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Estimation of compressive strength of BFS and WTRP blended cement mortars with machine learning models

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Abstract. The aim of this study is to build Machine Learning models to evaluate the effect of blast furnace slag (BFS) and waste tire rubber powder (WTRP) on the compressive strength of cement mortars. In order to develop these models, 12 different mixes with 288 specimens of the 2, 7, 28, and 90 days compressive strength experimental results of cement mortars containing BFS, WTRP and BFS+WTRP were used in training and testing by Random Forest, Ada Boost, SVM and Bayes classifier machine learning models, which implement standard cement tests. The machine learning models were trained with 288 data that acquired from experimental results. The models had four input parameters that cover the amount of Portland cement, BFS, WTRP and sample ages. Furthermore, it had one output parameter which is compressive strength of cement mortars. Experimental observations from compressive strength tests were compared with predictions of machine learning methods. In order to do predictive experimentation, we exploit R programming language and corresponding packages. During experimentation on the dataset, Random Forest, Ada Boost and SVM models have produced notable good outputs with higher coefficients of determination of R2, RMS and MAPE. Among the machine learning algorithms, Ada Boost presented the best R2, RMS and MAPE values, which are 0.9831, 5.2425 and 0.1105, respectively. As a result, in the model, the testing results indicated that experimental data can be estimated to a notable close extent by the model.

Keywords: blast furnace slag; waste tire rubber powder; compressive strength; random forest; ada boost; SVM; Bayes classifier models

1. Introduction

Waste materials such as blast furnace slag (BFS) and waste tire rubber (WTR) have been continuously increased with the advancement of industrial activity. As a result, management and disposal of BFS and WTR have become a great concern.

BFS is one of the most important supplementary cementitious materials, and widely used in cement and concrete industries. BFS is a by-product obtained while melting iron ore in blast furnace. By melting the iron ore at 1400-1600°C, pig iron is produced and the floating impurities, containing mainly lime, silica and alumina from the BFS arises (Duggal 2008). The use of BFS in cements reduces raw material consumption, the CO_2 emissions and other environmental impacts, while improving their technical properties such as high resistance to chloride penetration, sulfate attack and ASR, improved workability, pumpability and compaction characteristics for concrete placement, increased strength and durability, reduced permeability (Crossin 2015, Siddiquea and Bennacer 2012, Deb *et al.* 2014, Atis and Bilim 2007, Dellinghausen *et al.* 2012, Teng *et al.* 2013, Zhu *et al.* 2012, Yung *et al.* 2013, Saade 2015).

Disposal of waste tire rubber has become a major environmental issue in all parts of the world. Every year millions of tires are discarded, thrown away or buried all over the world, causing a very serious threat to the ecology. Tire burning, which was the easiest and cheapest method of disposal, causes serious fire hazards (Thomas 2016). One way of utilizing waste rubber tires is to recycle them. Concerning the reuse of recycled rubber in mortars and concrete, extensive studies have been conducted on used tires modified concrete and mortars. Results have indicated that rubberized concrete mixtures show lower density, increased toughness and ductility, higher impact resistance, lower compressive and splitting tensile strength, and more efficient sound insulation (Yilmaz and Degirmenci 2009, Al-Akhras and Smadi 2004, Eiras *et al.* 2014, Uygunoglu and Topcu 2010).

Because of the economic, ecological and technical advantages, waste materials such as blast furnace slag (BFS) and waste tire rubber powder (WTRP) are used as supplementary cement and concrete material, or artificial pozzolan in cement and concrete industry. In this industry, it causes losses in both time and financial costs for preparing the cement mortars and concretes by using

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Table 1 Chemical compounds of PC, BFS and WTRP

Materials	PC	BFS	WTRP
Chemical compounds, wt.%			
SiO_2	19.88	37.61	18.30
Al_2O_3	5.24	15.37	4.08
Fe_2O_3	2.66	0.63	3.88
CaO	63.50	33.09	9.94
MgO	1.11	8.55	2.30
SO_3	2.78	0.00	3.57
Na_2O	0.40	0.70	1.06
K_2O	0.78	0.96	0.45
Loss on ignition	3.72	0.17	-

