Artificial intelligence algorithms for prediction and sensitivity analysis of mechanical properties of recycled aggregate concrete: A review

Tien-Dung Nguyen, Rachid Cherif, Pierre-Yves Mahieux, Jérome Lux, Abdelkarim Aït-Mokhtar, Emilio Bastidas-Arteaga

Journal of Building Engineering 66 (2023) 105929

Contents lists available at ScienceDirect

Journal of Building Engineering

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

Artificial intelligence algorithms for prediction and sensitivity analysis of mechanical properties of recycled aggregate concrete: A review

Tien-Dung Nguyen [a,b], Rachid Cherif [a], Pierre-Yves Mahieux [a], Jérome Lux [a], Abdelkarim Aït-Mokhtar [a], Emilio Bastidas-Arteaga [a,*]

[a] Laboratory of Engineering Sciences for the Environment (LaSIE - UMR CNRS 7356), La Rochelle University, La Rochelle, France
[b] Faculty of Road and Bridge Engineering, The University of Danang - University of Science and Technology, 54 Nguyen Luong Bang Street, Lien Chieu District, Danang City, Viet Nam

ARTICLE INFO

Keywords:
Recycled aggregates concrete
Mechanical properties
Sensitivity analysis
Artificial intelligence

ABSTRACT

Using recycled aggregates generated from demolition waste for concrete production is a promissory option to reduce the environmental footprint of the built environment. However, predicting the hardened performance of recycled aggregate concrete is one of the main barriers to its intensive deployment in the construction sector. Since traditional empirical approaches are less reliable for predicting the performance of new recycled aggregate formulations, artificial intelligence approaches have been widely developed in recent years towards this aim. In this paper, we conducted an extensive literature review on artificial intelligence (AI) methods that predict the mechanical performance of recycled aggregate concretes and perform sensitivity analysis. The primary methodologies and algorithms found in the literature have been thoroughly described, examined, and discussed in this study concerning their applicability, accuracy, and computational requirements. Furthermore, the benefits and drawbacks of various algorithms have been highlighted. AI algorithms have demonstrated success in a variety of prediction applications with high accuracy. Although these algorithms are robust predictive tools for estimating recycled aggregate concrete's mixture composition and mechanical properties, their performance is highly dependent on data structure and hyperparameter selection. This study could help engineers and researchers to make better decisions about using AI algorithms for mechanical properties prediction and/or to optimise formulations for recycled aggregate concrete.

Abbreviations:

AI	artificial Intelligence
Anns	Artificial Neural Networks
Bns	Bayesian Networks
CDW	Construction and Demolition Waste
XGBoost	Extreme Gradient Boosting
FL	Fuzzy Logic

* Corresponding author.
E-mail address: ebastida@univ-lr.fr (E. Bastidas-Arteaga).

https://doi.org/10.1016/j.jobe.2023.105929
Received 16 November 2022; Received in revised form 4 January 2023; Accepted 16 January 2023
Available online 20 January 2023

HPC	High-Performance Concrete
ICA	Imperialist Competitive Algorithm
LR	Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLR	Multiple Linear Regression
MT	Model Tree
NA	Natural Aggregate
Xgboost	Extreme Gradient Boosting
FNA	Fine Natural Aggregate
CNA	Coarse Natural Aggregate
NLR	Non-Linear Regression
PLC	Portland Limestone Cement
RA	Recycled Aggregates
RAC	Recycled Aggregate Concrete
CRA	Coarse Recycled Aggregate
FRA	Fine Recycled Aggregate
RMSE	Root Mean Square Error
RF	Random Forest
SA	Sensitivity Analysis
SCC	Self-Compacting Concrete
W/C	Water-Cement Ratio

1. Introduction

Earth faces environmental degradation, resulting for instance from global warming. To counteract these effects, the Paris Agreement was signed in 2015 with a focus on reducing greenhouse gas emissions. The European Union has determined the initiative of the European Green Agreement that there will have to zero-carbon emissions in 2050 and an economic growth separated from the use of resources [1]. The Chinese government has also enacted a similar strategy, stating that carbon neutrality will be attained by 2060 [2]. Since the 1900s, concrete has been the most widely used construction material [3]. However, it accounts for approximately 8% of total global carbon dioxide emissions [4] and requires a significant amount of natural stone as natural coarse aggregate (NCA) for concrete manufacturing [5]. Because of the quick expansion of construction and demolition activities, China generally has the highest construction and demolition waste (CDW) production (i.e., around 2360 million tons) [6], followed by the United States (i.e., around 600 million tons) [7] and India (i.e., around 530 million tons in 2016) [8]. The EU also produced a large quantity of CDW, with France and Germany leading the way with 240 and 225 million tons, respectively [9].

Recycled aggregate concrete (RAC) from processed CDW [1,10] might help to mitigate natural aggregate (NA) depletion, contribute to the sustainability of concrete production, and avoid the disposal of massive volumes of CDW [11]. The studies on the RAC's performance have concentrated on using recycled aggregate (RA) as a partial or complete substitute for NA, reducing RAC's characteristics [12]. The compressive strength of RAC is affected by complex elements such as RA's nature and physical properties [13–16]. The variable composition of RA has resulted in very non-linear interactions between RA addition and the mechanical characteristic of RAC [17]. One of the primary sources of heterogeneity is that recycled concrete, except for laboratory test concretes, often contains materials such as glass, metal, bricks, stones, and paper [18]. Moreover, the old mortar attached to the recycled concrete leads to a poor link between the aggregates and the cement matrix of RAC [19,20].

Many studies employ traditional methods as statistical procedures for estimating the mechanical behaviour of RAC. These approaches are mainly based on statistical analysis, which builds linear and non-linear regression algorithms for prediction [21]. For example, Revilla-Cuesta et al. [22] estimated the mechanical properties of Self-Compacting Concrete (SCC) containing recycled concrete aggregate based on porosity indices. Al-Qadi et al. [23] forecasted SCC's workability and hardened characteristics by using mathematical tools to model the impact of crucial mixture variables (cement, water-to-binder ratio, fly ash, and superplasticiser). Revilla-Cuesta et al. [24] predict the elastic modulus of SCC with RA and slag cement through the hammer rebound index and ultrasonic pulse velocity using simple and multiple-regression models. In addition, Hariharan et al. [25] proposed a model using regression analysis to predict the mechanical behaviour of binary and ternary cementitious materials. Shin et al. [26] suggested a multiple regression model for forecasting the strength properties of RAC.

Moreover, Nepomuceno et al. [27] evaluated SCC strength with non-destructive tests by statistical procedures. Younis et al. [28] used multi-linear and non-linear regressing analysis and relationships between the physical properties of RA and the strength of RAC. The studies mentioned above show that all models can reasonably predict the compressive strength of RAC. However, these statistical approaches are inaccurate for determining the mix proportion parameters [29–31].

AI approaches have been deployed to capture the impacts of mixture composition on concrete properties. AI algorithms refer to the capacity of a computer to learn the underlying mechanisms of a complicated system and make accurate predictions about it [32]. These methods include artificial neural networks, genetic approaches, tree-based models, and other techniques. AI algorithms are often split

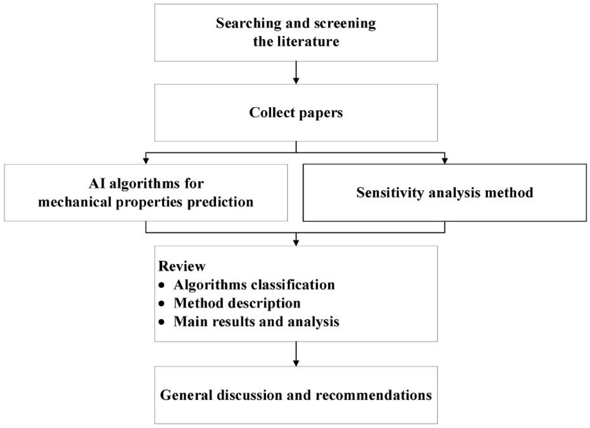

Fig. 1. Review methodology.

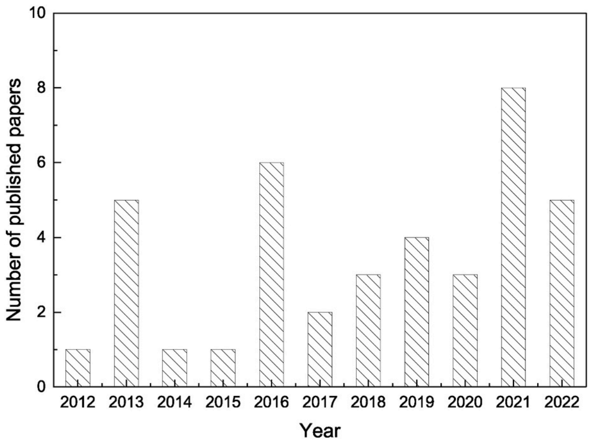

Fig. 2. Published papers on AI algorithms in predicting RAC's mechanical properties from 2012 to 2022.

into four categories based on the learning method: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [33]. Supervised learning, the most common type of AI algorithm, uses previously known pairings to predict the output of new data [34]. Unsupervised learning is an approach in which we know the input data. Reinforcement learning is a topic that aids the ability of a system to autonomously choose a behaviour depending on conditions that maximize target advantages [35]. Because of the nature of the problem, supervised regression techniques are recommended for estimating mechanical performance and determining the relevance of input parameters in each AI approach [36].

In recent years, AI approaches in civil and construction engineering have sparked much interest in various applications because of their adaptability and robust performance [37]. They have primarily been used for optimisation and prediction [38,39]. Civil engineering optimisation tries to minimise a cost function subject to specific performance constraints [40,41]. For example, AI may be used to optimise the size, topology, and form of structural elements such that the structure fulfils minimal design/performance criteria [34,42,43]. On the other hand, the prediction approaches were created to learn patterns from a dataset and generalise them to make accurate predictions [44–46]. The literature has extensively addressed the prediction of many properties of concretes, such as mechanical, thermal, and durability qualities, and the prediction performance of various methods has been investigated and published [47,48]. Through sensitivity studies, several researchers looked at the impact of input characteristics (e.g., mixing water, cement, and fine and coarse aggregate contents [49]) on the hardened properties of RAC [20,50–54]. By developing a sensitivity measurement procedure, sensitivity analysis assessed how much each input information influenced the output prediction [55].

This study offers a comprehensive review of the AI algorithms available to estimate the hardened performance of RAC. We also analyse some advantages and disadvantages of using AI to predict the performance of RAC based on a literature review of studies applying AI algorithms for the prediction of RAC's mechanical properties. Furthermore, the paper presents and discusses available studies about sensitivity analysis applied to this problem. The paper is organised as follows: section 2 presents the review methodology. A critical review of artificial intelligence algorithms for determining the mechanical properties of RAC is provided in section 3. Section 4 presents a review of studies that use AI algorithms for sensitivity analysis. The discussions and recommendations of this paper are provided in section 5. Finally, the conclusion is presented in section 6.

Table 1
Hyperparameters used in ANNs models.

Data size	Input	Hidden layers	Hidden neurons	Activation function	Ref.
1178	17	1	3	Hyperbolic tan, linear	[13]
139	6	1	18	Sigmoid	[65]
168	14	1	16	Sigmoid	[18]
257	9	1	28–53	Sigmoid, linear	[20]
257	9	1	29	Sigmoid, linear	[66]
210	8	2	9	Sigmoid	[67]
297	14	1	16	Sigmoid	[68]
62	7	6	7	Log-sigmoid	[52]
121	6	1	N/A	Log-sigmoid	[69]
177	11	1	15–20	Log-sigmoid	[70]
88	8	2	1–20	Log-sigmoid, Tan-sigmoid	[54]
185	10	1	8	Log-sigmoid	[71]

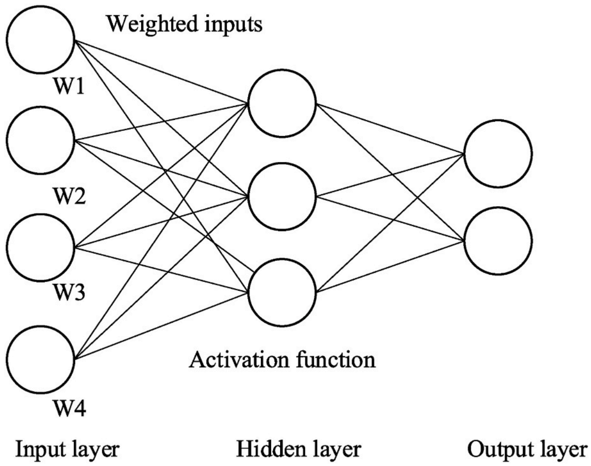

Fig. 3. Structure of the ANNs model.

2. Review methodology

The paper's scope focused on the hardened performance of RAC, excluding other concretes such as HPC and SCC. We exclude these materials because the relationship between mechanical behaviour and mixture design of RAC has been established using statistical methods with acceptable results, whereas having an accurate model for emerging concrete mixtures is more complex [56]. Fig. 1 depicts the review method. After gathering and examining the parameters and hyperparameters utilised in all the models. AI algorithms were classified and described at the beginning, followed by the presentation of the main works, including the statistical indicators of model performance. A discussion about the advantages and drawbacks of each model is also presented. This discussion also includes potential applications of AI algorithms and recommendations to be examined in future research.

Fig. 2 presents studies of AI algorithms in predicting RAC's mechanical properties. About 40 papers were included in this review. The figure shows that the number of published papers progressively increased over time. Especially the number of articles in the last four years is equal to the number of articles published before 2018. This trend implies that AI algorithms have been quickly and widely applied to predict RAC's mechanical properties in this decade. In other words, AI algorithms are gaining popularity for resolving various issues for the prediction of RAC's properties.

