random Forest" (RF), operation tree (OT), and Extreme Gradient Boosting (XGBoost) and were mainly applied to forecast the mechanical characteristics of RAC. The method and its applications are shown infra.

8.1 M5P-tree model

M5P (or M5′) algorithm is an expanded and reconstructed M5 algorithm version that includes three main steps (splitting, pruning, and smoothing), as shown in **Fig. 8** (Behnood *et al.* 2015a, 2015b, 2017; Wang and Witten 1997;), i.e., 1) Splitting, a procedure is constructed utilizing a partition criterion that splits up the datasets into small subgroups. 2) Pruning, for removing or merging unwanted sub-trees to overwhelm datasets over-smoothing that occurred through model building

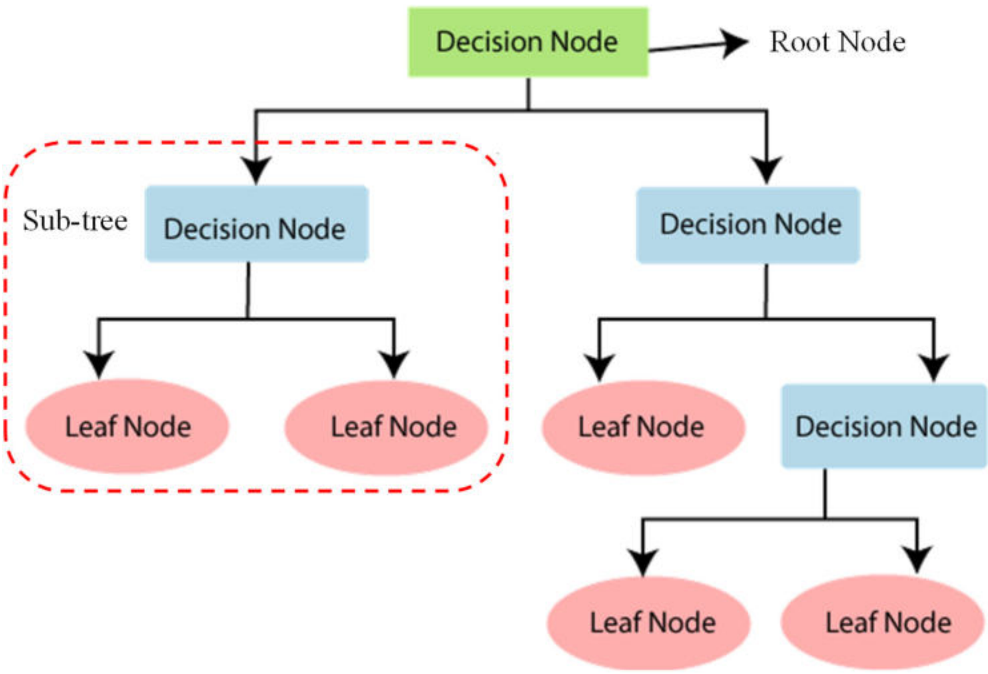

Fig. 7 General schematic of decision tree models.

Table 5 Outline of applied DT-based RAC models.

Method	Size of datasets	TD, %	VD, %	TSD, %	Input parameters	Output of model	Statistical index	Reference
M5P-Tree	257	70	15	15	CEM, RFA, W/C/S, NFA, NCA (10, 20 mm), RFA, RCA (10, 20 mm), WCR, PCA, WMR, RAN, ACR	CS	$\mathcal{R}$, $\mathcal{RMSE}$, $\mathcal{M}$	Deshpande *et al.* (2014)
	270	80	N/A	20	WCR, ADM, PFA, PCA, CAC, FTA, VRA, SSD, ARC	CS	$\mathcal{RMSE}$, $\mathcal{R}^2$, $\mathcal{R}$	Behnood *et al.* (2015a, 2015b)
	454	80	N/A	20	CS, WCR, CAC, FTA, VRA, SSD, ARC	EM	$\mathcal{R}^2$, $\mathcal{R}$	Behnood *et al.* (2015a, 2015b)
	650	50	N/A	50	PCA, ACR, DRC, ARC, WCR	CS	$\mathcal{RMSE}$, $\mathcal{M}$, $\mathcal{M}_{\%}$	Gholampour *et al.* (2018)
	346	51	N/A	49		CT		
	421	47	N/A	53		EM		
RF	138	10-fold cross-validation			W, CEM, SP, CRA, FRA, SCM, AGE, NFA, NCA	CS	$\mathcal{R}$, $\mathcal{RMSE}$	Sun *et al.* (2019)
ICA-XGBoost	209	80	N/A	20	RFA, RCA, WCR, WMR, ARC, NCA	CS	$\mathcal{R}$, σ, $\mathcal{RMSE}$, $\mathcal{M}$	Duan *et al.* (2020)