Table 2 Physical characteristics of PC, BFS and WTRP

Materials	Range dimension (over sieve), %			Specific gravity, g/cm^3	Blaine, cm^2/g
	>45 μm	>90 μm	>200 μm		
PC	4.7	0.3	0.0	3.15	3504
WTRP	45.4	17.9	2.2	1.70	2404
BFS	60.9	46.0	25.5	2.88	1848

Table 3 Codes and mix proportions of blended cements

Cement type	PC, g	BFS, g	WTRP, g	PC, %	BFS, %	WTRP, %
S1	450	0	0	100	0	0
S2	427.5	22.5	0	95	5	0
S3	405	45	0	90	10	0
S4	382.5	67.5	0	85	15	0
S5	360	90	0	80	20	0
S6	438.75	0	11.25	97.5	0	2.5
S7	427.5	0	22.5	95	0	5
S8	427.5	11.25	11.25	95	2.5	2.5
S9	405	33.75	11.25	90	7.5	2.5
S10	405	22.5	22.5	90	5	5
S11	405	45	22.5	85	10	5
S12	405	67.5	22.5	80	15	5

various additives. By using various calculation methods, these losses are eliminated. While some researchers prefer statistical methods, other researchers prefer the expert systems. Artificial Neural Network (ANN) and fuzzy logic and expert systems have become popular and have been used by many researchers to solve a wide variety of problems in civil engineering applications (Sakthivel *et al.* 2016, Motamedi *et al.* 2015, Behnood *et al.* 2015a, Beynood *et al.* 2015b, Mansouri and Kisi 2015, Wang *et al.* 2015, Beycioğlu *et al.* 2015, Subasi 2009, Topcu and Saridemir 2008, Yaprak *et al.* 2013, Gulbandilar and Kocak 2013, Castelli *et al.* 2013, Kelestemur *et al.* 2014). On the other hand, Adaptive Neuro-Fuzzy Inference System (ANFIS) and multiple regression analysis are used in civil engineering to perform predictions.

In this study, we aimed to develop models to evaluate the effect of BFS and WTRP on compressive strength of cement mortars by using Machine Learning algorithms that classify observed data accurately. More clearly, we exploit Ada Boost (Freund and Schapire 1997), Random Forest (Breiman 2001), SVM (Boser *et al*. 1992) and Bayes classifier models (Russell and Norvig 2003). Respectively, Ada Boost algorithm becomes a good classification option, when observations comprise bias. The algorithm converts a set of weak learners into a strong learner. Another classification based method is Random Forest. The method is based on random decision tree learning and introduces ensemble learning strategy to reduce the risk of overfitting. The third strategy, Support Vector Machines constructs a hyperplane to distinguish each class. Finally, Bayes classification method applies Bayes theorem for learning and prediction.

For purpose of constructing the models, 12 different mixes with 288 specimens of the 2, 7, 28 and 90 days compressive strength experimental results of cement mortars containing Portland cement (PC), BFS, WTRP, BFS+WTRP used in training and testing for Random Forest, Ada Boost, SVM and Bayes classifier models were gathered from the standard cement tests. The models were trained with 288 data of experimental results. The Random Forest, Ada Boost, SVM and Bayes classifier models had four input parameters and one output parameter. The obtained results from compressive strength tests were compared with predicted results.

2. Experimental procedure

In this study, CEM I 42.5 R cement (PC), blast furnace slag (BFS), waste tire rubber powder (WTRP), standard aggregate and water were used as materials. The cement produced in the SET Istanbul Ambarli Cement Plant (Turkey). BFS was obtained from the Eregli Iron and Steel Plant in Zonguldak (Turkey). WTRP was obtained from a Commercial Business in Ankara (Turkey). WTRP, in the bottom during the making various grades and sizes of granules obtained from waste tires in very fine powder, and was obtained by sieving 125 μm sieve. For the preparation of mortar specimens, standard aggregate, conforming to TS EN 196-1 (TS EN 196-1 2009), and city water of the Istanbul Province Buyukcekmece District were used. Table 1 lists the chemical compounds of the PC, BFS and WTRP. Chemical analyses of the PC, BFS and WTRP were performed on ARL 8680 X-ray diffraction (Table 1).

