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Evaluating flexural strength of concrete with steel fibre by using machine learning techniques

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Abstract. In this study, potential of three machine learning techniques i.e., M5P, Support vector machines and Gaussian processes were evaluated to find the best algorithm for the prediction of flexural strength of concrete mix with steel fibre. The study comprises the comparison of results obtained from above-said techniques for given dataset. The dataset consists of 124 observations from past research studies and this dataset is randomly divided into two subsets namely training and testing datasets with (70-30)% proportion by weight. Cement, fine aggregates, coarse aggregates, water, super plasticizer/ high-range water reducer, steel fibre, fibre length and curing days were taken as input parameters whereas flexural strength of the concrete mix was taken as the output parameter. Performance of the techniques was checked by statistic evaluation parameters. Results show that the Gaussian process technique works better than other techniques with its minimum error bandwidth. Statistical analysis shows that the Gaussian process predicts better results with higher coefficient of correlation value (0.9138) and minimum mean absolute error (1.2954) and Root mean square error value (1.9672). Sensitivity analysis proves that steel fibre is the significant parameter among other parameters to predict the flexural strength of concrete mix. According to the shape of the fibre, the mixed type performs better for this data than the hooked shape of the steel fibre, which has a higher CC of 0.9649, which shows that the shape of fibers do effect the flexural strength of the concrete. However, the intricacy of the mixed fibres needs further investigations. For future mixes, the most favorable range for the increase in flexural strength of concrete mix found to be (1-3)%.

Keywords: concrete; flexural Strength; gaussian processes; M5P; support vector machines

1. Introduction

Concrete plays a promising role as a construction material. A mixture of concrete contains aggregates, water and cement, which bond together to form a concrete with good strength properties. Primary constituents of concrete: fine and coarse aggregate, cement and water (Zongjin 2011). Out of primary constituents of concrete, cement has economical as well as environmental issues. To solve the problem many researchers use different materials as a chemical or mineral admixture in concrete (Khater *et al*. 2020, Nalanth *et al*. 2014, Guo *et al*. 2014, Lee *et al*. 2020, Haddadou *et al*.

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2015, Fladra *et al*. 2019). Due to increase in demand of industries, there is a boom in industrialization which seems the responsible factor for the production of waste material that in turn pollutes the environment. Environmental problem must need a solution. To solve the problem, waste generated by these industries can be utilized by using these wastes in concrete mix either partial or full replacement with sand or cement (Siddique *et al*. 2020, Sharma *et al*. 2020). Also concrete is good in compressive strength but weak in tension so to enhance the structural properties, fibres plays a good role. Presence of the fibre in concrete, mortar and cement paste are able to enhance the many engineering properties like impact, flexural strength, thermal shock resistance to fatigue etc. (Nataraja *et al*. 2005). Al-Gemeel *et al*. (2018), use hybrid fibre consists of polyvinyl alcohol (PVA) and steel fibre (SF) with ratio of PVA and SF as (2.0:0, 1.75:0.25, 1.50:0.50 and 1.25:0.75) %. The result shows that the mono-fibre provides better strength as compare to the hybrid fibre. Steel fibre is one such type of fibre which can be helpful for the reduction of cracks which are formed due to applied loading or shrinkage etc. (Lau and Anson 2006). Zhang *et al*. (2017), investigates the mechanical properties of Poly-vinyl alcohol (PVA)-steel hybrid fibre reinforced engineered cementitious composite. Result proves that steel fibre has the ability to improve the strength properties of concrete mix as compare to the control mix. Also Ganesan *et al*. (2015), in the research study shows that as compared to conventional concrete, fibre reinforced concrete proves to be a more durable. Sounthararajan and Sivakumar (2013), experiment based on the replacement of fine sand with steel fibre in different percentages i.e., 0%, 10%, 20%, and 30%. The result proves that finer sand can be utilized as the high early strength concrete.

According to the literature, the usual test for evaluating the characteristics of concrete is tedious and time-consuming, which has an impact on the project's cost. The empirical formula method shows the non-linear behavior between dependent and independent variables. Other than these two methods machine learning techniques provides a good opportunity to predict the strength properties more accurately. According to the literature, researchers used a variety of machine learning methods to predict the outcome. Since last two decades various machine learning algorithms were applied on complex engineering problems for the prediction of the strength properties of the concrete mix such as: artificial neural network, M5P, support vector machines, Gaussian process, random forest and random tree etc. (Upadhya *et al*. 2021, Laghari *et al*. 2019, Han *et al*. 2019, Goldberg, 2017, Thakur *et al*. 2021, Sobhani *et al*. 2010, Vakharia and Gujar, 2019, Chopra *et al*. 2018, Singh *et al*. 2019, Rabia *et al*. 2021). Prediction of the desired results depends on the linear and non-linear behavior of the techniques. Researchers use concrete constituents as the input parameters, where the strength property as the output (Thakur *et al*. 2021). Sobhani *et al*. (2010), results showed that, NNT and ANFIS predicts comparatively better results for 28 days compressive strength of the concrete mix as compared to the traditional regression analysis with higher coefficient of correlation and minimum error. Chopra *et al*. (2018), in the research study; artificial intelligence (AI) techniques were applied for predicting the strength property of concrete mix. Algorithms like neural network and decision trees were applied on the data set. Results conclude that with high coefficient of correlation, neural network model seems more reliable techniques to predict the compressive strength of the concrete mix when compared with other techniques. Suthar (2019), shows in the investigation of unconfined compressive strength of stabilized pond ashes provides better results by Gaussian process algorithm with minimum error as compared to other models like random forest, random tress, artificial neural network and support vector machine.

Over the years, several studies have been done using support vector machines, Gaussian process, M5P on different engineering problems. Many researchers found that these techniques provide good results as well or better than the neural network method. The objective of the study is to explore these techniques to find the best algorithm for the prediction of flexural strength of concrete mix with steel fibre and the effects of input parameters to predict the flexural strength of the concrete mix.

2. Machine learning techniques

2.1 M5P

M5P is a supervise algorithm introduced by Quinlan in 1992. It can be used for both classification and regression. Generally it is used for the classification of data but in some instances it can be used for regression purpose (Wang and Witten 1996). M5 model tree is a binary decision tree with linear regression functions at the terminal (leaf) nodes that can predict continuous numerical characteristics. It is a decision tree learner for regression that is used to predict values of numerical response variable. The purpose of a model tree is to generate a decision tree hierarchy from simple model in order to suit numerous smaller sections of training set such that the overall model tree fits the entire training set well. Working of M5P model is divided into number of steps. In first step, decision tree algorithm is introduced to form a tree and then each sample is divided into sub-samples and form branches. Second step includes pruning of the data samples from individual leaf. For pruning of the decision tree, different techniques were used where one is to convert inner node into a leaf and second was calculating tree score with the help of sum of squared residual and number of leaves or terminal nodes. In prunning process extra trees are cut down or substituted by sub-trees (Sepahvand *et al*. 2019). Compared to regression trees, model trees prediction is more accurate (Deepa *et al*. 2010).

