Artificial intelligence-based modeling of compressive strength of slurry infiltrated fiber concrete

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Abstract

Purpose – The purpose of this paper is to develop a reliable model that would predict the compressive strength of slurry infiltrated fiber concrete (SIFCON) modified with various supplementary cementitious materials (SCMs) using artificial intelligence approach.

Design/methodology/approach – This study engaged the artificial intelligence to predict the compressive strength of SIFCON through deep neural networks (DNN), artificial neural networks, linear regression, regression trees, support vector machine, ensemble trees, Gaussian process regression and neural networks (NN). A thorough data set of 387 samples was gathered from relevant studies. Eleven variables (cement, silica fume, fly ash, metakaolin, steel slag, fine aggregates, steel fiber fraction, steel fiber aspect ratio, superplasticizer, water to binder ratio and curing ages) were taken as input to predict the output (compressive strength). The accuracy and reliability of the developed models were assessed using a variety of performance metrics.

Findings – The results showed that the DNN (11-20-20-20-1) predicted the compressive strength of SIFCON better than the other algorithms with R^2 and mean square error yielding 95.89% and 8.07. The sensitivity analysis revealed that steel fiber, cement, silica fume, steel fiber aspect ratio and superplasticizer are the most vital variables in estimating the compressive strength of SIFCON. Steel fiber contributed the highest value to the SIFCON's compressive strength with 16.90% impact.

Originality/value – This is a novel technique in predicting the compressive strength of SIFCON optimized with different SCMs using supervised learning algorithms, improving its quality and performance.

Keywords Artificial intelligence, Cement, Compressive strength, Slurry infiltrated fiber concrete, Modeling, Steel fiber

Paper type Research paper

1. Introduction

Concrete demand is increasing more quickly than that of steel or wood, and on a per capita basis, that is three times as much as it was 40 years ago (Monteiro *et al.*, 2017). All around the world, concrete is used in building construction due to its many advantageous qualities, including strength, durability, stiffness, hardness, density and fire and thermal resistance. These are considered to be most significant regarding the concrete element's durability and safety, especially its compressive strength (Khaloo *et al.*, 2008). The concrete's compressive strength is influenced by various constituents and their combinations, such as the proportion of water to binder, aggregate sizes, binder types and waste content (Cotsovos and Pavlović, 2008). Accurately determining or predicting the concrete's compressive strength in such a complex mixture is challenging. In laboratory studies, the concrete's compressive strength can be assessed by crushing standard-sized cylinders or cubes for the designated curing ages following sample

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Data and code availability: Detailed data set and code generation used in this study can be freely found via open access in the Zenodo Repository at www.zenodo.org/doi/10.5281/zenodo.11211973.

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casting (Li *et al.*, 2018). Nonetheless, because laboratory testing is expensive and time-consuming, it could be inefficient and uneconomical nowadays (Song *et al.*, 2021).

Fiber reinforced concrete (FRC) with a high fiber content that is distinct from other types is called slurry infiltrated fiber concrete (SIFCON). The fibers in SIFCON are molded and penetrated by a cement-based slurry or flowing mortar. SIFCON is more commonly used globally, particularly in explosive and impact structures; this is because SIFCON's mechanical and durability capabilities are generally superior to those of traditional FRC (Manolia *et al.*, 2018). SIFCON offers excellent potential for use in situations requiring high ductility and impact resistance, particularly in the design of seismic retrofits, in structures subject to impact, blast and dynamic loads and in the repair of RC structural elements (Ipek *et al.*, 2014; Vijayakumar and Kumar, 2017). In actuality, the clogged fibers prevent the normal mixing of concrete; instead, the fibers are installed first, and then the desired network is created. The fibers can be inserted manually or by fiber dispensing equipment for large areas, but the cement-based slurry (mortar) must be infiltrated manually (by gravity) (Thomas and Mathews, 2014). The steel fibers can be incorporated into the matrix using three different techniques, each accompanied by vibration (Parameswaran, 1993): preplacing steel fibers in a mold and allowing slurry to flow through the fibers (single-layer approach), carrying out the same process while dividing the mold's overall height into three equal portions (three-layer method); and inserting the steel fibers after the prefilled slurry till the mold reach its full height (immersion approach).

Sand and cement are typically combined in 1:1, 1:1.5 or 1:2 ratios to manufacture SIFCON. Fly ash or silica fume at a ratio of between 10 and 15 wt.% of cement could also be added to the mixture (Hamed and Abass, 2021). Typically, only fine sand that can pass through a sieve with a 1.18 mm opening or with a maximum particle size of 1, 0.6 and 0.5 mm will fully penetrate a matrix made of steel fibers (Hamed and Abass, 2021). The water-cement ratio varies from 0.3 to 0.4, while super plasticizer takes 2–5 wt.% of cement. SIFCON generally comprises 4%–20% fibers, compared to 1%–3% in traditional FRC. Although, the currently available practical SIFCON ranges from 4% to 12% of fiber content (Ali, 2018; Rao *et al.*, 2010). SIFCON is created by saturating a bed of pre-placed fibers with cement slurry and packing it tightly inside a mold (Antoine, 2003; Yan *et al.*, 1999). On the other hand, various fiber types can be used to create SIFCON. Crimped and hooked are the most frequently used. Despite being less prevalent than other types, deformed and straight fibers can still be used (Antoine, 2003).

Some factors, including fiber content, % volume of fibers, aggregate-cement (a/c) ratio, fiber aspect ratio and water-cement (w/c) ratio, have significant effects on SIFCON's strength and workability characteristics (Sonebi, 2004). Thus, a thorough grasp of the relationship between these parameters and the characteristics of the final mix is necessary for creating a macro mechanical model for SIFCON mixtures. The statistical models apply to slurries prepared with a w/c ratio of 0.40–0.50, sand-to-cement ratios of 50%–100%, a silica fume ratio of 5%–10% and superplasticizer (SP) dosages of 0.6%–1.2% per mass of cement (Sonebi, 2004). The effect of using discontinuous, short fibers that are randomly dispersed in SIFCON results in increased compressive strength (CS), tensile strength (TS) and flexural strength (FS) as well as post-cracking capacity, stiffness, impact resistance and energy absorption capacity (Dagar, 2012; Vijayakumar and Kumar, 2017). The primary factors contributing to the increased compressive strength and ductility of SIFCON are the interlocking of the fibers and the cohesiveness between the fiber and matrix. A study examined the compressive properties of SIFCON under monotonic and cyclic loading using 6%–12% fibers and 62 fiber aspect ratio (Yan *et al.*, 1999). The results indicated increased compressive strength under monotonic and cyclic loading with increasing fiber content. After 28 days of curing, there were 89.80 and 83.40 MPa under monotonic and cyclic loading at 12% fiber content compared to 71 and 66.20 MPa at 6% fiber content. A study developed a high-performance concrete along with the experimental work on properties of SIFCON using 3%–11% fiber. After 28 days of curing, the experimental results revealed that 9% fiber content provided the best compressive, split tensile and flexural strengths (Sonone* *et al.*, 2020). Previous studies compared the mechanical performance of micro straight end, hooked end, crimped and hybrid steel fibers (Khamees *et al.*, 2020, 2021). The findings revealed that straight end micro steel fibers (0.20 mm diameter, 13 mm long and 65 aspect ratio) exhibited better mechanical properties than hooked ends (0.50 mm diameter, 30 mm long and 60 aspect ratio) and hybrid (50% micro steel + 50% hooked end fibers) steel fibers.

Artificial intelligence (AI) models have recently been used to predict concrete strength. This is because the objective recognition of diverse patterns encompassing extensive data sets not specifically tailored for a particular activity (Song *et al.*, 2021). AI makes it possible for computers to perform intricate jobs that were previously too sophisticated. As opposed to simple human programming, these algorithms could identify patterns in the data. Most of these algorithms work by having the computer understand the characteristics of the data set for the topic at hand through training (Song *et al.*, 2021). After that, the computer interprets the information to create explanations for other data sets that are accessible. Machine learning (ML) algorithms such as regression, clustering and classification can be applied to estimate other parameters with varying degrees of effectiveness and assist in precisely predicting the compressive strength of concrete (Ahmad *et al.*, 2022; Song *et al.*, 2021). Table 1 displays the existing ML approaches used in forecasting the strength properties of SIFCON. Table 1 clearly shows that many gaps in the knowledge need to be filled. To compare the distinctive performance of SIFCON and enhance its quality, additional ML algorithms are needed. There is little to no information available regarding the use of support vector machines (SVM), ensemble trees (ET), deep neural networks (DNN), linear regression (LR), regression trees (RT), Gaussian process regression (GPR) and neural networks (NN) in predicting the compressive strength of SIFCON. In the existing literature, there is insufficient sensitivity analysis to measure the degree to which an input variable responds to modifications of the output variable, hence, justifying this study.

In this research, the effects of 11 input variables such as cement, silica fume (SF), fly ash (FA), metakaolin (MK), steel

Table 1 AI-based ML algorithms used in forecasting the strength properties of SIFCON

S/N	Technique	Input	Output	Data set	Finding	Reference
1	Levenberg–Marquardt (LM) algorithm and steepest descent (SD) algorithm based artificial neural networks (ANN)	Cement, sand, steel fibers, superplasticizer (SP), water and curing ages	CS	32	LM algorithm performs more accurately and efficiently than SD approach	Santosh Kumar and Rajasekhar (2017)
2	Genetic algorithm (GA)-based ANN	Steel fiber aspect ratio, % volume of steel fiber, a/c ratio, w/b ratio	CS, TS and FS	108	GA-based ANN exhibited satisfactory performance with 95% accuracy	Gopala Krishna Sastry (2014)
3	GA-based ANN	Cement, manufactured sand, steel fiber volumes, water and curing ages	CS	90	GA-based ANN yielded satisfactory performance with 85% accuracy	Gottapu Santosh Kumar (2018)
4	ANN	Cement, sand, w/b ratio, SP, % fiber volume, % mineral admixture, fiber aspect ratio	CS, TS and FS	84	The performance of ANN with 4-14-3 topology was better than other structures	Reddy (2018)
5	Multilinear regression (MLR)	Cement, steel fiber, fly ash, metakaolin, fine aggregate, blast furnace slag, bottom ash, w/c ratio	CS, TS and FS	36	The MLR model yielded good correlation between predicted and actual values of output variables	Shelorkar Ajay (2022)

Source: Table by authors

slag (SS), fine aggregates (Fagg), steel fiber fraction (SFF), steel fiber aspect ratio (SFAR), superplasticizer (SP), water to binder (WBR) ratio and curing ages (CA) were engaged to predict the output (compressive strength, CS) of SIFCON. The study used 387 samples from relevant literature, and 8 different ML techniques (ANN, DNN, LR, RT, SVM, ET, GPR and NN) were used to model the relationship. Several performance indicators were used to evaluate the created models' accuracy and reliability. Besides, the response of each input variable to the compressive strength of SIFCON was investigated with the use of sensitivity analysis.