and 3) Smoothing to reimburse for keen cut-outs that occur between neighbouring linear models at tree leaves. To divide the datainput space and produce the model of regression tree, a rate named the factor of standard deviation (σ), which is the highest reduction of data-output errors after splitting, is recognised (Behnood *et al.* 2015, 2017). The M5 model has been modified to the M5P-tree model to handle numeric attributes besides missing attribute rates. In the M5P-tree model, all numeric characteristics are converted to binary datasets before the model is built (Almasi *et al.* 2017; Omran *et al.* 2016; Yi *et al.* 2018). M5P algorithm has been adopted in many investigations to foresee the mechanical characteristics of RAC (Behnood *et al.* 2015a, 2015b; Deshpande *et al.* 2014; Gholampour *et al.* 2018). Use of this tree algorithm contained prediction of the CS, modulus of elasticity (ME), and tensile strength (TS) of RAC. The tree model in these studies includes various input variables, as listed in **Table 5**. They were demonstrated that the M5P-tree algorithm accurately forecast the CS, TS, and ME, as indicated by the statistical measures.

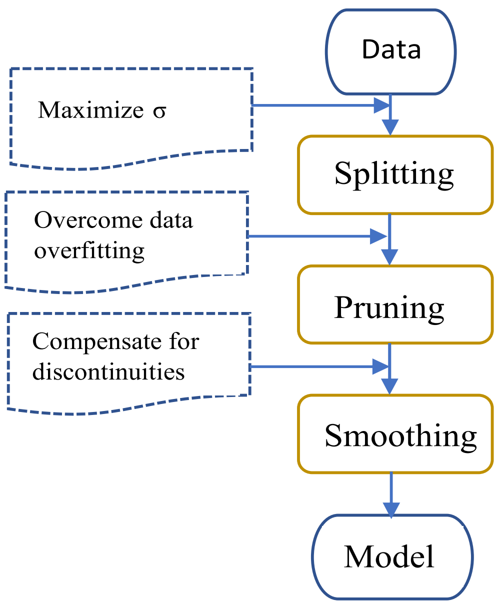

Fig. 8 Processes of M5-tree model.

8.2 Random forest (RF)

The RF model has been used in several investigations as a prediction tool, too. This model mixes several decision tree algorithms, each developed from a modern training process according to the "bagging" approach (Chehreh Chelgani *et al.* 2016; Han *et al.* 2019). This bagging approach (or bootstrap, aggregation) is a group training process consisting of these two main steps. During bootstrap, the first one, independent datasets and correspondingly distributed are generated by randomly resampling the raw data-input. In the aggregation stage, the modified data sets are utilized to independently in training the primary forecasters (Han *et al.* 2019). The outcomes are achieved using averaging the forecasts of each tree forecaster within this stage. The RF models have outstanding achievement in classification tasks such as strong robustness in terms of big feature datasets, integrating interactions between predictor variables, great quality, and free applications (Breiman 2004; Han *et al.* 2020; Janitza *et al.* 2016). The schematic diagram of the RF structure is shown in **Fig. 9**. This model has been extensively used to deal with classification and regression issues in civil engineering, e.g., Ghiasi *et al.* (2018), Huang and Burton (2019), Rahman *et al.* (2021) and Zhang *et al.* (2019). The RF model has been improved with a BAS algorithm to predict the CS of RAC that contains waste of rubbers by Sun *et al.* (2019). The

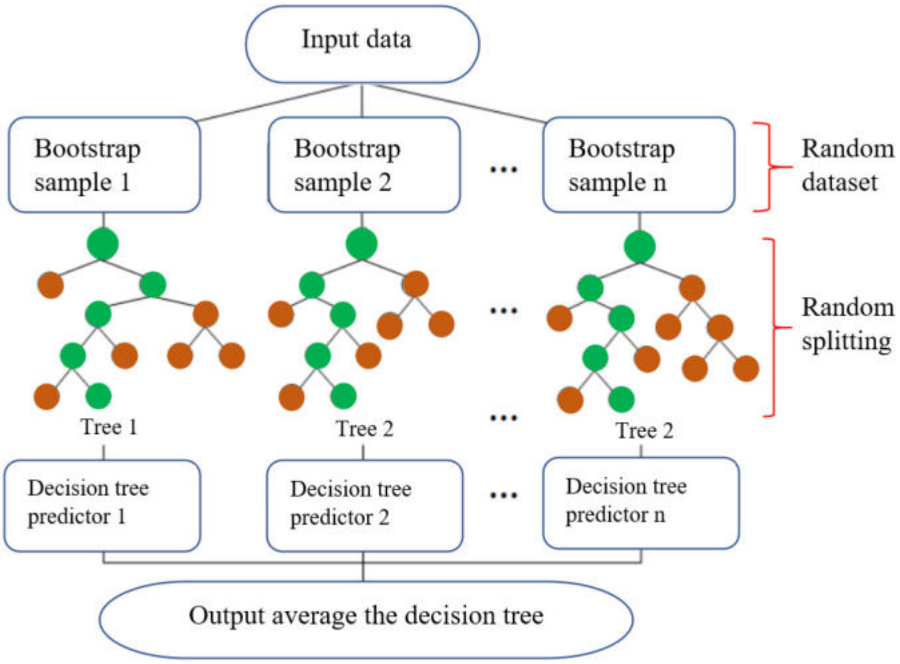

Fig. 9 The schematic structure of the RF algorithm.

