Predictive Capabilities of Multilayer Perceptron (MLP) in WEKA Algorithm for High Strength Concrete with Steel Fiber Addition

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Abstract

In this study, a neural network based model available in Weka Algorithms, was utilized to test the predictive capacity of compressive strength in high strength concrete (HSC) with steel fiber addition. Fiber addition levels ranged from 0.19 – 2.0% were utilized obtained from literature with a total of 192 instances (datasets) and 10 attributes. To test the performance of the algorithm, a 10 – fold cross-validation method was used to assess the effectiveness which was later compared with full training sets. Also, seven learning schemes were utilized to determine the optimum using percentage split. Results generated from the model include correlation coefficient, mean absolute error, root mean squared error, and relative absolute error. It was observed a good correlation coefficient was obtained which was close to unity at 70-30 and 80-20% of training to testing, and significant reduction in the associated errors were observed. Results for coefficient of determination are also presented and follow the same trend observed in the percentage split results. Time taken to generate the model was much shorter an indication of efficiency.

1. Introduction

Optimization of concrete mix constituents now feature prominently in concrete making process, and a considerable effort has been placed in other to perfect the process so as to obtain the best mixture available using minimum resources at the disposal of the designer [1-4].

Trial mix of a proportioned mix involves testing a particular response. However, this does not stop there, engineers now use mathematical models to predict a particular response to validate the performance of the prediction by using linear regression, neural networks (NN), or support vector regression (SVR). This is done because the relationship that exists between attributes and concrete properties is highly nonlinear [5].

In neural networks, the network is created and trained at the first step and validated with new input variables. The key advantages of neural networks are that it has the ability to learn, recognize, generalize, classify, and interpret incomplete and noisy inputs to represent both linear and nonlinear relationships with great accuracy [6]. Artificial neural networks (ANN) has been successfully used to predict multiple variables and nonlinear behavior of different parameters in the concrete mixture to obtain compressive strength under different ages [5,7-10].

Khashman and Akpinar [11] designed an ANN model that predict and classify compressive strength in low, moderate, and high strength. This consist of eight (8) attributes and 1030 datasets with three learning scheme (LS) ratio for training-to-testing of datasets. They were LS1 (40:60), LS2 (50:50), and LS3 (60:40). The work of Oh et al., [12] applied ANNs to optimize the proportion of four concrete ingredients (water, cement, fine, and coarse aggregates). In Kasperkiewicz and Dubrawski [13] fuzzy-ARTMAP ANNs was used to predict 28-day compressive strength of HPC with six components (cement, silica fume, superplasticizer, water, fine and coarse aggregates). A combination of fuzzy neural networks and polynomial neural networks has been experimented with six input parameters

(ingredients) and 28-day compressive strength as the output parameter [14].

This study is aimed utilizing a free algorithm that was hitherto used for classification and clustering of data in computer science to be able to predict compressive strength of HSC with steel fiber addition. There are no available published literatures on the utilization of Weka Algorithm in Civil Engineering applications, as such previous studies have been focused on ANNs mainly. Utilization will improve the application of information technology tools in civil engineering. This is because, continuous development of systems is needed to predict properties of concrete mixing to achieve required performance [15]. The significant contribution of this paper is in customizing the use of this algorithms and their potential applicability in civil engineering.

2. Prediction methodology

The algorithm used is a neural network (NN) called MLP, and a simple explanation of the mode of operation is presented.

Multi-Layer Perceptron (MLP) has a neural network architecture consisting of a layer with several nodes, where each node connects to a subsequent node in another layer. The concept of NN is that each input into the neuron has its own weight, that is adjusted to train the network. The inputs can be represented as:

$$\text{Inputs} = X_1, X_2, X_3, \dots, X_n \quad (\text{Eq. 1})$$

$$\text{Weights} = Y_1, Y_2, Y_3, \dots, Y_n \quad (\text{Eq. 2})$$

$$\text{Outputs} = X_1Y_1 + X_2Y_2 + X_3Y_3 + \dots, X_nY_n \quad (\text{Eq. 3})$$

In between the inputs and the output layer, there may be several hidden layers, and in this case, it consists of one hidden layer and five sigmoid nodes (Table 1).

The software utilized was Weka Version 3.8.3, an open source Java based machine learning algorithm created by University of Waikato, New Zealand.

To utilize the software, the inputs known as 'attributes' had to be prepared in either .csv or .arff format where all the attributes (parameters – mix design constituents) were defined, including the

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response compressive strength. It should be noted that the **attributes** are written as a single word for titles with more than one words such as "SteelFiber" or "FiberDiameter". The data is entered as according to how the attributes were arranged. There were ten (10) attributes: cement, water, Dmax, coarse, fine, superplasticizer, volume fraction, fiber length, fiber diameter, compressive strength, used to define the properties of the response. Data used for the attributes were primarily obtained from the work of Ackgenc et al., [16] and other sources [17-28] listed in Table 2.

