PREDICTION OF CONCRETE COMPRESSIVE STRENGTH USING SUPERVISED MACHINE LEARNING MODELS THROUGH ULTRASONIC PULSE VELOCITY AND MIX PARAMETERS

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As a non-destructive technique for concrete compressive strength assessment for existing concrete structures, Ultrasonic Pulse Velocity (UPV) test method has been widely used. Since the UPV affected by many factors, it is not easy to accurately assess the concrete compressive strength. Effect of some factors which are coarse aggregate grading type, slump, the water-cement ratio (w/c), sand volume ratio, coarse aggregate volume ratio, testing age, concrete density, and pressure of steam curing, were analyzed on the relationship between ultrasonic pulse velocity and concrete strength. 436 records of data, extracted from published research work, were used to build seven supervised machine learning regression models which are; Artificial Neural Network (ANN), Support Vector Machine (SVM), Chi-squared Automatic Interaction Detector (CHAID) decision tree, Classification and Regression Trees (CART) decision tree, non-linear regression, linear regression, and stepwise linear regression models. Also, the independent variable importance for each predictor was analyzed and for each model. With an adequate tuning of parameters, ANN models have produced the highest accuracy in prediction, followed in sequent with SVM, CHAID, CART, non-linear regression. Linear and stepwise linear regression models have present low values of predictive accuracy. w/c was observed to be the highest importance factor in prediction of concrete strength, and the forecasting of the concrete strength was efficient when using w/c and UPV only as predictors in any of the used predictive models.

Keywords: *Concrete Compressive Strength, Ultrasonic Pulse Velocity, Machine Learning Models, Artificial Neural Network ANN, Support Vector Machine, Decision tree, Regression.*

Abbreviation:

AI. : *Artificial Intelligence*
ANN. : *Artificial Neural Network*
C. : *Regularization parameter for Support vector machine technique*
CA. : *coarse aggregate volume ratio*
CAgrade. : *coarse aggregate gradation*
CART. : *Classification and Regression Trees*
CHAID. : *Chi-squared Automatic Interaction Detector*
curing. : *pressure of steam curing in bar*
Density. : *concrete density in gm/cm3*
DUPV. : *Direct Ultrasonic Pulse Velocity*
fcu. *observed concrete compressive strength*
fcu_Predicted. : *Predicted concrete compressive strength*
LSD. : *Least Squares Deviation*
NDT. : *Non-Destructive Test*
R^2. : *coefficient of determination*
RBF. : *Radial Basis Function*
sand. : *sand volume ratio*
slump. : *slump in mm*
SUPV. : *Surface Ultrasonic Pulse Velocity*
SVM. : *Support Vector Machine*
UPV. : *Ultrasonic Pulse Velocity*
w/c. : *water-cement ratio*
γ. : *Gamma parameter for Support Vector Machine technique*
ε. : *regression precision for Support Vector Machine technique*

1. Introduction

In the present infrastructure advancement, structural health observing is urgent in evaluating existing structures against man-made and catastrophic events. Exact evaluation after an occasion in an arrangement for repair, recovery, or retrofitting is the normal issue. The vast majority of the current structures are made out of a complex material known as concrete. Concrete can be evaluated by numerous methods where elements to be considered in the test are time, cost, and level of accuracy. Improvement of this precise evaluation can be made with fast appraisal utilizing non-destructive testing. Non-destructive test in concrete is intricate because of its inhomogeneous elements and it's molecule sizes.

Such Non-Destructive Test (NDT) as UPV is exceptionally powerful measures to assess the strength of concrete in existing structures. This test is quick and simple to perform and is of minimal effort. In this manner, such a strategy is considered by numerous specialists and scientists to evaluate the strength and state of concretes.

In the literature, numerous methodologies were displayed to find the best correlation between the recorded UPV and the observed (real) compressive strength. Some researchers have

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Table 1

Different equations that suggested by some researchers and corresponding data

Researcher	Ref.	Equations fcu (MPa) – UPV (km/s)	Data points	fcu Range (MPa)	w/c	R^2
(Qasrawi 2000)	[3]	$fcu = 36.72(DUPV) - 129.077$	115	6-42	/	0.956
(Nash't et al. 2005)	[4]	$fcu = 0.356(RN)^{0.866}e^{0.32(DUPV)}$	161	11.1-53.3	0.45	0.8
(Gül et al. 2006)	[5]	$fcu = 0.1414e^{1.5(DUPV)}$	42	3-65	0.5	0.94
(Hobbs & Tchoketch Kebir 2007)	[6]	$fcu = -173.033 - 4.069(DUPV)^2 + 57.693(DUPV) + 1.307(RI)$	25	20-50	0.6-0.7	0.949
(Solís-Carcaño & Moreno 2008)	[7]	$fcu = 0.5697e^{(DUPV)}$	100	10.6-44.7	/	0.78
(Lawson et al. 2011)	[1]	$fcu = 1x10^{-15}e^{8(DUPV)}$ $fcu = 0.022e^{(DUPV)}$ $fcu = 0.053e^{(DUPV)}$ $fcu = 0.097e^{(DUPV)}$ $fcu = 0.205e^{(DUPV)}$	4 4 4 4 4	8-28 17-37 10-21 11-24 10-23	0.35 0.4 0.5 0.6 0.75	0.866 0.981 0.888 0.994 0.989
(Khan 2012)	[8]	$DUPV = (fcu)^{0.2}$	62	46-113	0.3	0.6
(Bayan et al. 2015)	[2]	$fcu = 8.88e^{0.42(DUPV)}$ for CA=1000 kg/m^3 $fcu = 0.06e^{1.6(DUPV)}$ for CA=1200 kg/m^3 $fcu = 1.03e^{0.87(DUPV)}$ for CA=1300 kg/m^3 $fcu = 1.39e^{0.78(DUPV)}$ for CA=1400 kg/m^3	800	18-55	/	0.83 0.87 0.88 0.84
(Rao et al. 2016)	[9]	$fcu = 1.52e^{0.761(DUPV)}$	64	6.6-52	0.39-0.5	0.895
(Yoon et al. 2017)	[10]	$fcu = 0.0098e^{3.412(SUPV)}$	20	40-80	0.35-0.39	0.908
(Rashid & Waqas 2017)	[11]	$f_c' = 38.05(DUPV)^2 - 316.76(DUPV) + 681.62$	27	20-50	0.25-0.5	0.79
(Najim 2017)	[12]	$fcu = 0.0036(DUPV) + 0.87(RI)$ $fcu = 0.0037(SUPV) + 1.03(RI)$	150	25-50	/	0.792 0.74
(Ali-Benyahia et al. 2017)	[13]	$fcu = 1.3947e^{0.034(RN)}e^{0.374(DUPV)}$	205	5-37	/	0.84

used other NDT data, such as Rebound Index (RI), to improve the correlation between predicted concrete strength (fcu_Predicted) and the actual ones (fcu). Most of the suggested equations had an exponential order obtained from the nonlinear regression analysis.