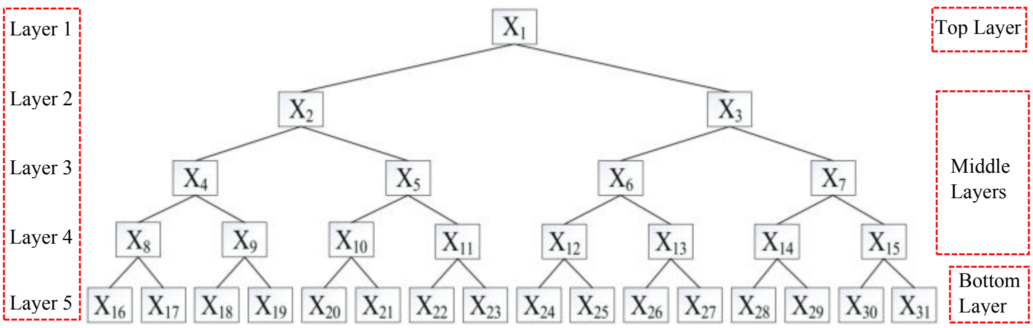

Fig. 10 The OT architecture with 5 layers and 31 nodes.

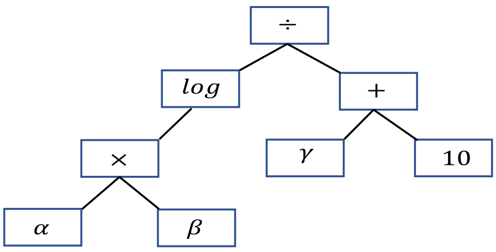

Fig. 11 Illustration of an example of OT model.

authors concluded that the BAS could tune the RF model efficiently, and consequently, the hyperparameters of the RF model were obtained. Their proposed model showed precisely predicted the CS of RAC with a correlation coefficient is 96%.

8.3 Operation tree (OT)

Operation tree (OT) is a tree data structure that describes a mathematical formula (Chen *et al.* 2013; Tsai 2011; Yeh *et al.* 2010). These sets are created hierarchically together (layer by layer) in such a way that they describe a pattern of a tree. As an example, an OT model consisting of 5 layers with a total of 31 nodes is exhibited in **Fig. 10**, where X1 is the root meant a mathematical operation (+, −, etc.), X2 to X15 are tree branches meant a constant, a variable or a mathematical operation and X16 to X31 are leaves meant as a constant or a variable (Chen and Wang 2010). For instance, **Fig. 11** shows the OT algorithm for the mathematical formula shown below. The algorithm applied mathematical operations (÷, ×, − and *log*), variables (α, β and γ) and a constant 10.

$$Z = \frac{log(\alpha \times \beta)}{\gamma - 10} \tag{1}$$

Building a regression model by an OT needs to set suitable mathematical operations, constants, and variables on the root, branches, and leaves of the OT. When the OT structure is set up to describe a particular mathematical equation, the OT can produce a predicted output value for each dataset by replacing the dataset entry values with variables on the tree branches or leaves. The model performance of this process can be assessed by statistical indexes such as the *RMSE* between the original and predicted output values. Minimum $\mathcal{R}MSE$ for the OT is the best-fit tree model for the datasets (Chen and Wang 2010). An advantage of the OT model compared to traditional models is that it does not require a predetermined formula structure. In addition, the OT model has a flexible mathematical equation. But optimizing the architecture to better fit the data is a separate optimization problem. Hence, the process of OT cannot be solved by traditional mathematical programming. To overcome this shortcoming, genetic algorithms have been proposed to optimize the process of the OT model to fit the data best (Cheng and Gosno 2010; Peng *et al.* 2009, 2010). Cheng and Gosno (2010) used the OT model to predict the elastic modulus of RAC. They have proposed the symbiotic polyhedron algorithm combined with OR to improve the performance of the OT model. Their results revealed that the proposed algorithm had shown superiority over other conventional methods in terms of robustness and stability.