The importance and novelty of this research lie in its assurance of applying the created models in the built environment, devoid of any theoretical examination. The study is innovative in that four mineral admixtures (silica fume, fly ash, metakaolin and steel slag) are included in the model. It conducts statistical analysis and assesses how different parameters affect SIFCON's compressive strength. The study measures and provides ML models to predict the SIFCON's compressive strength made up of a wide range of constituents. The findings from the sensitivity analysis would help identify the variables of significant input in the SIFCON's strength forecast and ensure that they are strictly controlled during SIFCON production.

2. Methodology

2.1 Data source and generation

A thorough analysis of peer-reviewed publications over the past 20 years in the fields of engineering, building materials and material sciences served as the basis for both the data source and its generation. Data was acquired from several publishers, including Taylor & Francis, Elsevier, Springer and Multidisciplinary Digital Publishing Institute (MDPI). The references were limited to databases such as Scopus, Scimago Journal & Country Rank (Sjr) and Web of Science (WoS) websites to guarantee the inclusion of only peer-reviewed references and to confirm the data collection. A total of 387 pairs of input/target values were generated from various SIFCON mix proportions of several experimental studies, obtaining the data required to train the ML (Abbas and Kadhum, 2020; Ali, 2018; Ali *et al.*, 2022; Drdlová *et al.*, 2016, 2018; Elavarasi D, 2018; Gopala Krishna Sastry, 2014; Hashim and Kadhum, 2020; Jerry and Fawzi, 2022; Khamees *et al.*, 2020; Kim *et al.*, 2019, 2020; Mohammed *et al.*, 2020; Muthukannan M, 2019; Naser and Abeer, 2020; P.Sampath, 2020; Qasim and Abdul Rahman, 2022; Reddy, 2018; R. Giridhar, 2015; Salih *et al.*, 2018; Santosh Kumar and Rajasekhar, 2017; Sengul, 2018; Shashi Sharma, 2017; Shelorkar Ajay, 2022; Sonone* *et al.*, 2020; Soylu and Bingöl, 2019; Vijayakumar and Kumar, 2017; Yan *et al.*, 1999; Yas *et al.*, 2023; Yazıcı *et al.*, 2006). The summary of the data set is presented in Table 2. The detailed data set and the code generation are freely available via open access in the Zenodo Repository at www.zenodo.org/doi/10.5281/zenodo.11211973.

Based on the aforementioned studies, ordinary Portland cement with a specific gravity of 3.15 and grades ranging from 43 to 53 was used. River sand was primarily used as fine aggregates, with particle sizes varying between 1.18 and 4.74 mm. In most cases, 1.18 mm maximum particle sizes were used as fine aggregates. Micro straight end, hook-end, crimped and hybrid steel fibers are the different forms of steel fibers used. As shown in Figure 1, the fresh SIFCON requires a mixing period of approximately 10 min. Mini-slump flow ranging from 257 to 364 mm and V-funnel times varying between 7 and 11 s were indicated by the rheological properties.

2.2 Artificial intelligence (AI)

The flowchart detailing the procedure for the training of data set is shown in Figure 2.

2.2.1 Deep neural networks (DNN)

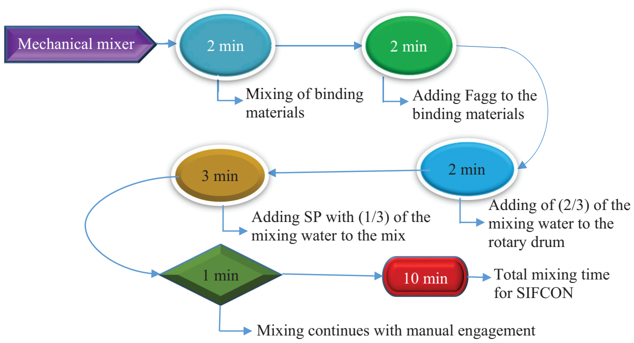
The application of DNN, a subset of AI, to address challenging issues has become increasingly common in scientific and technical

Table 2 Statistical summary of data set

Statistics	Cement	SF	MK	(kg/m^3) FA	SS	Fagg	SP	SFF (%)	SFAR	WBR	CA (day)	CS (MPa)
Minimum	320	0	0	0	0	352	0	0	0	0.27	3	11.68
Maximum	1000	290.70	290.70	484.50	142.58	1114.35	117	35	297.17	0.50	90	142
Median	816	78	0	0	0	960	13.08	6	58	0.40	28	60
Mean	776.98	64.25	15.44	29.30	3.32	856.55	15.22	7.09	55.35	0.38	26.10	63.64
SD	198.39	73.44	55.62	107.73	19.60	194.79	14.70	5.03	37.49	0.07	13.95	23.90

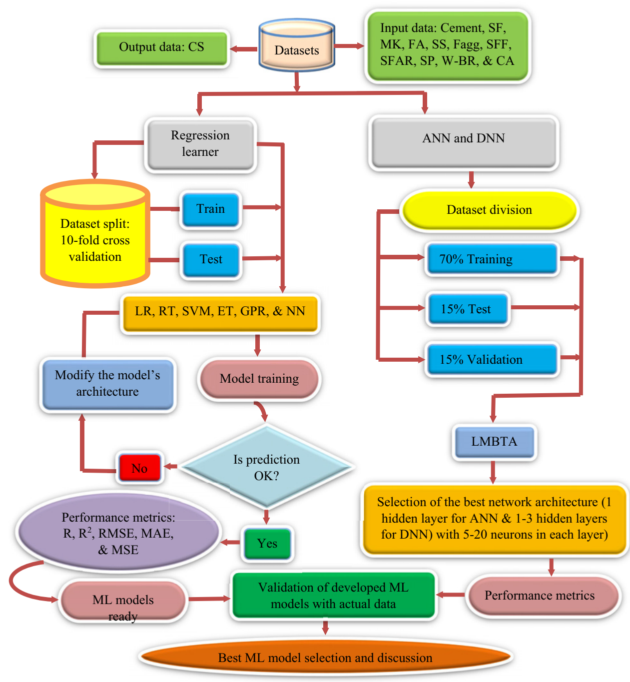
Source: Table by authors

Figure 1 Mixing time flowchart



Source: Figure by authors

Figure 2 Flowchart showing the methodology approach for AI modeling



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computing. For this study, a DNN model with a sizable data set was generated to accurately forecast the SIFCON's compressive strength. A total of 387 data set obtained from the relevant studies was used as training, validation and testing data sets, accounting for 70%, 15% and 15%, respectively. From Figure 3, the training matrix is identified as 271 samples with accuracy. This is equivalent to 70% of all samples. Thus, the training matrix is 100% accurate. Besides, 58 samples, or 15% of total samples are labeled as test and validation matrices with 100% accuracy. Finally, a total of 387 samples are identified in training, validation and test matrices with 100% accuracy.

A total of 15 experimental data sets from relevant literature (Aliyaa M. Alsheameri, 2023; Elavarasi *et al.*, 2014; Nadia Moneem Al-Abdalay, 2020) was used to validate the developed ML models, and a comparison was made. The multilayer perceptron, or DNN, learns using backpropagation training techniques. Levenberg–Marquardt (LM) and three-hidden layer have been found to perform better when backpropagation training techniques (scaled conjugate gradient [SCG], resilient and Bayesian regularization [BR]) and two to five hidden layers are taken into account (Martin *et al.*, 2014; Oyebisi and Alomayri, 2023a, 2023b; Oyebisi and Owamah, 2023). In real neural networks, two or three layers are the usual number. Rarely are four or more layers used (Martin *et al.*, 2014; Uzair and Jamil, 2020). As a result, this study used LM as the backpropagation training algorithm. To investigate the effects of various neurons on DNN architecture, a three-hidden layer network with 5–20 neurons in each layer was engaged, and the best network structure was used. A model is prone to overfitting due to the additional classes of abstraction that enable rare-dependent training of data sets (Ly *et al.*, 2021). For this reason, a random stream-fitted function was set to prevent overfitting. Figure 4 cascades the example of a DNN with three-hidden layer. The first network's output becomes the second network's input, and the second network's output becomes the third network's input. Therefore, the best DNN topology for this study is shown in Figure 5.

The number of neurons in each layer and the transfer function may vary. As a result, the outcome of the third network is shown in equation (1), and the operation is shown in equation (2). Equation (2) indicates that M is the number of network layers:

$$a^3 = f^3\left(W^3 f^2\left(W^2 f^1\left(W^1 p + b^1\right) + b^2 + b^3\right)\right) \quad (1)$$

$$a^{m+1} = f^{m+1}\left(W^{m+1} a^m + b^{m+1}\right) \; for \; m = 0, 1, \ldots, M-1 \quad (2)$$

Equation (3) forms the basis of equation (4). First-layer neurons receive inputs from external sources, as shown by equation (4). Encoding the network output, then, is shown by equation (4):