Table 1 presents a list of authors and their findings of some of the recently published work. Some researchers have found that better coefficient of determination (R^2) can be obtained if the collected data are separated into sub-groups according to the effect of certain independent variables. Other researchers, [1] and [2], have suggested various equations for prediction of concrete compressive strength according to values of w/c or coarse aggregate (CA) volume in the concrete mixture, respectively.

Recently, researchers have the trend toward using more advanced techniques like machine learning techniques. Table 2 presents some ANN models used by some authors to predict the concrete compressive strength in comparison with different regression methods. As an indication for the performance of each technique, the coefficients of determination R^2 were presented. The listed models selected to be having UPV reading within recorded data.

Machine learning band together statistics and software engineering to empower computers to figure out how to complete a given task without being programmed to do as such. Just as our brain

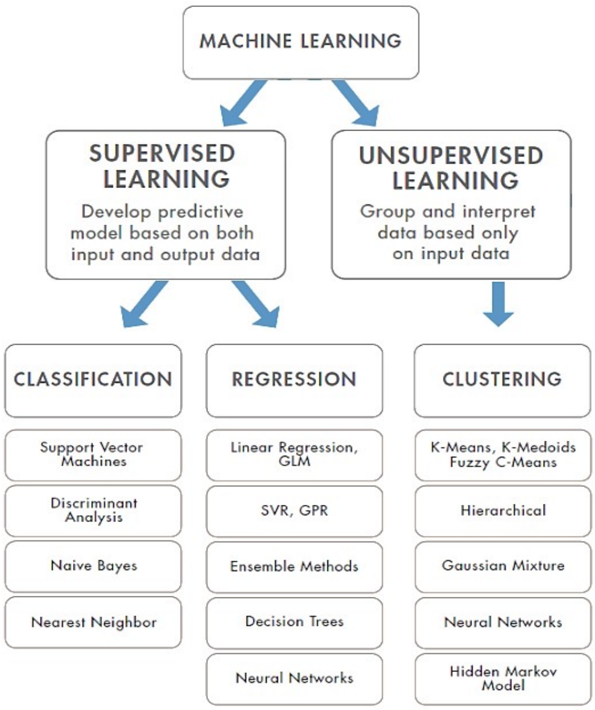

Fig.1 - Machine Learning algorithms. Source: MATLAB Help.

uses the experience to improve a task so can computers. The more information the computer gets the all the more finely tune its algorithm moves toward becoming and the more precise it can be in its forecasts.

Machine learning is divided into two kinds of algorithms: Supervised learning, that trains a

Table 2

Different models by some researchers for predicting concrete compressive strength

Researcher	Ref.	Model	Input variables	Data points	f_{cu} Range (MPa)	R^2
(Kewalramani & Gupta 2006)	[14]	ANN: 2-3-3-1 multiple regression	weight of concrete and UPV	336	10-60	e<12% e<18%
(Trtnik et al. 2009)	[15]	ANN: 5-30-30-1 nonlinear regression	aggregate, shape of aggregate, aggregate type, maximum aggregate size, and UPV	≈200	2-49	0.995 0.64
(Bilgehan & Turgut 2010)	[16]	ANN: 2-50-1 nonlinear regression	UPV and density of concrete	238	4.4-81.4	0.999 0.85
(Prasopchaichana 2012)	[17]	ANN: 11-10-1 nonlinear regression	eight wavelet packet-Root Mean Square, w/c ratio, flay ash/cement ratio and UPV	40	10-40	0.85 0.69
(Sbartaï et al. 2012)	[18]	ANN: 3-n-1 Response Surface	UPV, electrical resistivity and ground penetrating radar	81	20-73	0.73 0.75
(Lande & Gadewar 2012)	[19]	ANN: 1-10-1 nonlinear regression	UPV	216	2.2-40	0.957 0.877
(A.S.Gadewar 2013)	[20]	ANN: 1-40-1 nonlinear regression	UPV	216	2.2- 40	0.999 0.949
(Lorenzi et al. 2015)	[21]	ANN: 6-20-20-1	UPV, humidity, age, cement type, w/c and temperature	2200	5-100	0.98
(Vidivelli & Subbulakshmi 2016)	[22]	ANN: 2-n-1 nonlinear regression	UPV and RI	32	31.8-38.2	/ 0.748
(Khademi et al. 2016)	[23]	ANN: 6-12-1	water, cement, microsilica, gravel, sand and UPV	90	9-22	0.937
(Nobile & Bonagura 2016)	[24]	ANN: 2-n-1 multi-variable regression	UPV and RI	16	10-57	/
(Hadianfard & Nikmohammadi 2017)	[25]	ANN: 2-n-1	UPV and RI	36	7.8-37.9	0.8

Table 3

Statistical properties of predictors and target

Statistical property	Slump (mm)	w/c	sand	CA	Age (days)	Density gm/cm^3	Curing (bar)	DUPV km/s	SUPV km/s	*fcu* (MPa)
Minimum	8	0.4	1.13	1.7	2	2.07	0	1.32	0.49	3.57
Maximum	115	0.9	5.29	6.68	150	2.54	4	5.19	5.42	64.73
Mean	54.6	0.5	2.1	3.1	40.3	2.4	1.0	4.5	4.5	30.8
Stander Deviation	29.95	0.15	0.91	1.17	35.45	0.05	1.50	0.44	0.74	13.08
Coefficient of Variance	0.55	0.27	0.44	0.38	0.88	0.02	1.51	0.10	0.16	0.42

Table 4

Pearson product – Moment correlation coefficients

	Slump	w/c	sand	CA	age	Density	curing	DUPV	SUPV	*fcu*
Slump	1	0.156	-0.001	-0.439	0.025	-0.378	-0.128	-0.123	-0.105	-0.123
w/c	0.156	1	0.950	0.781	-0.061	-0.360	0.090	-0.579	-0.615	-0.766
sand	-0.001	0.950	1	0.848	-0.057	-0.297	0.108	-0.559	-0.581	-0.700
CA	-0.439	0.781	0.848	1	-0.076	-0.020	0.168	-0.395	-0.463	-0.597
age	0.025	-0.061	-0.057	-0.076	1	0.077	-0.245	0.398	0.373	0.424
Density	-0.378	-0.360	-0.297	-0.020	0.077	1	-0.260	0.517	0.471	0.433
curing	-0.128	0.090	0.108	0.168	-0.245	-0.260	1	-0.575	-0.565	-0.363
DUPV	-0.123	-0.579	-0.559	-0.395	0.398	0.517	-0.575	1	0.950	0.741
SUPV	-0.105	-0.615	-0.581	-0.463	0.373	0.471	-0.565	0.950	1	0.784
fcu	-0.123	-0.766	-0.700	-0.597	0.424	0.433	-0.363	0.741	0.784	1

model on identified predictors and target data so that it can predict future response. Unsupervised learning, that discovers concealed shapes or fundamental structures in predictors. Figure 1 shows the flowchart of the classification of the machine learning algorithms.