8.4 Extreme gradient boosting (XGBoost)

Extreme gradient boosting (XGBoost) is one of the well-known ensemble tree algorithms developed by Tianqi Chen and co-workers (Chen and Guestrin 2016; Chen *et al.* 2020b). Also, it is a modification for gradient boosting (GB) technique to improve the speed and accuracy in tree-based ML models (sequential decision trees) (Biau *et al.* 2019; Friedman 2002). The XGBoost model deals with both regression and classification problems efficiently as the boosted trees are produced and worked parallel (Agapitos *et al.* 2017; Zhou *et al.* 2019b). Alike the GB decision tree and GB machine model, XGBoost proposes a strong and fast algorithm for several engineering simulation problems based on the parallel boosting trees, e.g., Li (2019), Lloyd (2014), Nguyen-Sy *et al.* (2020), Nguyen *et al.* (2021) and Zhou *et al.* (2019b). To increase its accuracy of predicting, Duan *et al.* (2020) combined a novel algorithm, ICA, with XGBoost algorithm for predicting the CS of RAC. They compared their proposed hybrid model with three other AI models (ICA-ANN, ICA-ANFIS, and ICA-SVR models), and the proposed model was superior to the other models.

9. Evolutionary algorithms (EAs)

Evolutionary algorithms (EAs) are a set of heuristic exploration algorithms in which the procedure of determining an answer in the exploration dataspace is according to the biological evolution system that has five steps: 1) selection; 2) mutation; 3) recombination; 4) reproduction; and 5) recombination (Mashwani 2013). These steps of evolutionary algorithms are shown in **Fig. 12**. In the first step, an initial population that describes the candidate solutions set is randomly generated. Next step, this group is evaluated by a fitness task. Then, the following generation with a finer set of nominees is thereafter developed via recombination and mutation stages. The recombination stage comprises of producing new nominees by a binary operator that is used to the prior group (parents). After that, the mutation only transforms a nominee from prior groups. Next applying both these operators a modified data set generation is generated according to a fitness task. This reiterative manner breaks once the wanted target of the fitness task is obtained or once the highest mass of the generations is given (Deb *et al.* 2005; Lücken *et al.* 2014).

EAs have been adopted for assessing RAC strength. Golafshani and Behnood (2018b) used a set of the EA models, namely Artificial Bee-Colony algorithm (ABC), Genetic Programming (GP), and Biogeography-Based Programming (BBP), to predict an EM for RAC. Their proposed methods delivered high performance, as shown by error measures used to evaluate and compare the performance of their developed models, see Golafshani and Behnood (2018b). Additionally, fine aggregate-to-total aggregate ratio (FTA) along with water absorption and CS of concrete had a notable effect on the EM of RAC.

10. Useful AI libraries and tools

The availability of open-source libraries and tools has made the modelling process much easier than before. These libraries and tools such as WEKA (Witten *et al.* 1999), a graphical user interface (GUI) for developing ML and data mining designs. And TensorFlow library is a big platform for ML and DL (Abadi *et al.* 2016). It has wide, flexible tools and community resources that give researchers advanced the state-of-the-art in DL and ML and developers efficiently build and expand AI-powered applications. And Torch is an ML library with a focus on ANN. It was originally written by Lua, a scripting language (Collobert *et al.* 2002). Also, PyTorch, rewritten by Python, is one of the most popular DL frameworks (Paszke *et al.* 2019). Furthermore, LibSVM (Chang and Lin 2011), which efficiently implements SVMs. In addition, the Scikit-Learn and Theano libraries were re-

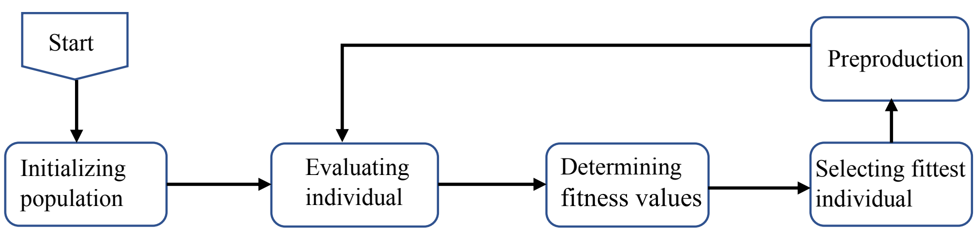

Fig. 12 Outline of evolutionary algorithms process.

leased and publicly licensed and written by Python (Theano Development Team 2016; Pedregosa *et al.* 2011; Pölsterl 2010). They implement many different ML algorithms, including ANN, SVMs, and RF. Besides, they use functions such as stratification, train-test splitting, cross-validation, and metrics needed to develop and evaluate a robust ML model. All these libraries, tools, and many more have helped develop AI-based RAC models quickly and efficiently.

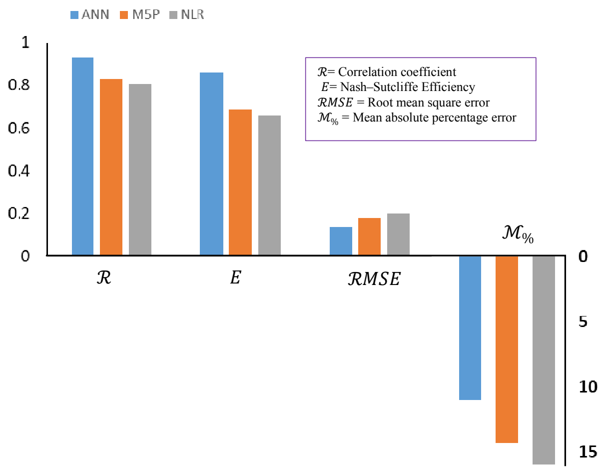

Fig. 13 Comparison between AI algorithms (ANN, M5P) and non-linear regression (NLR) (Deshpande *et al.* 2014).

