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Analysis of Different Deep Learning Networks for Estimating the Tensile Strength of Self-Compacting Concrete Containing Recycled Aggregates

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ABSTRACT

The composition of self-compacting concrete (SCC) contains 60–70% coarse and fine aggregates, which are replaced by construction waste, such as recycled aggregates (RA). However, the complexity of its structure requires a time-consuming mixed design. In order to solve this problem this writing evaluates and contrasts the performance of various deep learning models (Levenberg–Marquardt (LM), Bayesian regularization (BR), and Scaled Conjugate Gradient Backpropagation (SCGB) in predicting the tensile strength of SCC incorporating RA. Experimental data sourced from existing literature were used to create test, training, and validation sets. A range of artificial intelligence models and optimization algorithms were explored to train these networks, with adjustments made to their architectures and parameters. The models were assessed using the mean squared error (MSE) and the correlation coefficient (R). The results demonstrated that all three models achieved optimal accuracy; however, the BR model outperformed the others, with an R value of 0.91 and an MSE of 0.2087, surpassing the performance of LM and SCG. Thus, BR was identified as the most effective model for predicting the tensile strength (TS) of SCC with RA at 28 days. The results revealed patterns that offer valuable insights into the relative efficacy of the models, advancing the understanding of how deep learning can be applied to predict concrete properties. This study serves as a strong reference point for researchers and building industry professionals.

1. Introduction

Concrete most influential mechanical property is the tensile strength (TS), critically impacting its performance in structural applications. Moreover, this becomes more critical in the case of self-compacting concretes (SCC) with recycled aggregates (RA). Accurate prediction of this property is essential for ensuring the safety and durability of structures built with this innovative material. SCC

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is regarded as innovative due to its (1) ease of use in confined spaces where concrete placement is challenging, (2) reduction of noise pollution, and (3) enhanced fillability and construction speed [1-3]. In recent years, deep learning (DL) models have been applied to predict the TS of RA-SCC, leveraging their capacity to identify specific features, extract complex patterns, and learn nonlinear relationships from large datasets. However, few studies have focused explicitly on using DL techniques to predict the TS of SCC with RA. This research aims to compare various deep learning models to identify the most effective approach for calculating the TS of RA-SCC using artificial neural networks (ANN), before this concrete were made, only knowing the mix that will be used.

1.1 Hypothesis

Deep learning models, such as ANN, can predict the TS of SCC with RA with greater accuracy than traditional methods. Furthermore, optimizing specific architectures and parameters is anticipated to enhance the performance and robustness of deep learning models in this context.

2. Methodology

2.1 Data collection

The data were gathered from a range of research papers. Table 1 presents 381 different concrete mixes that encompass the TS of SCC with RA, utilizing various variables such as water (W), cement (C), admixtures (A), coarse aggregates (CA), fine aggregates (FA), and superplasticizer (SP). The database incorporates reference numbers for the total number of research articles, author citations, the amount of data provided for each article (#data), and the percentage of the overall dataset (%data).