In this paper, several validation techniques found in the literature are presented, including the coefficient of determination (R^2), mean absolute error (MAE) or mean absolute percentage error (MAPE), and root mean square error (RMSE), which several authors used to validate the models' performance. These measurements are based on well-established methods for determining how accurate AI models are [57]. In these methods, RMSE is inferred by mean squared difference between outputs and the targets, MAE, the mean magnitude of the errors infers MAPE, and R^2 denotes the correlation between the two [58]. Lower RMSE, MAE and MAPE indicate a more accurate model. In contrast, a higher R^2 (which ranges from 0 to 1) denotes a model with higher accuracy.

3. AI algorithms for mechanical properties prediction

3.1. *Artificial neural networks*

Artificial neural networks (ANNs), also known as neural networks, are computing systems modelled after neural networks [59,60]. ANNs parallel processing, inspired by the working of the human brain, provides computers with an extra benefit in concurrently processing massive quantities of data. ANNs are highly suited to issues whose solutions need difficult-to-specify knowledge but for which there is sufficient data or observations [61]. It has been stated that ANNs can extract patterns in the phenomenon and overcome obstacles caused by model form selection, such as linear, power, or polynomial [62]. Multivariate interrelationships drive the parameters being modelled, and the data supplied could be "noisy" or incomplete, typical features when predicting and modelling [63]. ANNs learn the effect of input data to predict output through a learning process that calculates the weight of each unit called a neuron. An artificial neuron receives a signal, analyses it, and then sends signals to the linked neurons. Non-linear functions generate each output by the sum of its inputs, and the "signal" at a connection is an actual number. Edges are the terms for the links. The weight of neurons and edges is frequently adjusted as learning progresses. The signal strength at a connection is increased or decreased by the weight. Neurons may have a threshold that allows them to send a signal only if the aggregate signal exceeds it.

Neurons are usually grouped into layers. On their inputs, separate layers may apply different transformations. Signals move from the first to the last layer, perhaps after traversing the layers several times. ANNs come in various shapes and sizes, each with hyperparameters [64]. Table 1 shows the hyperparameters of ANNs models that were used to forecast the compressive strength of RAC. The researchers utilised the sigmoid function as an activation function. In all studies, the number of hidden layers was one or two, with a maximum of 53 hidden neurons. Fig. 3 presents ANNs model, which has an input layer, hidden layer, and output layer. The ANNs model predicts output through a learning process that calculates the weight of each neuron. By computing the weighted sum and then adding bias to it, the activation function determines whether or not a neuron should be activated. The activation function's objective is to add non-linearity to a neuron's output.

Numerous researchers have used ANNs approaches to forecast the compressive strength of RAC [13,18,65,66]. Dantas et al. [13] proposed ANNs models for forecasting compressive strength at 3, 7, 28, and 91 days. This study began with 24 input variables and was reduced to 17 after conducting a Principal Component Analysis. The R^2 are 0.928 and 0.971, respectively, for ANNs training and testing, and the frequency of outcomes with errors is less than 7.5% and more significant than 20% for ANNs testing, indicating that the output values are incredibly similar to the experimental values. For the 28-day compressive strength output parameter, Deshpande et al. [68] proposed five ANNs and Non-Linear Regression (NLR) techniques for modelling with 14 inputs, which were classified into mandatory and non-dimensional parameters. The results demonstrated that ANNs outperform NLR equations with better statistical parameters [68]. Similarly, ANNs and NLR were used to predict RAC's compressive strength, with 9 mandatory input parameters and 5 input non-dimensional parameters [20]. Because the R^2 values for the ANNs models and NLR were 0.93 and 0.82, respectively, ANNs predict concrete strength better than NLR, while the NLR technique can generate a single equation that can be easily employed.

Duan et al. [18] also proposed an ANNs model for predicting the compressive strength of RAC at 28 days using 14 input parameters. The model showed a good concordance between predictions and experimental measurements by the R^2, RMSE, and MAPE in the training and testing sets. The R^2 values in the training and testing sets were 0.998 and 0.9955, respectively; the values of RMSE and MAPE in the training set were 1.79% and 0.26%, respectively; and the values of RMSE and MAPE in the testing set were 3.68% and 1.67%. They also look at how ANNs may be used to model the modulus of elasticity of RAC [72]. The first ANNs, called ANNs-I, are built into their work by employing 324 datasets obtained from 21 articles in the literature and randomly separated into three groups: training, testing, and validation sets. A second ANN, called ANNs-II, is also created, with 16 more data sets from the authors' experiments added to the learning database of the first ANNs-I to see if the performance of ANNs can be enhanced further. The built ANNs model is then used to forecast further experimental data received from third-party articles (Case I) and test results produced in the authors' laboratory (Case II) and assess its applicability to RA obtained from other sources. The projected findings are compared to those obtained through experimentation and those modelled using traditional regression analysis. The results showed that applying the created ANNs-I to Case I and Case II can provide results that are extremely near to the real values, with MAPE values of just 5.21% and 3.92%, respectively, and R^2 of 0.9941 and 0.9982. The performance of the ANNs-II is greatly enhanced when some of the data is added to the training sets of ANNs-I.

Miličević et al. [52] introduced a multi-layer back-propagation algorithm in ANNs, the most widely used ANNs methodology and mathematical model, for predicting different output parameters concerning RAC mechanical properties. A lower MAE, RMSE, and MAPE value indicates that the model is efficient and predictable [52]. The results showed that the mathematical model fared the best in terms of RMSE regarding outputs, flexural strength, and modulus of elasticity. The ANNs model, on the other hand, had reduced error rates for three additional performance indicators, which was true for all three outcomes. Compared to ANNs, the mathematical model resulted in poorer prediction accuracy and greater residuals.

ANNs were also utilised to estimate compressive strength with six input features [65,69]. R^2-values are above 0.9, and the low RMSE determined that the ANNs technique can estimate the compressive strength of RAC with excellent accuracy. Suescum-Morales et al. [70] proposed a new ANNs model to estimate the 28-day strength properties of RAC with four training pieces completed using the Levenberg–Marquardt and Bayesian Regularization training procedures to combine 15 and 20 hidden layers. The Bayesian Regularization training approach has proved superior to Levenberg–Marquardt for predicting the output. Besides, Bu et al. [54] presented how the dataset was used to develop ANNs whose optimal structure was determined using the trial and error method. The R^2 of 0.96650 and the RMSE of 2.42 showed that the model could predict real compressive strength and regulate all sample deviations to within 15%. Patil et al. [71] used multiple linear regression (MLR) and ANNs models for the mechanical parameters of RAC. The R^2 of the three models based on ANNs were 0.9295, 0.9345 and 0.9347, respectively, indicating that the discrepancy between actual and predicted values is slight. In contrast, the MLR model fails to forecast the mechanical properties of RAC and has limited capabilities.

Previous literature review indicates that ANNs are the most often used approach for predicting the mechanical properties of RAC with higher accuracy. However, this method has the drawback of being a "black box" instrument. It also requires a high computational power due to many hidden layers or hidden neurons when compared to other AI techniques, such as the Imperialist competitive algorithm with Extreme gradient boosting [73].

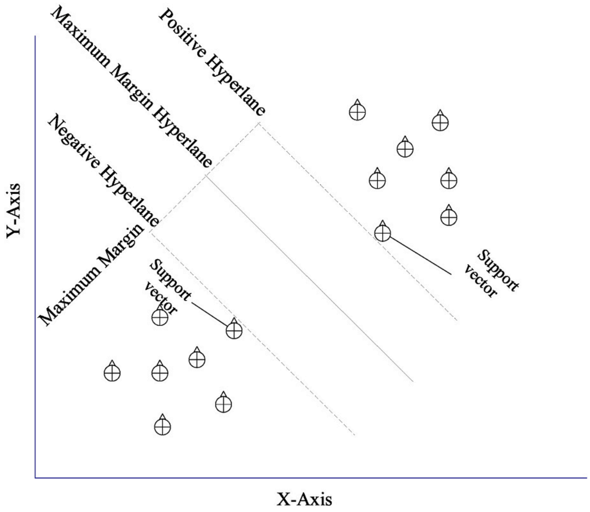

Fig. 4. Architecture of the support vector machine algorithm.

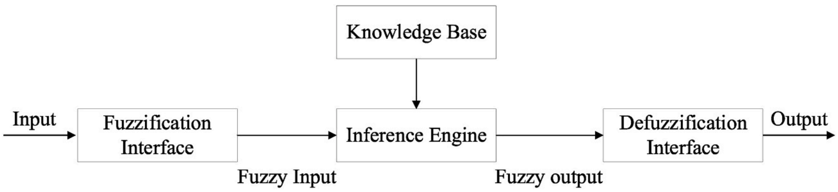

Fig. 5. Architecture of a fuzzy inference system.

3.2. Support vector machine

Cortes and Vapnik created a supervised learning model called support vector machines (SVM) [74]. It has been utilised extensively in various data mining situations for classification and regression. Fig. 4 presents the architecture of the Support Vector Machine Algorithm. It can be observed that the SVM algorithm assists in determining the best line or decision boundary; this best boundary or region is referred to as a hyperplane. The SVM algorithm determines the nearest point of the lines from both classes. These are known as support vectors. The margin is the distance between the vectors and the hyperplane. SVM's goal is to maximize this margin. The optimal hyperplane is the one with the maximum margin [75].

Omran et al. [50] showed the effectiveness of nine data mining models in forecasting the compressive strength of a novel type of concrete using three different components, such as fly ash (FA), Haydite aggregate, and Portland limestone cement (PLC), which were tested and compared. Three advanced predictive models (multi-layer perceptron, sequential minimal optimisation regression-based SVM, and Gaussian processes regression), three regression tree models (M5P, REPTree, M5-Rules), and two ensemble methods (additive regression and bagging) are used as the base classifiers for each of the seven individual models. The correlation coefficient values for additive and Gaussian processes regression are the greatest of all the models examined for specific data sets, whereas SVM approaches had a medium accuracy. In terms of MAE and RMSE, these findings also show that additive regression has the best forecast accuracy for the comprehensive strength of PLC samples, but the individual Gaussian processes regression model has the best prediction accuracy for both the Portland Cement and the entire dataset.

Tran et al. [53] estimated the compressive strength of RAC by using six machine learning models as Gradient Boosting (GB), Extreme Gradient Boosting (XGB), Support Vector Regression (SVR), and three hybrid models of those single models with Particle Swarm Optimisation (PSO), namely GB-PSO, XGB-PSO, and SVR-PSO. As seen from Table 4, all algorithms performed well with a very low standard deviation, indicating good forecast accuracy. It may be concluded that hybrid models outperform single models. The results of the GB_PSO approach for training and testing sets showed that the predicted and actual values are extremely closely related, with a correlation coefficient between $R = 0.9789$ and $R = 0.9356$ for the training and testing sets, respectively. Similarly, the training set outperforms the testing set in the XGB_PSO model. R values for the training and testing sets are 0.9728 and 0.9342, respectively, while RMSE and MAE values are 3.2524 MPa and 8.1984 MPa for the training and 2.2642 MPa and 6.0073 MPa for the testing sets. The SVR_PSO has the lowest prediction accuracy for the training and testing sets, and the R-values are 0.8969 and 0.8617, respectively.

To summarise, the SVM model is a strategy for dealing with tiny sample sizes that requires less computational effort than the ANNs model. However, it is less accurate than ANNs models and highly depends on the weighting function chosen.

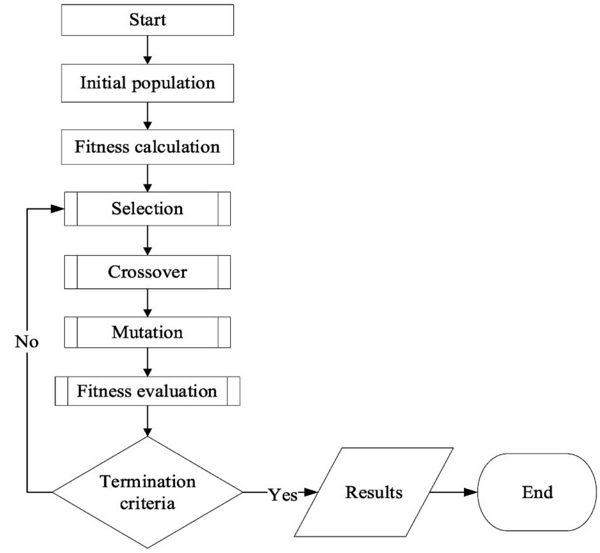

Fig. 6. Simple genetic algorithm structure.

3.3. Fuzzy logic

Zadeh [76] proposed fuzzy logic (FL) as an AI approach in 1965. Fig. 5 shows the architecture of a fuzzy inference system. Fuzzification, knowledge base, fuzzy inference engine, and defuzzification are the four main steps of this approach [77]. A model describes the input data in the first step, fuzzification, which yields an intermediary-truth value, a number inside the range of [0,1]. In other words, the model shows "how true" the input is, where 1 means true and 0 means false. The knowledge base calculates the value assigned by the essential functions in the second step, employing rules of the type "if … and … then … else." [77,78]. The inference engine considers the knowledge base in the third step so that all data is calculated into a fuzzy output. Defuzzification turns the fuzzy output into a representative value in the end.