2.2 Support Vector Machines (SVMs)

Support vector machine is a powerful tool in machine learning which was first introduced by Vapnik in 1995. It is a part of artificial intelligence and researchers use this method to the complex engineering problem for classification, forecasting and regression analysis (Salcedo-Sanz *et al*. 2014, Goh and Goh 2007). Support vectors are number of observations which are closer to the vector space and have an impact on the hyperplane's coordinates. Classifiers are optimized by using support vector. Analysis procedure for SVM involves training and testing data set associated with input and output parameters. SVM analysis has two methods one is optimum margin classifier (linear classifier) which separates the decision surface. Other method is kernel function method which calculates the products of two vectors. With fixed mapping procedure input data is first mapped with n-dimensional features then non-linear kernel function was fitted in high dimensional space. By applying the kernel mapping on actual data, the information separates linearly during high dimensional feature with no change in actual input space (Goh and Goh 2007). The kernel parameters should be carefully set as they have a significant impact on the accuracy and complexity of the SVM solution. The performance of SVMs is primarily determined by the kernel function employed; therefore, selecting a suitable kernel function and kernel parameters for each application problem is critical in ensuring good results (Suthar 2019).

2.3 Gaussian Processes (GPs)

Over the last few years a lot of work has been done in the area of machine learning. Different soft computing techniques were applied to improve the properties of concrete (Sharma *et al*. 2021).

Gaussian process is a part of machine learning which uses kernels for the interpretation of models. To learn the kernel machines it provides a practical approach towards it (Rasmussen and Williams, 2006). It is a cluster of random variables where any finite variable features a joint normal distribution. Gaussian process, l(x) consists of mainly two functions: one is mean function m(x) and another one is kernel function n(x,x') as shown in Eqs. (1)-(3). The Gaussian process stated that l(x) is:

$$l(x) \sim GP(m(x), n(x,x')), \tag{1}$$

The main goal of the function is to find out how target can be achieved by using input variables. Every targeted value say: z is linked with arbitrary regression function l(x) and independent identically distributed Gaussian noise (ɜ).

$$\text{i.e., } z = l(x) + ɜ \tag{2}$$

where, ɜ is a Gaussian noise with zero mean and variance $(\sigma_n)^2$. i.e., ɜ ~ $L(0, \sigma_n^2)$. Then eq. 1 devlop to Eq. (3):

$$l(x) \sim GP(m(x), n(x,x')+ \sigma_n^2 I), \tag{3}$$

where, I represent the identity matrix.

3. Methodology and dataset

Dataset plays the crucial role for the prediction of the output. The study consists of 124 observations which were extracted from the literature. Table 1 presents the details of the observations used in the study. 124 observations were then randomly distributed in two subset keeping the ratio of 70-30 for training and testing subset respectively. In this study, three techniques namely M5P, Support vector machines and Gaussian processes were applied through weka 3.9 with input parameters such as: Cement (C), fine aggregate (FA), coarse aggregate (CA), water (w), super plasticizer/ high-range water reducer (SP/HRWR), steel fibre, fibre length and curing days to achieve the desired outcome where flexural strength (F.S.) was taken as output parameter. Features of total, training and testing dataset are listed in Table 2. Performance of each model was judged by five statistical evaluating parameters namely, coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), and root relative squared error (RRSE). These parameters were helpful for the assessment of the best model. Higher value of CC and lower value of errors predicts better results.

User defined parameters for the testing of flexural strength of concrete mix with steel fibres was listed in Table 3. These optimal user defined values for different techniques are the result of great number of trials. Performance of each model was dependent upon the optimal values. Selection of the optimal values is very critical because these will affect the performance of each model. So the values used in these cases were best suited for both training and testing datasets.

4. Model evaluation

For checking the performance of the applied algorithms, evaluating parameters has to be applied on them. Evaluating parameters used in this study are: coefficient of coefficient of correlation (CC), Mean absolute error (MAE), Root mean square error (RMSE), Relative absolute error (RAE), and Root relative squared error (RRSE).

Table 1 Detail of dataset

Sr. no.	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	Water (kg/m^3)	SP/HRWR (%)	Steel (%)	Fibre length (mm)	Curing Days	F.S. (MPa)	Author Name and Year
1	605	483	0	338.6	3.6	0.25	12	28	8.7	Al-Gemeel *et al.* 2018
2	544	435	0	304.8	3.3	0.25	12	28	8.9	
3	605	483	0	338.6	3.6	0.5	12	28	11.7	
4	544	435	0	304.8	3.3	0.5	12	28	8.6	
5	605	483	0	338.6	3.6	0.75	12	28	5.6	
6	544	435	0	304.8	3.3	0.75	12	28	5.6	
7	0	600	1248	14.5	10.2	0	0	28	4.1	Ganesan *et al.* 2015
8	0	600	1248	16	10.2	0.25	30	28	4.32	
9	0	600	1248	16	14.5	0.5	30	28	4.57	
10	0	600	1248	18	14.5	0.75	30	28	4.88	
11	0	600	1248	18	16	1	30	28	5.1	
12	360	598	1266	192	0	0	0	28	3.77	
13	360	598	1266	192	4	0.5	30	28	4.2	
14	440	1225	366	220	3	0	0	28	4.45	Soulioti *et al.* 2011
15	440	1215	363	220	3.2	0.5	31	28	3.8	
16	440	1205	360	220	3.7	1	31	28	4.6	
17	440	1193	356	220	4	1.5	31	28	5.8	
18	440	1215	363	220	3.2	0.5	25	28	3.95	
19	440	1205	360	220	3.7	1	25	28	4.75	
20	440	1193	356	220	4	1.5	25	28	6	
21	460	626.2	1113.2	184	6.9	0	0	28	8.5	Jian-he *et al.* 2015
22	460	626.2	994.5	222	6.9	1	32	28	7.8	
23	443	660	1105	143	0	0	0	28	5.6	Balendran *et al.*2002
24	443	660	1105	143	0	1	15	28	6.1	
25	443	660	646	143	0	0	0	28	3.3	
26	443	660	646	143	0	1	15	28	9.3	
27	473	672	1113	142	0	0	0	7	4.28	Manoharan and Anandan 2014
28	355	672	1113	142	0	0.5	35	7	4.32	
29	355	672	1113	142	0	1	35	7	4.36	
30	237	672	1113	142	0	1.5	35	7	4.65	
31	237	672	1113	142	0	0.5	35	7	3.83	
32	237	672	1113	142	0	1	35	7	3.43	
33	237	672	1113	142	0	1.5	35	7	4.13	
34	473	672	1113	142	0	0	0	28	5.63	
35	355	672	1113	142	0	0.5	35	28	5.89	
36	355	672	1113	142	0	1	35	28	5.89	
37	237	672	1113	142	0	1.5	35	28	6.7	