Table 1
Description of data collected

No	Reference	mixture	% data	No	Reference	mixture	% data
1	Ali and Al-Tersawy [4]	18	4.73	22	Nieto *et al.,* [5]	22	5.78
2	Aslani *et al.,* [6]	15	3.94	23	Nili *et al.,* [7]	10	2.63
3	Babalola *et al.,* [8]	14	3.68	24	Pan *et al.,* [9]	6	1.57
4	Bahrami *et al.,* [10]	10	2.63	25	Revathi *et al.,* [11]	5	1.31
5	Behera *et al.,* [12]	6	1.57	26	Revilla-Cuesta *et al.,* [13]	5	1.31
6	Chakkamalayath *et al.,* [14]	6	1.57	27	Sadeghi-Nik *et al.,* [15]	12	3.15
7	Duan *et al.,* [16]	10	2.63	28	Señas *et al.,* [17]	6	1.57
8	Fiol *et al.,* [18]	12	2.33	29	Sharifi *et al.,* [19]	6	1.57
9	Gesoglu *et al.,* [20]	24	6.3	30	Sherif and Ali [21]	15	3.94
10	Grdic *et al.,* [22]	3	0.79	31	Silva *et al.,* [23]	5	1.31
11	Güneyisi *et al.,* [24]	5	1.31	32	Singh *et al.,* [25]	12	3.15
12	Guo *et al.,* [26]	11	2.89	33	Sun *et al.,* [27]	10	2.63
13	Katar *et al.,* [28]	4	1.05	34	Surendar *et al.,* [29]	7	1.84
14	Khodair *et al.,* [30]	20	5.25	35	Tang *et al.,* [31]	5	1.31
15	Kou & Poon [32]	13	3.41	36	Thomas *et al.,* [33]	4	1.05
16	Krishna *et al.,* [34]	5	1.31	37	Tuyan *et al.,* [35]	12	3.15
17	Kumar *et al.,* [36]	4	1.05	38	Uygunoğlu *et al.,* [37]	8	2.10
18	Long *et al.,* [38]	4	1.05	39	Wang *et al.,* [39]	5	1.31
19	Mahakavi and Chithra [40]	25	6.56	40	Yu *et al.,* [41]	3	0.79
20	Manziz [42]	4	1.05	41	Zhou *et al.,* [43]	6	1.57
21	Martínez-García *et al.,* [44]	4	1.05		Total	381	100

Table 2 displays the statistical characteristics, including minimum, maximum, mean, median, mode, and standard deviation, of specific input variables (W, C, A, CA, W, FA and SP). These variables were utilized to model the TS of SCC with RA using DL techniques.

Table 2
Minimum, mean and maximum values of input and output variables

Variables		Abbreviation	Minimum	Mean	Maximum
Input	Cement	C	78.00	368.73	550.00
	Additives	A	0.00	138.27	515.00
	Water	W	45.50	167.29	246.00
	Fine aggregates	FA	532.20	844.71	1200.00
	Coarse aggregates	CA	328.00	196.05	1170.00
	Superplasticizers	SP	0.00	5.07	16.00
Output	Tensile strength	TS	0.96	3.52	7.20

2.2 Data visualization

Relationships among the input characteristics (independent variables), which will be the different components of the concrete (C, W, FA, CA, SP), and the output variable, TS of SCC with RA, were analyzed to assess the relationships among the different characteristics. This statistical evaluation aids in optimizing predictive models [45] by enhancing the accuracy of predictions. To achieve this, a Pearson correlation matrix was constructed to examine the correlations between the independent variables. Notably, none of the correlations exceeded 0.80, indicating the absence of multicollinearity [46,47].

Table 3
Division of the data for model testing

Step	Percentage %	No. of samples
Levenberg-Marquardt Algorithm (LM)		
Training	60	229
Validation	10	38
Test	30	114
Total	100	381
Bayesian Regularization (BR)		
Training	70	267
Validation	-	0
Test	30	114
Total	100	381
Back propagation scaled conjugate gradient (SCGB)		
Training	60	229
Validation	10	38
Test	30	114
Total	100	381

2.3 Artificial Neural Networks (ANNs)

DL is a subgroup of machine learning (ML) that enables the calculation of multilayer neural networks. The primary distinction between ML and DL lies in their approaches to feature extraction and classification: DL performs both tasks automatically, while in ML, feature extraction must be conducted separately, with the machine handling classification and prediction [48].

Artificial neural networks (ANNs) are mathematical or computational models inspired by the complex biological neural networks of the human brain [49]. They are utilized to process information and execute machine learning tasks, particularly in artificial intelligence applications that tackle problems of greater complexity [50]. Each ANN operates using its own specific algorithm tailored to its type. In the context of this article, three algorithms were analyzed and compared: LM, BR, and SCGB

2.3.1 Levenbert-Marquardt Algorithm

This algorithm serves as a training method for ANNs, providing information and control before an event occurs. It consists of a series of iterations designed to locate the minimum of a multivariate function represented as the sum of squares of nonlinear real-valued functions [51,52]. Although this approach generally demands greater memory resources, it usually results in faster implementation times.

2.3.2 Bayesian Regularization

BR is a technique for training neural networks that mitigates overfitting by incorporating probability distributions into the model parameters. Bayesian regularized artificial neural networks (BRANNs) can reduce or even eliminate the need for extensive cross-validation [53].