Machine learning is one of the most exciting areas of Artificial Intelligence (AI). The following supervised machine learning algorithms for regression have been used in this research; SVM, ANN, Decision Tree Models (CART and CHAID) and Regression (non-linear regression, stepwise linear regression, and linear regression).

2.Statistical properties

Using IBM SPSS Statistics and Modeler all the supervised learning machine models, used in this research, have been built. The statistical properties of the input and target data are presented in Table-3.

Pearson correlation coefficients were calculated to measure the linear relationship between variables, as shown in Table-4.

It can be seen that the target (fcu) has a strong positive relation to SUPV and DUPV of 0.784 and 0.741, respectively and strong negative relation to w/c and sand of -0.766 and -0.700, respectively. Also, the sand volume ratio in mixture proportions has a strong positive relation to coarse aggregate volume ratio CA of 0.848. The negative correlation of fcu and some predictors (Slump, w/c, sand, and CA) are expected but not (curing).

3. Experimental data collection and materials

The data used in this research have been extracted from previously published M.sc thesis in civil engineering [26], but not been analyzed by the predictive models presented here.

The total record of 626 sample data has been listed in tables. The materials used were local materials. The cement types were Sulphate resisting Portland cement and ordinary Portland cement. Three grading types of sand were used. Two of them were out of limits of Iraqi Specifications IQS(No.45:1980) and the data regarding them have been extracted from the data of present research. Five coarse aggregates (CA) gradation, (Labeled A, B, C, D, and E), were used that classified according to a maximum size of coarse aggregate and sieve analysis according to IQS(No.45:1980). Different curing methods were utilized, normal curing, pressure steam curing of 2, 4 and 8 bar. The data of 8 bar pressure of steam curing have been excluded also from the considered data because they were limited number of data.

The concrete tested specimens were cubes of 100mm and prisms of 300x100x100mm. Different water-cement ratios (w/c) and mixture proportions have been used. The mixture proportions were designed using British Design Method to produce concrete of compressive strength of (15-55) MPa.

Full details of materials, apparatus, experimental works, and recorded data were presented in reference [26]. The final number of samples considered here was 436. The input data (predictors) and their used labels were; coarse aggregate gradation (CAgrade), slump in mm (slump), water-cement ratio (wc), sand volume ratio (sand), coarse aggregate volume ratio (CA), testing age in days (age), concrete density in gm/cm^3 (Density), pressure of steam curing in bar (curing), Direct Ultrasonic Pulse Velocity in km/sec (DUPV) and Surface Ultrasonic Pulse Velocity in km/sec (SUPV). The target value is concrete compressive strength in MPa (fcu).

4.Artificial Neural Network Model

Neural networks are a simplified technique that attempts to simulate the work of the nervous system. The fundamental units that are put in order of layers called neurons. The Neural Network is a simple technique works like the brain of a human in dealing with data. It contains a huge number of processing units that are interconnected among each other like neurons. The configuration of the network consists of three layers of processing units; one input layer, one or more hidden layer and one output layer that representing the target. The units of each layer have a varying weighted connection to the unit of next layer. Input layer receives the data first, and values are spread from each unit to every unit in the subsequent layer. At last, the output layer will generate the results.

The learning process of the network being done by examining every set of input data, producing a forecast for each set, and doing tunings to the weights when it performs unfitting forecasting. This procedure is repeated, and the network remains to enhance its forecasting, and the processes are stopped when the stopping criteria have been reached. This is called training processes that make the network learned, and at this stage, the network can predict new values for new cases of records.

Using IBM SPSS statistics to construct the Artificial Neural Network prediction model, first, the data have been specified in measure tab as nominal for gradation of coarse aggregate (CAgrade) and as a scale for the other data. Also, all data were specified as inputs, but the observed concrete strength (fcu) was specified as a target in the role tab.

Then, the data were analyzed using multilayer perceptron neural networks. To build the architecture of network the multilayer perceptron interface has been used. To train the network the data values should be between 0 and 1. To do so the rescaling method has been used was standardization, which transforms predictors so that they have standard deviation=1 and mean=0, which removes the dependence on arbitrary scales in the input variables and usually improves performance [27].

The nominal input (CAgrade) was converted to binary with the nominal encoding system. The training data have been set to be 70% (295) and the testing data to be 30% (141) of the total data, which were randomly selected using the partitions tab. The architecture was set to be automatic with minimum neurons in hidden layers of 9. This is done because there was not a specific method from literature can be followed to build the best network topology. The options of the batch

Table 5

Performance of different ANN architecture and nonlinear regression

Predictor	ANN Architecture	ANN R^2	Nonlinear Equation *fcu*=	Nonlinear Regression R^2
SUPV	1-3-1	0.748	$0.971e^{0.74SUPV}$	0.719
DUPV	1-4-1	0.624	$0.36e^{0.975DUPV}$	0.608
DUPV, SUPV	2-5-1	0.759	$0.017e^{1.541SUPV} - 4.815x10^{-8}e^{3.96DUPV} + 10.211$	0.760
DUPV, SUPV, w/c	3-4-1	0.864	$0.006e^{1.644SUPV} - 4.246x10^{-10}e^{4.745DUPV} + 283.64/1128.9^{w/c} + 8.033$	0.870
SUPV, w/c	2-5-1	0.867	$0.037e^{1.268SUPV} + 386.309/2198.6^{w/c} + 7.133$	0.862
DUPV, w/c	2-4-1	0.822	$0.057e^{1.252DUPV} + 502.054/2789.1^{w/c} + 2.906$	0.815
All Possible Predictors	14-10-1	0.944	$0.002\ e^{1.865SUPV} - 3.05x10^{-9}e^{4.362DUPV} + \frac{298.436}{1165.501^{\left(\frac{w}{c}\right)}} + 0.033(\mathrm{Slump})$ $-1.163(\mathrm{sand}) + 0.416(\mathrm{CA}) + 1.606\mathrm{Ln}(\mathrm{age}) - 4.083(\mathrm{Density}) + 0.358(\mathrm{curing}) + 13.750$	0.890

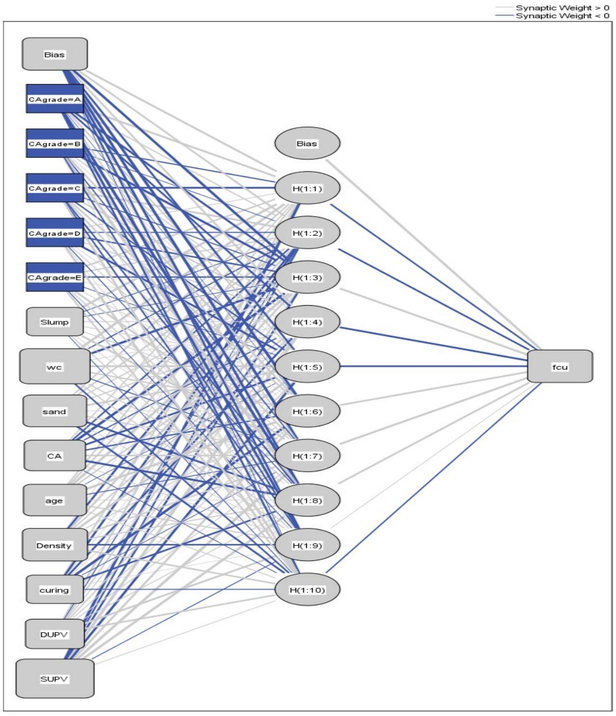

Fig.2 - ANN architecture.