Table 1 Continued

Sr. no.	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	Water (kg/m^3)	SP/HRWR (%)	Steel (%)	Fibre length (mm)	Curing Days	F.S. (MPa)	Author Name and Year
38	237	672	1113	142	0	0.5	35	28	5.14	Manoharan and Anandan 2014
39	237	672	1113	142	0	1	35	28	5.73	
40	237	672	1113	142	0	1.5	35	28	6.16	
41	487	785	850	170	8.8	0	0	28	4.4	Koksal *et al.* 2013
42	487	785	850	170	8.8	0.33	60	28	5.4	
43	487	785	850	170	8.8	0.67	60	28	7.6	
44	487	785	850	170	8.8	1	60	28	14	
45	487	785	850	170	8.8	0.33	60	28	11.5	
46	487	785	850	170	8.8	0.67	60	28	16.5	
47	487	785	850	170	8.8	1	60	28	17.3	
48	396	842	913	178	5.3	0	0	28	3.8	
49	396	842	913	178	5.3	0.33	60	28	5.4	
50	396	842	913	178	5.3	0.67	60	28	8.8	
51	396	842	913	178	5.3	1	60	28	12.1	
52	396	842	913	178	5.3	0.33	60	28	10.7	
53	396	842	913	178	5.3	0.67	60	28	15.7	
54	396	842	913	178	5.3	1	60	28	16.1	
55	325	891	965	179	2.9	0	0	28	3.3	
56	325	891	965	179	2.9	0.33	60	28	4.9	
57	325	891	965	179	2.9	0.67	60	28	6.8	
58	325	891	965	179	2.9	1	60	28	11.7	
59	325	891	965	179	2.9	0.33	60	28	6.4	
60	325	891	965	179	2.9	0.67	60	28	8.3	
61	325	891	965	179	2.9	1	60	28	15	
62	550	1410	0	260	1.8	0	0	28	7.6	Dawood and Ramli 2011
63	550	1410	0	260	2.2	2	30	28	15.9	
64	550	1410	0	260	2.2	1.75	30	28	15.92	
65	550	1410	0	260	2.2	1.5	30	28	17.67	
66	550	1410	0	260	2.2	1.25	30	28	13.12	
67	550	1410	0	260	2.2	1	30	28	11.65	
68	550	1410	0	260	2.2	1.5	30	28	18.23	
69	550	1410	0	260	2.2	1.25	30	28	13.67	
70	550	1410	0	260	2.2	1.25	30	28	14.06	
71	550	1410	0	260	2.2	1	30	28	12.1	
72	550	1410	0	260	2.2	1	30	28	10.92	
73	550	1410	0	260	1.8	0	0	90	9.12	
74	550	1410	0	260	2.2	2	30	90	17.36	

Table 1 Continued

Sr. no.	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	Water (kg/m^3)	SP/HRWR (%)	Steel (%)	Fibre length (mm)	Curing Days	F.S. (MPa)	Author Name and Year
75	550	1410	0	260	2.2	1.75	30	90	17.64	
76	550	1410	0	260	2.2	1.5	30	90	19.22	
77	550	1410	0	260	2.2	1.25	30	90	14.95	
78	550	1410	0	260	2.2	1	30	90	13.26	
79	550	1410	0	260	2.2	1.5	30	90	19.67	
80	550	1410	0	260	2.2	1.25	30	90	15.11	
81	550	1410	0	260	2.2	1.25	30	90	15.24	
82	550	1410	0	260	2.2	1	30	90	14.15	
83	550	1410	0	260	2.2	1	30	90	12.44	
84	370	704	1120	144.3	3.8	0.5	60	28	10.07	Tadepalli *et al*. 2015
85	370	704	1120	144.3	3.8	0.5	30	28	6.96	
86	370	704	1120	144.3	3.8	0.5	25	28	8.94	
87	370	704	1120	144.3	3.8	0.5	40	28	7	
88	370	704	1120	144.3	3.8	1.5	60	28	9.22	
89	370	704	1120	144.3	3.8	1.5	30	28	15.37	
90	370	704	1120	144.3	3.8	1.5	40	28	12.16	
91	370	704	1120	144.3	3.8	1.5	25	28	15	
92	370	704	1120	144.3	3.8	0	0	28	6.67	
93	340	894	952	204	0	0.5	30	28	6.96	
94	340	894	952	204	0	0.5	30	28	4.93	
95	340	894	952	204	0	1.5	30	28	8.98	
96	340	894	952	204	0	1.5	30	28	8.44	
97	275	830	910	178	0	0	0	28	2.33	Boulekbache *et al*. 2016
98	275	820	900	178	1.92	0.5	35	28	3.54	
99	275	820	900	178	1.92	1	35	28	5.49	
100	275	820	900	178	1.92	0.5	60	28	4.38	
101	275	820	900	178	1.92	1	60	28	5.82	
102	425	750	825	192	5.1	0	0	28	2.3	
103	425	740	814	192	7.22	0.5	35	28	3.8	
104	425	740	814	192	7.22	1	35	28	7.04	
105	425	740	814	192	7.22	0.5	60	28	5.67	
106	425	740	814	192	7.22	1	60	28	7.86	
107	425	750	825	161	4.25	0	0	28	2.85	
108	425	740	814	161	6.8	0.5	35	28	4.24	
109	425	740	814	161	6.8	1	35	28	7.22	
110	425	740	814	161	6.8	0.5	60	28	5.39	
111	425	740	814	161	6.8	1	60	28	7.82	