2.3.3 Conjugate scaled gradient of back propagation

This algorithm is employed to train type-independent neural networks, optimizing weights and biases. It integrates the conjugate gradient method with error backpropagation to enhance both efficiency and convergence speed in the DL process [54]. During each iteration, the design parameters are updated independently, a crucial factor for the algorithm's success. This feature represents a significant advantage of line search-based algorithms [55].

2.4 Model validation
2.4.1 Division of the data set

The network was organized into three distinct phases: training, validation, and testing. During the training phase, 10 neurons were selected for the hidden layer. The data were randomly allocated according to predetermined percentages, with 60% designated for training, 10% for validation, and 30% for testing. This allocation resulted in 229 examples for training, 38 examples for validation, and 114 examples for testing. Since BR (BR) does not necessitate a validation phase, the number of samples used for training and testing was adjusted to 267 and 114, respectively. This adjustment is due to the fact that validation typically serves as a form of regularization, while the BR algorithm incorporates its own validation mechanism.

2.5 Model evaluation

Training, validation, and testing are the three essential phases of artificial neural networks (ANNs). During the training phase, the model undergoes multiple iterations until the desired outcomes are achieved. Errors identified in the validation phase are detected during training [56]. ANNs typically consist of multiple layers, including an input/output layer that contains the input and output data. Depending on the architecture, there may be one or more hidden layers between these layers, composed of neurons interconnected by weights. The output of each neuron is determined by its activation function, which can take various forms. Nonlinear activation functions, such as sigmoid and step functions, are frequently employed [57].

The initial step in constructing an ANN model is selecting the most suitable architecture. Subsequently, data are entered into the chosen model, specifying the inputs and outputs. Finally, the activation function, the number of layers, the number of hidden layers, and the number of neurons in each hidden layer must be selected empirically [58,59]. In this study, a feedforward backpropagation neural network was utilized, and three algorithms—LM, BR, and SCGB—were employed and compared. The design and execution of the network were performed using MATLAB software.

The LMalgorithm generally requires more memory but takes less time for training. Training concludes when generalization ceases to improve, indicated by an increase in the mean square error of the validation samples. In contrast, BR, while slower, offers robust generalization capabilities for complex, small, or noisy datasets. Adaptive weight reduction facilitates the completion of training (regularization). Conversely, the SCGB Gradient backpropagation algorithm utilizes less memory than the LM algorithm. Training automatically terminates when generalization stops improving, as evidenced by an increase in the mean square error of the validation samples [58,60-62].

Using the ANN tool for neural network development, the performance of the models was assessed through two metrics: the Correlation Coefficient (R) and Mean Squared Error (MSE) [63,64] Regression serves as a key evaluation metric for assessing the accuracy of the overall network. The correlation between the actual outputs and the predicted targets was quantified using R-values, where an R of 1 indicates a strong relationship, while an R of 0 signifies a random relationship [65,66]. The Mean Squared Error represents the average squared difference between the actual results and the estimated values, with lower values indicating better performance; a value of zero indicates no error.

3. Results and Discussion

The model has been implemented using three algorithms as a basis: LM, BR and SCGB independently and then their results were compared and analyzed.

3.1 Levenberg-Marquardt algorithm

The network was trained repeatedly to identify the most suitable model, utilizing 10 neurons for performance evaluation. This process generated lines of varying colors representing training, validation, and testing phases. The performance criteria results indicate that the model is effective in predicting the TS of SCC with RA.

3.2 Bayesian Regularization

BR approach, the model was trained with an equal number of neurons, acknowledging that this algorithm incorporates a built-in validation mechanism during the training process. The results for R and MSE performance parameters for both the training and testing phases indicate that the model trained with BR demonstrates excellent accuracy in predicting the TS of SCC with RA.