Topcu et al. [67,79] predicted the compressive strength of RAC by using ANNs and FL. The high values of R^2 from training and testing demonstrated that the values are highly similar to the experimental outcomes in ANNs and FL models. Khademi et al. [66] used 14 different input parameters divided into two categorisations of mandatory and non-dimensional elements in ANNs, ANFIS, and MLR to predict the 28-day compressive strength of RAC. The ANNs and ANFIS models could estimate compressive strength, but ANNs were more efficient than ANFIS, with R^2 of 0.9185 in the ANNs model and R^2 of 0.9075 in the ANFIS model. The MLR model, with an R^2 of 0.6085, was ineffective in predicting concrete's 28-day compressive strength.

Fuzzy logic may be used to imitate non-linear phenomena. Without undertaking quantitative studies, the IF-THEN rules can mimic qualitative human-like reasoning. However, to acquire reliable findings, this technique necessitates a vast dataset and relies on many hyperparameters, which are the main drawbacks.

3.4. Genetic algorithms

The compressive strength of several types of concrete has been effectively predicted using genetic approaches. They are based on the 'survival of the fittest' theory of evolution. Many AI systems, such as ANNs, have a 'black box' procedure, whereas genetic methods provide an alternative [39]. Fig. 6 shows a simple genetic algorithm structure. It can be seen that the process of a genetic algorithm begins with the generation of a population of individuals. Each individual is the answer to the given problem. The fitness calculation is used to determine an individual's level of fitness. It refers to an individual's ability to compete with other individuals. The selection phase entails the selection of individuals for offspring reproduction. Following the selection process, the reproduction step results in the creation of a child. The genetic algorithm uses crossover and mutation operators applied to the parent population in this step. Following the reproduction phase, a stopping criterion is used to terminate the algorithm when the threshold fitness solution is reached.

Gene expression programming (GEP), genetic programming (GP), and genetic algorithms are the most often utilised genetic approaches (GAs). These strategies look for the best match in a population of potential solutions. The character of the individuals is the fundamental difference between these three strategies. Individuals in GP and GAs rely exclusively on their qualities to live. GEP, on the other hand, analyses traits that enable individuals to live using external qualities known as expression trees. Individuals in GAs and GEP approaches are fixed-length linear strings, whereas GP individuals are non-linear strings of varying sizes [80]. However, until paired with additional algorithms, genetic models have not been able to attain greater prediction accuracy than ANNs or evolutionary support vector machine models in most scenarios. Table 2 shows the range of hyperparameters used in studies that used GAs to estimate the compressive strength of RAC.

Kim et al. [81] employed genetic algorithms to optimise the mixing fraction of RAC. This model optimised the number of input variables, the number of hidden neurons, and the coefficient of learning rates. The results showed the model's performance was

Table 2
Hyperparameters used in genetic models.

Data size	Input	Population size	Number of generations	Crossover, gene recombination rate	Mutation rate	Ref.
360	7	100	50	N/A	N/A	[81]
228	7	61	20	0.1	0.044	[82]
234/163/85	4	50/100/150	3 or 4	0.00277	0.00138	[83]

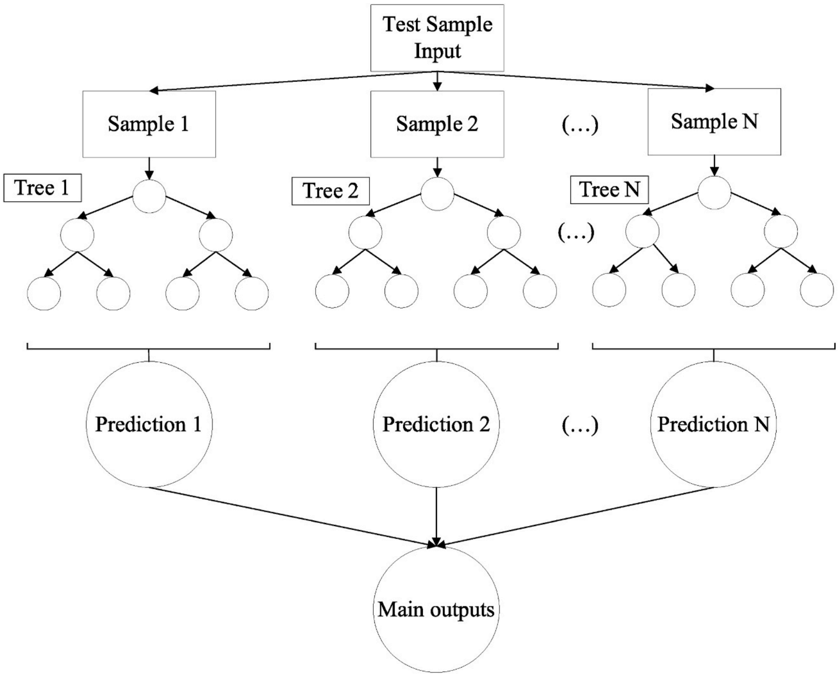

Fig. 7. Simple tree-based ensembles structure.

excellent, with an average error of 5.10% (lowest 0.21% and highest 9.23%). Abdollahzadeh et al. [82] used Gene expression programming with seven input parameters. The R^2 values for training set vary from 0.8745 to 0.9442, and R^2 values for testing are between 0.8852 and 0.9387 of 20 GEP models. Iqbal et al. [83] suggested a GEP model used to construct empirical models for predicting the mechanical properties of waste foundry sand concrete (WFS). The values of RMSE, MAE, and RSE for validation and testing demonstrated that the suggested models effectively included the influence of input factors to accurately forecast the trends of compressive strength of concrete made of WFS.

Finally, one benefit of GAs is that the result can be represented by simplified mathematical formulas that are useful for practical applications with a higher prediction accuracy and that it can handle different kinds of optimisation methods that overcomes the disadvantage of black-box algorithms. However, because this technique is computationally complex, resulting in the calculation is time-consuming.

3.5. Tree-based ensembles

Tree-based ensemble algorithms start with a decision tree and then employ boosting or bagging to decrease variance and bias. Tree-based algorithms provide outstanding accuracy, stability, and interpretability to prediction models. They map non-linear interactions effectively, unlike linear models. Fig. 7 displays a generic tree-based ensembles structure. It is observed that tree-based ensembles are a method in which many trees are built depending on the sampling process. Each tree could provide at least one prediction output. These prediction outputs could be combined to solve classification and regression problems (main outputs).

They can adjust to any situation and solve any challenge (classification or regression) [84]. Bagging and boosting are two critical ensemble approaches for creating new robust algorithms like the random forest, additional trees, and gradient boosting, among others. Random forest and gradient boosting are two of the best machine-learning models for solving regression problems with tabular data, and they have been used to predict the compressive strength of various concretes, including HPC, UHPC, and RAC [85]. Dabiri et al. [86] developed prediction models for assessing the compressive strength of RAC, such as LR, NLR, and RF approaches and then compared them to the ANNs and M5P models. ANNs and RF are the most accurate models, with approximately comparable performance. Finally, the LR model received the lowest R^2 score, indicating that it is less reliable than the other models. In other studies, Behnood et al. [87] indicated that the compressive strength and elasticity modulus of RAC were predicted using the M5 model tree

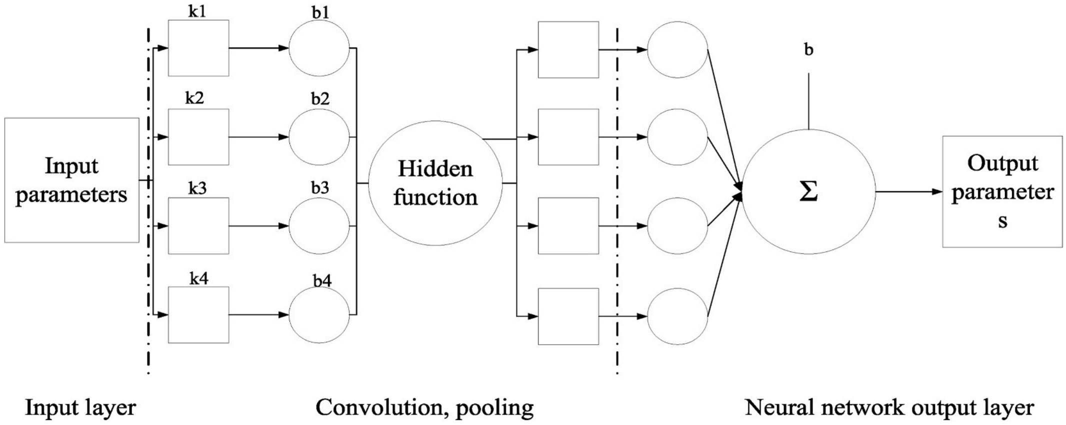

Fig. 8. Convolution neural network prediction model structure.

technique. The findings show that the model is exact for predicting mechanical properties because the R and R^2 values for the Model Tree (MT) technique were above 0.859 and 0.837, respectively, which are the best results among this family of approaches. In circumstances when compressive strength and mixture proportions are given, the presented model appears to offer a straightforward and accurate technique for forecasting the modulus of elasticity of RAC.

The bagging approach is good at handling non-linear, complicated relationships but less accurate for regression problems. Regarding boosting method, it is powerful and precise but slower to train because trees need to be constructed in order. Furthermore, if the data are noisy, overfitting is likely.

3.6. Hybrid and ensemble procedures

Hybrid processes can solve the limitation of most AI approaches, which is that they rely on good hyperparameter tweaking. Some research employed a supplemental approach to finding the critical tuned value of hyperparameters for the primary model [38]. For instance, Vakhshouri et al. [88] employed an ANFIS model to forecast the compressive strength of SCC, emphasising the significance of taking into account the slump of fresh concrete as an input element for improved results. It uses the membership function to describe the input data before converting it to an output using conditional layers. Other research has looked at the potential of ensemble procedures, which are learning algorithms that may minimise variance and improve the predictive power of basic algorithms [89,90]. The bagging technique introduced by Breiman in 1994 is the most often used ensemble procedures algorithm [91]. Although ensemble approaches have shown good forecast accuracy in various domains, they have been underutilised in the concrete technology sector. As a result, an intense study is required to investigate their potential in simulating concrete engineering features.

Falade et al. [92] estimated the 28-day compressive strength of RAC. These researchers employed two independent data-driven models, ANFIS and MLR. For estimating the 28-day strength of concrete, they employed 16 distinct inputs, including both dimensional and non-dimensional data. The results revealed that the MLR model was ineffective in predicting the 28-day compressive strength of concrete with low R^2, whereas the ANFIS model successfully approximated the 28-day compressive strength of concrete. Additionally, Khademi et al. [93] estimated the compressive strength of recycled brick aggregate concrete using AI models such as ANFIS, ANNs, and MLR. Mixed design parameters were used as input variables; the output variable is the 28-day concrete strength. Following the ANFIS model with an R^2 value of 0.8538, the data demonstrated that ANNs with an R^2 value of 0.9102 had enormous application potential in predicting the compressive strength of concrete.

Furthermore, Nash-Sutcliffe Efficiency, MAPE, RMSE, and MAE in the ANNs model and the ANFIS model confirm that both ANNs and ANFIS models are better than the MLR model. Han et al. [94] suggested an ensemble AI model for predicting the elasticity modulus of RAC by using SVM, Multi-layer perceptron ANNs (MLP-ANNs), LR, Gaussian process regression (GPR), and RF. The model (RF + SVM) was used to produce optimum mixture designs for RAC that fulfil the mandated goal modulus of elasticity. The results presented that all ML models yielded good predictions, with R ranging from 0.67 to 0.93 and RMSE ranging from 6.02 GPa to 2.93 GPa. The results presented the composite performance index (CPI), created by integrating five statistical parameters. CPI can range from 0 to 1. The worst ML model would obtain a value of 1, while the best ML model would obtain a CPI value of 0. The prediction performance of ML models may be graded based on CPI values – the suitable measure of prediction accuracy (or mistakes associated with) predictions. (voting: Ensemble ML model > RF > MLP-ANNS > GPR > LR > SVM).

Hybrid approaches are, on average, more accurate than most machine learning techniques because they combine the benefits of the approaches while reducing the inherent drawbacks of the preceding ways. To get the best results, we must understand how to select the proper combination of methods.

3.7. Deep learning

Deep learning is a sophisticated AI algorithm [95] with a multilayered ANNs structure at its core [96]. Because of their tremendous capacity to tackle exceedingly complicated problems, these algorithms have gotten much attention in recent years [97,98]. However, most applications of deep learning models in civil engineering issues are confined to fracture detection or structural health monitoring

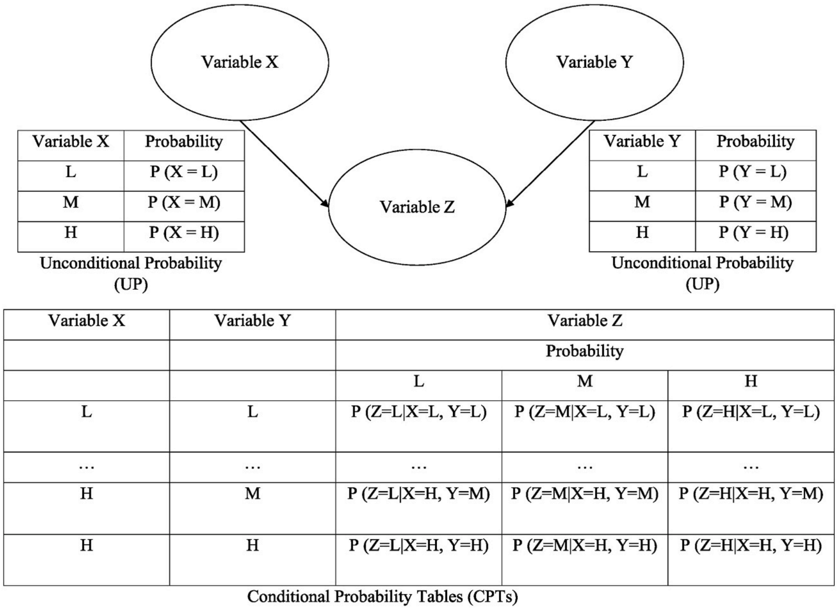

Fig. 9. Architecture of bayesian networks.

since promising findings often require more extensive datasets [11,97,99–105]. Deng et al. [96] used the deep learning approach to determine the compressive strength of RAC. Fig. 8 depicts the structure of the prediction model. First, convolutional neural networks (CNNs) are used to learn the deep features of input parameters, and then the prediction model is developed using softmax regression. The input layer is two-by-two pixels with four types of matching parameters. The convolution kernel k and the bias b were specified in the characteristic convolution layer. The sigmoid function was chosen as the activation function. The impact of the four input parameters on the strength of the sample may be derived via convolution between pixels, and it can be described using four convolution kernels. The results showed that the values produced by CNNs model training and testing are highly similar for experimental outcomes, demonstrating a significant correlation between the input and output parameters. When compared to the back propagation neural network and the SVM, Deng et al. [96] concluded that this method is better suited for predicting compressive strength.