Table 1 Continued

Sr. no.	C (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	Water (kg/m^3)	SP/HRWR (%)	Steel (%)	Fibre length (mm)	Curing Days	F.S. (MPa)	Author Name and Year
112	809	1079	0	177	21.6	0	0	28	19	Wu *et al.* 2016
113	800	1067	0	175	21.3	1	13	28	21.7	
114	784	1045	0	171	20.9	3	13	28	38.3	
115	792	1056	0	173	21.1	2	13	28	31.8	
116	480	716.5	989.5	264	0	0	0	28	4.32	Zang *et al.* 2020
117	480	727.8	965.8	264	0	0.5	32.34	28	5.4	
118	480	739.2	942.3	264	0	1	32.34	28	6.25	
119	480	750.5	917.3	264	0	1.5	32.34	28	7.39	
120	480	761.9	895.1	264	0	2	32.34	28	7.95	
121	480	727.8	965.8	264	0	0.5	32.19	28	6.09	
122	480	739.2	942.3	264	0	1	32.19	28	7.26	
123	480	750.5	917.3	264	0	1.5	32.19	28	7.55	
124	480	761.9	895.1	264	0	2	32.19	28	8.68	

Table 2 Statistical parameters of datasets

Dataset	Statistics	Minimum	Maximum	Mean	Standard Deviation	Kurtosis	Skewness
Total dataset (124 observations)	Cement (kg/m^3)	0.0000	809.0000	424.0081	144.1956	2.0913	-0.5104
	Fine Aggregate (kg/m^3)	435.0000	1410.0000	884.7718	289.9654	-0.5770	0.8414
	Coarse Aggregate (kg/m^3)	0.0000	1266.0000	698.1790	453.2483	-1.2006	-0.6724
	Water (kg/m^3)	14.5000	338.6000	194.7855	63.0674	1.0216	-0.3424
	SP/HRWR (kg/m$^{3)}$	0.0000	21.6000	3.9315	4.5308	5.4443	2.1552
	Steel %	0.0000	3.0000	0.8306	0.5820	0.4073	0.5292
	Fibre Length (mm)	0.0000	60.0000	31.0413	19.0100	-0.6437	-0.0033
	Curing Days	7.0000	90.0000	32.3145	18.7111	5.6111	2.5095
	Flexural Strngth (MPa)	2.3000	38.3000	9.0078	5.7193	6.0460	1.9593
Training dataset (87 Observations)	Cement (kg/m^3)	0.0000	809.0000	428.3563	148.4038	2.1509	-0.6116
	Fine Aggregate (kg/m^3)	435.0000	1410.0000	896.5885	293.7433	-0.6870	0.8156
	Coarse Aggregate (kg/m^3)	0.0000	1266.0000	679.5977	457.2089	-1.2861	-0.6182
	Water (kg/m$^{3)}$	14.5000	338.6000	195.0563	65.0151	1.1135	-0.3717
	SP/HRWR (kg/m^3)	0.0000	21.6000	4.1318	4.6917	4.8363	2.0834
	Steel %	0.0000	3.0000	0.8103	0.5855	1.0417	0.6980
	Fibre Length (mm)	0.0000	60.0000	30.7424	19.1183	-0.6372	0.0072
	Curing Days	7.0000	90.0000	33.4483	19.8182	4.4959	2.3573
	Flexural Strength (MPa)	2.3000	38.3000	9.2624	6.0490	6.6163	2.0689
Testing dataset (37 Observations)	Cement (kg/m^3)	0.0000	800.0000	413.7838	135.1863	2.4773	-0.2585
	Fine Aggregate (kg/m^3)	435.0000	1410.0000	856.9865	282.8720	-0.1833	0.9382
	Coarse Aggregate (kg/m^3)	0.0000	1266.0000	741.8703	446.9116	-0.9317	-0.8405

Table 2 Continued

Dataset	Statistics	Minimum	Maximum	Mean	Standard Deviation	Kurtosis	Skewness
Testing dataset (37 Observations)	Water (kg/m^3)	16.0000	304.8000	194.1486	59.0884	0.8965	-0.2658
	SP/HRWR (kg/m^3)	0.0000	21.3000	3.4605	4.1506	8.5874	2.4314
	Steel %	0.0000	2.0000	0.8784	0.5790	-0.8582	0.1394
	Fibre Length (mm)	0.0000	60.0000	31.7441	18.9954	-0.5736	-0.0266
	Curing Days	7.0000	90.0000	29.6486	15.7325	11.3700	3.0514
	Flexural Strength (MPa)	3.4300	21.7000	8.4092	4.8810	0.7087	1.2686

Table 3 User defined parameters

Model Used	User Defined Parameters
M5P	M 4.0 -num-decimal-places 4
SVM	C-1, RBF kernel, gamma (Ɣ)-3
GP	Noise-0.1, RBF kernel, gamma (Ɣ)-3

$$\mathrm{CC} = \frac{x(\sum_{i=1}^{x} OV)-(\sum_{i=1}^{x} O)(\sum_{i=1}^{x} V)}{\sqrt{[x\sum_{i=1}^{x} O^2-(\sum_{i=1}^{x} O)^2]}\sqrt{[x\sum_{i=1}^{x} V^2-(\sum_{i=1}^{x} V)^2]}} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{x}}(\sum_{i=1}^{x}(V-O)^2) \tag{5}$$

$$\mathrm{MAE} = \frac{1}{x}(\sum_{i=1}^{x}|V-O|) \tag{6}$$

$$\mathrm{RAE} = \frac{\sum_{i=1}^{x}|O-V|}{\sum_{i=1}^{x}(|O-\bar{O}|)} \tag{7}$$

$$\mathrm{RRSE} = \sqrt{\frac{\sum_{i=1}^{x}(O-V)^2}{\sum_{i=1}^{x}(|V-\bar{V}|)^2}} \tag{8}$$

O = Observed values
$\bar{O}$= Average of observed value
V = Predicted values
x = Number of observations

The range of Coefficient of correlation (CC) is from -1 to +1, higher the value of CC, better the predicted results. Similarly lower values of the evaluating parameters like RMSE, MAE, RAE and RRSE, predicts better results, i.e., if calculated error is low; it predicts better results for the output (Nhu *et al*. 2020).

5. Result and discussion

5.1 M5P

In this technique 9 attributes were used. Out of 9, cement, fine aggregate, coarse aggregate, water, SP/HRWR, steel fibre, fibre length and curing days were considered as input parameters and flexural strength was output parameter. A pruned model tree was developed using smoothed linear model.