Physical characteristics of the PC, BFS and WTRP are listed in Table 2. Surface areas were determined as Blaine values by Toni Technik 6565 Blaine and specific weights were determined by Quantachrome MVP-3.

In this study, the PC was used for the preparation of reference samples. The amount of PC is reduced by 5, 10, 15 and 20% by weight being substituted by the same amount of BFS. Similarly, the amount of WTRP substitution is 2.5 and 5% by weight. Besides, in order to investigate the properties of ternary mixtures, the amount of PC is reduced by 2.5+2.5%, 7.5+2.5%, 5+5%, 10+5%, 15+5% by weight being substituted by the same amount of BFS and WTRP, respectively. Codes and mix proportions of reference and blended cements are given in Table 3.

Mortar mixtures, used in compressive strength tests, each contained 450 g PC or blended cement, 1350 g standard sand and 225 ml water, and mixed in a mortar-mixing machine, conforming to TS EN 196-1 (TS EN 196-1 2009). The prepared mortars were poured into the 40×40×160 mm three-segmented rectangular prismatic formworks. These specimens were then shaken for one minute on a shaking table so the mortar settled into the formworks, and were kept in a laboratory environment for 24 hours. At the end of this duration, the specimens were taken out of the formworks and kept in a curing pool. The specimens, taken from the pool at the end of 2, 7, 28 and 90 days using Atom Technik device, were tested compressive strength in accordance with TS EN 196-1 (TS EN 196-1 2009).

3. Machine learning models with random forest, ada boost, SVM and naïve bayes classifier

Classification algorithms identify the observed data and put them into categories as a result of common features of data. Based on observations, where both instances and category memberships are known, classification algorithms predict the categories of new observations.

3.1 Ada boost

Ada Boost is an adaptive algorithm that unveil a strong learner from multiple weak learners (Freund and Schapire 1997). It is commonly preferred when the classification algorithms suffer from high-dimensional data. The algorithm has the ability to select only the features that improve prediction performance. The form of the boost classifier is as follows

$$F_T(x) = \sum_{t=1}^{T} f_t(x) \tag{1}$$

Where, f_t is a weak learner that takes the object x as input and yield the sum of the weak learners as the final classifier as output. Here, computation of each weak learner depends on a hypothesis, $h(x_i)$ and minimized training error at step t, a_t. Formally,

$$f_t(x) = \alpha_t h(x) \tag{2}$$

3.2 Random forest

Random Forest, which is an extension of decision trees, is a remarkable classifier. In order to prevent overfitting possibilities of decision trees, Random Forests are proposed. Since, deep decision trees have tendency to have high variance, Random Forest computes the average of the multiple decision trees, which are trained from the same data set. In other words, training of Random Forests implements the bagging to reduce variance. Detailed explanations about Random Forests can be founded in literature (Breiman 2001).

In terms of R, we exploit Random Forest package (Liaw and Wiener 2002). During programming execution, we assume proximity and importance parameters are TRUE and trace is 100. We exploit all other default parameters.

3.3 Support vector machines

In contrast to Boosting and Random Forest, Suppor Vector Machines, SVM, are non-probabilistic classifier. SVM assumes that each train sample is a vector point in multi-dimensional space. Afterwards, it constructs hyperplanes in the multi-dimensional space to classify vector points. In order achieve optimal classification, distance between such hyperplanes and nearest train point samples of each class should be maximized. In order to enable non-linear classifiers, SVM exploits kernel trick. Detailed explanations about SVM can be founded in literature (Boser *et al*. 1992).

3.4 Naïve bayes classifier

Similar to SVM, Naïve Bayes algorithm is a deterministic classifier. Naïve Bayes Classifier algorithm is based upon Bayes Theorem (Russell and Norvig 2003). The algorithm assumes that there is strong independence among features. Let assume a problem instance is represented by n features. Formally,

$$x = (x_1, x_2, ..., x_n) \tag{3}$$

Bayes classifier computes the probability of the instance is a member of k^{th} class, C_k. Formally,

$$C_k = p(C_k \mid x_1, x_2, ..., x_n) \tag{4}$$

When all probabilities are computed, the instance is assigned into C_k with highest probability.