Figure 3 Data matrix

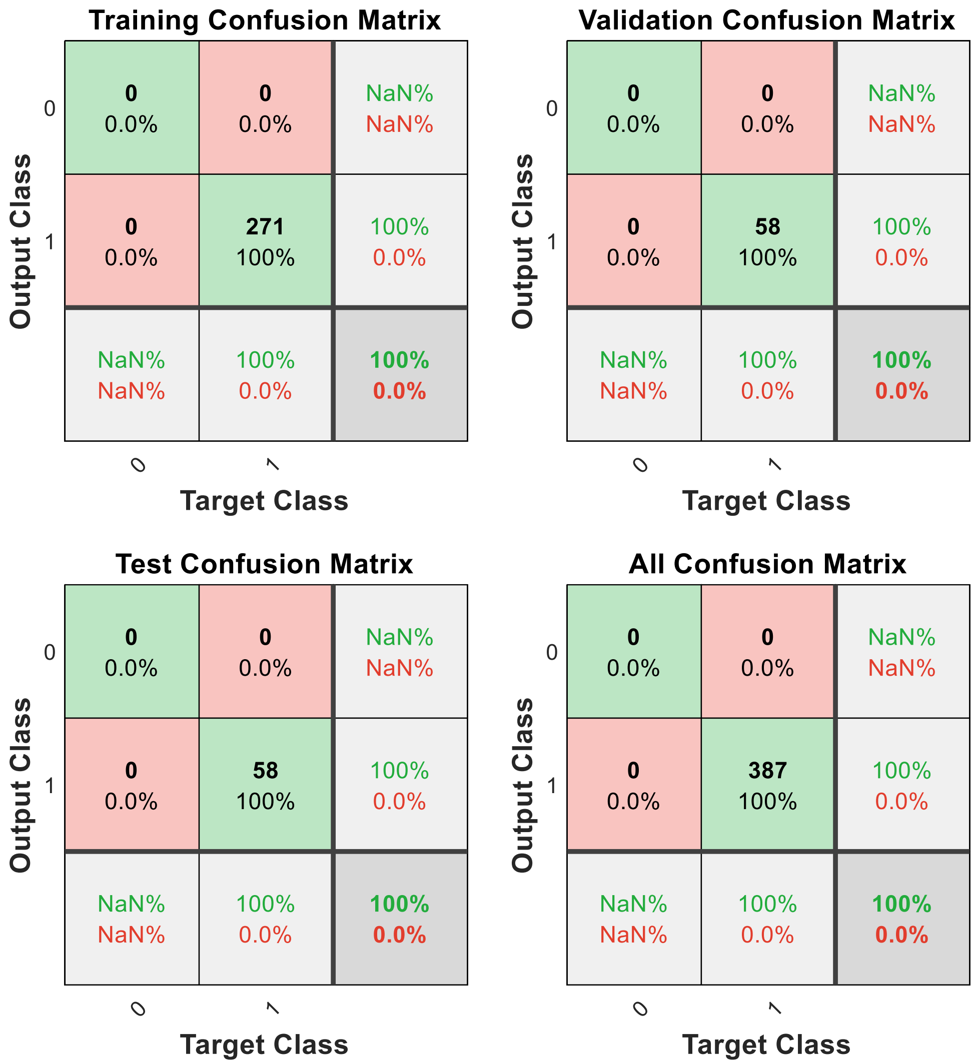

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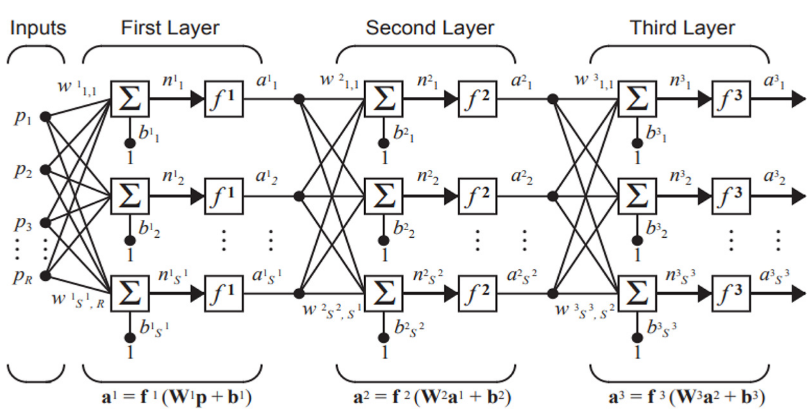
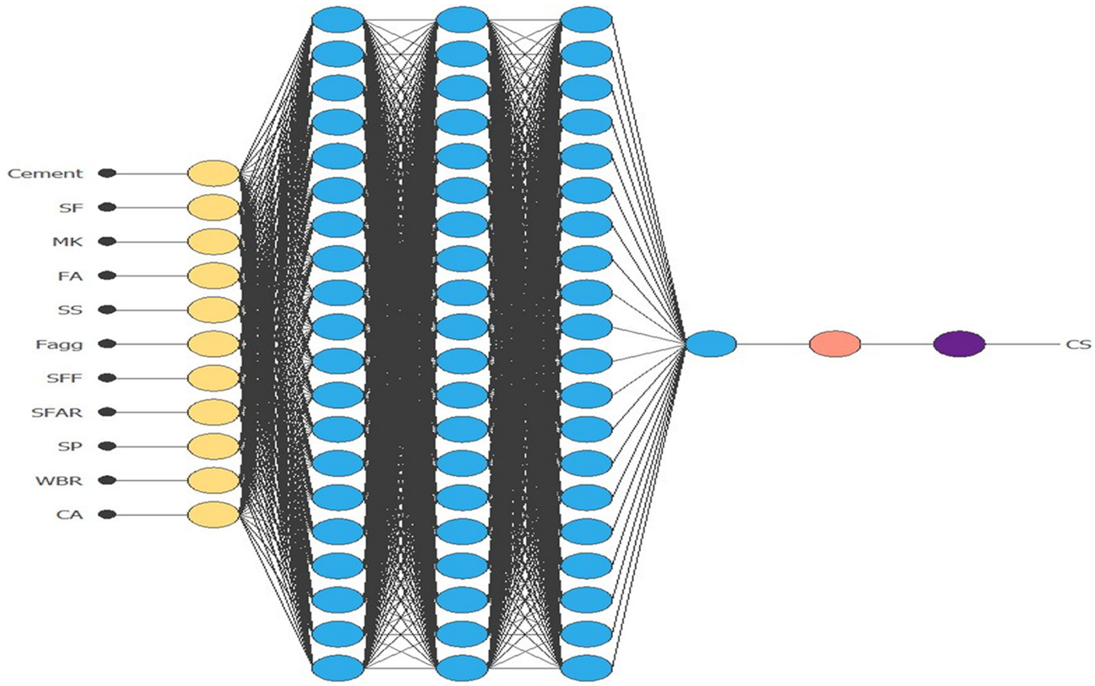
Figure 4 A three-hidden layer network



Source: Figure by Martin *et al.* (2014)

Figure 5 The best DNN topology (11-20-20-20-1)



Source: Figure by authors

$$a^0 = p \quad (3)$$

$$a = a^M \quad (4)$$

where *a, f, m, p, W and b* represent output vector, transfer function, network layers, input vector, weight matrix and bias vector.

2.2.2 Artificial neural networks (ANN)
An ANN is a network made up of connections between neurons, which are processing units. The fundamental computational components of a network that process data are called neurons (Martin *et al.*, 2014). Weights, also known as parameters, are interneuron connection strengths that encode the network's processing capacity. Weights are obtained through the process of adaption. Thus, this study created 11 input variables and a target (output) variable, as highlighted in Table 1. All data were randomly divided as 70% for training, 15% for validation and 15% for testing (see Figure 5). The number of hidden neurons varied from 5 to 20, and the best neuron was selected.

For the purpose of training and testing models, the input layer transmits and stores input variables. The connection between an ANN's input and output layers is made possible by the hidden layer, also known as the middle layer. Every hidden layer has a group of neurons in it. The layer responsible for producing the result is called the output layer. This process involves feeding the network training data throughout the training phase and adjusting the network weights to either get a predetermined number of training iterations or minimize the error between the output and the target. LM was engaged as a training algorithm due to its accurate and reliable performance compared to SCG and BR (Oyebisi *et al.*, 2023; Oyebisi and Alomayri, 2023a; Oyebisi and Owamah, 2023; Santosh Kumar and Rajasekhar, 2017).

Equation (5) illustrates the mathematical description of an ANN. The activation function is a sigmoid operation, which sets all values of input variables to 0 and 1. Equation (6) demonstrates the sigmoid operation (Mohtasham Moein *et al.*, 2023):

$$Y(t) = F\left(\sum_{i=1}^{n}(Xi(t)Wi(t) + b)\right) \quad (5)$$

where *Y*(t) is the output value at time *t*, *Xi*(t) is the input value at time *t*, *Wi*(t) is the neural input's weight at time *t*, *b* is the bias and *F* is a transfer function:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (6)$$

2.2.3 Regression learner
This study used Matlab R2021a version 9.10.0 1602886's supervised learning of regression learners to carry out LR, RT, SVM, ET, GPR and NN. These ML techniques demonstrate increased efficacy, robust accuracy and rapid estimation (Mohana *et al.*, 2020; Oyebisi and Owamah, 2023). Regression learner trains regression models for data prediction. It examines data, chooses characteristics, outlines validation plans, trains models and evaluates outcomes (DeRousseau *et al.*, 2019; Güçlüer *et al.*, 2021; Thilakarathna *et al.*, 2020). The model outputs were generated by training 11 input variables (cement, SF, MK, FA, SS, Fagg, SFF, SFAR, SP, w/b and CA) and response (CS) using LR, RT, SVM, ET, GPR and NN in regression learner of ML algorithms.

Achieving a good fit for training and testing variables is a major problem for the ML process due to the variance in the training and testing data set. Therefore, getting precise data that accurately represents real data for model testing (Baduge *et al.*, 2022; Thilakarathna *et al.*, 2020). According to Kim (Kim, 2017), a model created using regression learners needs to be generalized without overfitting. For this reason, data validation is required to avoid data overfitting. Consequently, the created model's performance is often validated and improved by applying a 10-fold cross-validation procedure (Feng *et al.*, 2020; Pereira, 2019). This method reduces the bias associated with the training data set's random sampling.

This research engaged 10-fold cross-validation because of its outstanding performance. The holdout size of the data set, by default, was set at 25% for testing, while the remainder was used for training the model. This study identified the algorithm with the best performance metrics. The features of the regression learners are highlighted in Table 3.