11. Discussion and interpretation

AI systems have been used by many researchers as an innovative strategy to predict the mechanical characteristics of RAC. As shown in **Figs. 13**, **14** and **Table 6**, the statistical indexes regained from the list of most recent investigations reflect the remarkable advantage of the AI algorithms over non-linear regression (NLR) and conventional empirical methods of the similar test datasets. This could be interpreted by the powerful AI algorithms to precisely predict the characteristics of intricate RAC mixtures as the relations between the constituents of the concrete mix and its resultant CS are a highly nonlinear problem. Moreover, in **Tables 3** to **5** show that the AI algorithms have been developed based on massive and comprehensive databases, which means that the number of datasets applied to develop these methods is much greater than that of the empirically-based generated formulas. Hence, the use of empirical formulas is restricted to a small number of cases, leading to a greater error in predicting an "unseen" dataset. In addition, a likely problem correlated with conventional statistical and empirical methods is their insufficiency to

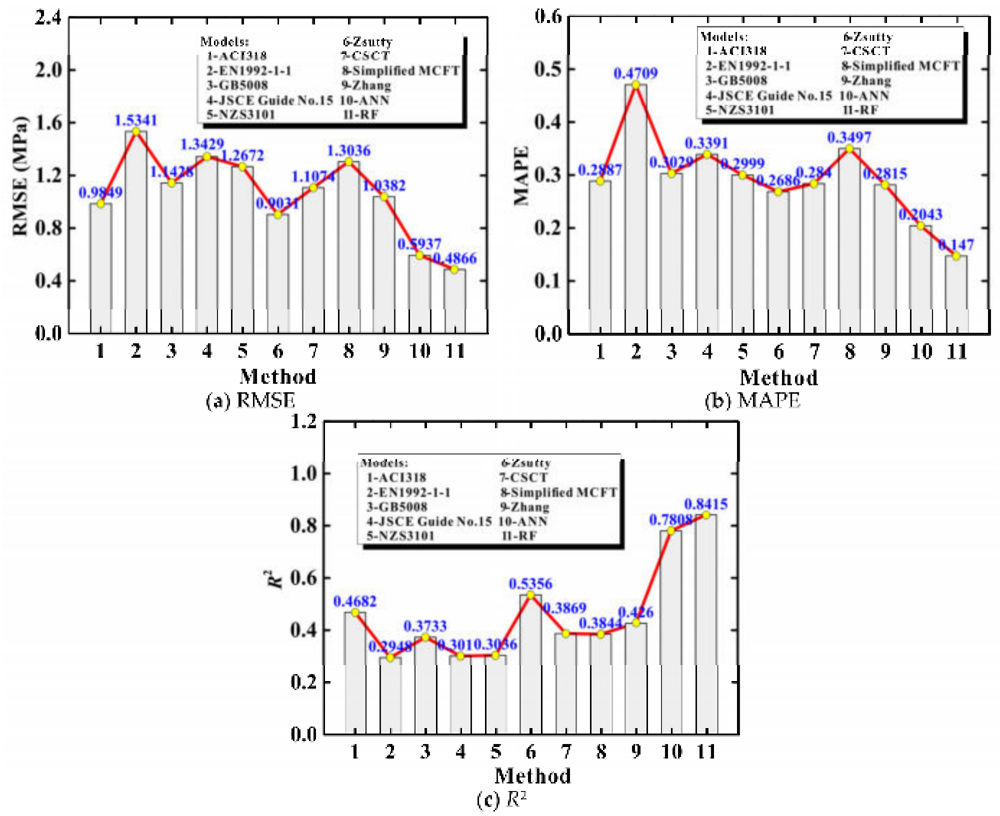

Fig. 14 AI models (RF, ANN) performance compared to conventional models: Method 1: ACI 318 (ACI 2011), Method 2: EN 1992-1-1 (Beeby and Narayanan 1993), Method 3: GB 50008 (Kaklauskas *et al.* 2015), Method 4: JSCE Guideline No. 15 (Ueda and Takewaka 2007), Method 5: NZS 3101 (Inwood 1999), Method 6: Zsutty (*fib* 2010; Bentz and Collins, 2017), Method 7: Critical Shear Crack Theory (CSCT), Method 8: Simplified MCFT (Vecchio and Collins 1986), Method 9: Zhang (1997), Method 10: ANN, Method 11: RF (Yu *et al.* 2020).