4. Experimental design and model parameters

In terms of experimentation, we have exploited R language and corresponding R packages. R is an open source statistical analysis programming language and first appeared in 1993. It is commonly preferred during machine learning techniques, including classification algorithms.

R introduces an archive network to download necessary packages to execute required algorithms. In this study, we have exploited maboost (Naghibi and Pfister 2014), random Forest (Liaw and Wiener 2002), and e1071 packages to execute multiclass Ada Boost, Random Forest, SVM and Naïve Bayes algorithms respectively.

In training and testing of the Random Forest, Ada Boost, SVM and Bayes classifier models the age of samples (Days), PC, WTRP and BFS were entered as input; while compressive strength values of cement mortars were used as output (Table 4). The comprehensive sensitivity analysis of input variables for output variable was determined using Automatic Linear Modelling in SPSS 22.0 software package (Fig. 1). The importance of sensitivity for Days, WTRP and PC as input variables were 0.9, 0.08 and 0.002, respectively. We have used all the input variables in our

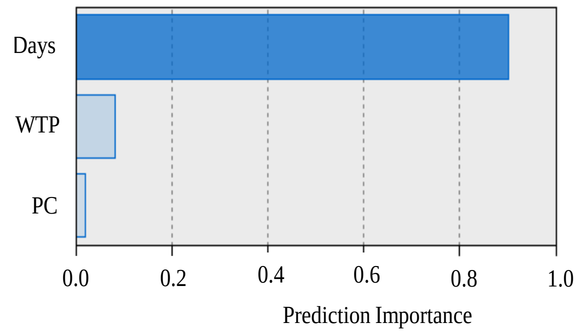

Fig. 1 The importance level of input variable sensitivities for output variable

Table 4 The input and output quantities used in random forest, ada boost, SVM and bayes classifier models

		Data used in training and testing the models	
		Minimum	Maximum
Input variable	Age of samples, Days	2	90
	PC, g	360	450
	BFS, g	0	90
	WTRP, g	0	22.5
Output variable	Compressive strength, MPa	12.4	64.4

study since the results of the analysis were almost identical.

In the Random Forest, Ada Boost, SVM and Bayes classifier models, 288 of the experimental data were used for the training of the models and other 48 data (the average of the 6 experimental data) were used for testing the trained models.

5. Results and discussion

In this study, the values of compressive strength were modeled using Random Forest, Ada Boost, SVM and Bayes classifier models.

The models tried to be compared according to the absolute fraction of variance (R^2), mean absolute percentage error (MAPE) and a root-mean squared (RMS) error criteria. These criteria are defined by Eqs. (5), (6) and (7), respectively (Ozcan *et al.* 2009).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|t_{i\_}o_i\right|^2} \tag{5}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(o_i)^2}\right) \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\left(\frac{t_i - o_i}{o_i}\right)\right| * 100 \tag{7}$$

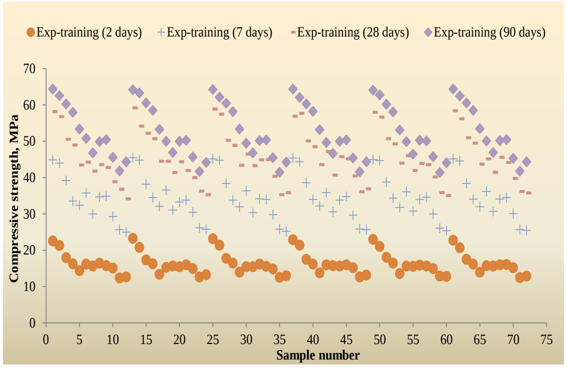

Fig. 2 Compressive strengths for training random forest, ada boost, SVM and bayes classifier models with sample number