In the Weka Software interface, the menu "Explorer" is selected followed by "Preprocess" where the csv or arff file is uploaded, in this study arff file format was used. Next, "Classify" input function is selected where the classifier of choice is selected, in this case 'Functions - MLP'. The classifier has one hidden layer with five nodes using back-propagation technique. The properties of the MLP are such that it has a learning rate (L) of 0.3, momentum (M) of 0.2 and a training time (N) of 500. This can be seen in Fig. 1.

After running the program, the output is displayed in the right hand corner of the software interface. The programmer has to decide the mode of storage. It can be stored in CSV format in the form of excel spreadsheet, plain text that can be opened with text editors, or store the model for future use when more data is available.

To determine the predictive accuracy of the model, X-fold cross-validation was employed, and 10-folds was chosen. This is by dividing the data at random into 10 pieces, D1,...,D10 and by:

Fitting the predictor to D2,...,D10; Predicting D1 (Eq.4)

Fitting the predictor to D1, D3, ..., D10; Predicting D2 (Eq.5)

Fitting the predictor to D1, D2, D4, ..., D10; Predicting D3 (Eq.6)

Results obtained from cross-validation was compared with full set. Followed by different learning schemes employed to find the optimal scheme.

Table 1. Attributes utilized and their maximum and minimum values

S/No	Attributes	Minimum	Maximum	Mean	StdDev
1.	Cement (kg/m ³)	280	565	427.8	86.7
2.	Water (kg/m ³)	123	230.2	176.4	16.9
3.	Dmax (mm)	10	31.5	18.4	5.5
4.	Coarse (kg/m ³)	749.2	1398.8	1067.3	172.7
5.	Fine (kg/m ³)	530	1064.2	792.6	140.6
6.	Superplasticizer (kg/m ³)	0.5	17	8.5	5.9
7.	Volume Fraction (%)	0.19	2.00	0.19	0.51
8.	Fiber Length (mm)	30	60	52.5	11.4
9.	Fiber Diameter (mm)	0.1	1	0.7	0.2
10.	Compressive Strength (Mpa)	18.2	116	56.2	21.7

Table 2. Data utilized from literature with their maximum and minimum values

References	Cement (kg/m ³)	Water (kg/m ³)	Dmax (mm)	Coarse (kg/m ³)	Fine (kg/m ³)	SP (kg/m ³)	Vf (%)	Lf (mm)	Df (mm)	Fc (Mpa)
Yalcin (1994)	280 - 400	180.0 - 192.5	31.5	1027.2 - 1037.2	713.8 - 762.6	3.4 - 6.6	0.19 - 0.64	30;60	0.55; 0.75; 0.90	29.72 - 46.65
Cantin & Pigeon (1996)	341 - 429	150.0 - 168.0	14.0	975.0	800.0	2.8 - 11.0	0.51	54;60	1	40.10 - 67.62
Pigeon & Cantin (1998)	331 - 439	123.0 - 167.0	14.0	855.0 - 998.0	741.0 - 885.0	0.5 - 11.4	0.48 - 0.75	54;60	1	38.20 - 69.60
Eren etal (1999)	550	190.6	20.0	1066.0	710.0	16.5	0.50 - 2.00	60	0.90	58.50 - 71.9
Unal etal (2007)	322 - 324	190.1 - 191.6	22.0	749.2 - 758.3	1051.6 - 1064.2	3.2	0.19 - 0.76	30; 60	0.50; 0.75	29.00 - 42.00
Eren & Marar (2009)	350	175.0	20.0	1398.8 - 1321.2	952.2	4.5	0.50 - 1.50	50;60	0.10 - 0.90	18.18 - 45.33
Nili & Afrouhsabet (2010)	354 - 453	162.0 - 177.0	19.0	858.0 - 877.0	893.0 - 914.0	3.9 - 6.5	0.50 - 1.00	60	0.75	38.70 - 60.92
Ibrahim & Che Bakar (2011)	338	230.2	10.0	760.0	1049.2	0.7	0.50 - 1.25	60	0.75	25.60 - 28.01
Nguyen-Minh etal (2011)	453	181.2	22.0	1242.0	624.0	1.0	0.40 - 0.80	60	0.75	22.06 - 25.33
Marar etal (2011)	565	191.0	20.0	1150.0	530.0	17.0	0.50 - 2.00	30; 50;60	0.50; 0.60; 0.80	73.50 - 93.56
Sahin & Koksai (2011)	325 - 487	170.0 - 179.0	19.0	850.0 - 965.0	785.0 - 891.0	0.9 - 1.8	0.33 - 1.00	60	0.71; 0.75	47.50 - 71.90
Abubakar (2018)	470	165.0	10.0	1050.0	700.0	14.0	0.50 - 2.00	30;60	0.50; 0.80	71.10 - 116.00

Figure 1. Typical input and user interface in an MLP neural network subjected to 10-fold cross-validation

Figure 2. Typical output and user interface in an MLP neural network subjected to 10-fold cross-validation

3. Results and discussion

An annotated computer printout of the result using cross-validation is presented in Fig. 2. The total number of datasets called “instances” is clearly stated as well as other validation parameters, followed by the percentage of split; and the time it takes to generate the model. It is particularly important because it determines how efficient the model is when the duration is short compared with when it takes a long period.