LM 1:

$$\text{Flexural Strength (MPa)} = 0.0235 * \text{Cement (kg/m}^3) - 0.0222 * \text{Water (kg/m}^3) + 0.312 * \text{SP/HRWR} + 5.4434 * \text{Steel\%} + 0.0505 * \text{Curing Days} - 3.8617 \tag{9}$$

Performance of M5P model is listed in table 4. For training dataset CC is 0.8907 and MAE and RMSE are 2.1448 and 2.7345 respectively. Also RAE and RRSE are 47.35% and 45.46%, whereas, in testing dataset quality of model decreases as CC is 0.8026 and MAE and RMSE are 2.5746 and 3.0908 respectively also RAE and RRSE are 63.06% and 63.21%. Fig. 1 represents the agreement plot between actual and predicted flexural strength of concrete mix. It also has been seen that most of the predicted values of novel model lie under the range of ±35% error band.

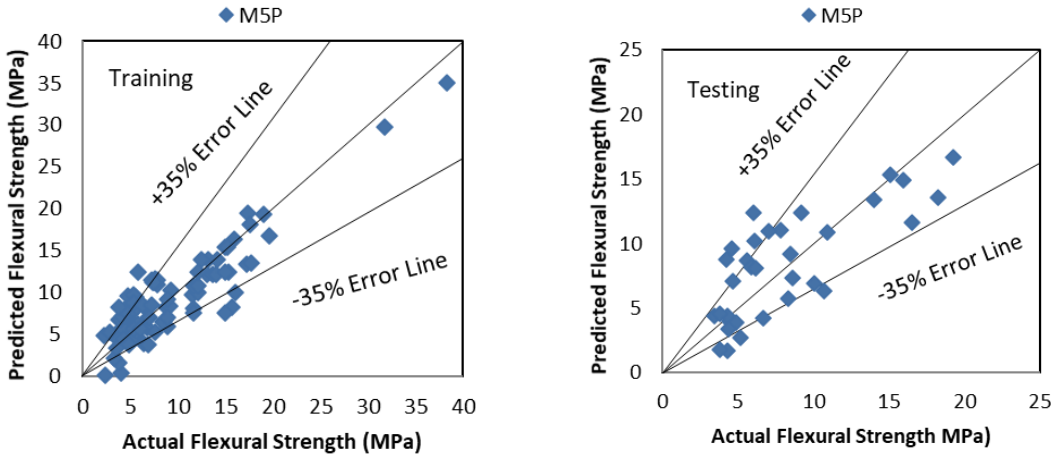


Fig. 1 Agreement plot between observed and predicted flexural strength of training and testing dataset by M5P technique

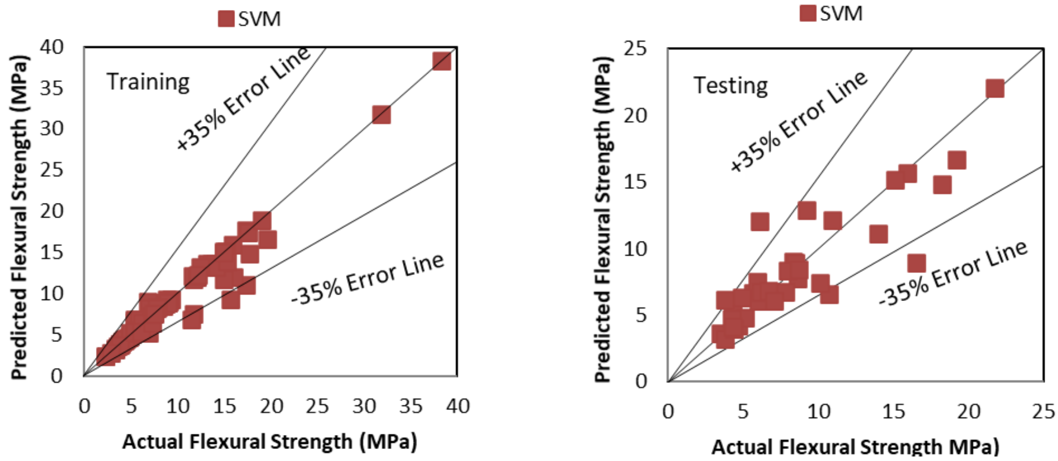


Fig. 2 Agreement plot between observed and predicted flexural strength of training and testing dataset by SVM technique

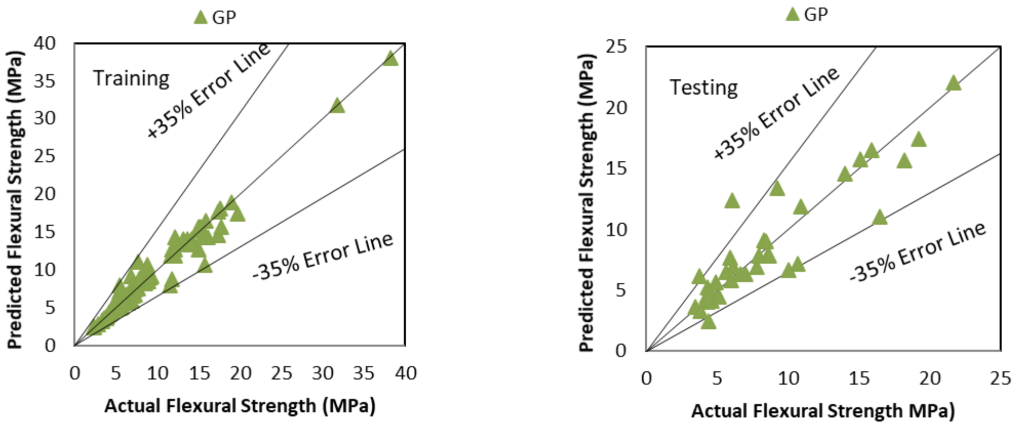


Fig. 3 Agreement plot between observed and predicted flexural strength of training and testing dataset by GP technique

5.2 Support Vector Machines (SVMs)

This model consists of radial basis function kernel (RBF kernel), with some user defined parameters such as C and gamma (Ɣ). Number of trials has been made to reach the optimum value i.e maximum CC value and minimum errors. Dataset used in this study found its best result using c value as 1.0 and Ɣ as 3. SVM's performance measures are listed in table 4 for both training and testing dataset. SVM models had its CC value 0.9718 in case of training dataset and 0.8916 for testing dataset and MAE and RMSE are 0.651 and 1.4603 respectively for training dataset with minimum MAE (1.3837) and RMSE (2.1871) for testing dataset also. Fig. 2 represents the agreement plot between actual and predicted flexural strength of concrete mix. It also has been seen that most of the predicted values of novel model lie under the range of ±35% error band.