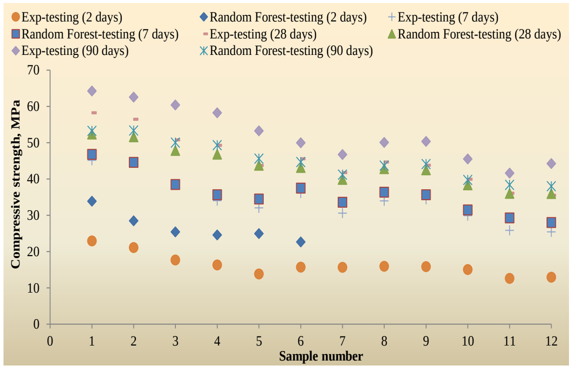

Fig. 3 Comparison of compressive strength experimental and testing results of the random forest model with sample number

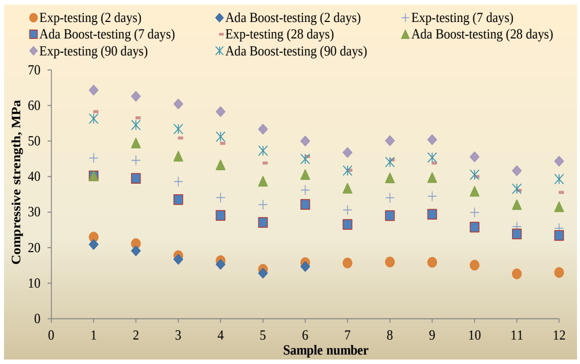

Fig. 4 Comparison of compressive strength experimental and testing results of the ada boost model with sample number with sample number

Here *t* is the target value, *o* is the network output value, *N* is the total number of pattern.

In the training and testing of Random Forest, Ada Boost, SVM and Bayes classifier models from experimental data are used. During our model, we exploited 288 of the data as experimental and remaining 48 data as training. Sample number and experimental results for training were given in Fig. 2.

Sample number and experimental results from the Random Forest, Ada Boost, SVM and Bayes classifier models are presented in Figs. 3, 4, 5, and 6, respectively.

All results obtained from experimental studies and

Table 5 Comparison of compressive strength experimental results with testing results obtained from the random forest, ada boost, SVM and bayes classifier models

Data used in the models construction				Compressive strength, MPa				
Days	PC, g	BFS, g	WTRP, g	Exp.	Random Forest	Ada Boost	SVM	Bayes
2	450	0	0	23.0	33.9	20.9	39.6	20.9
2	427.5	22.5	0	21.1	28.5	19.1	31.5	19.1
2	405	45	0	17.7	25.4	16.7	28.9	16.7
2	382.5	67.5	0	16.3	24.6	15.3	27.9	43.9
2	360	90	0	13.9	25.0	12.8	28.3	50.1
2	438.75	0	11.25	15.8	22.7	14.7	25.2	21.0
2	427.5	0	22.5	15.7	22.5	14.6	24.6	19.8
2	427.5	11.25	11.25	16.0	22.2	14.9	21.0	20.2
2	405	33.75	11.25	15.9	21.9	14.8	18.5	11.6
2	405	22.5	22.5	15.1	20.7	14.1	18.9	11.0
2	405	45	22.5	12.6	20.9	11.6	17.7	11.6
2	405	67.5	22.5	13.0	21.2	11.9	20.9	11.9
7	450	0	0	45.2	46.8	40.2	42.1	56.2
7	427.5	22.5	0	44.6	44.6	39.5	36.7	54.7
7	405	45	0	38.6	38.5	33.5	33.0	53.8
7	382.5	67.5	0	34.1	35.7	29.1	31.6	43.1
7	360	90	0	32.1	34.5	27.1	29.6	28.1
7	438.75	0	11.25	36.2	37.5	32.1	28.5	29.1
7	427.5	0	22.5	30.6	33.6	26.5	27.8	26.5
7	427.5	11.25	11.25	34.0	36.4	29.0	24.8	29.0
7	405	33.75	11.25	34.4	35.7	29.4	23.0	23.3
7	405	22.5	22.5	29.9	31.5	25.8	23.6	23.7
7	405	45	22.5	25.9	29.3	23.8	21.5	24.9
7	405	67.5	22.5	25.4	28.0	23.4	22.9	23.4
28	450	0	0	58.3	52.4	40.2	57.8	56.3
28	427.5	22.5	0	56.5	51.6	49.5	56.0	54.5
28	405	45	0	50.8	47.9	45.7	52.3	53.9
28	382.5	67.5	0	49.3	46.8	43.3	48.8	43.3
28	360	90	0	43.8	43.8	38.7	43.1	47.9
28	438.75	0	11.25	45.6	43.2	40.5	46.1	49.7
28	427.5	0	22.5	41.8	39.9	36.7	42.3	35.7
28	427.5	11.25	11.25	44.7	42.9	39.6	45.2	49.8
28	405	33.75	11.25	43.8	42.6	39.7	44.1	34.6
28	405	22.5	22.5	40.0	38.4	35.9	39.9	35.9
28	405	45	22.5	36.1	36.1	32.1	36.6	24.1
28	405	67.5	22.5	35.5	36.0	31.5	36.0	23.4
90	450	0	0	64.3	53.3	56.3	62.8	56.3
90	427.5	22.5	0	62.6	53.4	54.5	62.1	54.5
90	405	45	0	60.4	50.0	53.4	58.9	53.4
90	382.5	67.5	0	58.3	49.3	51.2	57.1	43.2
90	360	90	0	53.3	45.6	47.3	51.8	47.3
90	438.75	0	11.25	50.0	44.7	44.9	51.5	57.1
90	427.5	0	22.5	46.8	41.2	41.7	45.3	56.9
90	427.5	11.25	11.25	50.1	43.7	44.1	50.6	54.1
90	405	33.75	11.25	50.4	44.2	45.3	50.8	53.4
90	405	22.5	22.5	45.6	39.8	40.5	44.0	11.1
90	405	45	22.5	41.7	38.4	36.6	43.2	53.8
90	405	67.5	22.5	44.3	38.1	39.3	42.8	23.2