Even though this method has only been used to select and optimise the design and predict mechanical properties of recycled aggregate concrete, the results show that it is a promising method for many future applications, with higher accuracy, efficiency, and generalisation ability than the traditional neural network model.

3.8. Bayesian networks

The Bayesian networks method was created in the late 1970s to mimic dispersed processing in reading comprehension and is currently used in a range of domains where uncertainty-based reasoning is necessary [106]. BNs, often known as belief networks (or Bayes nets for short), blend graph theory and probability theory in which nodes have probabilistic associations [107]. In BNs, confidence in diagnosis outcomes is determined using probability theory. The probability that evidence E will reveal whether or not hypothesis H is correct is shown in Eq. (1) [108].

$$P(H/E)=\frac{P(E/H)P(H)}{P(E)} \tag{1}$$

where $P(H/E)$ is the posterior probability of H providing evidence that E is true, P(H) is the prior probability of H, and $P(E/H)$ is the probability of evidence E given that hypothesis H is correct. P(E) is the probability that the evidence takes place.

Fig. 9 depicts the architecture of Bayesian networks. It is observed that a directed acyclic graph represents a BNs, where the nodes stand in for the variables of interest (such as the type of concrete and environmental exposure), and the links between them denote any informational or causal relationships between the variables. A BNs is composed of (a) a set of variables (e.g., X, Y, and Z): and a set of directed links between the variables; (b) a set of mutually exclusive states for each variable (e.g., for X, Y, and Z the states are {L, M, H}); and (c) an assigned conditional probability for each variable with 'parents', which will be defined shortly (e.g., for Z). Given its network parents, conditional probabilities for each node are used to quantify the dependencies. A set of conditional probability tables (CPTs) is used to quantify these dependencies; each variable is given a CPT of the variable given its parents. The conditional probability structure becomes the unconditional probability of the variable without parents (e.g., X and Y). By explicitly illustrating the conditional probability dependencies between variables, Bayes' theorem, based on BNs, is a clear and compelling method to manage uncertainty [109].

This approach has been primarily used in civil engineering to analyse the seismic risk of reinforced concrete girder bridges [110], to

Table 3
Summary of recent studies conducting AI-aided parametric studies.

Input	Method	Ref.
The ratio of recycled concrete	MLR	[26]
W/C, cement content, ratio of dry mortar, content of total dry aggregate, substitution ratio of RFA, substitution ratio of RCA, chemical admixture rate, CDW composition, ratio of recycled mortar, ratio of recycled concrete, ratio of recycled red ceramic, ratio of other recycled materials, fineness modulus of NFA, fineness modulus of RFA, fineness modulus of NCA, fineness modulus of RCA, maximum aggregate size of NFA, maximum aggregate size of RFA, maximum aggregate size of NCA, maximum aggregate size of RCA, compensation rate of the water absorption rate of RFA, compensation rate of the water absorption rate of RCA, water absorption rate of RFA, water absorption rate of RCA, age.	ANNs	[13]
Cement content, sand content, NCA content, RCA content, water content, admixture content, sand to aggregate ratio, water to binder ratio, substitution ratio of RCA.	NNs and Regression	[68]
NFA content, NCA content, RFA content, RCA content, superplasticiser dosage, air content, slump.	GAs	[81]
Particle density, strength of aggregate, water absorption, recycled aggregate content.	MLR and NLR	[123]
Water content, cement content, sand content, NCA content, RCA content, W/C, fineness modulus of NFA, water absorption, saturated surface-dried density, maximum aggregate size of RCA, impurity content of RCA, substitution ratio of RCA.	ANNs	[18]
Cement content, NFA content, RFA content, NCA-20 content, NCA-10 content, RCA-20 content, RCA-10 content, water content, admixture content, aggregate to cement ratio, W/C ratio, sand to aggregate, replacement ratio, water-to-binder ratio	ANNs, MT, NLR	[20]
W/C, coarse aggregate to cement ratio, fine aggregate to total aggregate, substitution ratio of RCA	M5' MODEL	[124]
Water content, W/C, cement content, sand content, NCA content, RCA content, water absorption	ANNs	[125]
Age, water content, Portland cement or Portland limestone cement content, Fly ash content, gravel content, admixture content.	ANNs, SVM, Gaussian processes regression	[50]
Cement content, NFA content, RFA content, NCA20 content, NCA10 content, RCA20 content, RCA10 content, water content, admixture content, aggregate to cement ratio, W/C, sand to aggregate ratio, replacement ratio, water to binder ratio	ANNs, ANFIS, MLR	[66]
Cement content, water content, RA content, silica fume content and admixture content.	GAs	[82]
Cement content, NA content, RA content, sand content, water content	NNs and Kernel Ridge Regression	[126]
Cement content, W/C, admixture content, Ratio of Recycled Red Ceramic, Ratio of Recycled Concrete	ANNs	[52]
W/C, substitution ratio of RCA, NCA content	Polynomial regression model	[127]
W/C, water absorption, NFA content, NCA content, RCA content, water-to-binder ratio	ANNs	[128]
W/C, substitution ratio of RCA, substitution ratio of RFA, fly ash ratio	Deep learning	[129]
W/C, Ratio of Recycled Concrete, replacement ratio, temperature, age	Least Absolute Shrinkage and Selection Operator	[130]
Effective W/C, aggregate to cement, lateral stress conditions, exposure temperature, substitution ratio of RCA	Multivariable regression and ANNs	[46]
W/C, WFS replacement ratio, cement content, WFS-to-cement content, specific gravity of WFS and fine aggregates, fineness modulus of WFS	GEP	[83]
Cement content, NFA content, NCA-20 content, NCA-10 content, RCA-20 content, RCA-10 content, admixture content, water content, W/C, sand to aggregate, water-to-binder ratio, substitution ratio of RCA, aggregate to cement ratio.	ANFIS and MLR	[92]
W/C, substitution ratio of RCA	Gray correlation analysis	[131]
Water absorption of RCA, slag content, metakaolin, fly ash, cement content, silica fume, water absorption, water-to-binder ratio, sand content, gravel content, RA content, admixture content, CO_2 content, exposure time	Machine Learning	[73]
Water absorption, W/C, RCA content, NCA content, water-to-binder ratio	AI technique	[121]
Binder type, cement content, Supplementary Cementitious Materials content, NCA content, RCA content, NFA content, NA content, water content, water absorption, NA density, RCA density, Maximum Aggregate Size of Natural Coarse Aggregate, Maximum Aggregate Size of Natural Fine Aggregate, Maximum Aggregate Size of RCA, Maximum Aggregate Size of RFA, water content	Ensemble machine learning	[94]
Substitution ratio of RFA, substitution ratio of RCA	Two-phase composite material theory and the Bazant crack band theory	[132]
Cement content, fly ash content, water content, admixture content, NFA content, RCA content, Fineness Modulus of Natural Fine Aggregate, water absorption, Saturated surface-dried of RCA, Maximum Aggregate Size of RCA, Maximum Aggregate Size of RFA	ANNs	[70]
W/C, substitution ratio of RCA, NCA content, RCA content, water absorption.	ANNs and cuckoo search method	[69]
W/C, substitution ratio of RCA, substitution ratio of RFA, GGBFS ratio of replacement as of slag, admixture content, age	Multivariate Polynomial Regression Combined with Stepwise Method	[133]
Cement content, sand content, NCA content, RCA content, water content, W/C, substitution ratio of RCA	ANNs	[54]
Cement content, slag content, fly ash content, water content, admixture content, NA content, age	ANNs	[134]
Cement content, W/C, fine clay tile content, coarse clay tile content, fine clay brick content, coarse clay brick content, NA content.	Machine Learning	[93]
Slump depression, age, calcium carbide waste content	AI technique	[122]
Cement content, sand content, NA content, W/C, superplasticiser to cement ratio, substitution ratio of RCA, age, substitution ratio of RFA	Machine learning	[86]
Cement content, water content, NA content, sand content, water absorption of NA, RCA content	GB_PSO, XGB_PSO, and SVR_PSO	[53]

Table 4
Error analysis of mechanical properties predictions using AI models.

AI algorithms	Mechanical properties	MAE	MAPE	RSME	RMS	R^2	R	Ref.
ANNs	Compressive strength	–	–	–	–	0.94	–	[13]
	Compressive strength	11.02	–	–	–	0.86	–	[20]
	Compressive strength	–	–	5.09	–	0.90	–	[66]
	Compressive strength	–	3.32	–	0.91	0.99	–	[79]
	Modulus of elasticity	–	2.01	–	1.03	0.99	–	[79]
	Compressive strength	–	3.36	–	2.39	0.99	–	[67]
	Splitting tensile strength	–	3.55	–	0.19	0.99	–	[67]
	Compressive strength	–	1.67	3.684	–	0.99	–	[18]
	Modulus of Elasticity	–	7.12	2.7381	–	0.98	–	[72]
	Compressive strength	0.97	4.46	0.075	–	–	0.99	[52]
	Flexural strength	0.19	4.06	0.2087	–	–	0.98	[52]
	Modulus of Elasticity	538.28	3.28	13.298	–	–	0.98	[52]
	Compressive strength	–	–	–	–	0.92	–	[69]
	Compressive strength	–	–	2.42	–	0.96	–	[54]
	Compressive strength	–	1.97	0.83	–	0.92	–	[71]
	Flexural strength	–	0.99	0.04	–	0.93	–	[71]
	Splitting tensile strength	–	0.99	0.04	–	0.93	–	[71]
SVM	Compressive strength	–	–	–	–	–	0.98	[50]
	Compressive strength	9.52	–	12.79	–	–	0.45	[53]
FL	Compressive strength		5.52		3.86	0.99		[67]
	Splitting tensile strength		5.73		0.29	0.99		[67]
GAs	Compressive strength	–	–	–	–	–	0.91	[81]
	Compressive strength	–	–	–	–	0.93	–	[82]
	Compressive strength	3.15	–	3.63	–	–	–	[83]
	Splitting tensile strength	0.36	–	0.45	–	–	–	[83]
	Modulus of elasticity	1.89		2.42	–	–	–	[83]
Tree-based Ensembles	Compressive strength	–	–	–	–	0.9	–	[86]
	Compressive strength	–	–	–	–	0.83	0.85	[124]
	Modulus of elasticity	–	–	–	–	0.83	0.85	[87]
Hybrid and ensemble procedure	Compressive strength	–	–	–	–	0.90	–	[92]
	Compressive strength	3.84	12.76	5.14		0.85		[93]
	Modulus of elasticity	2.14	33.719	2.92		0.87	0.93	[94]
Deep learning	Compressive strength					N/A		[129]
Other AI techniques	Compressive strength	1.14	0.03	1.47	–	0.98	–	[121]
	Compressive strength	–	–	0.03	–	0.98	–	[122]

predict the durability of concrete constructions [111–113], and to predict water main failures [114,115]. Regarding applications in predicting the mechanical features of concrete, Ke et al. [106] showed a predictive approach of HPC materials with specified performance using a Bayesian machine learning technique. At the same time, Caspeele et al. [116] highlighted that prior distributions for concrete strength attributes can be updated by evidence while conformity control is taken into account. Najm et al. [117,118] proposed to predict SCC's compressive strength prepared with various supplementary cementitious ingredients and basalt fibres using BNs called Naive Bayes and Markov Blanket. The anticipated accuracy was then equivalent to that achieved from an ANNs model. With integral absolute error and R^2 of 4.26% and 0.91%, respectively, the Naive Bayes method utilised in BNs was determined to be better than Markov Blanket.

Furthermore, the Markov Blanket technique, which only depends on the 'days' parameter, failed to forecast compressive strength behaviour. The ANNs and BNs models predicted compressive strength with comparable precision. To the author's knowledge, just one study applies a Bayesian model updating technique to the mechanical properties of RAC under uniaxial or triaxial compression [119]. Based on Bayesian theory and the Markov Chain Monte Carlo approach, a probabilistic calibration method for evaluating the accuracy and applicability of known deterministic models for the mechanical performances of RAC is suggested. According to the findings, the suggested probabilistic model may be modified when fresh, experimental data becomes available using a Bayesian updating procedure.

The approach of BNs produced extremely trustworthy findings; this method has been successfully applied to predict the compressive strength of SCC. Therefore, it seems to be a promising method to be extensively used to predict recycled aggregate concrete's mechanical characteristics.