5.3 Gaussian Processes (GPs)

Gaussian Processes is a regression process consists of radial basis function kernel (RBF kernel), with some user defined parameters such as L and gamma (Ɣ). Various trials have been carried out to reach the optimum value i.e., maximum CC value and minimum errors. Dataset used in this study found its best result using L value as 0.1 and Ɣ as 3. GPs performance measures are listed in table 4 for both training and testing dataset. GPs model had its CC value 0.98 in case of training dataset and 0.9138 for testing dataset and MAE and RMSE are 0.7071 and 1.198 respectively for training dataset with minimum MAE (1.2954) and RMSE (1.9672) for testing dataset also. Fig. 3 represents the agreement plot between actual and predicted flexural strength of concrete mix. It also has been seen that most of the predicted values of novel model lie under the range of ±35% error band.

6. Comparisons of results

6.1 Comparisons on the basis of soft computing techniques

In this study various machine learning techniques were applied. Comparison of these models suggests that performance of GP model is better than the other models for both training and testing

Table 4 Performance Measures for different models

Model No.	M5P	SVM Training	GP	M5P	SVM Testing	GP
CC	0.8907	0.9718	0.98	0.8026	0.8916	0.9138
MAE	2.1448	0.651	0.7071	2.5746	1.3837	1.2954
RMSE	2.7345	1.4603	1.198	3.0908	2.1871	1.9672
RAE	47.35%	14.37%	15.61%	63.06%	33.89%	31.73%
RRSE	45.47%	24.28%	19.92%	63.21%	44.73%	40.23%

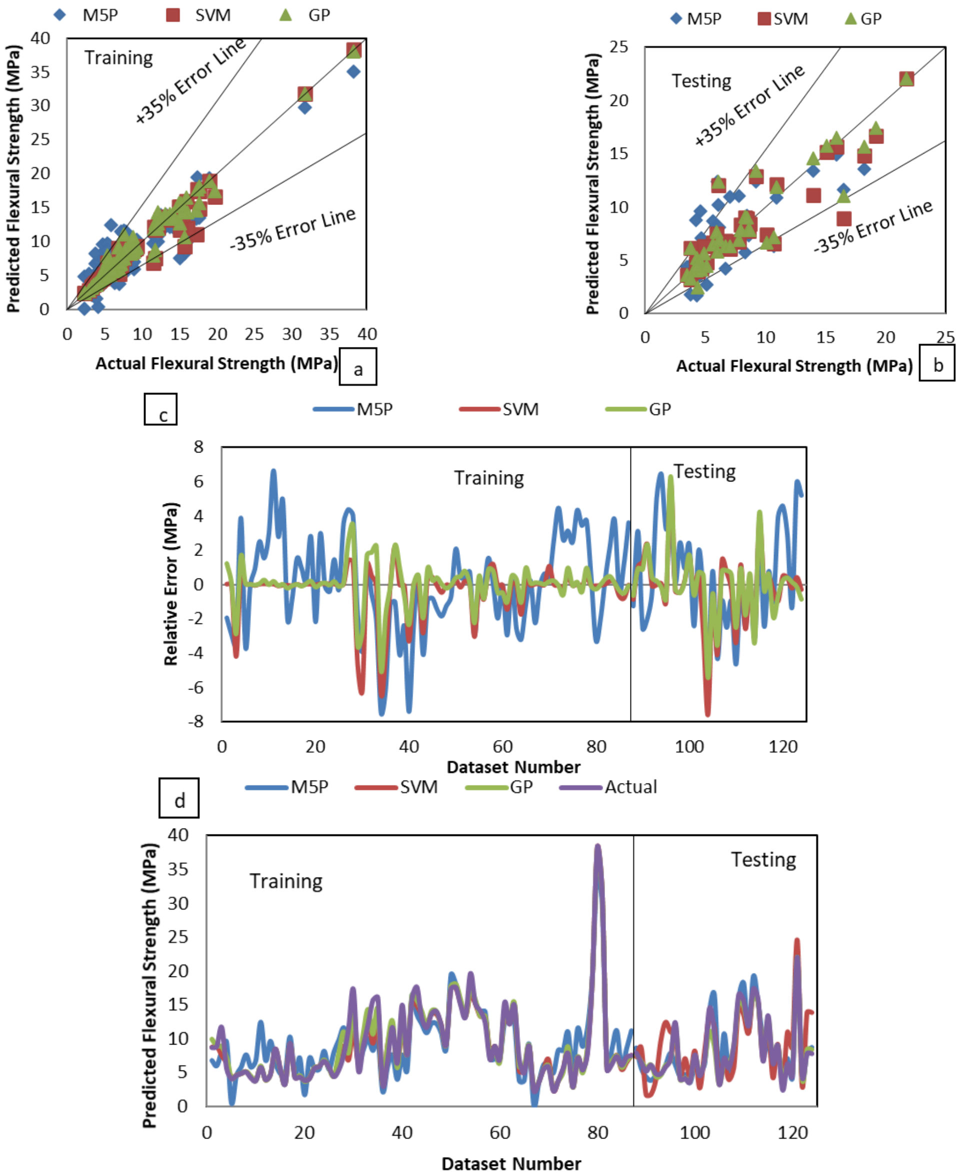


Fig. 4 Comparison between M5P, SVM and GP, predicted and actual values for Flexural Strength