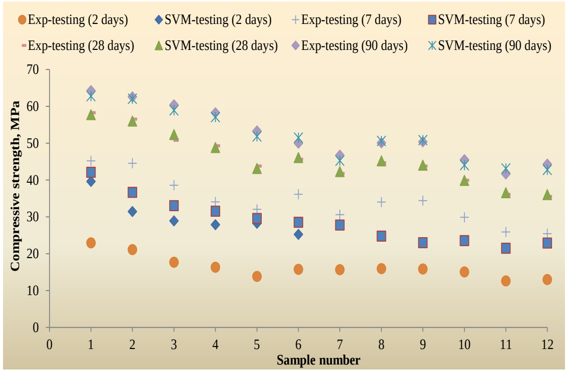

Fig. 5 Comparison of compressive strength experimental and testing results of the SVM model with sample number

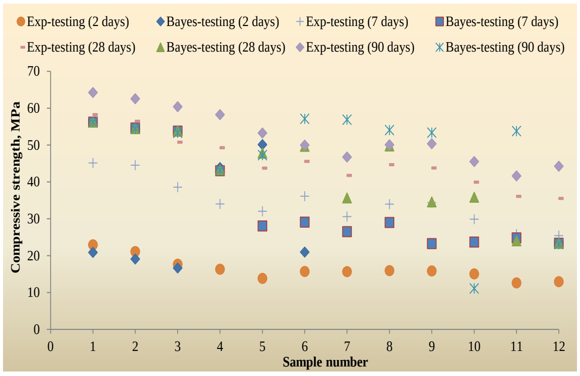

Fig. 6 Comparison of compressive strength experimental and testing results of the bayes classifier model with sample number

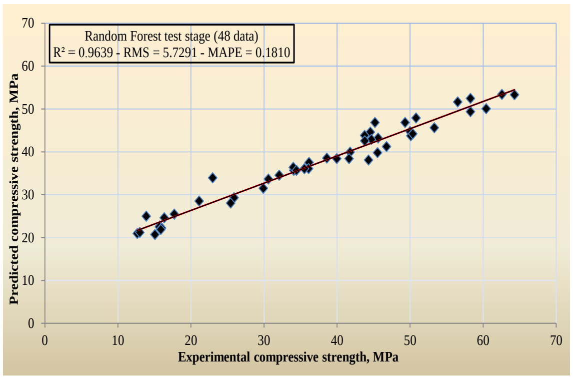

Fig. 7 Comparison of compressive strength experimental results with training results of the random forest model