Table 6 Comparison between some AI models and empirical methods with the same dataset.

Model (AI: Empirical)	Statistical indexes		Output	Reference
	$\mathcal{RMSE}$	$\mathcal{M}_{\%}$		
ANN (Pereira *et al.* 2012)	7.71:28.15	15.13:54.22	CS	Xu *et al.* (2019b)
	0.480:0.720	11.890:14.650	TS	
ANN (Bui *et al.* 2018)	4425.89:5749.73	11.21:17.85	ME	
ANN (Jalal *et al.* 2020)	0.24:1.26	5.85:6.7	CS	Chen *et al.* (2020a)

Table 7 Comparison between some AI models with the same data used.

AI Model	Statistical indexes			The amount of data	Output	Reference
	$\mathcal{RMSE}$	$\mathcal{M}_{\%}$	$\mathcal{R}^2$			
ANN	-	19.7676	0.9185	257	CS	Khademi *et al.* (2016)
ANFIS	-	25.4530	0.9075			
GEP	14.18	31.29	-	332	CS	Xu *et al.* (2019b)
ANN	7.71	15.13	-			
GEP	9287.91	30.19	-	421	EM	
ANN	4425.89	11.21	-			
GEP	1.60	28.11	-	152	FS	
ANN	0.64	9.39	-			
GEP	1.86	64.26	-	346	STS	
ANN	0.48	11.89	-			
ANN	1.602	11.971	0.982	72	CS	Jalal *et al.* (2020)
ANFIS	1.725	3.904	0.975			
SVM	1.393	7.453	0.989			

afford a precise estimate of the characteristics of RAC with new combinations, neglecting the impact of these new components on the desired product. In contrast, the models from AI give the choice of modernizing the prediction methodology via managing the number of data-inputs (characteristics) and components deemed in the model. Besides, the effect of each input parameter on RAC strength can be estimated by AI systems through sensitivity analysis, such as in (Xu *et al.* 2019b). These merits of AI models mean that the application of conventional methods is limited to specific problems where the mixture understudy has a simple structure, as conventional methods conveniently provide explicit mathematical formulae.

Besides the differences between conventional approaches and AI algorithms, there are contrasts in procedure and performance between AI algorithms. Thus, each AI algorithm has many advantages and disadvantages comparing with other algorithms. This can be interpreted by the values of the statistical indexes in **Table 7**, which shows the performance of some AI models over the same test datasets.

As noted earlier, numerous investigations have adopted the ANN due to its powerful benefits. With an obvious vector set of weight and bias as well as a limit number of hidden neurons and hidden layers obtained after many iterations, the structure of the ANN model can be well defined. But such a repetitive process of trying and adjusting errors takes a lot of time. Another significant gap in the ANN algorithms is related to a BP strategy, as the training stage is done by the gradient descent approach toward resulting errors that may lead to local optimal (Ayaz *et al.* 2015; Jafrasteh and Fathianpour 2017; Wang *et al.* 2015). In **Fig. 15**, a convergence process of BNN toward local optimum solution and prevention of global solution was a big concern (Chandwani *et al.* 2015; Yang *et al.* 2021). Applying the extreme learning machine (ELM) as another option can alleviate the convergence concern with the local minima and contribute further easiness as there are no stopping criteria and learning rates are needed (Christou *et al.* 2019; Sussner and Campiotti 2010). The ELM has been compared to BNN by Alshamiri *et al.* (2019) and performed better with the ELM paradigm. Despite this, the model adopted may need more hidden layers than the BNN methodology because of the arbitrary perception

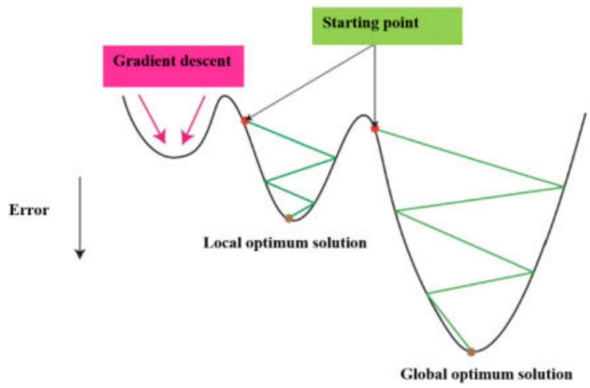

Fig. 15 BNN fitting mechanism (Ben Chaabene *et al.* 2020).