2.2.4 Performance indicators

This study explored five distinct performance metrics: correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE). The higher R and R^2 values to 1, the stronger the forecast. Nonetheless, the more accurate the forecast, the lower the MAE, MSE and RMSE to zero (Willmott and Matsuura, 2005). Equations (7)–(11) show the performance metrics:

$$R = 1 - \frac{\sum_{i=1}^{n}\left(y_i^{pred} - y_i^{actual}\right)}{\sum_{i=1}^{n}\left(y_i^{pred} - \overline{y_i^{actual}}\right)} \quad (7)$$

Table 3 Features of ML techniques used

ML technique	Feature
LR	Initial terms: linear Upper bound on terms: interactions Maximum number of steps: 1,000
RT	Minimum leaf size: 4 Surrogate decision splits: off
SVM	Kernel function: Gaussian Kernel scale: 0.83 Box constraint: automatic
ET	Minimum leaf size: 8 Number of learners: 30 Learning rate: 0.1
GPR	Basic function: constant Kernel function: exponential Isotropic kernel: true
NN	Number of fully connected layers: 1 First layer size: 25 Activation: ReLU Iteration limit: 1000

Source: Table by authors

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i^{pred} - y_i^{true}\right)^2}{\sum_{i=1}^{n}\left(y_i^{pred} - \overline{y^{true}}\right)^2} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{pred} - y_i^{true}\right) \quad (9)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i^{pred} - y_i^{true}\right)^2 \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{pred} - y_i^{true}\right)^2} \quad (11)$$

2.3 Sensitivity analysis

Understanding which variables have the biggest impact on model predictions is crucial. This can be accomplished by computing the derivatives of a model's outputs with respect to its inputs. Sensitivity analyses are a helpful technique for determining the potential significance of model parameters as sources of uncertainty in model predictions (Khan *et al.*, 2022). Greater significance is indicated by high derivative values, and smaller significance is indicated by values near zero (Khan *et al.*, 2022). Numerous tests are necessary in ML to assess and validate the reliability and quality of the generated model across a variety of data sets. Accuracy and efficacy gains made during training, testing and validation of the available data sets may not necessarily indicate or guarantee better performance in the end (Alabi *et al.*, 2023). Thus, the relative significance of the input variables (SFF, cement, SF, SFAR, SP, WBR, CA, Fagg, FA, MK and SS) on the output variable (CS) is assessed using equations (12) and (13):

$$Sensitivity\ analysis = \frac{Range_{\ output}}{\sum_{i=1}^{p} Range_{\ output}} \quad (12)$$

$$Range_{output} = Max\ (\bar{x}_{output}) - Min\ (\bar{x}_{output}) \quad (13)$$

3. Results and discussion

3.1 Effects of input variables on output (SIFCON's CS)

Figure 6 presents the influence of input variables (cement, SF, MK, FA, SS, Fagg, SF, SFAR, SP, WBR and CA) on the performance of SIFCON's compressive strength (response). Figure 6(a) clearly shows that the compressive strength rose as the cement content increased. The strength matrix is formed when cement particles and water react during the hydration process, binding the aggregates and fibers. However, 28-day compressive strength requires that a minimum cement content be satisfied. Cement added over this threshold did not considerably improve the compressive strength (Taylor *et al.*, 2015). The SIFCON's compressive strength was improved by partially substituting supplementary cementitious materials (SCMs) (SF, MK and FA) for cement in Figure 6(b)–(d) and steel slag (SS) for fine aggregates in Figure 6(e). This can be attributed to the fillability and pozzolanic or hydraulic activity of SCMs, aligning with findings from the literature (Salih *et al.*, 2018; Shashi Sharma, 2017). Nonetheless, adding SCMs beyond the required content, as indicated in Figure 6(b)–(e), results in a strength decline. The diluting effect of SCM in the SIFCON matrix and the slow rate of the hydration reactions could be ascribed to the decrease in strength (Elavarasi D, 2018). From Figure 6(e), the optimum replacement of fine aggregates with steel slag was 9%. There was a strength reduction beyond this replacement level (9%).

SIFCON's mechanical performance is primarily influenced by the qualities of its fine aggregates, which make up 50% of its volume (Lankard, 1984). The quantities of fine aggregates vary according to the design mix needed for application. From Figure 6(f), the SIFCON's compressive strength increased as the proportion of fine aggregates in the mix increased. This can be explained by these aggregates' intrinsic physical and chemical characteristics, particularly high silica content, low silt content and fineness modulus (Kiambigi Maina, 2018). Figure 6(g) and (h), demonstrated an increase in compressive strength of SIFCON with increasing steel fibers and aspect ratio in the mix. This supports results from a related study that showed adding steel fibers to slurry concrete can greatly improve its strength characteristics, including compressive,

Figure 6 Response of output (CS) to (a) cement, (b) silica fume, (c) metakaolin, (d) fly ash, (e) steel slag, (f) fine aggregates, (g) steel fiber fraction, (h) steel fiber aspect ratio, (i) superplasticizer, (j) water-to-binder ratio and (k) curing age

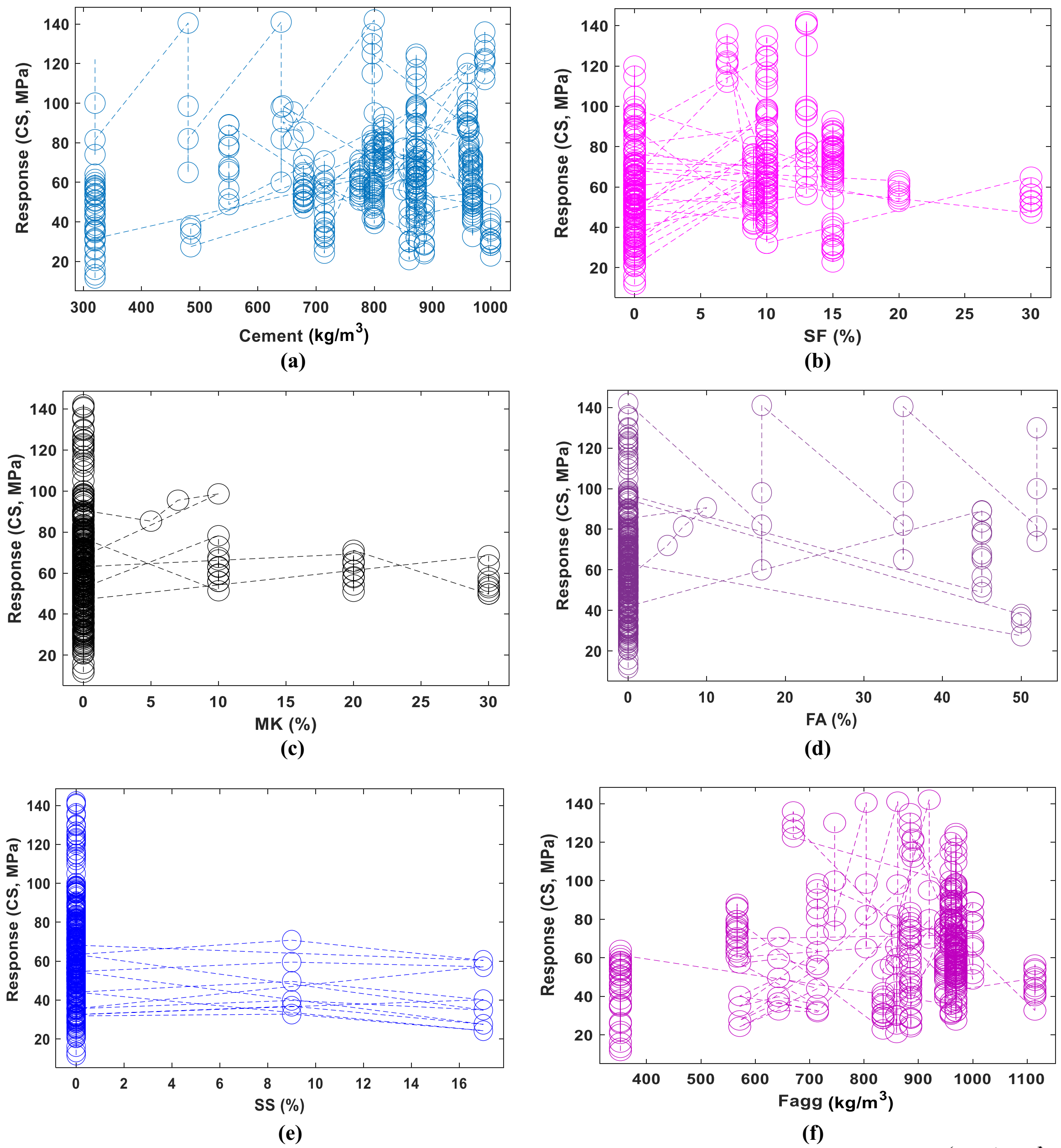


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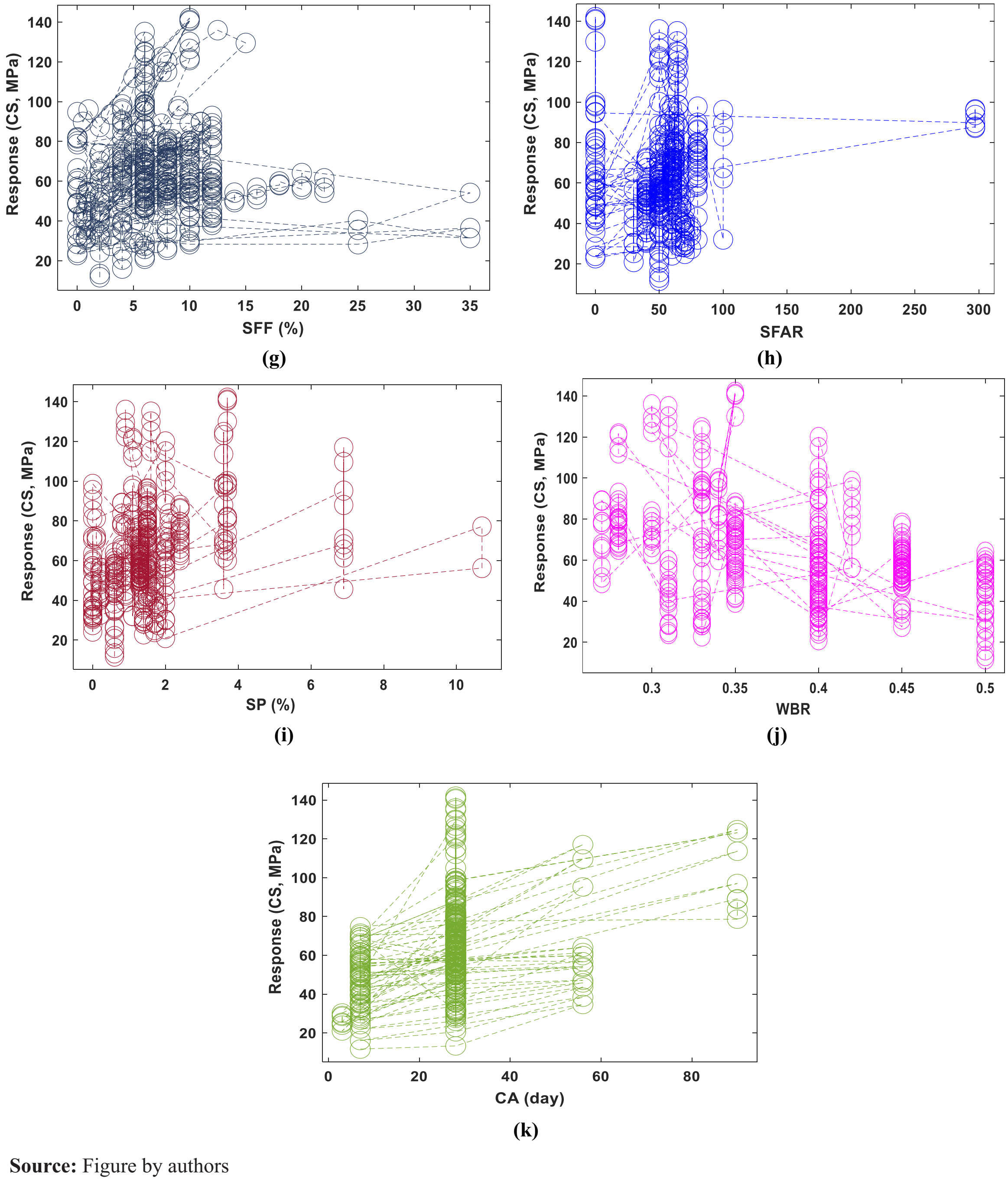
Figure 6