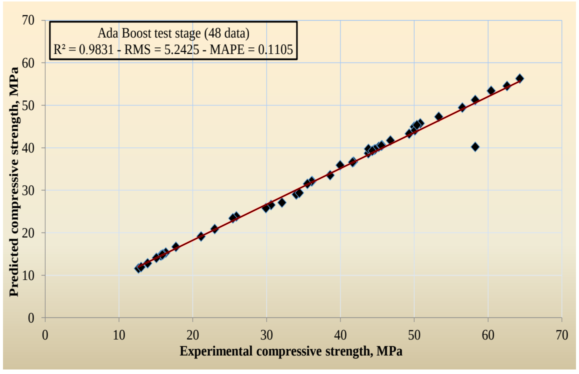

Fig. 8 Comparison of compressive strength experimental results with training results of the ada boost model

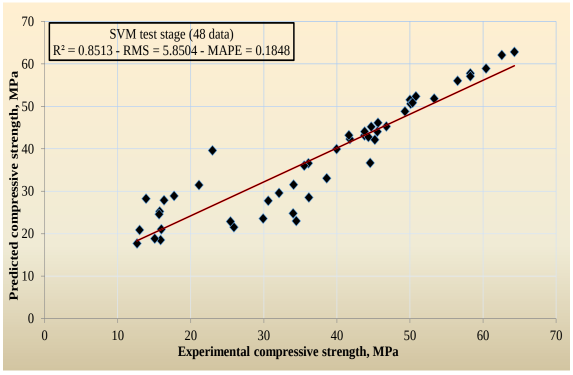

Fig. 9 Comparison of compressive strength experimental results with training results of the SVM model

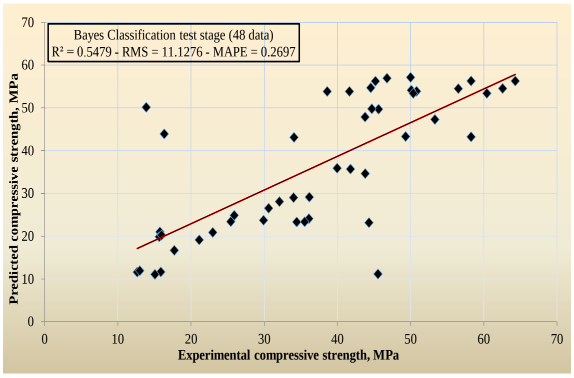

Fig. 10 Comparison of compressive strength experimental results with training results of the bayes classifier model

predicted by using the testing results of the Random Forest, Ada Boost, SVM and Bayes classifier models, for 2, 7, 28 and 90 days compressive strength were given in Figs. 7, 8, 9 and 10, respectively.

The linear least square fit line, its equation and the R^2 values were shown in these figures for the testing data. As it is visible in Figs. 8 and 7 the values obtained from the testing in the Ada Boost and Random Forest models are very closer to the experimental results, respectively. However, As it is visible in Figs. 9 and 10 the values obtained from the testing in the SVM and Bayes classifier models are farther to the experimental results. The result of testing phase in Figs. 8 and 7 show that the Ada Boost and Random Forest models are capable of generalizing between input and output variables with reasonably good predictions.

The statistical values for all the station such as RMS, R^2 and MAPE for testing were given in Table 6.