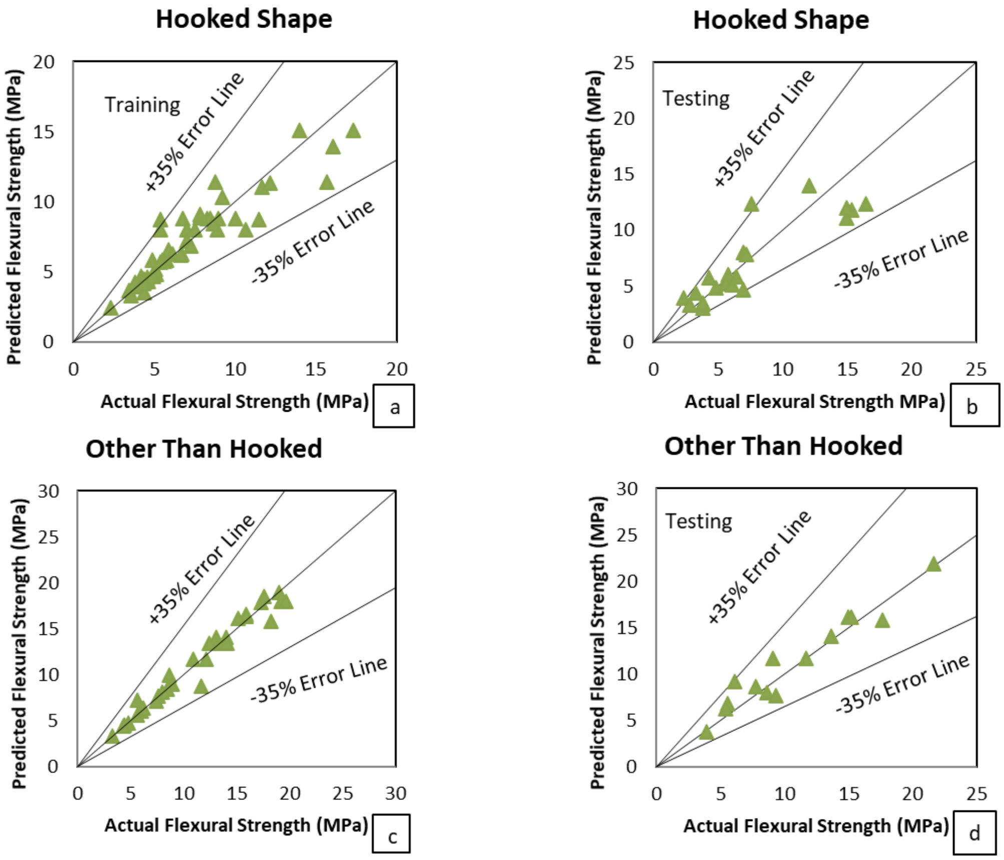


Fig. 5 Comparison between predicted and actual values for Flexural Strength on the Basis of Shape by GP technique

datasets. Compared results of these models are presents in table 4 which shows that GP model has highest CC value for training as well as testing dataset i.e., 0.98 and 0.9138 respectively also lowest error values i.e MAE (1.2954), RMSE (1.9672), RAE (31.728%) and RRSE (40.2315%) for testing dataset. Figs. 4(a) and 4(b) show the variation between the predicted and actual dataset of applied machine learning algorithms. Figs. 4(c) and 4(d) indicate that the projected readings of the GP model are near to the actual data, resulting in a small error bandwidth when compared to other models.

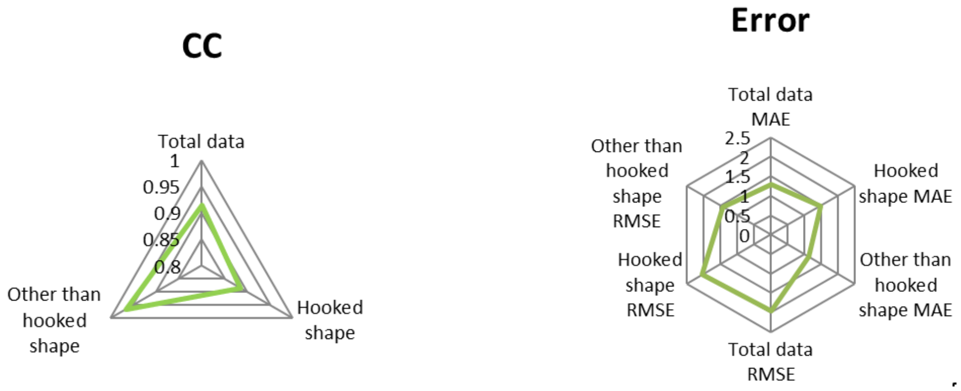
6.2 Comparisons on the basis of shape

Furthermore, entire data was compared based on shape. A total of 124 observations were split into two groups, one with a hooked shape and the other with a mixed shape (straight and waved). Table 5 summarizes the results of this data. As is evident from the table 5, by comparing the two fibre according to shape other than hooked shape (straight and waved) has better CC (0.9649) as compared to hooked ones (0.8844).

The variation between the predicted and observed dataset of applied machine learning algorithms on concrete mix containing steel fibre is presented in Figs. 5(a)-5(d). Figs. 6(a) and 6(b) shows that GP model predicted readings lies close to the actual observations which results in minimum error

Table 5 Measures of performance based on the shape of the steel fibre by GP technique

	Total data 124 observations	Hooked shape 79 observations	Other than hooked shape 47 observations
CC	0.9138	0.8844	0.9649
MAE	1.2954	1.4784	1.1211
RMSE	1.9672	2.0427	1.4215



(a) (b)

Fig. 6 Error graph for flexural strength of concrete on the basis of shape by GP technique

Table 6 Measures of performance based on the percentage of the steel fibre

	Steel fibre range (0%-1%) 92 observations GP	Steel fibre range (1%-3%) 32 observations GP
CC	0.7094	0.9768
MAE	1.9752	0.9024
RMSE	2.5457	1.1504

bandwidth compared to other models with maximum CC(0.9649) for other than hooked shape type. It also predicts that the mixed shape of the fibre shows better results as compare to the hooked ones. Different bonding characteristics linked with fibre shape were responsible for the results.

6.3 Comparisons on the basis of fibre percentage

On the basis of steel fibre percentage, Table 6 and Figs. 7(a)-7(f), depicts the variance between the predicted and real dataset of applied machine learning algorithms on concrete mix with steel fibre. It also shows that GP model predicted readings lies close to the actual observations which results in minimum error bandwidth compared to other models. As per the analysis it has been found that the steel fibre percent do affect the flexural strength of the concrete to a greater extent. But so far as the active percentage of the steel fibres (0-3) % shows that the fibre percentage range between (1-3)% shows better results as compare to the other with higher CC value(0.9768) and lower MAE value(0.9024).