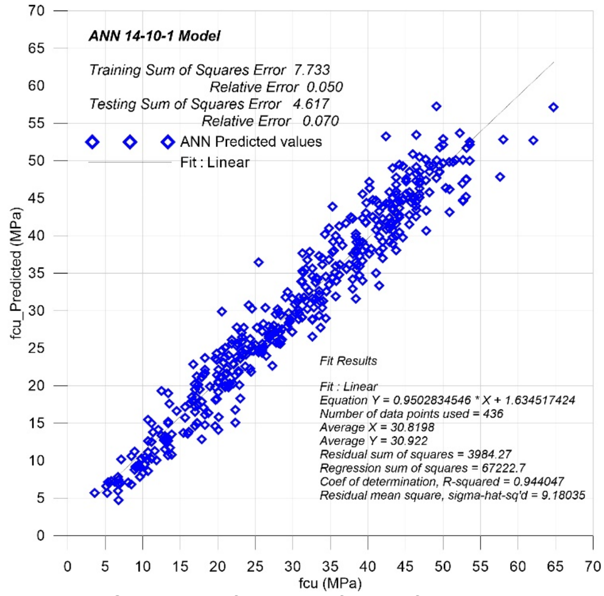

Fig.3 - Correlation of observed fcu and fcu_ predicted using ANN Model.

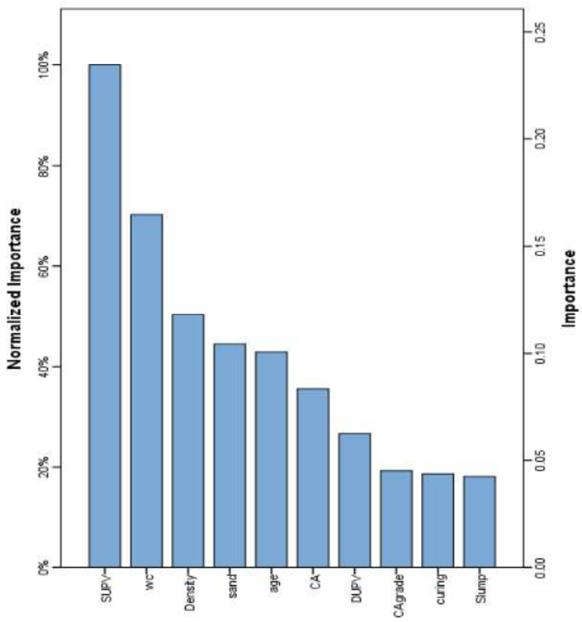

Fig.4 - Relative importance of predictors of ANN Model.

type of training specified were; initial learning rate=0.01, momentum=0.1, and interval offset=±0.5. The activation function for hidden layer was hyperbolic tangent and for the output layer was linear which have been set automatically.

With multi-training processes and with some trials of tuning the options available for training, a best possible trained network has been achieved. The network architecture and results of the model are presented in Figs. 2, 3 and 4. The coefficient of determination for the predictive values versus observed ones was (R^2=0.944), which is referred to high correlation. Fig.4 shows that, regardless of DUPV and SUPV, the most important predictor is w/c.

With selecting the most important predictors and examining different probabilities of ANN architectures, and with DUPV, SUPV, and w/c as predictors while fcu as a target, different performances for prediction models can be obtained. Table-5 shows the results corresponding to these probabilities.

5.Linear regression

Linear regression is the simplest traditional method of regression models. The prediction equation consists of a polynomial of linear parameters associated with predictor variables. For more than one predictor, the regression called multiple linear regression. The values of the unknown parameters were mostly calculated using the least square method.

Fig. 5a shows the performance of linear regression represented by R^2 which equal to 0.816, and this refers to good correlation. Also, the linear regression equation has been presented with the figure. Focusing on the most important predictor w/c with the practically selected predictor DUPV, Fig. 5-b shows the correlation between real values of fcu and predicted values using w/c and DUPV in the model. Models of linear regression for different sets of input variables can give a different performance as listed in Table 6.

Table 6

Prediction of different prediction models

Predictor	Linear Regression R^2	Stepwise linear Regression R^2	CHAID tree R^2	CART R^2	SVM R^2
SUPV	0.614	0.61	0.74	0.74	0.69
DUPV	0.549	0.55	0.62	0.64	0.60
DUPV, SUPV	0.615	0.61	0.74	0.77	0.69
DUPV, SUPV, w/c	0.744	0.74	0.87	0.87	0.84
SUPV, w/c	0.744	0.74	0.87	0.89	0.83
DUPV, w/c	0.719	0.72	0.84	0.83	0.80
All Possible Predictors	0.816	0.814	0.92	0.89	0.93

6. Nonlinear regression

Nonlinear regression is a method of regression based on finding a nonlinear mathematical expression that can relate the predictors to the target value. In this method, the types of mathematical function and its parameters should be specified first. An estimation method of Levenberg–Marquardt was used by SPSS software, which is an iteration method, to find the values of these parameters. As other mentioned researchers in literature did, an exponential relationship between DUPV or SUPV with fcu has been assumed. Fig.6a and Fig. 6b shows the nonlinear regression of DUPV versus fcu and SUPV versus fcu, respectively. The regression equations and R^2 for each case were stated in these figures.

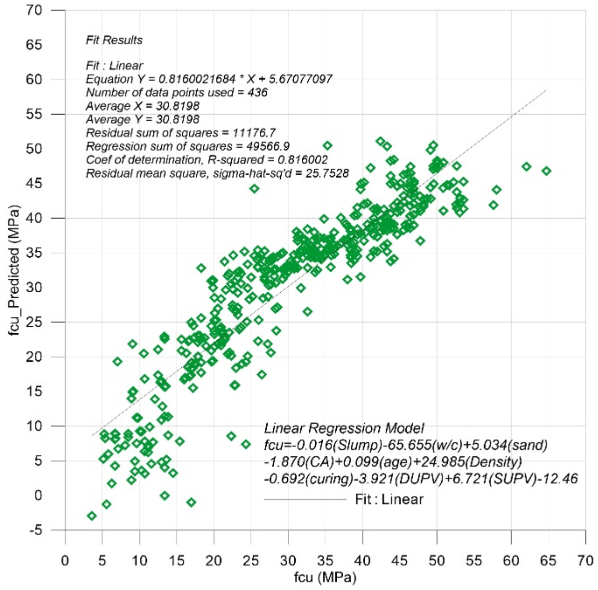

Fig.5a - Performance of Linear Regression for all continuous predictors.