3.3 Conjugate Gradient Scaled of back propagation

Training the model using this algorithm with 10 neurons revealed its performance, yielding an overall R-value of 0.64. This indicates that the correlation deviates significantly from a linear fit, confirming that the model's predictive ability for the TS of SCC with RA is below average. The results of the performance parameters, including the R-value MSE for the overall model, as well as for training, validation, and testing, suggest that SCGB backpropagation is a less effective algorithm compared to LM and BR for predicting the TS of recycled aggregate SCC

3.4 Comparison of the results of the LR, BR and SCGB approaches

Comparisons between the three algorithms were conducted by evaluating the experimental outcome against the ANN-predicted values. Figure 1 demonstrates that the quantities predicted for the TS values by all three algorithms show a good correlation with the experimental data. However, larger deviations between the two lines indicate a greater error between predicted and actual results. Figure 2 presents the total R-values and root mean square for the three algorithms. The BR approach outperformed the others, particularly when dealing with data heterogeneity, as it allows for strong generalization in complex datasets [68]. Overall, BR emerged as the most accurate algorithm, with a predictive accuracy exceeding 90% for the TS of SCC with RA, outperforming both LM and SCGB.

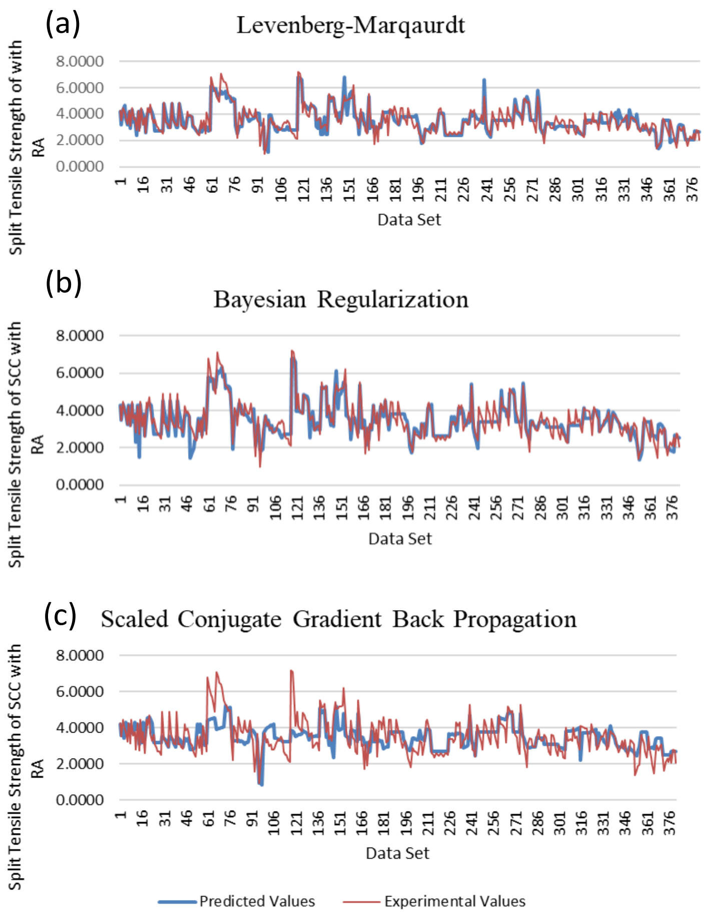

Fig.1. Comparison of experimental and predicted values for the ANN algorithms: LM, BR, and SCGB