The printout concludes by presenting a summary of model performance evaluation. First is Correlation Coefficient (CC) which measures the statistical correlation between the predicted values and the actual values. For good performance of the model, large values should be expected. This should not be confused with coefficient of determination (R^2) which measures the quality describing the proportion of variability explained by the fitted model.

Mean Absolute Error (MAE) is another index that measures the performance of a model. It measures how close predictions are to the eventual outcomes by measuring average magnitude of the errors in a set of forecasts:

$$MAE = \frac{1}{n} \sum_{i=1}^n |f_i - y_i| \quad (\text{Eq.7})$$

Where f_i = prediction; y_i = true value

To measure the differences between values (sample values) predicted by a model and the values actually observed, Root Mean Square Error (RMSE) was also utilized. This represents the sample standard deviation of the differences between predicted values and observed values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (f_i - y_i)^2}{n}} \quad (\text{Eq.8})$$

RMSE is preferred when large errors are undesirable, and it is always larger than MAE.

Two other errors evaluated were Root Absolute Error (RAE) and Root Relative Squared Error (RRSE) where the former shows much the results deviates from actual value, and the latter is a measure in percent compared to the actual value. Both shows how far the prediction deviates from the actual value.

$$RAE = \frac{\sum_{i=1}^n |f_i - y_i|}{\sum_{i=1}^n |t_i - y_i|} \quad (\text{Eq.9})$$

Where t_i = mean value of y

$$RRSE = \sqrt{\frac{\sum_{i=1}^n (f_i - y_i)^2}{\sum_{i=1}^n (t_i - y_i)^2}} \quad (\text{Eq.10})$$

Lower values of these errors and a high CC values indicates that the model is suitable and prediction accuracy is very high, however, if the results is otherwise, it is an indication that more data might be required to improve the model performance.

To access the accuracy of the model, the comparison between 10-folds cross-validation and full training set was made and is presented in Table 3. In the former, the model performance was 88% and 93% in the latter. The associated errors were small in the latter compared to the former. The time to build the model was just 0.20 seconds in full training compared with cross-validation at 0.42 seconds.

In order to find the optimal learning scheme, seven schemes were evaluated as can be seen in Table 4. Scheme 70-30% training –to-testing outperform the others with a 95% accuracy and a much lower error rates, though it has one of the highest time taken to build a model. This is an indication that the model can be utilized in prediction of concrete compressive strength.

Evaluation of the variability usually explained by the line of best fit on a model was done using prediction versus actual for the seven levels of learning schemes, and results presented in Fig. 3. Polynomial equation provided the best fit for all the models with the highest coefficient of determination at 70-30% scheme $R^2 = 91.3\%$. This corresponds with what has been put forward by Kashman & Akpınar [11] on the non-linear relationship.

Table 3. Model accuracy evaluation

Multilayer Perceptron		
Test Options	10-fold X-Validation	Full Test Set (192)
Correlation Coefficient (CC)	0.8848	0.9393
Mean Absolute Error (MAE)	8.0501	5.6568
Root Mean Squared Error (RMSE)	10.3484	7.4623
Relative Absolute Error (RAE) %	43.768%	30.8059%
Root Relative Sq. Error (RRSE) %	47.6166%	34.8059%
Time to build model (s)	0.42	0.20

Table 4. Model evaluation using percentage split (Train – Test)

Multilayer Perceptron							
Test	20-80	30-70	40-60	50-50	60-40	70-30	80-20
CC	0.7874	0.8006	0.8637	0.8836	0.8693	0.9543	0.9503
MAE	11.3985	10.2261	12.8086	8.5751	9.229	5.4372	6.9577
RMSE	14.8955	13.9226	15.2646	11.5322	12.1217	7.1753	8.4902
RAE %	61.8204	55.2897	66.759	43.3268	47.0364	27.7972	37.08
RRSE %	68.7425	63.5497	68.1911	49.3821	52.7025	31.3035	37.6339
Instances	154	134	115	96	77	58	38
Time, s	0.23	0.19	0.2	0.19	0.19	0.23	0.19

Figure 3. Fitted line plots for predicted vs actual

4. Conclusion

This study involving HSC with steel fiber addition evaluated the performance of Weka algorithm in the prediction of concrete compressive strength, and the following conclusions have been drawn:

1. Model prediction accuracy with correlation coefficient was 88% using 10-folds cross-validation, and 93.9% with full test set.
2. Different learning schemes for training and testing showed 70-30 to be the optimal percentage.
3. Measurement of variability showed a coefficient of determination of between 63% - 91% for all the learning schemes with polynomial as best fit.

Further study should explore matrix properties and workability and see how it influences the outcome.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest.

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