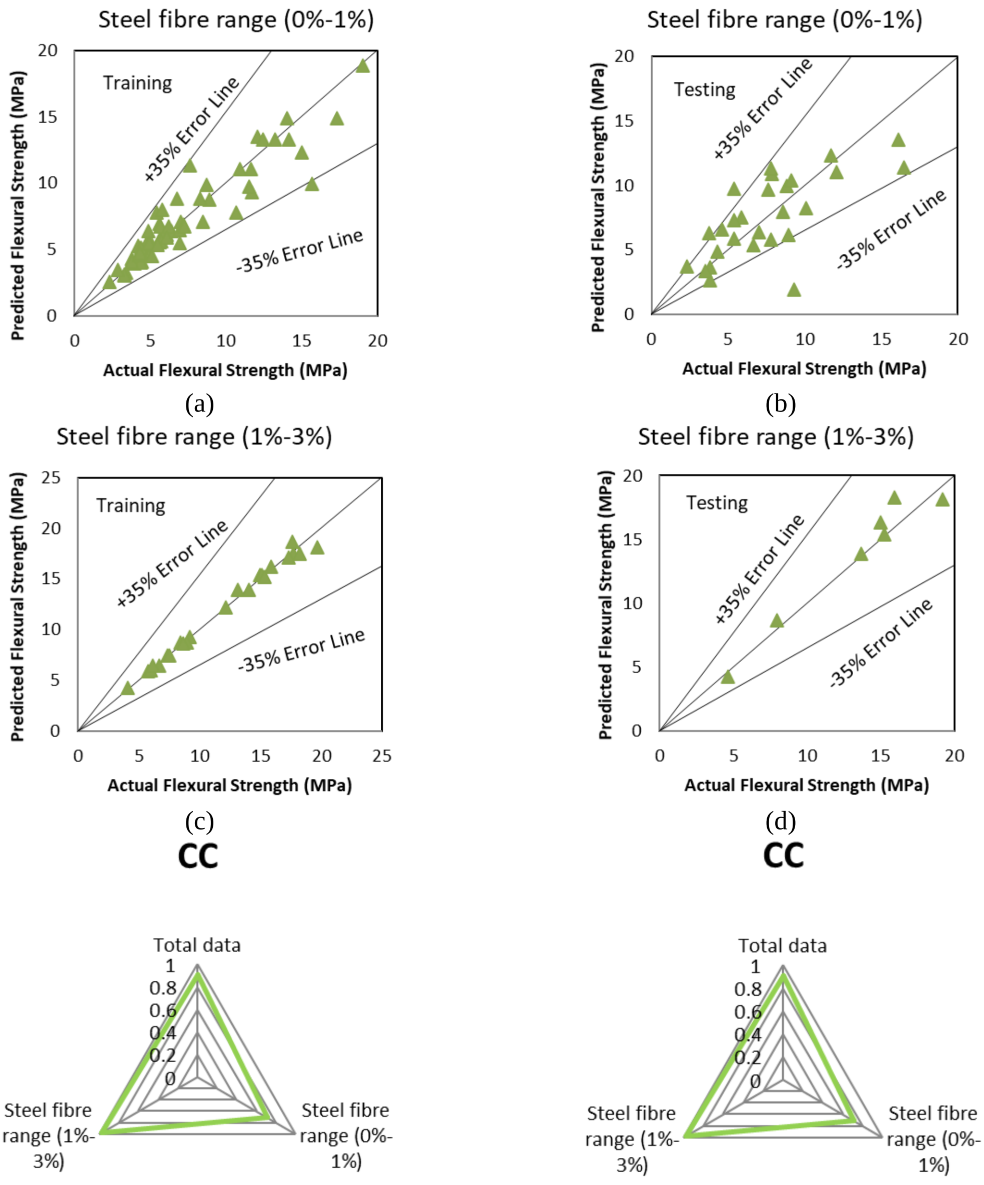


Fig. 7 Comparison between predicted and actual values for flexural strength on the basis of steel fibre percentage by GP technique

7. Analysis of variance (ANOVA) single factor test

Table 7 shows the single factor ANOVA results for flexural strength of concrete mix with steel fibre, which was performed to test the difference in actual and predicted values by all models. Results shows that, F value for all the models namely M5P (0.000051), SVM (0.008601) and GP (0.004782) models are less than the F critical value (3.879538) and P-values for M5P (0.994324),

Table 7 Single factor ANOVA results

Source of Variation	F	P-value	F critical	Difference Among groups
Actual and M5P	0.000051	0.994324	3.879538	Insignificant
Actual and SVM	0.008601	0.926184	3.879538	Insignificant
Actual and GP	0.004782	0.944925	3.879538	Insignificant

Table 8 Results of Sensitivity Analysis

Input combination								Output		GP based model		
Cement (kg/m^3)	Fine Aggregate (kg/m^3)	Coarse Aggregate (kg/m^3)	Water (kg/m^3)	SP/HRWR (kg/m^3)	Steel %	Fibre Length	Curing Days	F.S (MPa)	Removed Parameter	CC	MAE	RMSE
									-	0.9138	1.2954	1.9672
									SP/HRWR	0.8689	1.6794	2.4347
									W	0.9158	1.2582	1.9513
									CA	0.8955	1.5116	2.2411
									F.A	0.8392	1.6412	2.8787
									Curing Days	0.9237	1.2636	1.8495
									Cement	0.9161	1.2291	1.9368
									Steel (%)	0.8286	2.111	3.0845
									Fibre Length	0.9244	1.3273	1.8504

SVM (0.926184) and GP (0.944925) are greater than 0.05 which is the significance level of α. This suggests that difference between actual and predicted results of flexural strength is insignificant for all the models.

8. Sensitivity analysis

Sensitivity analysis was carried out to find the most significant parameter among input parameters for the prediction of flexural strength of concrete mix with steel fibre. GP model was best among other models for this dataset so sensitivity analysis was performed on GP model by varying the input combination with the removal of one input parameter at a time as listed in Table 8. The performance of each model was based on the statistic evaluation parameters such as CC, MAE, and RMSE. Steel fibre has a critical role in predicting the flexural strength of concrete mix, as shown in Table 8. Because concrete has a low flexural strength, the inclusion of steel fibre will help to improve the flexural strength of the mix.

9. Conclusions

This paper presented the comparison of three machine learning techniques namely; M5P, SVM, and GP based models to predict the flexural strength of concrete mix using steel fibres. Performance of these models were checked by computing coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE), relative absolute error (RAE), and root relative squared error (RRSE). Results obtained in this study are summarized as follows:

1. Results obtained from GP model were found to be most suitable to predict the concrete flexural strength.
2. Among all three algorithms, GP predicts better results followed SVM with highest CC value 0.9138 and 0.8916, lower MAE values 1.2954 and 1.3837 and lower RMSE values 1.9672 and 2.1871, respectively for testing dataset.
3. Scatter diagram shows that the GP has minimum error band width, and it is good fit for predicting the output.
4. According to the shape of the fibre, the mixed type performs better for this data than the hooked shape of the steel fibre, which has a higher CC of 0.9649, which shows that the shape of fibers do effect the flexural strength of the concrete. However, the intricacy of the mixed fibres needs further investigations.
5. The most appropriate range for increasing flexural strength of concrete mix was found to be (1-3) percent, with a greater CC value (0.9768) and a lower MAE value (0.9024) than the (0-1) percent range. Therefore, for better performance of concrete flexural strength, steel fibre between (1-3) % ranges optimistically can be used.
6. Results of the study also conclude that steel fibre has a major impact in the prediction of the flexural strength of concrete mix with GP based model in comparison to other input parameters for this data set.

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The interest of conflict statement

There is no interest in conflict by the authors with anyone whosoever is connected to this research paper.

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