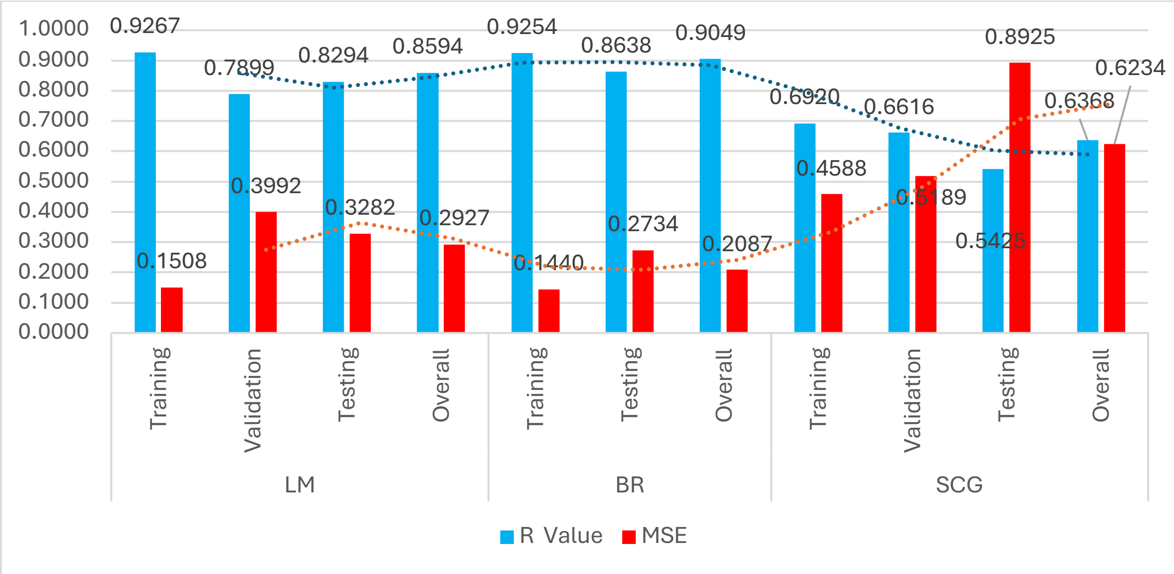

Fig. 2. R and MSE of the LM, BR and SCGB algorithm

3.5 Sensitivity analysis

C (30.07%), FA (22.83%), and A (22.08%) were the primary contributors to the TS of SCC with RA. Shang *et al.,* [67] emphasize that C is a crucial factor in predicting TS for SCC with RA. The enter variables of SP and CA contributed 9.61% and 13.02% respectively, to the TS evaluation (Figure 3). In contrast, W had the least influence on predicting TS for SCC with RA, contributing only 2.39%, a result that aligns with previous studies [67].

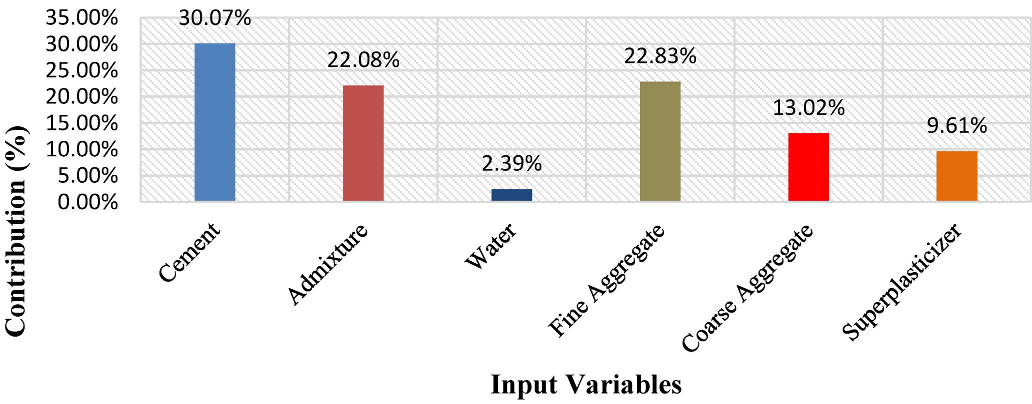

Fig. 3. Contribution of input variables to the slit TS of SCC with RA in the BR approach

4. Conclusion

For the training of the LM, BR, and SCGB models, 381 samples were collected from scientific journals and arbitrarily divided into 60% for training (267 samples), 10% for validation (38 samples), and 30% for testing (114 samples). However, to make the BR algorithm work, the samples were split into 30% for testing and 70% for training, as validation is integrated into the training phase. The overall accuracy of each algorithm after training and testing was 85% for LM, 91% for BR, and 64% for SCGB, with MSE values of 0.2927, 0.2087, and 0.6234, respectively. The SCGB algorithm had the lowest R-value and the highest MSE, indicating it was a poor model for predicting the TS of

SCC with RA. BR, on the other hand, achieved the lowest MSE (0.2087) compared to LM and SCGB, and its correlation coefficient (R = 90%) demonstrated that it is a strong model, suitable for predicting the 28-day TS of SCC with RA. Sensitivity analysis revealed that cement (30.07%) was the most significant input variable in predicting the 28-day TS of SCC with RA, while water had the least influence (2.39%).

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