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tensile, flexural and impact strengths (Khamees *et al.*, 2020, 2021; Patil A.R, 2018). Steel fiber creates a strong bond that delays the formation of microcracks and the specimen's expansion, improving the tensile strength at the tensile region (Ali, 2018) and the compressive strength at the compression zone (Khamees *et al.*, 2020, 2021). However, the maximum levels of steel fiber and steel fiber aspect ratio in the SIFCON mix for the best compressive strength are shown in Figure 6(g) and (h): 10% SFF and 50%–60% SFAR. Beyond these, the SFF content and SFAR could cause a reduction in strength. The higher fraction of steel fiber results in the balling effect, where fibers stick together to create balls. Hence, providing a uniform distribution of fibers in the mold is impossible if the percentage of fibers is more than necessary (Patil A.R, 2018). In addition, longer fibers hinder the aggregates during compaction, which prevents the fibers from orienting properly (Patil A.R, 2018).

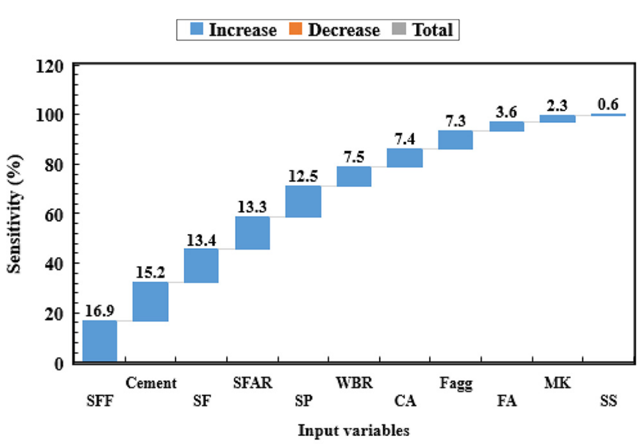
Superplasticizers are commonly used in producing SIFCON, which is strong, flowable and long-lasting. The superplasticizer dosage, as shown in Figure 6(i), improved the compressive strength of SIFCON. This can be attributable to the stimulation of the cement's hydration reaction, which displays high early strength characteristics. Some superplasticizers have a significant steric hindrance effect that can expedite cement hydration due to their ultra-long side chains, enhancing the contact area between cement particles and water, stimulating the calcium-silicate-hydrate formation and increasing the concrete's strength (Xun *et al.*, 2020). Nevertheless, the dosage that produced the best strength performance was 3.7% of the binder content. It is significant to note that while the percentage of SP fluctuates with the water-to-binder ratio and SF or pozzolan content, changes in these variables might likewise cause changes in compressive strength (Mashrei, 2018).

Findings from Figure 6(j) and (k), revealed that the compressive strength of SIFCON increased with reducing water-to-binder ratio and increasing curing age. These are consistent with similar studies (Ejiogu IK, 2018; Neville, 1995). The reasons could be that the SIFCON's hydration degree is complete under lowered W/C and the hydration products, such as C-A-H and C-S-H, are sufficient (Chen *et al.*, 2021). Less gel/space ratio results from cured concrete having larger pores due to higher free water content in the fresh concrete mix (Neville, 1995). In addition, the compressive strength of SIFCON increased due to the cement hydration with increasing curing age (Neville, 1995). At long-term curing ages, dicalcium silicate (C_2S) is produced during the cement hydration process (Mohseni pour asl *et al.*, 2022; Pachideh *et al.*, 2019; Toufigh and Pachideh, 2022). This product forms denser C-S-H and less $Ca(OH)_2$ as it slowly hydrates and produces less heat of hydration (Ejiogu IK, 2018). Ultimately, this study avails the effects of independent parameters on the strength performance of SIFCON. This will help design the appropriate SIFCON's mix proportions.

3.2 Sensitivity analysis

Figure 7 shows the effects of the input variables on the output variable (CS) in order of their importance. When an input variable is positive, the output variable also increases. Negative values indicate a decrease in the output variable with an increase in the input variable. The output variable does not change as the input variable changes when the value is near to zero. The results of all input variables, as indicated in Figure 7, revealed a positive value, demonstrating that an increase in output (CS) with increasing SFF, cement, SF, SFAR, SP, WBR, CA, Fagg, FA, MK and SS contents in the SIFCON mix. These outcomes support the patterns displayed in Figure 6. Figure 7 makes it abundantly evident that the compressive strength of SIFCON was significantly influenced by SFF, cement, SF, SFAR and SP with 16.90%, 15.20%, 13.40%, 13.30% and 12.50% order of importance. The partial replacement of fine aggregates with steel slag was the least significant factor, with a 0.6% impact. These results align with the outcome of the previous study, which noted that steel fiber fraction and steel fiber aspect ratio are part of the most important variables influencing the performance characteristics of SIFCON (Jerry and Fawzi, 2022). However, sensitivity analysis relies on the quantity of input variables and data points used to train the model. Besides, as ML techniques affect all factors, altering the quantities of the concrete mix and adding more input variables yields various outcomes. Ultimately, this study infers that the compressive strength of SIFCON incorporating FA, MK, SF and SS as SCMs is mostly influenced by SFF, cement, SFAR and SP.

Figure 7 Sensitivity analysis



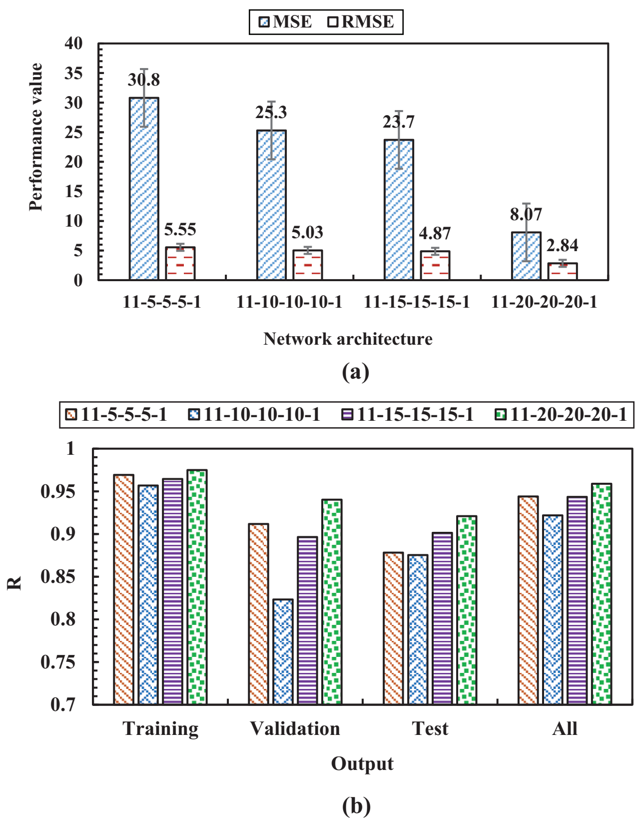
Source: Figure by authors

3.3 Performance metrics of machine learning techniques

3.3.1 Deep neural network

The outcomes of performance indicators (R, R^2, MSE and RMSE) for DNN are shown in Figure 8. As the number of neurons in each hidden layer increases, the findings, as illustrated in Figure 8, showed an increase in performance measures. These findings suggest that the LM backpropagation training technique's prediction of SIFCON's compressive strength learned best at 20 neurons in each hidden layer. The outcomes support a prior study that found that in comparison to 1–19 neurons, 20 neurons in each of the three hidden layers provided the greatest performance measures for predicting the compressive strength of the concrete (Oyebisi and Alomayri, 2023b). The explanations stem from the various layers' ability to generalize, enabling them to identify every feature between the input data and high-level classification (Uzair and Jamil, 2020). The MSE performance, as shown in Figure 8(a), revealed that the 11-20-20-20-1 network structure yielded 8.07 compared to 11-5-5-5-1, 11-10-10-10-1 and 11-15-15-15-1 network architectures having MSEs of 30.80, 25.30 and 23.70. Besides, the 11-20-20-20-1 network structure in Figure 8(b) yielded the best all-R (95.89%) compared to 11-5-5-5-1, 11-10-10-10-1 and 11-15-15-15-1 network structures with 94.40%, 92.18% and 94.35% R. Besides, Figure 10 is confirmed by the best validation performance displayed in Figure 9. The 11-5-5-5-1, 11-10-10-10-1, 11-15-15-15-1 and 11-20-20-20-1 network architectures, as indicated in Figure 9(a)–(d), yielded 109.75, 197.30, 138.84 and 89 best validation performances at epochs 36, 15, 8 and 14, respectively. From Figure 9, the 11-20-20-20-1 network architecture gave the best validation performance with the lowest MSE with 18.91%, 54.89% and 35.90% more than 11-5-5-5-1, 11-10-10-10-1 and 11-15-15-15-1 network structures.