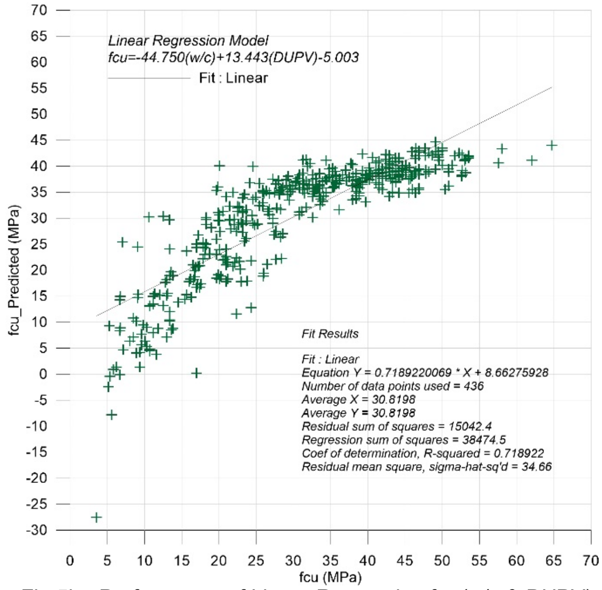

Fig.5b - Performance of Linear Regression for (w/c & DUPV) predictors.

Using only the Models with predictors that are listed in Table-5 and taking in consideration that each of DUPV and SUPV behave as exponential function with respect to fcu, w/c as in Abram's law fcu=A/B$^{(w/c)}$ [28], Density behave as linear function [29] and (age) behave logarithmic function [30] with respect to target fcu. The performance of nonlinear regressions represented by R^2 and corresponding suggested equations were listed in Table 5. Fig. 6c shows the performance of the prediction model for the nonlinear regression method for all continuous input variables (CAgarde excluded because it is categorical variable), while Fig. 6d represents the performance of the model with the two selected predictors w/c and DUPV.

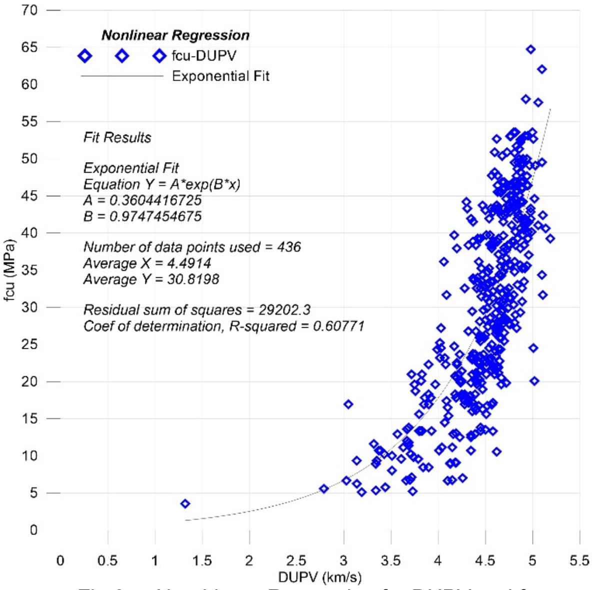

Fig.6a - Non-Linear Regression for DUPV and fcu.

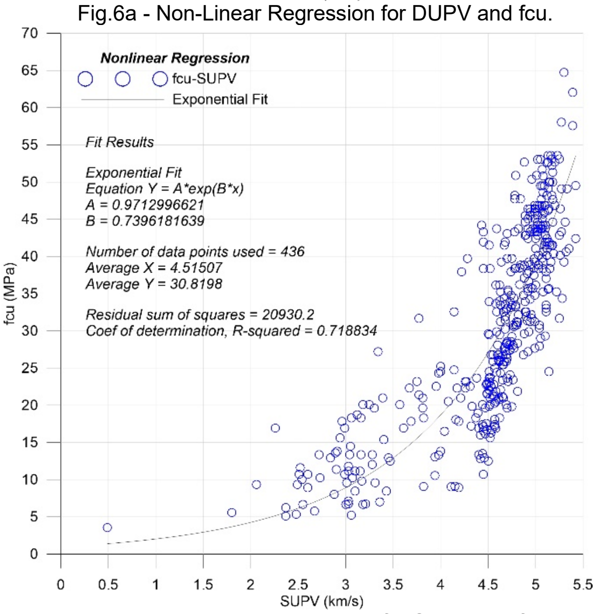

Fig.6b - Non-Linear Regression for SUPV and fcu.