The statistical values of R^2, RMS and MAPE from testing in the Random Forest model were found as 0.9639, 5.7291 and 0.1810, in the Ada Boost 0.9831, 5.2425 and 0.1105, in the SVM 0.8513, 5.8504 and 0.1848, in the

Table 6 The compressive strength statistical values of proposed the random forest, ada boost, SVM and bayes classifier models

Statistical parameters	Random Forest	Ada Boost	SVM	Bayes
R^2	0.9639	0.9831	0.8513	0.5479
RMS	5.7291	5.2425	5.8504	11.1276
MAPE	0.1810	0.1105	0.1848	0.2697

Table 7 Correlations for all this models

Statistical parameters		Random Forest	Ada Boost	SVM	Bayes	Experimental
Random Forest	Pearson Correlation	1	0.969**	0.919**	0.775**	0.982**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000
Adaboost	Pearson Correlation	0.969**	1	0.918**	0.733**	0.991**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000
SVM	Pearson Correlation	0.919**	0.918**	1	0.748**	0.923**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000
Bayes	Pearson Correlation	0.775**	0.733**	0.748**	1	0.740**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000
Experimental	Pearson Correlation	0.982**	0.991**	0.923**	0.740**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	

** Correlation is significant at the 0.01 level (2-tailed)

Bayes 0.5479, 11.1276 and 0.2697, respectively. All of the statistical values in Table 7 show that the proposed the Ada Boost and Random Forest models are suitable and predict the 2, 7, 28 and 90 days compressive strength values very close to the experimental values.

Furthermore, four models and experimental output values were compared by SPSS 22.0 software package (Table 7). We have found statistically significant relationship within all models (p<0.000). Hence, we observed high level correlation among four models and experimental output values (Pearson correlation values between 0.982 and 0.733).

Hence, the comprehensive sensitivity analysis of four model sensitivities for experimental output values was determined by Automatic Linear Modelling (Fig. 11). The importance of sensitivity for the Ada Boost, Random Forest, SVM and Bayes classifier models were 0.79, 0.021, 0.000 and 0.000, respectively. The Ada Boost and Random Forest models yielded better prediction performances.
Results imply that Bayes model does not present efficient prediction outputs for this study. In fact, Bayes model may not be sensitive to noisy data or outliers. Hence Bayes model doesn't present optimal yields for this data set.

6. Conclusions

In this study, the Random Forest, Ada Boost, SVM and Bayes classifier models were used for the prediction the 2, 7, 28 and 90 days compressive strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP. In

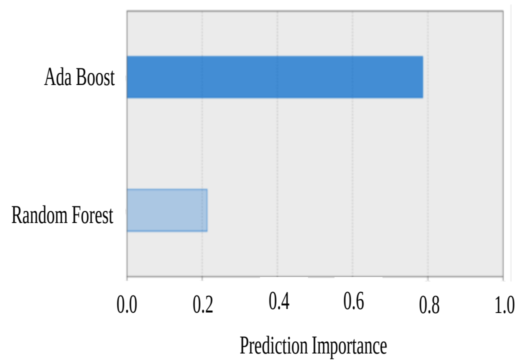

Fig. 11 The importance level of four model sensitivities for experimental output values

order to train the models, we exploited 288 experimental data, whereas 48 data were used for testing machine learning models. Analysis of the prediction results denote that Adaboost model presented the most accurate outputs.

During Adaboost model R^2, RMS and MAPE were found as 0.9831, 5.2425 and 0.1105, respectively. We also observed accurate results from Random Forest model. R^2, RMS and MAPE outputs of Random Forest were 0.9639, 5.7291 and 0.1810 respectively. The prediction results of SVM were also acceptable. In other words, R^2, RMS and MAPE results of SVM were 0.8513, 5.8504 and 0.1848 respectively. Finally, we conclude that Naïve Bayes presented the worst prediction performance. Particularly, R^2, RMS and MAPE yields of Bayes classifier model were found as 0.5479, 11.1276 and 0.2697 respectively. We assume Adaboost and Random Forest models may be compatible to similar problems when overfitting is a problem. Furthermore, the two models may be convenient to prediction from noisy or high dimensional data.

As a result, compressive strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP can be predicted in the Random Forest, Ada Boost, SVM and Bayes classifier models in a quite short period of time. The conclusions have shown that the Ada Boost and Random Forest models are practicable methods for predicting compressive strength values of cement mortars containing PC, BFS, WTRP and BFS+WTRP. Furthermore, these systems can reduce losses in both elapsed time and financial costs during the preparation of the cement mortars and concretes by exploiting various additives. In the future, new studies can be made by removing limitations such as the cement type prepared with various mineral additives.

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