3.9. Other artificial intelligence techniques

In the recent two decades, researchers in the domains of civil engineering have widely embraced AI technologies [120]. Duan et al. [121] estimated the compressive strength of RAC by using the ICA-XGBoost model combined with the Imperialist competitive algorithm (ICA) with Extreme gradient boosting (XGBoost). After that, the suggested ICA-XGBoost model was compared to other models, including ICA-ANN, ICA-SVR, and ICA-ANFIS. The performance of the designed soft computing models (ICA-XGBoost, ICA-ANN, ICA-SVR, and ICA-ANFIS) is quantitatively evaluated in the training and testing phases using the four performance indexes given in Table 4. The ICA-XGBoost model outperformed the other models based on four performance indexes, and it may be used to precisely evaluate the mechanical performance of RAC. Moreover, Jiang et al. [122] used AI techniques to predict the mechanical properties of self-compacting green concrete, including Emotional Neural Network chaotic particle swarm optimisation (EANN-CPSO),

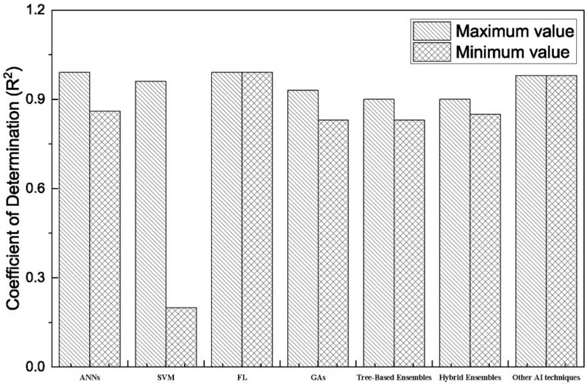

Fig. 10. Coefficient of Determination (R^2 values) for AI algorithms.

First-principles molecular dynamic (FPMD), and the conventional Linear Regression (LR) model. All models performed as expected in the results, with R^2 values greater than 0.9 in both the training and testing phases. At the training and testing stages, the evaluations of $R^2 = 0.997$ and 0.970 for the EANN-CPSO model, $R^2 = 0.967$ and 0.954 for the FPMD model, and $R^2 = 0.934$ and 0.929 for the LR model, respectively.

3.10. Summary and error analysis

The input data, selected model and hyperparameters are all crucial aspects in achieving the desired accuracy when using AI approaches to forecast the mechanical properties of RAC. The inputs and related AI methods found in the literature are summarised in Table 3. It was observed that almost all research in the literature employed similar input properties, including cement content, water content, and W/C ratio, as well as the testing age. At the same time, some studies included physical characteristics like maximum aggregate size and water absorption of aggregate. In Table 4, we compared the prediction accuracy of various models proposed in the literature. All algorithms give high-accuracy results. In Fig. 10, we compared the coefficient of determination of all AI algorithms. It can be observed that ANNs, FL, and other AI techniques are excellent models for predicting the RAC's mechanical properties.

This comparison shows that AI approaches, on the whole, could become high-precision tools. Combining AI with other models, such as hybrid and developing algorithms, might increase their performance. AI techniques might be a different approach to overtraining issues between training and testing data sets.

The accuracy of AI algorithms depends on data availability and quality. Collected data is frequently separated into training, testing, and validation sets in AI algorithms. The training set is used to teach the model the underlying principles, and the testing and validation sets are used to assess the prediction error and evaluate the model's application. However, cross-validation is employed when the collected data is inadequate to avoid overfitting by subset selection [135,136]. Subset selection procedures commonly use Monte Carlo and k-Fold cross-validation techniques [106,135]. Among the studies dedicated to forecasting the mechanical properties of RAC, k-Fold cross-validation was the most common used approach. This method entails segmenting the data into k segments and running the model k times over each segment [44]. k-Fold cross-validation is recommended for cross-validation on the basis of the positive feedback found in the literature [137,138].

4. Sensitivity analysis methods

4.1. Methods

Using sensitivity analysis, several researchers looked at the impact of each input characteristic on the regular mechanical performance of RAC [44,66]. For example, the partial derivatives approach, the weights method, and the conventional stepwise method can all be used to analyse the ANNs model [139]. In the ANNs and MLR models, the sensitivity approach is based on the R^2, SSE, and MSE investigating the influence of input parameters. For instance, adding non-dimensional parameters such as sand to coarse aggregate ratio and replacement ratio to the model using only raw data would increase the accuracy of forecasting the 28-day compressive strength of concrete [66]. Deshpande et al. [68] presented each extra parameter's influence on the network's performance or non-linear regression equations using the Hinton diagrams. In another study, Deshpande et al. [20] also investigated the effect of various parameters by drawing the Hinton diagram, which employs this presentation style to illustrate the weight matrix of a neural network. Bu et al. [54] determine the contribution of a single input parameter to the output parameter by employing a sensitivity analysis approach based on weight, as presented in Eq. (2) by Naderpour et al. [65].

Table 5
Sensitivity analysis results.

Results	Sensitivity analysis methods	Reference	Method for prediction
Water content, water-to-cement ratio	Hinton diagram	[20]	ANNs, MT, NLR
Sand to aggregate ratio, replacement ratio	R^2, SSE, and MSE values	[66]	ANNs, ANFIS
Cement content, water-to-cement ratio	Forward stepwise sensitivity analysis	[52]	ANNs
Water absorption, Water to total material ratio	Importance of weights	[65]	ANNs
Cement content	Importance of weights	[54]	ANNs
Cement content, water-to-cement ratio	Correlation Matrix	[93]	ANNs
Water content, cement content	Correlation Matrix	[50]	ANNs, Support vector machines, and Gaussian processes regression
Concrete age and W/C	Pearson correlation coefficients	[86]	Linear, nonlinear regression, Random Forest, ANNs
Cement content	multi-correlation matrix	[53]	GB, XGB, SVR, GB-PSO, XGB-PSO, and SVR-PSO
Replacement ratio and water absorption	R^2, SSE, and MSE values	[69]	ANNs and cuckoo search method
Replacement ratio and admixture	Frequency analysis	[81]	Genetic Algorithms

$$\mathrm{IIF} = \frac{\sum_{j=1}^{n_{hidden}} \frac{w_{ji}}{\sum_{l=1}^{n_{inputs}} |w_{jl}|} W_{oj}}{\sum_{k=1}^{n_{inputs}} \left(\sum_{j=1}^{n_{hidden}} \left| \frac{w_{jk}}{\sum_{l=1}^{n_{inputs}} |w_{jl}|} . W_{oj} \right| \right)} \tag{2}$$

where IIF denotes the importance of the input parameters, also known as contributory factors; w denotes the connection weight among two connected neurons; w_{ji} denotes the connection weight between the hidden (j) and input (i) layers. The input layer neuron (i) is represented by l, I, and k, while n_{inputs} is the number of input parameters and n_{hidden} is the number of hidden neurons (first hidden layer). W_{oj} denotes the connection weight between the output and hidden layers (product of the first hidden layer's weight and the second hidden layer).

Khademi et al. [93] investigated the impact of the number of input parameters on the output element by building new models, adding parameters to each model in turn, and calculating R^2 values for all the displayed models. Another research by Omran et al. [50] presented the Waikato Environment for Knowledge Analysis attribute selector and stepwise regression analysis to provide a Correlation Matrix for Dependent and Independent Variables.

Dabiri et al. [86] presented a sensitivity analysis based on the Pearson correlation coefficient $\rho_{X,Y}$, see Eq. (3)

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{3}$$

where $\mathrm{cov}(X,Y)$ is the covariance of two variables and σ_X, σ_Y is the standard deviation of variables. $\rho_{X,Y} \approx 1$ indicates a high level of dependency between two variables whereas $\rho_{X,Y} \approx 0$ denotes an independent linear connection between X and Y.

The multi-correlation matrix of the input parameters and output was supplied by Tran et al. [53]. A simple way to conduct sensitivity analysis in GAs is to determine the frequency with which the input parameters emerge. A value of 1.0 in the results means the parameter significantly affects the predictions [82]. Kim et al. [81] proposed a neural network model to evaluate the effect of input parameters on the compressive strength of RAC.

4.2. Summary and main findings

The sensitivity analysis results are summarised in Table 5. Regarding sensitivity analysis, in ANNs, these techniques demonstrate the most significant effect of the cement content of RAC's compressive strength. Water to cement ratio appears to be the most influential parameter affecting on RAC's properties, followed by replacement ratio and water content. Miličević et al. [52] concluded that cement content, W/C, superplasticiser, crushed roof tile, and RA comprised of crushed brick fractions 0–4 mm and 4–16 mm are pretty essential and have a significant impact on all four outputs such as density, compressive strength, flexural strength, modulus of elasticity. Naderpour et al. [65] indicated that the essential characteristic determining compressive strength is RA's water-to-binder ratio and water absorption. Vasanthalin P. et al. [69] found that the replacement ratio and water absorption of RA were the two most influential parameters on the compressive strength of RAC. Omran et al. [50] suggested that the input parameters could be diminished to a subset of three: cement content, concrete age, and micro air to give the best merit for this modelling problem. Dabiri et al. [86] show that concrete age and W/C significantly impact compressive strength. Water and cement content provided the strongest correlation among the input variables [140]. Only compressive strength is associated with cement content, followed by NA content [53]. Kim et al. revealed that the replacement ratio and admixture content are the most critical drivers for the RAC's compressive strength [81]. In conclusion, despite the approaches using many input factors, we can deduce that the water-to-cement ratio and the cement content are the most relevant.

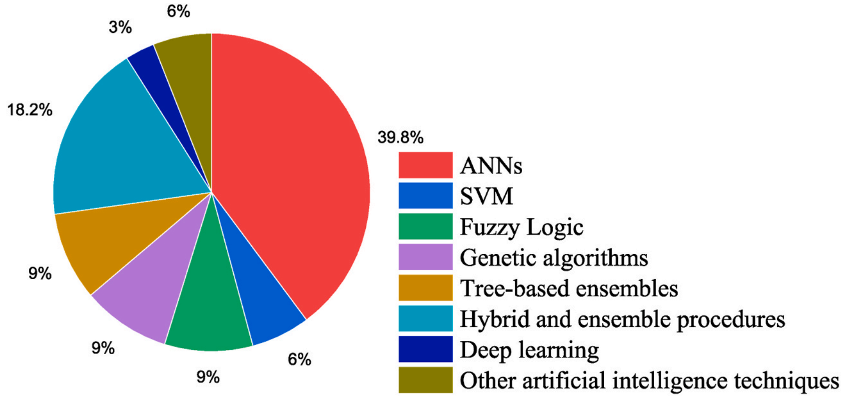

Fig. 11. Percentage of AI algorithms found in this review.

5. Discussion and recommendations

The use of AI methods in research and industry is becoming popular in the construction field as the internet of things, big data, and automation are regulating the industrial world. This review found that AI can be used to (1) predict RAC's mechanical properties with high accuracy and (2) optimise the mechanical performance of RAC. AI models can conduct extensive numerical experiments to examine the effects of various mixture designs and curing parameters on the mechanical properties of RAC. These numerical experiments can help to decrease the economic and environmental costs of real experiments and provide insights into creating more performant mixtures.

Fig. 11 describes the percentage of each AI technique found in this review. The most popular model is ANNs. However, with a "black-box" approach, ANNs have several drawbacks; for instance, the models are hard to explain and the training phase requires a significant amount of data. Other AI approaches, such as decision trees, sidestep the ambiguity of black-box models and produce easy-to-understand outcomes [87]. However, decision tree models were shown to be less accurate than most AI approaches, particularly tree-based ensembles [73]. Using ANNs to extend an existing model to a different dataset is recommended based on the analyses performed in this review and noting that selecting an appropriate AI model depends on the study's purpose and the available dataset [120].

Fig. 11 also shows that there are less used AI approaches that provide promising performance. While ensemble method approaches have not been widely used in RAC, they have surpassed other strategies in accuracy and speed [73]. As a result, ensemble approaches appear to be among the most promising techniques for future research in this sector and should be further investigated. In addition, other AI approaches, such as XGB and ICA, have demonstrated that they provide remarkable results, but they are still under development. The deep learning technique is also a promising method giving accurate prediction results. Compared to the traditional neural network model, this algorithm has high precision, efficiency, and generalization ability.

Bayesian Networks is another category of AI in which the knowledge of statistical probabilities has been firmly applied to predict the durability properties of concrete [141] or seismic risk analysis [142]. BN algorithms have been also used to predict high-performance concrete's properties [106] or to update information applied to mechanical properties of RCA under uniaxial or triaxial compression [119]. However, the BNs have not yet been applied to predict RAC's properties, although the findings of the BNs approach for HPC are encouraging.

The selection of a given AI algorithm depend on the objective of the study and/or the data availability. Most part of AI models could be coupled with optimisation techniques to improve the mixture design of RAC while taking into account a variety of mechanical, environmental, and cost constraints. For example, genetic algorithms are advised if the goal is to find the RAC formulation that optimise the toughened performance [81,82,143]. SVM models are suitable if the objective is to reduce the computational cost. When data is scarce, BNs could be useful to predict RAC mechanical properties with acceptable accuracy; however, the results depend on the BN structure and its development requires a higher degree of expertise. Further studies on this type of method are necessary to provide accurate BN structures.