of entrance hidden biases and weights (Alaba *et al.* 2019; Tripathi *et al.* 2020; Zhang and Zhang 2017). An intemperate amount of hidden layers utilized in intricate shapes may result in overfitting, meaning that the intricacy of RAC characteristics can be overestimated with ANN (Behnood and Golafshani 2018). For overwhelming the disadvantages mentioned above, several meta-heuristic and combined algorithms were suggested to improve the ANN process and its performance, such as GA, Grasshopper Optimization (GO), and Salp Swarm (SS) algorithms (Kandiri *et al.* 2021). For case, utilizing GA algorithms and ensembles such as bagging and gradient enhancement for improving ANN foretelling performance have been demonstrated to be viable (Yuan *et al.* 2014). Nevertheless, the GA-ANN approach proposed before by Yuan *et al.* (2014) led to increasing algorithm intricacy and calculation loads. Another elective comprises utilizing ANFIS algorithms, which association learning capabilities of the ANN and thinking abilities of FL. Sobhani *et al.* (2010) and Sahin and Erol (2017) detailed that ANFIS seems to identify the nonlinear form handle with fast learning ability. Additionally, this is confirmed through a comparative investigation carried out in Dao *et al.* (2019a, 2019b). Nevertheless, ANFIS has some concerns regarding fuzzy rule choice that influence its accuracy besides, a failure to produce multi-output parameters (Yu *et al.* 2018a).

Concerning SVMs models, they have appeared capable of nonlinear mapping and optimum generalization capacities (Yu *et al.* 2018a). They too can distinguish and coordinate SVs in the training stage, which blocks non-SVs from influencing the accuracy of the algorithm. Nevertheless, this method suffers from numerous drawbacks, e.g., a heuristic way for choosing a suitable kernel-function, as depending mainly on the trials and errors manner. Besides, the process of the nonlinear SVMR method and its performance cannot be simply performed since this method of a nonlinear data mapping can be complicated (Chamarczuk *et al.* 2020).

The previously mentioned strategies (ANN and SVMs) are deemed as “black-box” algorithms because of a gigantic number of nodes and inside relationships (Alimi *et al.* 2020; Elsheikh *et al.* 2019; Farquad *et al.* 2014; Han and Wang 2011; Yadav and Chandel 2014). So, producing a straightforward scientific equation that depicts the useful relationship between I and O factors during those algorithms is troublesome. To deal with this issue, choice EA and tree algorithms can be used. These algorithms have the capacity to create unequivocal mathematical equations that depict the relation among data attributes and their resultant data-outputs. Though, DT models may force to data-overfitting problems. Besides, the efficiency of both EA and DT models is regularly smaller than that of hybrid-based models and standalone SVMs and ANN algorithms, as proven using performance indexes recovered from distinctive past investigations (Behnood *et al.* 2015c; Bui *et al.* 2018). Weaknesses of DT algorithms can be moderated by tree-based combination algorithms like RF and Multiple Additive Regression Trees (MART). For example, Chou *et al.* (2011) showed better outcomes from the MART algorithm than those taken from standalone SVMs and ANN. But ensemble algorithms produce more complexity to the algorithm and further calculation time.

One critical measure of AI models is the input data-feature significance. Some articles have shown the effect of those input parameter traits on predicted RAC mechanical strengths via sensitivity analysis (Khademi *et al.* 2016). Sensitivity analysis defines the extent to which each input trait affects the prediction of the model output by calculating a sensitivity scale (Cortez and Embrechts 2011, 2013). According to the type of AI model, sensitivity analysis can be performed applying different techniques. For instance, sensitivity analysis of ANN algorithms can be done employing many systems, such as the weights system, the partial derivatives system, and the classical stepwise system. Naderpour *et al.* (2018) showed the significance of each data input trait by the significance of the weights system and inferred that the water absorption capacity and the ratio of water to total materials of the RA were the most effective data input traits for predicting the CS for RAC. Also, the number of datasets used to generate AI models to predict RAC strength varies from one investigation to another. The range was 72 (Deng *et al.* 2018) to 1178 (Dantas *et al.* 2013). Because no set rule defines how much data is required to create an AI model. However, as it is known, the more data used, the fewer errors and the higher the accuracy. For example, cases that considered fewer information examples might show accurate outcomes. However, in this case, the model can show a higher error when tested on unseen datasets compared to those generated from more comprehensive databases.

12. Recommendations and practical gaps

Since all AI algorithms discussed earlier have different merits and demerits, the choice of the most proper algorithm relies on diverse bases. The characteristic of the relation among RAC components and their mechanical properties is a key element that impacts the algorithm selection. If the relation is exceedingly nonlinear and influenced by many features, using SVM or ANN models would be the best alternative due to their excellent power to solve problems in a nonlinear context with lower errors. For better processes and more precise results, optimizing those algorithms with meta-heuristic models is more powerful. Still, when algorithm clarity is needed, the use of evolutionary algorithms and decision trees can be recommended as they can produce clear mathematical equations that well represent natural relations among I and O data. However, the efficiency of both algorithms is less than that of standalone and hybrid SVMs and ANN algorithms as shown by performance indexes exposed in **Table 7**. Using combination algorithms is able to improve the precision of DT but may lead to model complexity and greater computation time. Based on the present study, hybrid SVMs and ANN algorithms have given the best performance to foresee RAC characteristics in terms of process and accuracy. Despite the increased calculation time, using those algorithms on big datasets with suitable feature choices would produce the most precise outcomes. Nevertheless, the only system to choose the most proper meta-heuristic algorithm is according to a trials and errors process. Hence, no accurate system is available to choose the best optimization model because they can give diverse results from one case to another.