Figure 8 Performance indicators



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3.3.2 Artificial neural network

The ANN metrics shown in Table 4 had comparable performance values with that of DNN algorithm. The results revealed an increase in performance measures with increasing number of neurons in the hidden layer. In contrast to 5, 10 and 20 neuron numbers, the optimal performance metrics were observed with a neuron count of 15. This suggested that the hidden layer's optimal number of neurons for LM backpropagation for predicting the SIFCON's compressive strength is 15. For the 11-15-1 ANN topology, the MSE and R results in Table 4 were closer to 0 and 1 than the values for 11-5-1, 11-10-1 and 11-20-1. The 11-15-1 architecture produced 44.02%, 70.45% and 47.45% less error-free for training data sets; 42.15%, 53.19% and 45.98% less error-free for validating data sets; and 47.83%, 42.54% and 27.07% less error-free for testing data sets in comparison to the 11-5-1, 11-10-1 and 11-20-1 structures. These results support previous research, which indicated that the training and testing stages of the ANN approach based on 131 data sets strongly suggest the potential use of a 25-10-1 network structure to forecast the 28-day tensile strength of concrete containing manufactured sand and fly ash, ground granulated blast furnace slag, silica fume and metakaolin (Mane *et al.*, 2019). In contrast to performance metrics with 5–14 neuron counts, the prediction of compressive strength of the wood ash-cement-nano TiO_2-based mortar indicated that a structure with 4-neuron count (7-4-1) was the best ANN structure (Raheem *et al.*, 2023). This can be attributable to the size of the data, the types and properties of constituent materials and the mixed design characteristics. In comparison to structures with 5, 10 and 20 neuron counts, this study infers that an 11-15-1 ANN structure is the most effective for forecasting the compressive strength of the SIFCON. Corroborating this assertion, Figure 10 illustrates the best validation performance for the ANN network structures. The 11-5-1, 11-10-1, 11-15-1 and 11-20-1 network structures, as displayed in Figure 10(a)–(d), exhibited 116.18, 94, 54.38 and 90.46 best validation performances at epochs 34, 14, 23 and 21, respectively. From Figure 10, the 11-15-1 network topology yielded the best validation performance with the lowest MSE with 53.19%, 42.15% and 39.89% more than 11-5-1, 11-10-1 and 11-20-1 network structures, respectively.

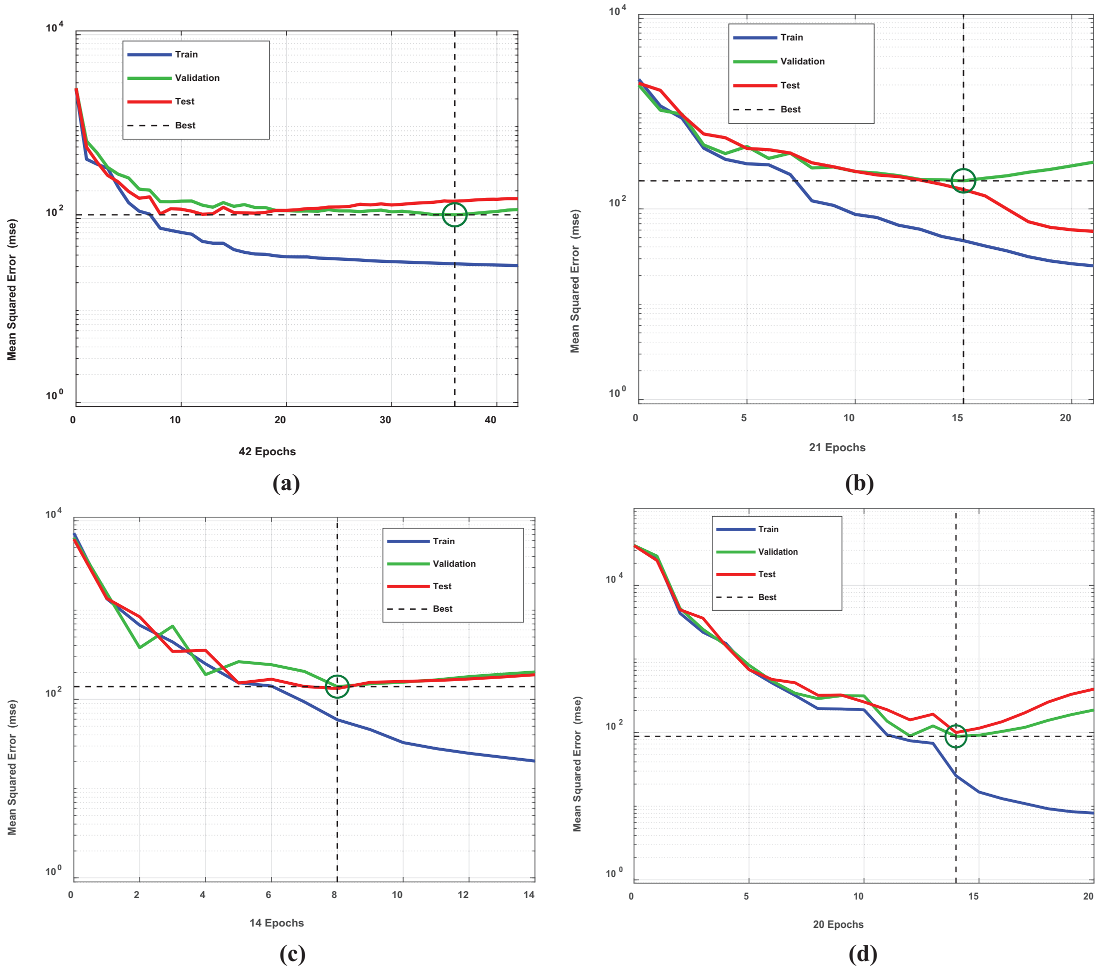
3.3.3 Other machine language methods

Performance metrics from regression learners are shown in Table 5. From the metric results shown in Table 5, GPR gave the best performance metrics with the lowest RMSE, MSE and MAE, and the highest R^2 for validating and testing the SIFCON's strength data set compared to other ML techniques. The range of results can be attributed to error scales, for which MAE provides a helpful generalization of the amount of mistakes. According to this, the effectiveness of various models' error handling is evaluated and compared using MAE (Willmott and Matsuura, 2005). Consequently, GPR was 47.42%, 21.84%, 26.94%, 30.14% and 22.04% error-free for validating the strength data and 80.81%, 55.05%, 55.81%, 70.56% and 28.18% error-free for testing the strength data compared to LR, RT, SVM, ET and NN. A previous study found that NN outperformed LR, RT, SVM, ET and GPR for testing the data set, but that LR approach is more accurate for validating alpha and gamma rays from agricultural byproducts (Oyebisi and Alomayri, 2023a). This could indicate that there is a nonlinear relationship between the SIFCON's input and output variables (CS). Hence, Figure 11 supports Table 5's findings, showing that datapoints for GPR were more closely aligned with the regression line than those for other ML approaches.

3.4 Regression outputs

Figure 12 shows the best regression outputs for each ML algorithm: 11-20-20-20-1 network architecture for DNN, 11-15-1 network topology for ANN and GPR for regression learner. For training, validation and test, the DNN (11-20-20-20-1) topology in Figure 12(a) yielded the strong correlation coefficients of 97.50%, 94.02% and 92.09%. These findings are consistent with a relevant study that found that, with correlation coefficients of 99.99% for training, 99.53% for validation and 98.91% for test, the 10-20-20-20-1 DNN structure provided the best performance metrics for forecasting the compressive strength of geopolymer concrete modified with corn cob ash compared to DNN architectures with 2–19 number of neurons in each of the three hidden layers (Oyebisi and Alomayri, 2023b). Similarly, ANN (11-15-1) structure in Figure 12(b) gave 97.89%, 95.88% and 93.04% for training, validating and testing the data set of SIFCON's compressive strength. These results are in line with previous studies, where the use of ANN in forecasting

Figure 9 Best validation performance for (a) 11-5-5-5-1, (b) 11-10-10-10-1, (c) 11-15-15-15-1 and (d) 11-20-20-20-1 DNN network structures



Source: Figure by authors

Table 4 Performance metrics of ANN technique

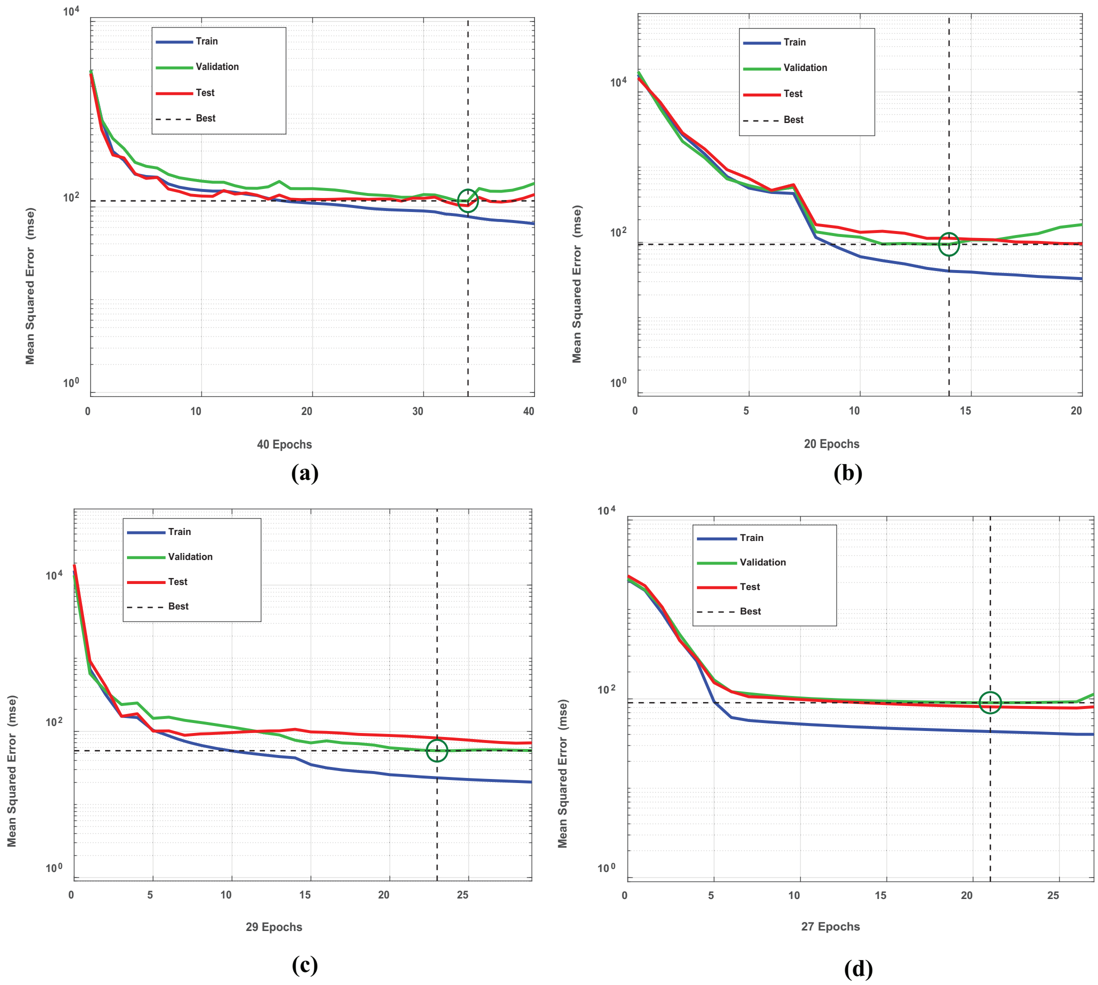
Structure	Training				Validation				Test			
	MSE	RMSE	R	R^2	MSE	RMSE	R	R^2	MSE	RMSE	R	R^2
11-5-1	41.37	6.43	0.9617	0.9807	94	9.70	0.9242	0.9614	113.50	10.65	0.9157	0.9569
11-10-1	78.38	8.85	0.9280	0.9633	116.18	10.78	0.9128	0.9554	103.02	10.15	0.8954	0.9463
11-15-1	23.16	4.81	0.9789	0.9894	54.38	7.37	0.9588	0.9792	59.21	7.69	0.9304	0.9646
11-20-1	44.07	6.64	0.9603	0.9799	100.67	10.03	0.9359	0.9674	81.19	9.01	0.9349	0.9669

Source: Table by authors

the mechanical properties of SIFCON (CS, FS and TS) exhibited good correlation between the predicted and actual values (Gottapu Santosh Kumar, 2018; Reddy, 2018). Finally, the correlation coefficient for GPR in Figure 12(c) yielded 99.13%.