Sensitivity analysis methods can determine how each input attribute affects the prediction of RAC's mechanical properties [81]. Sensitivity analysis is essential for genetic algorithms because a large number of inputs considerably reduces the evolution from one generation to the next in the early stages and could lead to unsatisfactory solutions. Sensitivity analysis results will be then useful in limiting the number of input parameters when applying new AI methods. Only two sensitivity analysis methods were reported in this paper. Future sensitivity analysis should include more advanced methods (e.g., Sobol method [144]), that are more valuable than the Pearson correlation coefficient when dealing with non-linear responses.

6. Conclusions

This paper reviewed recent research studies about the AI algorithms' ability to predict the mechanical properties of RAC as well as those focusing on sensitivity analysis. The main conclusions are summarised as follows.

- In general, all reviewed AI algorithms have been shown good accuracy to predict the mechanical properties of RAC.
- The most widely used algorithm for predicting RAC's mechanical properties is ANNs, which have shown superior accuracy. However, these black-box models are hard to explain and its training phase requires lots of data.
- SVM is an algorithm for dealing with a tiny dataset that requires less computational effort than the ANNs model. However, it is less accurate than ANNs models.
- FL technique necessitates a vast dataset and relies on many hyperparameters, which are the main drawbacks.
- GAs algorithm can handle different optimisation methods that overcome the disadvantage of black-box algorithms. However, calculations are time-consuming because this technique is computationally complex.
- Other AI algorithms, based on deep learning and Bayesian networks, are promissory tools to predict RAC's mechanical properties. Deep learning algorithms exhibit higher precision and higher efficiency by learning the in-depth features of input parameters, while BNs accurately predict HPC's properties with a small amount of data. Further research on these algorithms is required to confirm the advantages of both methods.
- Sensitivity analysis methods could help engineers and researchers to select the more important input parameters of each AI algorithm to predict RAC's mechanical properties. However, more robust sensitivity analysis methods should be considered in future works.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgements

The insightful and constructive comments from the anonymous reviewers are gratefully acknowledged. The authors would like to thank the Nouvelle Aquitaine Region and the French Agency for Ecological Transition (ADEME) for funding this work in the framework of the projects "DURCYL" and "SARECARB".

References

[1] B. Wang, L. Yan, Q. Fu, B. Kasal, A comprehensive review on recycled aggregate and recycled aggregate concrete, Resour. Conserv. Recycl. 171 (2021), 105565, https://doi.org/10.1016/j.resconrec.2021.105565.

[2] J. Xiao, W. Li, Y. Fan, X. Huang, An overview of study on recycled aggregate concrete in China (1996–2011), Construct. Build. Mater. 31 (2012) 364–383, https://doi.org/10.1016/j.conbuildmat.2011.12.074.

[3] D. Walberg, Solid and timber construction in residential buildings/Massiv- und Holzbau bei Wohngebäuden: solid and timber construction in residential buildings/Massiv- und Holzbau bei Wohngebäuden, Mauerwerk 20 (2016) 16–31, https://doi.org/10.1002/dama.201600685.

[4] S.M. Levy, P. Helene, Durability of recycled aggregates concrete: a safe way to sustainable development, Cement Concr. Res. 34 (2004) 1975–1980, https://doi.org/10.1016/j.cemconres.2004.02.009.

[5] G. Cordoba, C.I. Paulo, E.F. Irassar, Towards an eco-efficient ready mix-concrete industry: advances and opportunities. A study of the Metropolitan Region of Buenos Aires, J. Build. Eng. (2022), 105449, https://doi.org/10.1016/j.jobe.2022.105449.

[6] X. Li, Recycling and reuse of waste concrete in China, Resour. Conserv. Recycl. 53 (2008) 36–44, https://doi.org/10.1016/j.resconrec.2008.09.006.

[7] I. Sharaky, U. Issa, M. Alwetaishi, A. Abdelhafiz, A. Shamseldin, M. Al-Surf, M. Al-Harthi, A. Balabel, Strength and water absorption of sustainable concrete produced with recycled basaltic concrete aggregates and powder, Sustainability 13 (2021) 6277, https://doi.org/10.3390/su13116277.

[8] A. Rao, K.N. Jha, S. Misra, Use of aggregates from recycled construction and demolition waste in concrete, Resour. Conserv. Recycl. 50 (2007) 71–81, https://doi.org/10.1016/j.resconrec.2006.05.010.

[9] M. Mamirov, J. Hu, T. Cavalline, Geometrical, physical, mechanical, and compositional characterization of recycled concrete aggregates, J. Clean. Prod. 339 (2022), 130754, https://doi.org/10.1016/j.jclepro.2022.130754.

[10] H. Guo, C. Shi, X. Guan, J. Zhu, Y. Ding, T.-C. Ling, H. Zhang, Y. Wang, Durability of recycled aggregate concrete – a review, Cement Concr. Compos. 89 (2018) 251–259, https://doi.org/10.1016/j.cemconcomp.2018.03.008.

[11] J.D. Lau Hiu Hoong, J. Lux, P.-Y. Mahieux, P. Turcry, A. Aït-Mokhtar, Determination of the composition of recycled aggregates using a deep learning-based image analysis, Autom. ConStruct. 116 (2020), 103204, https://doi.org/10.1016/j.autcon.2020.103204.

[12] H. Dabiri, A. Faramarzi, A. Dall'Asta, E. Tondi, F. Micozzi, A machine learning-based analysis for predicting fragility curve parameters of buildings, J. Build. Eng. 62 (2022), 105367, https://doi.org/10.1016/j.jobe.2022.105367.

[13] A.T.A. Dantas, M. Batista Leite, K. de Jesus Nagahama, Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks, Construct. Build. Mater. 38 (2013) 717–722, https://doi.org/10.1016/j.conbuildmat.2012.09.026.

[14] R. Kurda, J. de Brito, J.D. Silvestre, Influence of recycled aggregates and high contents of fly ash on concrete fresh properties, Cement Concr. Compos. 84 (2017) 198–213, https://doi.org/10.1016/j.cemconcomp.2017.09.009.

[15] U. Annaluru, M. Potharaju, K.V. Ramesh, Influence of grade of parent concrete on recycled aggregate concrete made with pozzolanic materials, Cea 9 (2021) 1506–1512, https://doi.org/10.13189/cea.2021.090522.

[16] J.M. Khatib, Properties of concrete incorporating fine recycled aggregate, Cement Concr. Res. 35 (2005) 763–769, https://doi.org/10.1016/j.cemconres.2004.06.017.

[17] C. Dong, Q. Zhang, C. Chen, T. Jiang, Z. Guo, Y. Liu, S. Lin, Fresh and hardened properties of recycled plastic fiber reinforced self-compacting concrete made with recycled concrete aggregate and fly ash, slag, silica fume, J. Build. Eng. 62 (2022), 105384, https://doi.org/10.1016/j.jobe.2022.105384.

[18] Z.H. Duan, S.C. Kou, C.S. Poon, Prediction of compressive strength of recycled aggregate concrete using artificial neural networks, Construct. Build. Mater. 40 (2013) 1200–1206, https://doi.org/10.1016/j.conbuildmat.2012.04.063.

[19] J. de Brito, J. Ferreira, J. Pacheco, D. Soares, M. Guerreiro, Structural, material, mechanical and durability properties and behaviour of recycled aggregates concrete, J. Build. Eng. 6 (2016) 1–16, https://doi.org/10.1016/j.jobe.2016.02.003.

[20] N. Deshpande, S. Londhe, S. Kulkarni, Modeling compressive strength of recycled aggregate concrete by artificial neural network, model tree and non-linear regression, Int. J. Sustain. Built. Environ. 3 (2014) 187–198, https://doi.org/10.1016/j.ijsbe.2014.12.002.

[21] H.-G. Ni, J.-Z. Wang, Prediction of compressive strength of concrete by neural networks, Cement Concr. Res. 30 (2000) 1245–1250, https://doi.org/10.1016/S0008-8846(00)00345-8.

[22] V. Revilla-Cuesta, F. Faleschini, M.A. Zanini, M. Skaf, V. Ortega-López, Porosity-based models for estimating the mechanical properties of self-compacting concrete with coarse and fine recycled concrete aggregate, J. Build. Eng. 44 (2021), 103425, https://doi.org/10.1016/j.jobe.2021.103425.

[23] A.N.S. Al Qadi, K. Nasharuddi, H. Al-Mattarn, Q.N.S. Al-Kadi, Statistical models for hardened properties of self-compacting concrete, Am. J. Eng. Appl. Sci. 2 (2009) 764–770, https://doi.org/10.3844/ajeassp.2009.764.770.

[24] V. Revilla-Cuesta, J. Shi, M. Skaf, V. Ortega-López, J.M. Manso, Non-destructive density-corrected estimation of the elastic modulus of slag-cement self-compacting concrete containing recycled aggregate, Dev. Built. Environ. 12 (2022), 100097, https://doi.org/10.1016/j.dibe.2022.100097.

[25] A.R. Hariharan, A.S. Santhi, G. Mohan Ganesh, Statistical model to predict the mechanical properties of binary and ternary blended concrete using regression analysis, Int. J. Civ. Eng. 13 (2015), https://doi.org/10.22068/IJCE.13.3.331.

[26] Y.S. Shin, G.H. Kim, Predicting compressive strength of recycled aggregate concrete by multiple regression analysis, AMM 253–255 (2012) 546–549. https://doi.org/10.4028/www.scientific.net/AMM.253-255.546.

[27] M.C.S. Nepomuceno, L.F.A. Bernardo, Evaluation of self-compacting concrete strength with non-destructive tests for concrete structures, Appl. Sci. 9 (2019) 5109, https://doi.org/10.3390/app9235109.

[28] K.H. Younis, K. Pilakoutas, Strength prediction model and methods for improving recycled aggregate concrete, Construct. Build. Mater. 49 (2013) 688–701, https://doi.org/10.1016/j.conbuildmat.2013.09.003.

[29] J.-S. Chou, A.-D. Pham, Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength, Construct. Build. Mater. 49 (2013) 554–563, https://doi.org/10.1016/j.conbuildmat.2013.08.078.

[30] A. Karimipour, H. Jahangir, D. Rezazadeh Eidgahee, A thorough study on the effect of red mud, granite, limestone and marble slurry powder on the strengths of steel fibres-reinforced self-consolidation concrete: experimental and numerical prediction, J. Build. Eng. 44 (2021), 103398, https://doi.org/10.1016/j.jobe.2021.103398.

[31] P. Hamidian, P. Alidoust, E.M. Golafshani, K.P. Niavol, A. Behnood, Introduction of a novel evolutionary neural network for evaluating the compressive strength of concretes: a case of Rice Husk Ash concrete, J. Build. Eng. 61 (2022), 105293, https://doi.org/10.1016/j.jobe.2022.105293.

[32] Y. Wang, Y. Yu, S. Cao, X. Zhang, S. Gao, A review of applications of artificial intelligent algorithms in wind farms, Artif. Intell. Rev. 53 (2020) 3447–3500, https://doi.org/10.1007/s10462-019-09768-7.

[33] S.N. Londhe, P.S. Kulkarni, P.R. Dixit, A. Silva, R. Neves, J. de Brito, Predicting carbonation coefficient using Artificial neural networks and genetic programming, J. Build. Eng. 39 (2021), 102258, https://doi.org/10.1016/j.jobe.2021.102258.

[34] W.Z. Taffese, E. Sistonen, J. Puttonen, CaPrM: carbonation prediction model for reinforced concrete using machine learning methods, Construct. Build. Mater. 100 (2015) 70–82, https://doi.org/10.1016/j.conbuildmat.2015.09.058.

[35] L. Decastro, Fundamentals of natural computing: an overview, Phys. Life Rev. 4 (2007) 1–36, https://doi.org/10.1016/j.plrev.2006.10.002.

[36] N. Abdou, Y. El Mghouchi, K. Jraida, S. Hamdaoui, A. Hajou, M. Mouqallid, Prediction and optimization of heating and cooling loads for low energy buildings in Morocco: an application of hybrid machine learning methods, J. Build. Eng. 61 (2022), 105332, https://doi.org/10.1016/j.jobe.2022.105332.

[37] P. Ramadoss, P. Li, S. Fatima, M. Sofi, Mechanical performance and numerical simulation of high-performance steel fiber reinforced concrete, J. Build. Eng. (2022), 105424, https://doi.org/10.1016/j.jobe.2022.105424.

[38] M.-Y. Cheng, J.-S. Chou, A.F.V. Roy, Y.-W. Wu, High-performance concrete compressive strength prediction using time-weighted evolutionary fuzzy support vector machines inference model, Autom. ConStruct. 28 (2012) 106–115, https://doi.org/10.1016/j.autcon.2012.07.004.

[39] L. Chen, Study of applying macroevolutionary genetic programming to concrete strength estimation, J. Comput. Civ. Eng. 17 (2003) 290–294, https://doi.org/10.1061/(ASCE)0887-3801(2003)17:4(290).

[40] A. Mukherjee, J.M. Deshpande, Modeling initial design process using artificial neural networks, J. Comput. Civ. Eng. 9 (1995) 194–200, https://doi.org/10.1061/(ASCE)0887-3801(1995)9:3(194).

[41] I. Nunez, A. Marani, M.L. Nehdi, Mixture optimization of recycled aggregate concrete using hybrid machine learning model, Materials 13 (2020) 4331, https://doi.org/10.3390/ma13194331.

[42] H. Adeli, N. Cheng, Integrated genetic algorithm for optimization of space structures, J. Aero. Eng. 6 (1993) 315–328, https://doi.org/10.1061/(ASCE)0893-1321(1993)6:4(315).