Although most of the AI methods reviewed herein have proven reliable in predicting the mechanical strength of RAC, deep learning and assembly methods have not been widely applied to models of RAC materials, they have usually surpassed other methods in terms of speed and accuracy (Akinosho *et al.* 2020; Salehi and Burgueno 2018). Hence, these methods appear to be very promising for future investigations in this field and merit further investigation. Also, transfer learning is one of the modern trends that serve AI models that can be greatly benefited in future studies for predicting mechanical strength of RAC because of its effective role in training deep neural networks accurately with a small dataset compared to conventional training. This is very helpful in the data science field as most real-world challenges typically do not have enough data sets to train complex RAC models, e.g., Ford *et al.* (2022), Pan and Yang (2010) and Zhuang *et al.* (2021). It is worth noting that the number of contributions in the literature that includes joining AI models with meta-heuristic algorithms is very limited. Thus, there is an evident shortage of joining powerful algorithms such as, e.g., Particle Swarm Optimization (PSO), Tree Parzen Estimators (TPE), and Backtracking Search Algorithm (BSA), with AI models to improve the global optimization in predicting the mechanical strength of the RAC.

Furthermore, explainable AI (XAI) is an important research direction related to the challenge of illuminating ambiguous ML models in contexts where transparency is critical, as these models can be dealt with complex tasks (e.g., regression or classification). As shown before, most AI investigations usually focus on the RAC mechanical characteristics prediction goal but infrequently on providing explanations/justifications for them. Additionally, users in various fields need to comprehend before engaging in decisions with inherent risks. Also, XAI tools include a variety of interpretable ML methods that help people with understanding the relationship between I and O variables via interpretation of results of a predictive AI model to enable clarity and fairness in the AI algorithmic decision-making approaches. Details on the importance of XAI and its history, methodology, techniques, tools, etc., have been discussed in many studies such as, Agarwal and Das (2010), Biecek (2018), Islam *et al.* (2022), Liang *et al.* (2022) and Linardatos *et al.* (2021).

13. Conclusions

Numerous recent investigations have been carried out to forecast mechanical properties for concrete mixture, examining the advantages of some strategies and showing the shortcomings of others. Especially, predicting the RAC mechanical characteristics (as an intricate concrete mixture) by traditional empirical and statistical methods has been a major challenge as these methods are commonly imprecise, and their updating is time-consuming and costly. So, investigators have proposed AI algorithms to overwhelm such shortcomings. In this paper, the most popular AI algorithms used to predict the mechanical properties of RAC are organized into four categories, i.e., ANNs, SVMs, DTs, and EAs. The application of these algorithms in predicting the CS, SS, TS, and EM of RAC has been reviewed. Besides, the benefits and disadvantages of the given procedures have been critically examined and analysed. It has been noticed that numerous factors affect these algorithms' performance, such as the physical relation among RAC components and their mechanical strength, number of training dataset examples, and size of parameters selected in each algorithm. The review and analysis of the performance of AI algorithms, besides their advantages and disadvantages displayed in this paper, should help researchers and stakeholders in determining the proper technique to predict the RAC mechanical characteristics. Results revealed that AI models precisely forecast the RAC mechanical characteristics and that RA water-absorption and crush index, besides the proportion of water-to-total-materials, had the highest effect on the RAC mechanical characteristics. Finally, more research needs to be done to explore the reliability of AI models in predicting the properties of more innovative modification types performed on RAC.

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Appendix: List of the algorithm acronyms

Adaptive-Neuro-Fuzzy-Inference-System	ANFIS	Grasshopper Optimization	GO
Artificial Bee-Colony Algorithm	ABC	Imperialist Competitive Algorithm	ICA
Artificial Neural Networks	ANN	Least-Squares	LS
Backpropagation Neural Network	BNN	Levenberg-Marquardt Method	LMM
Biogeography-Based Programming	BBP	M5P-Tree Model	M5P
Cuckoo Search Method	CSM	Multi-Layer Perceptron	MLP
Decision Trees	DT	Multiple Additive Regression Trees	MART
Evolutionary Algorithms	EA	Multiple Linear Regression	MLR
Extreme Gradient Boosting	XGBoost	Multivariate Adaptive Regression Spline	MARS
Fuzzy Logic	FL	Non-Linear Regression	NLR
Gaussian Process Regression	GPR	Operation Tree	OT
Genetic Algorithm	GA	Radial-Based Neural Network	RNN
Genetic Programming	GP	Random Forest	RF
Gradient Boosting	GB	Salp Swarm	SS
Gradient Descent Method	GDM	Support Vector Machines	SVMs