Numbers of input and output data are not sufficient to determine an effective network topology. In reality, a sufficient number of hidden layers can effectively reduce training times while maintaining accuracy. The optimal number of hidden layers for neural networks can be standardized using a variety of techniques, however, the estimate varies depending on the kind of database (Gupta and Raza, 2020; Saurabh Karsoliya, 2012). Furthermore, factors such as the quantity of input and output numbers, the number of training cases, the level of noise in the targets, the intricacy of the function or classification that needs to be learned, the architecture of the ML technique, activation function and type and the training algorithm, affect the optimal number of hidden units (Panchal *et al.*, 2011). In light of this, a comparison of the study's overall top-performing ML technique was conducted. The results of Figure 8 (DNN),

Figure 10 Best validation performance for (a) 11-5-1, (b) 11-10-1, (c) 11-15-1 and (d) 11-20-1 ANN network structures



Source: Figure by authors

Table 5 Performance indicators for other ML approaches

ML algorithm	Training/validation RMSE	R^2	MSE	MAE	Test RMSE	R^2	MSE	MAE
LR (stepwise)	15.94	0.56	254.13	11.64	14.91	0.61	222.12	10.89
RT (fine)	10.78	0.80	116.11	7.83	6.22	0.93	38.67	4.65
SVM (fine Gaussian)	13.73	0.67	188.38	8.48	8.26	0.88	68.26	4.73
ET (boosted)	12.45	0.73	154.95	8.76	10.12	0.82	102.43	7.10
GPR (exponential)	9.24	0.85	85.45	6.12	3.22	0.98	10.38	2.09
NN (medium)	12.99	0.71	168.78	7.85	4.27	0.97	18.22	2.91

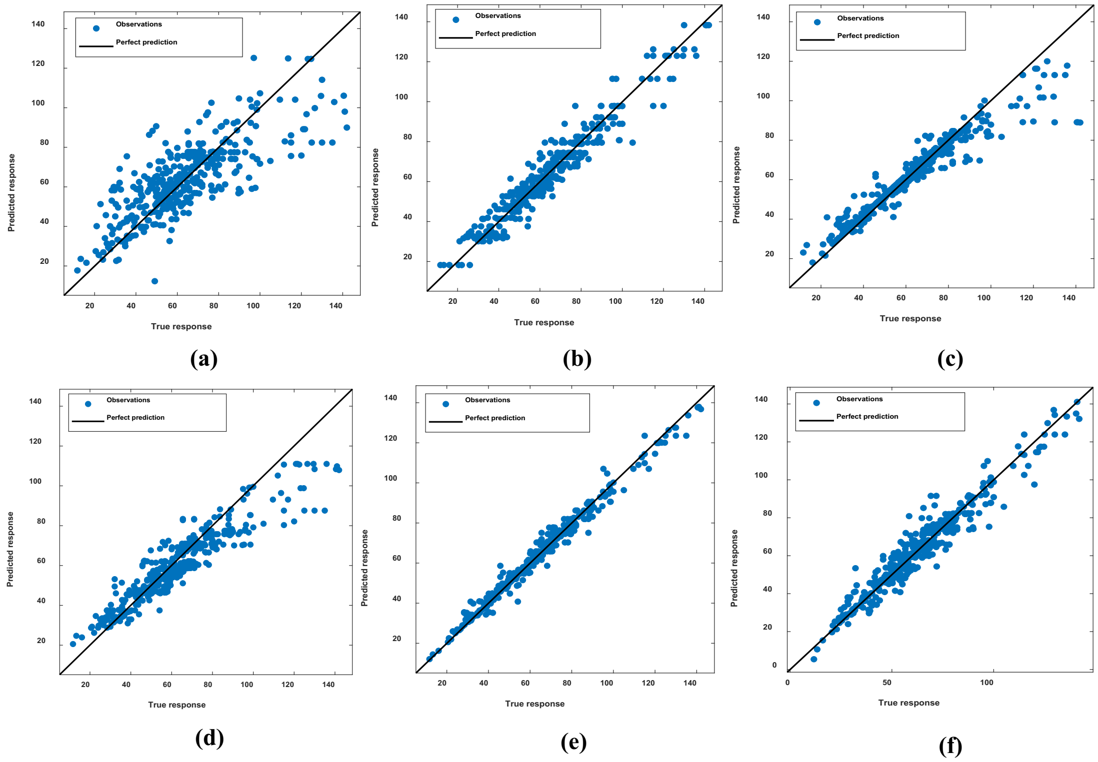
Source: Table by authors

Table 4 (ANN) and Table 5 (GPR) clearly show that the DNN (11-20-20-20-1) structure produced the best performance indicators for training, validation and testing. This is followed by an 11-15-1 ANN topology, and lastly, the GPR. The effectiveness of DNN can be ascribed to its capacity to capture intricate and nonlinear relationships, learn from raw data with little preprocessing and scale well with large and varied data sets. Ultimately, the prediction of SIFCON's compressive strength was learned best with the LM backpropagation training algorithm at a three-hidden layer network with 20 neurons in each hidden layer.

3.5 Validation of developed model

Validating any developed model's precision and accuracy with untrained data sets is crucial. In light of this, the 11-20-20-20-1 DNN, which produced the best network structure for

Figure 11 Predicted vs actual response for (a) LR, (b) RT, (c) SVM, (d) ET, (e) GPR and (f) NN



Source: Figure by authors

predicting CS of SIFCON, was validated using the untrained data sets obtained from the experimental test results (Aliyaa M. Alsheameri, 2023; Nadia Moneem Al-Abdalay, 2020). Details regarding the untrained data sets are shown in Table 6, along with projected values, absolute errors (AB) and relative errors (RE) arising from the relationship between the forecast and true of SIFCON's compressive strength. According to Table 6's validation, SIFCON's projected CS fell between −9.22% and 12.84% of the outcomes of the experimental tests. These corroborate pertinent literature in that the predicted values for the slag-ash geopolymer concrete's compressive strength fell between +15.22 and −7.83 for confirming the developed 10-20-20-20-1 DNN structure (Oyebisi and Alomayri, 2023b). In a different study, the model constructed was validated by the anticipated values of compressive strength of fly ash-based geopolymer concrete, which produced results of +15% and −10% of the experimental test findings (Ahmed *et al.*, 2022). As seen in Figure 13, the relationship between the experimental and predicted compressive strengths of SIFCON based on the validity of the 11-20-20-20-1 DNN structure demonstrated a strong correlation due to the 98.05% R^2. Ultimately, findings from Figure 13 confirm that the 11-20-20-20-1 DNN structure is precise and accurate in forecasting the SIFCON' CS.

4. Conclusions

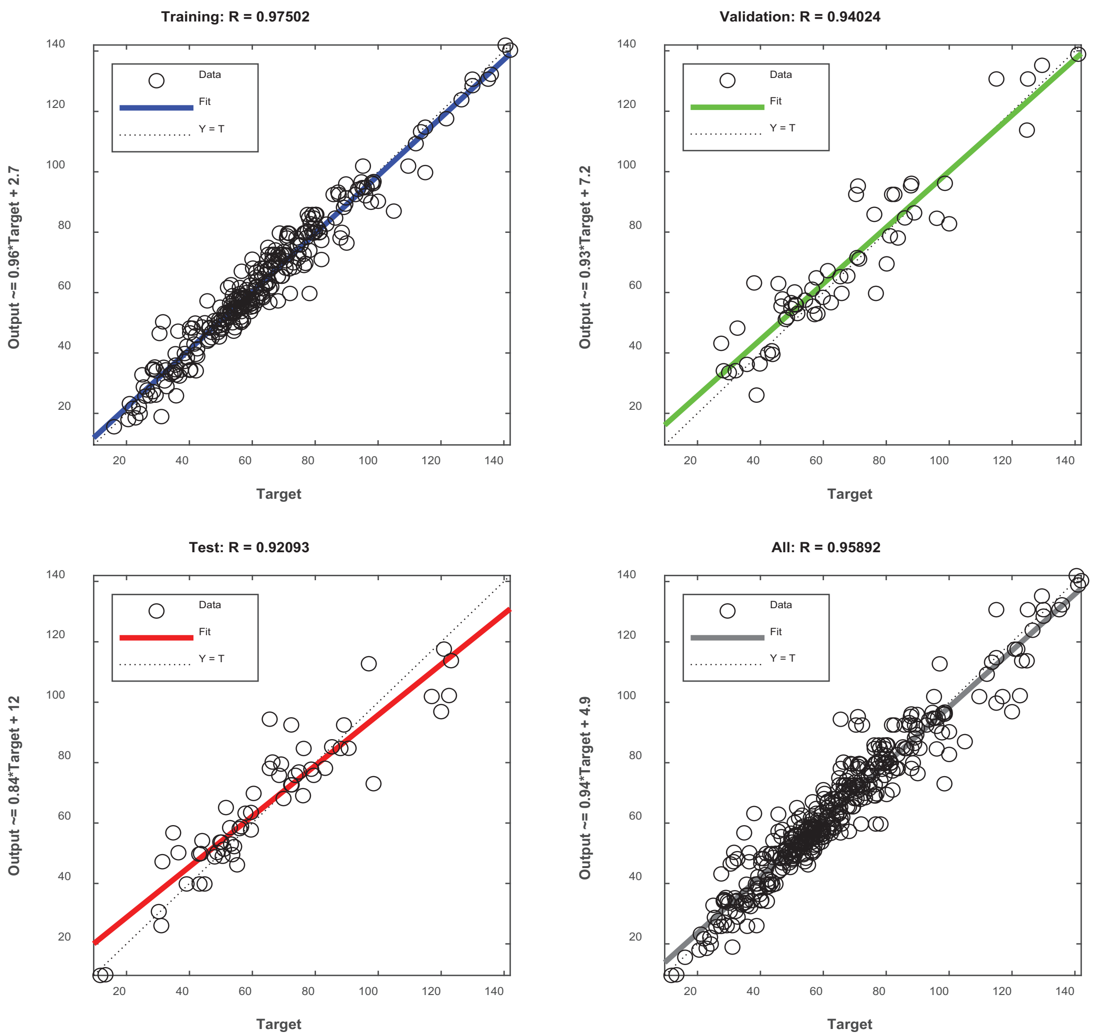
This study used the supervised ML techniques of AI to predict the compressive strength of SIFCON through DNN, ANN, LR, RT, SVM, ET, GPR and NN. A comprehensive data set comprising 387 samples was collected from pertinent research. The output (CS) was trained along with 11 input variables such as cement, SF, FA, MK, SS, Fagg, SFF, SFAR, SP, WBR and CA. The impact of each input variable on SIFCON's CS was assessed using sensitivity analysis. The following inferences can be made from the results obtained:

- All input variables had a beneficial effect on the compressive strength of SIFCON; however, SFF provided the highest value with an impact factor of almost 17%.
- The 11-20-20-20-1 DNN topology exhibited the best performance measures for forecasting the SIFCON' CS with 73.80%, 68.10% and 65.87% more error-free than 11-5-5-5-1, 11-10-10-10-1 and 11-15-15-15-1 network architectures.
- An 11-15-1 ANN structure produced the best performance metrics for predicting the SIFCON' CS with about 45%–71%, 43%–54% and 28%–48% more error-free than 11-5-1, 11-10-1 and 11-20-1 network architectures.
- In comparison to LR, RT, SVM, ET and NN, which yielded about 8–12 and 3–11 MAE values for validating and testing data sets, GPR produced the best performance metrics, with MAE values of 6 and 2 for validating and testing data sets.
- Strong correlations between the input and output variables were found in the regression outputs, with correlation coefficients of about 95.89%, 96.77% and 99.13% for DNN, ANN and GPR, respectively.
- The 11-20-20-20-1 DNN structure outperformed ANN and GPR in terms of performance measures when it came to forecasting the SIFCON's CS.

- There was a good correlation (98.05% R^2) between the predicted and experimental values, confirming the validity and accuracy of the generated model (11-20-20-20-1 DNN structure).

This study offers theoretical and practical guidance for optimizing SIFCON mix proportions. The engagement of AI in strength prediction saves time and increases efficiency. These methods will make it simpler to formulate and use

Figure 12 Best regression outputs for (a) DNN, (b) ANN and (c) GPR



(a)

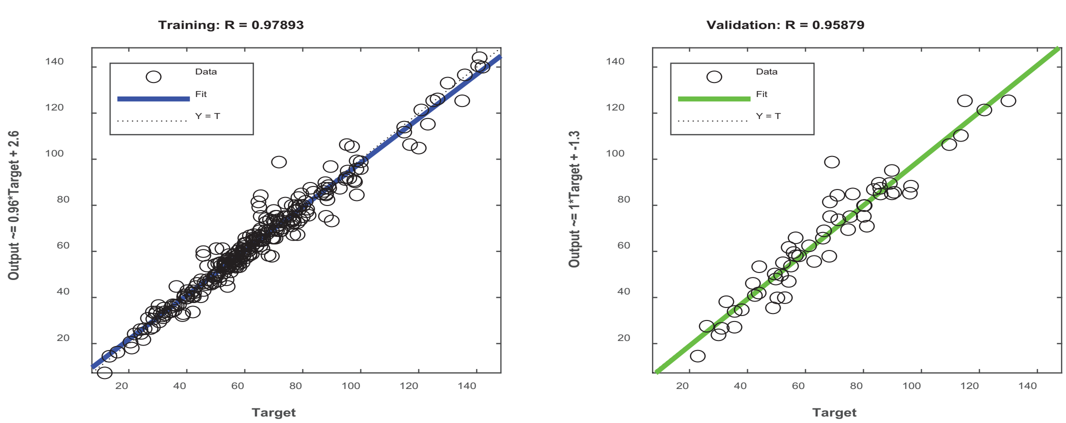


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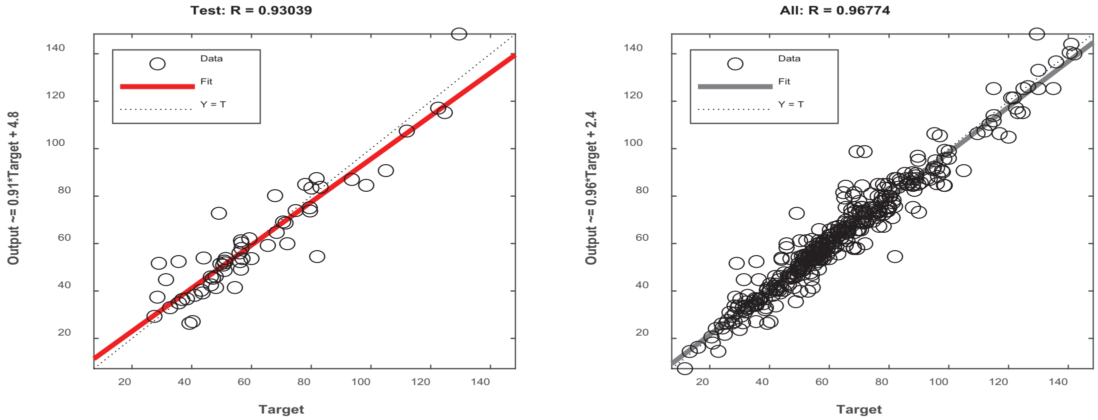
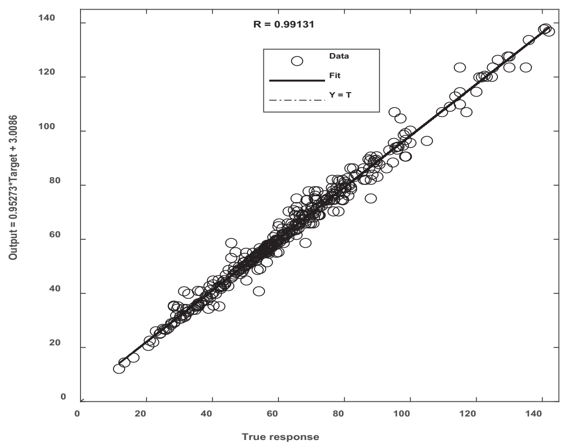
Figure 12



(b)



(c)

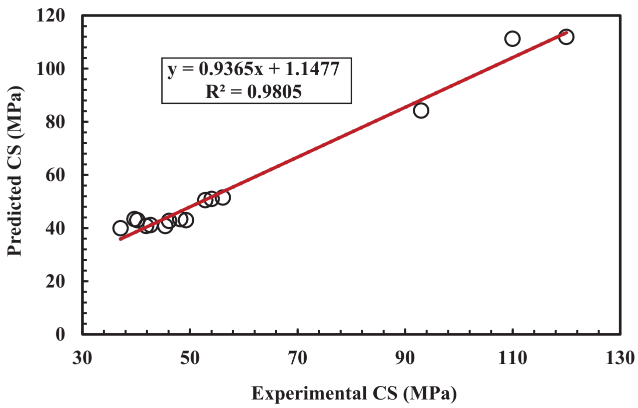
Notes: (a) 11-20-20-20-1-DNN network architecture; (b) 11-15-1 ANN network topology; (c) GPR technique
Source: Figure by authors

Table 6 Statistics of untrained data sets from experimental test results

Cement (kg/m^3)	SF (%)	MK (%)	FA (%)	SS (%)	Fagg (kg/m^3)	SFF (%)	SFAR	SP (%)	WBR	CA (day)	Exp. CS (MPa)	Pred. CS (MPa)	AB (MPa)	RE (%)
875.70	10	0	0	0	973	6	65	2.40	0.28	28	93	84.20	8.80	9.46
775.20	10	0	10	0	969	6	65	2.00	0.30	28	110	111	−1.23	−1.12
775.20	10	0	10	0	969	6	65	2.00	0.30	90	120	112	8.08	6.73
960	0	0	0	0	960	6	50	1.50	0.45	28	52.86	50.48	2.38	4.50
864	0	0	10	0	960	6	50	1.50	0.45	28	46.13	42.66	3.47	7.52
768	0	0	20	0	960	6	50	1.50	0.45	28	42.67	41.12	1.55	3.63
672	0	0	30	0	960	6	50	1.50	0.45	28	37.10	39.94	−2.84	−7.65
960	0	0	0	0	960	8	50	1.50	0.45	28	54.04	50.95	3.09	5.72
864	0	0	10	0	960	8	50	1.50	0.45	28	49.28	42.95	6.33	12.84
768	0	0	20	0	960	8	50	1.50	0.45	28	41.86	40.80	1.06	2.53
672	0	0	30	0	960	8	50	1.50	0.45	28	40.23	42.97	−2.74	−6.81
960	0	0	0	0	960	10	50	1.50	0.45	28	56.12	51.46	4.66	8.30
864	0	0	10	0	960	10	50	1.50	0.45	28	48.20	43.37	4.83	10.02
768	0	0	20	0	960	10	50	1.50	0.45	28	45.42	40.76	4.66	10.26
672	0	0	30	0	960	10	50	1.50	0.45	28	39.70	43.36	−3.66	−9.22

Source: Table by authors

Figure 13 Correlation between the predicted CS and experimental CS of 11-20-20-20-1 DNN validation



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SIFCON, which uses various binding ingredients, such as steel slag, fly ash, metakaolin and silica fume. Notwithstanding these benefits, other AI techniques and a larger data set with information on the properties of the SIFCON's compressive strength should be used to improve the models' performance. The following binding materials can be included as input parameters: powdered marble and granite waste, ground granulated blast furnace slag and rice husk ash. In addition, the effects of cement, SF, FA, MK, Fagg, SFF, SFAR, SP, WBR ratio and CA on the tensile strength, ductility and durability of SIFCON can be considered for future studies.

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