[43] J. Xu, Y. Wang, R. Ren, Z. Wu, T. Ozbakkaloglu, Performance evaluation of recycled aggregate concrete-filled steel tubes under different loading conditions: database analysis and modelling, J. Build. Eng. 30 (2020), 101308, https://doi.org/10.1016/j.jobe.2020.101308.

[44] D.V. Dao, H. Adeli, H.-B. Ly, L.M. Le, V.M. Le, T.-T. Le, B.T. Pham, A sensitivity and robustness analysis of GPR and ANN for high-performance concrete compressive strength prediction using a Monte Carlo simulation, Sustainability 12 (2020) 830, https://doi.org/10.3390/su12030830.

[45] E.A. Ohemeng, S.O. Ekolu, H. Quainoo, D. Kruger, Model for predicting compressive strength and elastic modulus of recycled concrete made with treated coarse aggregate: empirical approach, Construct. Build. Mater. 320 (2022), 126240, https://doi.org/10.1016/j.conbuildmat.2021.126240.

[46] J. Xu, Y. Chen, T. Xie, X. Zhao, B. Xiong, Z. Chen, Prediction of triaxial behavior of recycled aggregate concrete using multivariable regression and artificial neural network techniques, Construct. Build. Mater. 226 (2019) 534–554, https://doi.org/10.1016/j.conbuildmat.2019.07.155.

[47] X. Zhang, M.Z. Akber, W. Zheng, Prediction of seven-day compressive strength of field concrete, Construct. Build. Mater. 305 (2021), 124604, https://doi.org/10.1016/j.conbuildmat.2021.124604.

[48] K. Liu, C. Zou, X. Zhang, J. Yan, Innovative prediction models for the frost durability of recycled aggregate concrete using soft computing methods, J. Build. Eng. 34 (2021), 101822, https://doi.org/10.1016/j.jobe.2020.101822.

[49] L. Chen, T.-S. Wang, Modeling strength of high-performance concrete using an improved grammatical evolution combined with macrogenetic algorithm, J. Comput. Civ. Eng. 24 (2010) 281–288, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000031.

[50] B.A. Omran, Q. Chen, R. Jin, Comparison of data mining techniques for predicting compressive strength of environmentally friendly concrete, J. Comput. Civ. Eng. 30 (2016), 04016029, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000596.

[51] F. Khademi, S.M. Jamal, N. Deshpande, S. Londhe, Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression, Int. J. Sustain. Built. Environ. 5 (2016) 355–369, https://doi.org/10.1016/j.ijsbe.2016.09.003.

[52] Ivana Miličević, Prediction of properties of recycled aggregate concrete, JCE 69 (2017) 347–357, https://doi.org/10.14256/JCE.1867.2016.

[53] V. Quan Tran, V. Quoc Dang, L. Si Ho, Evaluating compressive strength of concrete made with recycled concrete aggregates using machine learning approach, Construct. Build. Mater. 323 (2022), 126578, https://doi.org/10.1016/j.conbuildmat.2022.126578.

[54] L. Bu, G. Du, Q. Hou, Prediction of the compressive strength of recycled aggregate concrete based on artificial neural network, Materials 14 (2021) 3921, https://doi.org/10.3390/ma14143921.

[55] O. May Tzuc, O. Rodríguez Gamboa, R. Aguilar Rosel, M. Che Poot, H. Edelman, M. Jiménez Torres, A. Bassam, Modeling of hygrothermal behavior for green facade's concrete wall exposed to nordic climate using artificial intelligence and global sensitivity analysis, J. Build. Eng. 33 (2021), 101625, https://doi.org/10.1016/j.jobe.2020.101625.

[56] A.M. Neville, Properties of Concrete, fifth ed., Pearson, Harlow Munich, 2011.

[57] K. Liu, M.S. Alam, J. Zhu, J. Zheng, L. Chi, Prediction of carbonation depth for recycled aggregate concrete using ANN hybridized with swarm intelligence algorithms, Construct. Build. Mater. 301 (2021), 124382, https://doi.org/10.1016/j.conbuildmat.2021.124382.

[58] M.S. Asghshahr, A. Rahai, H. Ashrafi, Prediction of chloride content in concrete using ANN and CART, Mag. Concr. Res. 68 (2016) 1085–1098, https://doi.org/10.1680/jmacr.15.00261.

[59] E.F. Felix, R. Carrazedo, E. Possan, Carbonation model for fly ash concrete based on artificial neural network: development and parametric analysis, Construct. Build. Mater. 266 (2021), 121050, https://doi.org/10.1016/j.conbuildmat.2020.121050.

[60] A. Yadollahi, E. Nazemi, A. Zolfaghari, A.M. Ajorloo, Application of artificial neural network for predicting the optimal mixture of radiation shielding concrete, Prog. Nucl. Energy 89 (2016) 69–77, https://doi.org/10.1016/j.pnucene.2016.02.010.
[61] G. Zhang, B. Eddy Patuwo, M.Y. Hu, Forecasting with artificial neural networks, Int. J. Forecast. 14 (1998) 35–62, https://doi.org/10.1016/S0169-2070(97)00044-7.
[62] A. Jain, S.K. Jha, S. Misra, Modeling and analysis of concrete slump using artificial neural networks, J. Mater. Civ. Eng. 20 (2008) 628–633, https://doi.org/10.1061/(ASCE)0899-1561(2008)20:9(628).
[63] A.W.C. Oreta, K. Kawashima, Neural network modeling of confined compressive strength and strain of circular concrete columns, J. Struct. Eng. 129 (2003) 554–561, https://doi.org/10.1061/(ASCE)0733-9445(2003)129:4(554).
[64] K. Liu, Z. Dai, R. Zhang, J. Zheng, J. Zhu, X. Yang, Prediction of the sulfate resistance for recycled aggregate concrete based on ensemble learning algorithms, Construct. Build. Mater. 317 (2022), 125917, https://doi.org/10.1016/j.conbuildmat.2021.125917.
[65] H. Naderpour, A.H. Rafiean, P. Fakharian, Compressive strength prediction of environmentally friendly concrete using artificial neural networks, J. Build. Eng. 16 (2018) 213–219, https://doi.org/10.1016/j.jobe.2018.01.007.
[66] F. Khademi, S.M. Jamal, N. Deshpande, S. Londhe, Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression, Int. J. Sustain. Built. Environ. 5 (2016) 355–369, https://doi.org/10.1016/j.ijsbe.2016.09.003.
[67] İ.B. Topçu, M. Sarıdemir, Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic, Comput. Mater. Sci. 42 (2008) 74–82, https://doi.org/10.1016/j.commatsci.2007.06.011.
[68] N. Deshpande, S. Londhe, SushamaS. Kulkarni, Modelling Compressive Strength of Recycled Aggregate Concrete Using Neural Networks and Regression, 2013, https://doi.org/10.13140/2.1.1181.5047.
[69] C.V. P, C.K. N, Prediction of compressive strength of recycled aggregate concrete using artificial neural network and cuckoo search method, Mater. Today Proc. 46 (2021) 8480–8488, https://doi.org/10.1016/j.matpr.2021.03.500.
[70] D. Suescum-Morales, L. Salas-Morera, J.R. Jiménez, L. García-Hernández, A novel artificial neural network to predict compressive strength of recycled aggregate concrete, Appl. Sci. 11 (2021), 11077, https://doi.org/10.3390/app112211077.
[71] S.V. Patil, K. Balakrishna Rao, G. Nayak, Prediction of Recycled Coarse Aggregate Concrete Mechanical Properties Using Multiple Linear Regression and Artificial Neural Network, JEDT, 2021, https://doi.org/10.1108/JEDT-07-2021-0373.
[72] Z.H. Duan, S.C. Kou, C.S. Poon, Using artificial neural networks for predicting the elastic modulus of recycled aggregate concrete, Construct. Build. Mater. 44 (2013) 524–532, https://doi.org/10.1016/j.conbuildmat.2013.02.064.
[73] I. Nunez, A. Marani, M. Flah, M.L. Nehdi, Estimating compressive strength of modern concrete mixtures using computational intelligence: a systematic review, Construct. Build. Mater. 310 (2021), 125279, https://doi.org/10.1016/j.conbuildmat.2021.125279.
[74] C. Cortes, V. Vapnik, Support-vector networks, Mach. Learn. 20 (1995) 273–297, https://doi.org/10.1007/BF00994018.
[75] R. Cai, T. Han, W. Liao, J. Huang, D. Li, A. Kumar, H. Ma, Prediction of surface chloride concentration of marine concrete using ensemble machine learning, Cement Concr. Res. 136 (2020), 106164, https://doi.org/10.1016/j.cemconres.2020.106164.
[76] K. Khosravi, M. Panahi, D. Tien Bui, Spatial prediction of groundwater spring potential mapping based on an adaptive neuro-fuzzy inference system and metaheuristic optimization, Hydrol. Earth Syst. Sci. 22 (2018) 4771–4792, https://doi.org/10.5194/hess-22-4771-2018.
[77] İ.B. Topçu, M. Sarıdemir, Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic, Comput. Mater. Sci. 41 (2008) 305–311, https://doi.org/10.1016/j.commatsci.2007.04.009.
[78] S.I. Malami, F.H. Anwar, S. Abdulrahman, S.I. Haruna, S.I.A. Ali, S.I. Abba, Implementation of hybrid neuro-fuzzy and self-turning predictive model for the prediction of concrete carbonation depth: a soft computing technique, Results Eng. 10 (2021), 100228, https://doi.org/10.1016/j.rineng.2021.100228.
[79] İ.B. Topçu, M. Sarıdemir, Prediction of properties of waste AAC aggregate concrete using artificial neural network, Comput. Mater. Sci. 41 (2007) 117–125, https://doi.org/10.1016/j.commatsci.2007.03.010.
[80] M.-Y. Cheng, P.M. Firdausi, D. Prayogo, High-performance concrete compressive strength prediction using genetic weighted pyramid operation tree (GWPOT), Eng. Appl. Artif. Intell. 29 (2014) 104–113, https://doi.org/10.1016/j.engappai.2013.11.014.
[81] S. Kim, H.-B. Choi, Y. Shin, G.-H. Kim, D.-S. Seo, Optimizing the mixing proportion with neural networks based on genetic algorithms for recycled aggregate concrete, Adv. Mater. Sci. Eng. (2013) 1–10, https://doi.org/10.1155/2013/527089.
[82] G. Abdollahzadeh, E. Jahani, Z. Kashir, Predicting of compressive strength of recycled aggregate concrete by genetic programming, Comput. Concr. 18 (2016) 155–163, https://doi.org/10.12989/CAC.2016.18.2.155.
[83] M.F. Iqbal, Q. Liu, I. Azim, X. Zhu, J. Yang, M.F. Javed, M. Rauf, Prediction of mechanical properties of green concrete incorporating waste foundry sand based on gene expression programming, J. Hazard Mater. 384 (2020), 121322, https://doi.org/10.1016/j.jhazmat.2019.121322.
[84] J.-S. Chou, C.-F. Tsai, A.-D. Pham, Y.-H. Lu, Machine learning in concrete strength simulations: multi-nation data analytics, Construct. Build. Mater. 73 (2014) 771–780, https://doi.org/10.1016/j.conbuildmat.2014.09.054.
[85] A. Ahmad, F. Farooq, K.A. Ostrowski, K. Śliwa-Wieczorek, S. Czarnecki, Application of novel machine learning techniques for predicting the surface chloride concentration in concrete containing waste, Material, Materials 14 (2021) 2297, https://doi.org/10.3390/ma14092297.
[86] H. Dabiri, M. Kioumarsi, A. Kheyroddin, A. Kandiri, F. Sartipi, Compressive strength of concrete with recycled aggregate; a machine learning-based evaluation, Clean. Mater. 3 (2022), 100044, https://doi.org/10.1016/j.clema.2022.100044.
[87] A. Behnood, J. Olek, M.A. Glinicki, Predicting modulus elasticity of recycled aggregate concrete using M5′ model tree algorithm, Construct. Build. Mater. 94 (2015) 137–147, https://doi.org/10.1016/j.conbuildmat.2015.06.055.
[88] B. Vakhshouri, S. Nejadi, Prediction of compressive strength of self-compacting concrete by ANFIS models, Neurocomputing 280 (2018) 13–22, https://doi.org/10.1016/j.neucom.2017.09.099.
[89] H.I. Erdal, O. Karakurt, E. Namli, High performance concrete compressive strength forecasting using ensemble models based on discrete wavelet transform, Eng. Appl. Artif. Intell. 26 (2013) 1246–1254, https://doi.org/10.1016/j.engappai.2012.10.014.
[90] T.G. Dietterich, Approximate statistical tests for comparing supervised classification learning algorithms, Neural Comput. 10 (1998) 1895–1923, https://doi.org/10.1162/089976698300017197.
[91] K. Khan, W. Ahmad, M.N. Amin, F. Aslam, A. Ahmad, M.A. Al-Faiad, Comparison of prediction models based on machine learning for the compressive strength estimation of recycled aggregate concrete, Materials 15 (2022) 3430, https://doi.org/10.3390/ma15103430.
[92] F. Falade, T. Iqbal, Compressive strength prediction recycled aggregate incorporated concrete using adaptive neuro-fuzzy system and multiple linear regression, Ijceae 1 (2019) 19–24, https://doi.org/10.34256/ijceae1913.
[93] A. Khademi, K. Behfarnia, T. Kalman Scaron, iposcaron, I. Miličević, The use of machine learning models in estimating the compressive strength of recycled brick aggregate concrete, Comput. Eng. Phys. Model. 4 (2021), https://doi.org/10.22115/cepm.2021.297016.1181.
[94] T. Han, A. Siddique, K. Khayat, J. Huang, A. Kumar, An ensemble machine learning approach for prediction and optimization of modulus of elasticity of recycled aggregate concrete, Construct. Build. Mater. 244 (2020), 118271, https://doi.org/10.1016/j.conbuildmat.2020.118271.
[95] Y.-J. Cha, W. Choi, O. Büyüköztürk, Deep learning-based crack damage detection using convolutional neural networks: deep learning-based crack damage detection using CNNs, Comput. Aided Civ. Infrastruct. Eng. 32 (2017) 361–378, https://doi.org/10.1111/mice.12263.
[96] F. Deng, Y. He, S. Zhou, Y. Yu, H. Cheng, X. Wu, Compressive strength prediction of recycled concrete based on deep learning, Construct. Build. Mater. 175 (2018) 562–569, https://doi.org/10.1016/j.conbuildmat.2018.04.169.
[97] S. Han, H. Li, M. Li, T. Rose, A deep learning based method for the non-destructive measuring of rock strength through hammering sound, Appl. Sci. 9 (2019) 3484, https://doi.org/10.3390/app9173484.
[98] R. Lv, Z. Yuan, B. Lei, J. Zheng, X. Luo, Building thermal load prediction using deep learning method considering time-shifting correlation in feature variables, J. Build. Eng. 61 (2022), 105316, https://doi.org/10.1016/j.jobe.2022.105316.
[99] C.V. Dung, L.D. Anh, Autonomous concrete crack detection using deep fully convolutional neural network, Autom. ConStruct. 99 (2019) 52–58, https://doi.org/10.1016/j.autcon.2018.11.028.