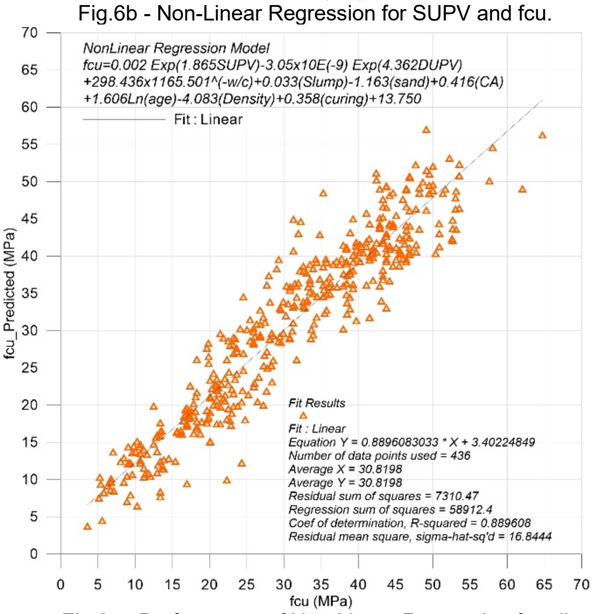

Fig.6c - Performance of Non-Linear Regression for all continuous predictors

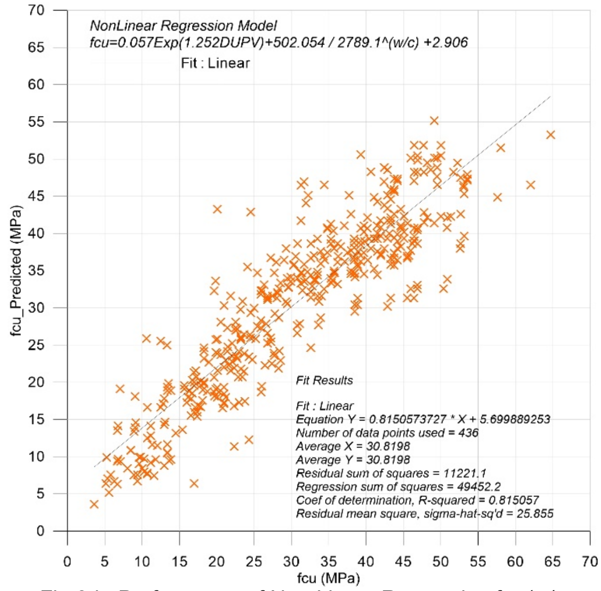

Fig.6d - Performance of Non-Linear Regression for (w/c and DUPV) predictors

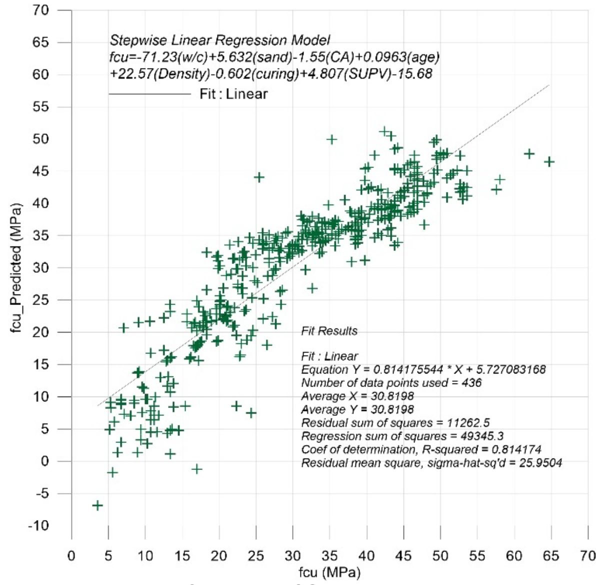

Fig.7a - Performance of Stepwise Linear Regression

7.Stepwise Linear Regression

Stepwise linear regression is a procedure for selecting the most essential predictors to be in the final prediction equation. The method implements a stepwise procedure which consists of a series of steps arranged to find the most useful predictors to include in the regression model. Using specific criteria, (Probability of F to remove >= 0.100, Probability of F to enter <= 0.050), at each step of the procedure, each predictor has been evaluated. However, selecting unimportant predictors or removing important one is quite likely to happen because the method uses the probability of F to select predictors. The results of this method were illustrated in Fig.7a. The method has excluded slump and DUPV from the regression model.

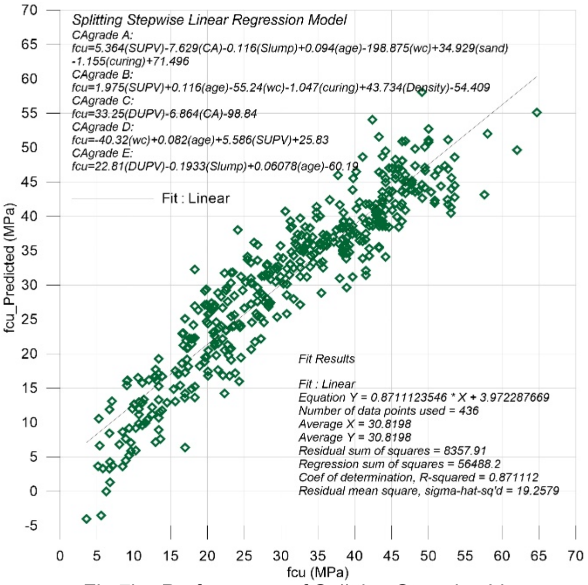

Fig.7b - Performance of Splitting Stepwise Linear Regression.

The benefit of this method is that it offers an objective checking procedure for predictors in developing a prediction model. Fig.7b shows the performance of a prediction model constructed by splitting the stepwise linear regression method according to coarse aggregate gradation (CAgrade). The coefficients of determination R^2 for each model constructed by stepwise linear regression technique using a different combination of manually selected predictors were listed in Table 6.

8.Decision Tree Models

Decision tree constructs regression models in the arrangement of a tree shaped like a flowchart. It split the data into minor and minor subset in a manner the related decision tree is step by step created. The last outcome is a tree with decision leaf nodes which are representing a decision on the numerical output. The root node is the first decision node in a tree which links to the superior input.

One of the first decision tree regression methods is a Chi-squared Automatic Interaction Detector (CHAID). Unlike Classification and Regression trees (CART), CHAID has a non-binary tree. It can have more than two branches from every single node.

CHAID regression tree calculates a predicted mean value for each node in the tree. In this method, categorial predictors are created first through the continuous input data by separating corresponding continuous distributions into a number of classes. The classes of categorical predictors remain as they defined.

Then, inspecting all predictors and trying to find a couple of categories, for each predictor, that is smallest significantly different with regard to target by using F-test for regression and Chi-square test for classification type of regression. If the particular test for a specified couple of input classes is not statistically significant as determined by an (alpha to merge) value, at that moment it will merge the particular input classes and repeat this step. To select the split variable, the input with the lowest adjusted p-value will be chosen. If the lowest adjusted p-value for any input is more than comparatively (alpha to split) value, then no further splits will be achieved.

A CART tree is a twofold decision tree, which is built by dividing each node in the tree into two other nodes sequentially, beginning with the root node that has the overall learning data. The tree growing process depends on splitting techniques. There are some possible splits of each predictor at each node. The basic idea of the regression algorithm is to find the purest child node in each possible split, and only univariate splits are taken into consideration. The tree is grown to start with finding every predictor's best split and then finding the node's best split. At each node, the best split is selected to maximize splitting criteria (In SPSS modeler is referred to as the improvement), which is corresponding to a decrease in the measure of impurity of a node. For continuous target, the splitting criteria use Least Squares Deviation (LSD) impurity measures [31].

SPSS modeler v.18 has been used to build CHAID and CART regression trees. For the two methods, the maximum tree depth was set up to the default value which is 5. As a stopping rule, minimum records in parent branch and minimum records in child branch were set to be 2% and 1%, respectively. Fig.8a and Fig 8b show the regression tree performance for each CHAID and CART, respectively.

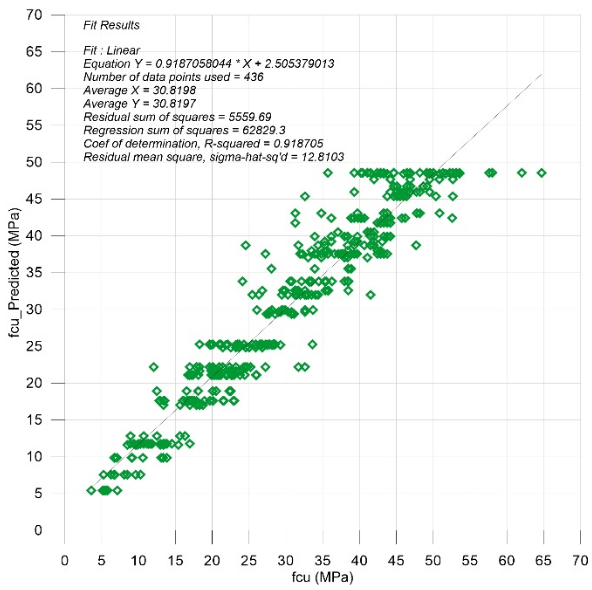

Fig.8a - Performance of CHAID Tree Regression Model

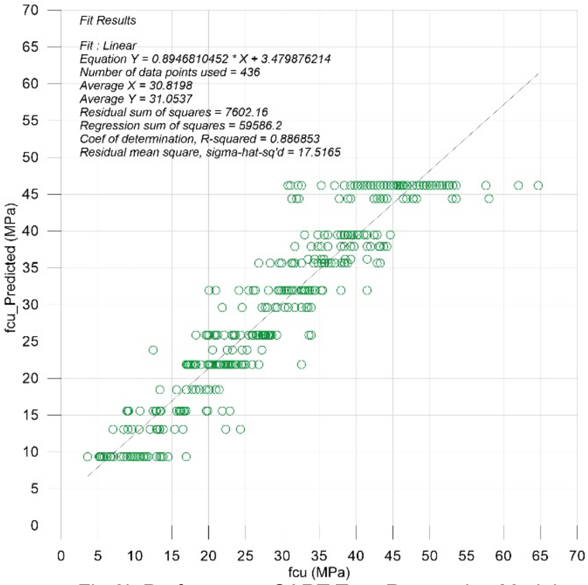

Fig.8b Performance CART Tree Regression Model.

9.Support Vector Machine (SVM)

Support vector machine is usually used as a classification technique, which first attempts to find optimum hyperplane, which able to separate data of different categories. The optimum hyperplane is a decision surface trying to maximumly expand the margin of separation between the two categories in the data. The coordinates of the training samples that are nearest to the separating hyperplane are called support vectors.

The first phase in the training process is mapping predictors (transformed to high-dimensional feature space) in order that the data is able to be classified, even when the data cannot be separated linearly. The transformation process is known as the kernel trick, which uses a mathematical function for transformation.

In SPSS modeler v.8, Radial Basis Function RBF, Linear, Polynomial and Sigmoid are the kernel function types are used. The second phase is solving the optimization problem to fit an optimal hyperplane to divide the transformed data points into two classes. The number of support vectors specifies the number of transformed features. The constructed decision surface required only support vectors of the training samples and the rest of the data points are irrelevant, once the training data has been trained.

Wide margins lead to best prediction models, therefore a small misclassified data points can be accepted. (C) is regularization parameter that regulates the tradeoff between the slight number of misclassified data and broad margin. Gamma parameter (γ) defines how far reaches the influence of a single training example. If Gama has a low value, then that means that every point has a far reach. And conversely, high value means that each training example only has close reach. The stopping criteria are the value that specifies the optimization algorithm when to stop. The parameters specified in SVM SPSS modeler were; C=10, regression precision ε=0.05, stopping criteria=1x10^{-6}, RBF kernel type with γ=1. As has been done with other models, Fig.9a and Fig.9b depict the performance of SVM models for all predictors and for (w/c and DUPV) only, respectively.

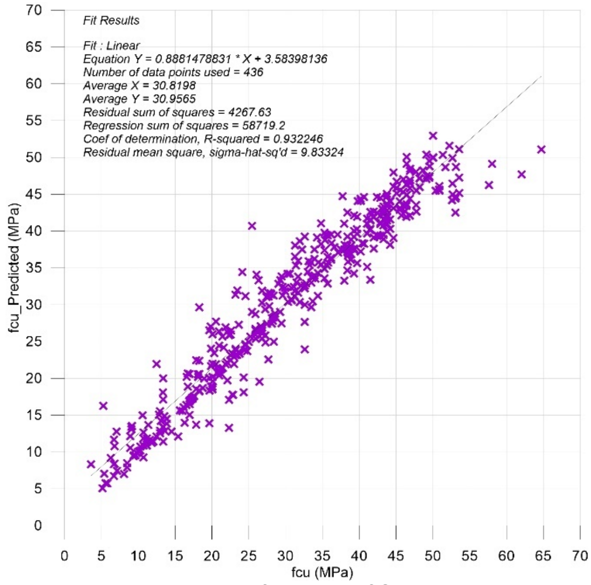

Fig.9a - Performance of SVM Model.

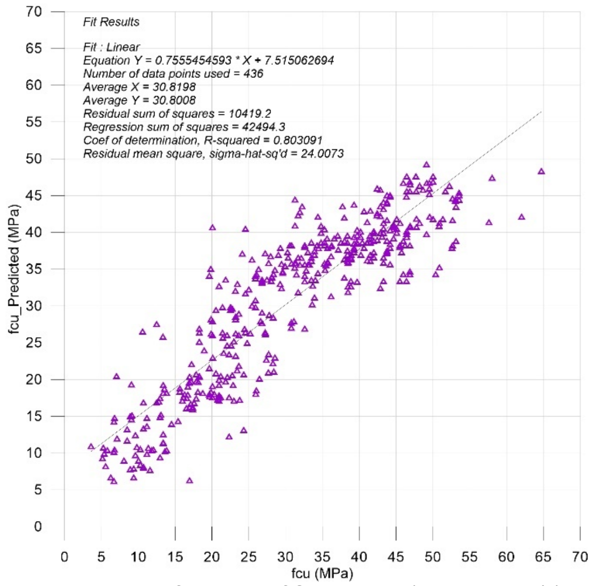

Fig.9b Performance of SVM Model (DUPV and w/c).

10. Predictor Importance

It's worth to focus on predictors domain that matters most in prediction model and ignoring those that matter least. Multicollinearity can occur when independent variables are correlated, and it can raise the standard error of the coefficient evaluations and produce the prediction sensitive to insignificant changes in the model. The predictor importance rank can be specified based on its contribution to R-Square. However, this rank cannot certify that the predictor is important or not in a practical sense, and subject area knowledge should be applied. There are different techniques can be used to calculate the predictor importance of a prediction model, one of them is sensitivity analysis that discussed in some research [25,32, 33]

Table 7 presents the independent variable importance for each used model. It is obvious that SUPV and w/c ratio are the superior predictors in all used models except in SVM model which produce that w/c and Age predictors have the most important predictors than the others. DUPV reflect low importance as shown in Table 7, but from the practical point of view it has major importance in all constructed prediction models and has a strong relation to the compressive strength. This is due to a high correlation between the two independent variables SUPV and DUPV which both duplicate much of the same information. This can be proofed by eliminating SUPV from each prediction model which leads to getting higher independent predictor importance of DUPV, but not so as SUPV. Anyway, the precision of the measurements for predictors can affect their importance and can cause a predictor to appear less predictive than it truly is.