[100] K. Jang, N. Kim, Y.-K. An, Deep learning–based autonomous concrete crack evaluation through hybrid image scanning, Struct. Health Monit. 18 (2019) 1722–1737, https://doi.org/10.1177/1475921718821719.
[101] B. Kim, S. Cho, Image-based concrete crack assessment using mask and region-based convolutional neural network, Struct. Control Health Monit. (2019), e2381, https://doi.org/10.1002/stc.2381.
[102] G. Toh, J. Park, Review of vibration-based structural health monitoring using deep learning, Appl. Sci. 10 (2020) 1680, https://doi.org/10.3390/app10051680.
[103] X.-W. Ye, T. Jin, P.-Y. Chen, Structural crack detection using deep learning–based fully convolutional networks, Adv. Struct. Eng. 22 (2019) 3412–3419, https://doi.org/10.1177/1369433219836292.
[104] X. Zhang, D. Rajan, B. Story, Concrete crack detection using context-aware deep semantic segmentation network, Comput. Aided Civ. Infrastruct. Eng. 34 (2019) 951–971, https://doi.org/10.1111/mice.12477.
[105] Y. Gao, K.M. Mosalam, Deep learning visual interpretation of structural damage images, J. Build. Eng. 60 (2022), 105144, https://doi.org/10.1016/j.jobe.2022.105144.
[106] X. Ke, Y. Duan, A Bayesian machine learning approach for inverse prediction of high-performance concrete ingredients with targeted performance, Construct. Build. Mater. 270 (2021), 121424, https://doi.org/10.1016/j.conbuildmat.2020.121424.
[107] A. Bakshan, I. Srour, G. Chehab, M. El-Fadel, J. Karaziwan, Behavioral determinants towards enhancing construction waste management: a Bayesian Network analysis, Resour. Conserv. Recycl. 117 (2017) 274–284, https://doi.org/10.1016/j.resconrec.2016.10.006.
[108] L. Antonio Pereira Silva, J. Batista Nunes Bezerra, M. Barbosa Perkusich, K. Costa Gorgônio, H. Oliveira de Almeida, A. Perkusich, Continuous learning of the structure of bayesian networks: a mapping study, in: D. McNair (Ed.), Bayesian Networks - Advances and Novel Applications, IntechOpen, 2019, https://doi.org/10.5772/intechopen.80064.
[109] G. Kabir, G. Demissie, R. Sadiq, S. Tesfamariam, Integrating failure prediction models for water mains: Bayesian belief network based data fusion, Knowl. Base Syst. 85 (2015) 159–169, https://doi.org/10.1016/j.knosys.2015.05.002.
[110] T.-B. Tran, E. Bastidas-Arteaga, Y. Aoues, A Dynamic Bayesian Network framework for spatial deterioration modelling and reliability updating of timber structures subjected to decay, Eng. Struct. 209 (2020), 110301, https://doi.org/10.1016/j.engstruct.2020.110301.
[111] T.-B. Tran, E. Bastidas-Arteaga, F. Schoefs, S. Bonnet, A Bayesian network framework for statistical characterisation of model parameters from accelerated tests: application to chloride ingress into concrete, Struct. Infrastruct. Eng. 14 (2018) 580–593, https://doi.org/10.1080/15732479.2017.1377737.
[112] F. Duprat, N.T. Vu, A. Sellier, Accelerated carbonation tests for the probabilistic prediction of the durability of concrete structures, Construct. Build. Mater. 66 (2014) 597–605, https://doi.org/10.1016/j.conbuildmat.2014.05.103.
[113] H.M. Imounga, E. Bastidas-Arteaga, R. Moutou Pitti, S. Ekomy Ango, X.-H. Wang, Bayesian assessment of the effects of cyclic loads on the chloride ingress process into reinforced concrete, Appl. Sci. 10 (2020) 2040, https://doi.org/10.3390/app10062040.
[114] G. Kabir, S. Tesfamariam, R. Sadiq, Bayesian model averaging for the prediction of water main failure for small to large Canadian municipalities, Can. J. Civ. Eng. 43 (2016) 233–240, https://doi.org/10.1139/cjce-2015-0374.
[115] G. Kabir, S. Tesfamariam, A. Francisque, R. Sadiq, Evaluating risk of water mains failure using a Bayesian belief network model, Eur. J. Oper. Res. 240 (2015) 220–234, https://doi.org/10.1016/j.ejor.2014.06.033.
[116] R. Caspeele, L. Taerwe, Numerical Bayesian updating of prior distributions for concrete strength properties considering conformity control, Adv. Concr. Construct. 1 (2013) 85–102, https://doi.org/10.12989/ACC.2013.1.1.085.
[117] O. Najm, H. El-Hassan, A. El-Dieb, H. Aljassmi, Utilization of a Bayesian Network Algorithm to Predict the Compressive Strength of Concrete, IJCI, 2021, https://doi.org/10.11159/ijci.2021.005.
[118] O. Najm, H. El-Hassan, A. El-Dieb, H. Aljassmi, Probabilistic inference approach for predicting concrete Compressive Strength - a bayesian network algorithm. https://doi.org/10.11159/iccste20.238, 2020.
[119] J.J. Xu, W.G. Chen, C. Demartino, T.Y. Xie, Y. Yu, C.F. Fang, M. Xu, A Bayesian model updating approach applied to mechanical properties of recycled aggregate concrete under uniaxial or triaxial compression, Construct. Build. Mater. 301 (2021), 124274, https://doi.org/10.1016/j.conbuildmat.2021.124274.
[120] S. Nasiri, M.R. Khosravani, K. Weinberg, Fracture mechanics and mechanical fault detection by artificial intelligence methods: a review, Eng. Fail. Anal. 81 (2017) 270–293, https://doi.org/10.1016/j.engfailanal.2017.07.011.
[121] J. Duan, P.G. Asteris, H. Nguyen, X.-N. Bui, H. Moayedi, A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model, Eng. Comput. 37 (2021) 3329–3346, https://doi.org/10.1007/s00366-020-01003-0.
[122] H. Jiang, G. Liu, H. Alyami, A. Alharbi, M. Jameel, M.A. Khadimallah, Intelligence decision mechanism for prediction of compressive strength of self-compaction green concrete via neural network, J. Clean. Prod. (2022), 130580, https://doi.org/10.1016/j.jclepro.2022.130580.
[123] K.H. Younis, K. Pilakoutas, Strength prediction model and methods for improving recycled aggregate concrete, Construct. Build. Mater. 49 (2013) 688–701, https://doi.org/10.1016/j.conbuildmat.2013.09.003.
[124] A. Behnood, E.M. Golafshani, Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves, J. Clean. Prod. 202 (2018) 54–64, https://doi.org/10.1016/j.jclepro.2018.08.065.
[125] K. Sahoo, P. Sarkar, R. Davis P, Artificial neural networks for prediction of compressive strength of recycled aggregate concrete, IJRCMCE 3 (2016), https://doi.org/10.15242/IJRCMCE.IAE0316414.
[126] M.A. Shafiq, Predicting the compressive strength of concrete using neural network and kernel ridge regression, in: 2016 Future Technologies Conference (FTC), IEEE, San Francisco, CA, USA, 2016, pp. 821–826, https://doi.org/10.1109/FTC.2016.7821698.
[127] A.W. Otunyo, B.G. Jephter, Predictive model for compressive strength of concrete made from recycled concrete coarse aggregates, Nig. J. Tech. 37 (2018) 633, https://doi.org/10.4314/njt.v37i3.11.
[128] H. Naderpour, A.H. Rafiean, P. Fakharian, Compressive strength prediction of environmentally friendly concrete using artificial neural networks, J. Build. Eng. 16 (2018) 213–219, https://doi.org/10.1016/j.jobe.2018.01.007.
[129] F. Deng, Y. He, S. Zhou, Y. Yu, H. Cheng, X. Wu, Compressive strength prediction of recycled concrete based on deep learning, Construct. Build. Mater. 175 (2018) 562–569, https://doi.org/10.1016/j.conbuildmat.2018.04.169.
[130] A. Cekic, Prediction of compressive strength of recycled aggregate concrete using LASSO, CERJ 5 (2018), https://doi.org/10.19080/CERJ.2018.05.555654.
[131] L. Zhu, C. Zhao, J. Dai, Prediction of compressive strength of recycled aggregate concrete based on gray correlation analysis, Construct. Build. Mater. 273 (2021), 121750, https://doi.org/10.1016/j.conbuildmat.2020.121750.
[132] M.-Z. Zhao, Y. Geng, Y.-Y. Wang, J.-X. Hu, Compounding effect and an expanded theoretical model for recycled coarse and fine aggregate concretes under uniaxial loading, Construct. Build. Mater. 320 (2022), 126226, https://doi.org/10.1016/j.conbuildmat.2021.126226.
[133] H. Imran, N.M. Al-Abdaly, M.H. Shamsa, A. Shatnawi, M. Ibrahim, K.A. Ostrowski, Development of prediction model to predict the compressive strength of eco-friendly concrete using multivariate polynomial regression combined with stepwise method, Materials 15 (2022) 317, https://doi.org/10.3390/ma15010317.
[134] M.A.R. B K A, C. Ngamkhanong, Y. Wu, S. Kaewunruen, Recycled aggregates concrete compressive strength prediction using artificial neural networks (ANNs), Infrastructure 6 (2021) 17, https://doi.org/10.3390/infrastructures6020017.
[135] I. Nunez, M.L. Nehdi, Machine learning prediction of carbonation depth in recycled aggregate concrete incorporating SCMs, Construct. Build. Mater. 287 (2021), 123027, https://doi.org/10.1016/j.conbuildmat.2021.123027.
[136] R.R. Picard, R.D. Cook, Cross-validation of regression models, J. Am. Stat. Assoc. 79 (1984) 575–583, https://doi.org/10.1080/01621459.1984.10478083.
[137] R. Siddique, P. Aggarwal, Y. Aggarwal, Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks, Adv. Eng. Software 42 (2011) 780–786, https://doi.org/10.1016/j.advengsoft.2011.05.016.
[138] D.-K. Bui, T. Nguyen, J.-S. Chou, H. Xuan, T.D. Ngo, A modified firefly algorithm-artificial neural network expert system for predicting compressive and tensile strength of high-performance concrete, Construct. Build. Mater. 180 (2018) 320–333, https://doi.org/10.1016/j.conbuildmat.2018.05.201.

[139] Y.-S. Park, J. Rabinovich, S. Lek, Sensitivity analysis and stability patterns of two-species pest models using artificial neural networks, Ecol. Model. 204 (2007) 427–438, https://doi.org/10.1016/j.ecolmodel.2007.01.021.

[140] J.M. Palomino Ojeda, S. Rosario Bocanegra, L. Quiñones Huatangari, Determination of the compressive strength of concrete using artificial neural network, Int. j. Eng. Technol. Innov. 11 (2021) 204–215, https://doi.org/10.46604/ijeti.2021.7479.

[141] S. Tesfamariam, B. Martín-Pérez, Bayesian belief network to assess carbonation-induced corrosion in reinforced concrete, J. Mater. Civ. Eng. 20 (2008) 707–717, https://doi.org/10.1061/(ASCE)0899-1561(2008)20:11(707).

[142] P. Franchin, A. Lupoi, F. Noto, S. Tesfamariam, Seismic fragility of reinforced concrete girder bridges using Bayesian belief network: BBN Model of Seismic Fragility of RC Girder Bridges, Earthq. Eng. Struct. Dynam. 45 (2016) 29–44, https://doi.org/10.1002/eqe.2613.

[143] I. González-Taboada, B. González-Fonteboa, F. Martínez-Abella, J.L. Pérez-Ordóñez, Prediction of the mechanical properties of structural recycled concrete using multivariable regression and genetic programming, Construct. Build. Mater. 106 (2016) 480–499, https://doi.org/10.1016/j.conbuildmat.2015.12.136.

[144] I.M. Sobol′, Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Math. Comput. Simulat. 55 (2001) 271–280, https://doi.org/10.1016/S0378-4754(00)00270-6.