Table 7

Independent variable importance by SPSS

Predictor	Linear Regression	Stepwise linear Regression	CHAID tree	CART tree	SVM	ANN
SUPV	**0.24**	**0.19**	**0.61**	**0.57**	0.13	**0.235**
DUPV	0.00	0.00	0.05	0.02	0.07	0.062
w/c	**0.37**	**0.50**	**0.25**	**0.31**	**0.28**	**0.165**
Age	0.15	0.15	0.03	0.00	**0.23**	0.101
Density	0.08	0.04	0.00	0.00	0.03	0.118
Sand	0.00	0.00	0.02	0.06	0.18	0.104
CA	0.09	0.07	0.00	0.02	0.08	0.083
Curing	0.04	0.05	0.00	0.00	0.00	0.044
CAgrade	/	/	0.05	0.02	0.00	0.045
Slump	0.02	0.00	0.00	0.00	0.00	0.043

11. Results Discussion

The first constructed model was ANN model which is an advanced predictive model. The ANN model topology and the tuned parameters were presented above. The coefficient of determination R^2 of the model was 0.944 when all predictors were included in the model, and this reflects high model performance, as shown in Fig.3.

To focus the research on the most effective predictors among the ten predictors, the relative importance of predictor has been calculated and depicted in Fig.4. This step was done to all tested predictive models except for non-linear regression, linear regression, and stepwise linear regression models. Table 6 list the independent variable importance of the predictors to the used predictive models. Regardless of SUPV and DUPV (which are important predictors from the practical point of view), It is clear that w/c have the highest importance in all of the predictive models, while CAgrade and Slump predictors have the lowest importance. The remaining predictors have a different importance rank in each model. It should be noted that while tuning the parameters of the predictive models the independent variable importance has variation in values accordingly and in its importance rank occasionally.

Different combinations of selected input variables (DUPV, SUPV, and w/c) were tested in the used predictive models. Table 5 and Table 6 summarize these combinations and corresponding predictive models. For all models, the first highest performance has been achieved by participating all predictors in the model, and approximately the second highest performance was reached with SUPV and w/c predictors.

When DUPV and w/c were selected as predictors for predictive models, the performance of models was parallel to the performance of models when using SUPV and w/c, but with a very small drop in the performance. Once comparing the performance of models of SUPV and w/c with the performance of models of SUPV, DUPV, and w/c no significant enhancements can be observed. Thus, when adding DUPV variable to the models of SUPV and w/c, this is will not improve the accuracy of these models, as can be seen from the comparison of their R^2 values in Table 5 and Table 6.

For all tested predictive models, in case of existing of only one predictor either SUPV or DUPV in the predictive model, the performance will be low and R^2 values are under 0.75. So, it is not enough to depend on ultrasonic pulse velocity reading, which may lead to an inaccurate assessment of concrete compressive strength.

From Table 5 and Table 6, best regression performances have been observed in ANN models, SVM, CHAID, CART, and non-linear regression models which there were approximately parallel in performance. Lower values of R^2, and consequently low performance, has been observed in linear regression models and stepwise linear regression models.

Comparing Fig.5a with Fig.7a, it seems that the stepwise linear regression did not produce more accuracy in prediction than linear regression. In addition, for the lowest values of the target, the models predict negative values which it is practically impossible. Fig.7b shows that the splitting technique can improve the accuracy but remains less than other models.

For nonlinear regression, when comparing Fig.6c and Fig.6d it can be concluded that the predictive model of DUPV and w/c predictors can give reasonable performance rather than going to model with full predictors. But the case with the SVM model was different because R^2 value reduced from 0.93 for a model of full predictors to

0.80 for the model of DUPV and w/c predictors, as shown in Fig.9a and Fig. 9b.

Fig.8a shows significant prediction accuracy with R^2 equal to 0.92 for CHAID model with all predictors. With slightly less accuracy than the CHAID model, the CART model produces a value of R^2 = 0.89 as depicted in Fig. 8b.

It is worth to mention that the accuracy or stability of ANN, CART, and CHAID models can be enhanced by creating an ensemble using boosting or bagging (bootstrap aggregation), which generate multiple models to obtain more accurate or reliable predictions, respectively. The standard models were used which are easier to interpret and can be faster to score. Boosting and bagging techniques can be subject for further research.

12. Conclusion

Many factors can influence the concrete compressive strength and the ultrasonic pulse velocity but not in the same way and extent. The research has two objectives; first is to identify the effect of mix parameters, including the slump, w/c, coarse aggregate grading type, volume ratio of coarse aggregate, volume ratio of sand, curing pressure, concrete density, and concrete age, on the relationship between concrete compressive strength and ultrasonic pulse velocity. Second is to find the most appropriate predictive models among different supervised machine learning models for regression.

It was concluded that the w/c ratio has a superior effect on the relationship between ultrasonic pulse velocity and corresponding concrete strength using any predictive model. Most of the used predictive models were improved in their performance by approximately +0.15 with R^2 when adding w/c to SUPV or DUPV predictive models. For all used predictive models, the lowest importance of predictor was observed in slump, coarse aggregate grading type, and curing. The other parameters have different influence depending on the predictive model used.

When using the two types of ultrasonic pulse velocity reading, (DUPV and SUPV), only in a predictive model would not improve the performance when compared with a model used one type of them. Best prediction performances were achieved with all mix parameters for all predictive models.

Artificial neural network algorithm is the most effective technique in prediction with the highest performance R^2 equal to 0.944 followed by the second advance model which was SVM with R^2 equal to 0.93. The decision tree models (CHAID and CART) have also high prediction accuracy with R^2 of 0.92 and 0.89, respectively. In these predictive models, the tuning parameters are very important and can change the accuracy of prediction significantly.

Modeling insignificant variations that might be noise is an overfitting problem. ANN algorithm is a flexible model and it tends to overfit data, but this has been avoided with overfitting prevention set of 30% of the data. Without overfitting the training data, the SVM model is a firm regression algorithm that increases the predictive performance of a model. Decision tree models are also able to overfit data, and SPSS modeler software has an option for overfit prevention which was activated in this research for these models.

Non-linear regression models present considerable prediction accuracy, and this is might be due to the good selection of nonlinear equation for each input value. The accuracy of the models was very close to the performance of CART tree regression models. This type of predictive model is easy to interpret. Therefore, the non-linear regression equations in Table 5 might be suggested to be the empirical equations that can be used for evaluation the concrete compressive strength using two input values w/c and UPV (DUPV or SUPV) only. These equations can be valid for fcu less than 65MPa with w/c between 0.4 and 0.9.

Linear regression and stepwise linear regression are simple models which are easy to interpret but have low accuracy.

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