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Prediction of compressive strength of concrete with various admixture

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1. ABSTRACT

Compressive strength of a concrete is the resistance against the external load. It is one of most crucial properties of hardened concrete. Concrete is very strong in compression and its determination is of utter importance. For years the traditional method of determining compressive strength has been UTM test in which sample cubes are prepared, cured, and tested under load in the Universal Testing Machine thereafter compressive strength can be obtained from strength-load relationship. In early 1940% non-destructive tests were introduced in which compressive strength was determined indirectly by relatively less time taking but a complex calibrated process. However, all these methods have time consuming and complexity drawbacks.

With the advent of Artificial Intelligence. Machine learning techniques are being used to predict the compressive strength. Various techniques have shown high accuracy in predicting the compressive strength. In this work I have used one important machine learning methods which is Back Propagation Neural network (BPNN) for forecasting the 28 days strength of concrete. The actual data after normalization to reduce the range of data difference is segregated randomly into training and testing datasets which are fed to the where from the predicted dataset is obtained. The relevance factor R is computed which establishes the relationship between actual and predicted data and it is highly important parameter for defining the accuracy of the used predicting model. On the basis of high valve of relevance factor and other parameters like RMSE, RSR, MAPE, NMBE, R, E, mean, standard variation and variance, I arrived at the conclusion that BPNN was accurate and efficient model for predicting the compressive strength of concrete.

2. INTRODUCTION

2.1. GENERAL

The compressive strength of concrete is one of the foremost vital properties of concrete. The main function of concrete is to resist the compressive stresses resulting in the structure due to loads. In a few cases where quality in tension or quality in shear is required, the compressive quality is utilized to calculate those properties indirectly. Hence the concrete fabricating properties of distinctive constituents of concrete are for the most part measured in terms of compressive quality Further more Compressive quality is utilized as a qualitative measure for different other properties of concrete. Till now no actual direct relationship between compressive strength of concrete and various other properties of concrete via flexural strength, strength in tension, young's modulus of elasticity, resistance against fire, and permeability nor it is possible to be established in near future. However, in some cases, applied math relationships are determined and they provide a lot of helpful data to engineers. However, it needs to be stressed that it can provide only the approximate results of those properties and if better results are needed other tests should be carried out have appropriate valves for example with an decrease in size of the sample specimen the compressive strength increases on the other hand modulus of elasticity decreases and in that case the modulus of elasticity doesn't follow the compressive strength. When the concrete is subjected to freezing and thawing compressive strength does not indicate the helpful property of concrete, Concrete having about 6% entrained air which is generally weaker in quality is found to be more tough than thick and solid concrete. The compressive strength is primarily decided in the laboratory or at field by testing cubes or cylinder specimens under UTM or by non-destructive methods.

Strength of the concrete is its resistance to cracking failure under loads. It is decided in numerous ways such as quality in-tension, compression shear and flexure of these shows' quality with respect to a chosen method of testing. In the event that concrete structure falls flat beneath the compressive stack the failure is really a combination of smashing and shear failure. This failure mechanism is often advanced phenomena. It's typically assumed that the concrete in resisting failure, generates every cohesion and internal friction. The cohesion and internal friction developed by concrete in resisting failure is found to be somehow related to one parameter that is water binder ratio. Strength may be defined as the capacity of the concrete to stand up to failure one it's subjected to the action of stresses caused by masses or the mix of all the masses the first common being compression, tension bending and impact. The significance of sorting out the changed qualities is highlighted from the genuine reality that materials like stones and concrete have high compressive quality be that as it may slightest (1/5 to 1/50) tensile, bending and impact qualities. Compressive Quality is pointed out from tests on cubes, cylinders or prisms that unit of measurement ordinarily smaller for consistently homogenized materials and bigger for non homogenized ones Prisms and cylinders have lower resistance than cubes of an identical cross-sectional zone, on the inverse hand crystals with heights littler than their sides have bigger quality than the cubes.

2.2. ARTIFICIAL INTELIGENCE

Artificial intelligence, an extensive method, was developed in 1956 when the term was first used in a summer research project meeting held in Darth mouth college, New Hampshire, USA and on the basis of the interaction of various disciplines like computer science, linguistics, psychology, neurophysiology, information theory and cybernetics. The primary goal of artificial intelligence is to explore ways to imitate and function like the human brain. Artificial intelligence (Al) is turning out to be a highly efficient alternate way of dealing with traditional modelling methods. Artificial intelligence is the branch of computer science that develops software which have the capability of solving a problem using human-like intelligence in contrast with classical methods. Artificial intelligence (Al) can deal with problems that are complex in nature with high uncertainties and provide effective solutions by saving considerable amount of time and human efforts. Artificial intelligence (Al) makes the process of decision making relatively faster. It can be incorporated to predict a solution from existing data when testing isn't possible. In the pool of various Artificial intelligence techniques, machine learning (ML), pattern recognition (PR), and deep learning (DL) have effectively garnered wide consideration owing to their high output accuracy in civil engineering related problems mostly in structural designing engineering. Machine learning (ML) is one of the main sub field of artificial intelligence (Al) that deals with the study, plan, and improvement of programs that can learn from the accessible information on their own and predict feasible solution to a problem using the learnt data without having the need of being programmed by user. It could be a information analytics method that enables computers to do what comes naturally to people and creatures that's to leam from the experiences. It employs computational strategies to "learn" data specifically from information without depending on an already determined equation as demonstration, As the number of samples available for learning increases the calculations adaptively move forward their execution higher the number of data sets is the output accuracy.

Machine learning employs two sorts of procedures:

Supervised learning in which a model is prepared on known input and yield information sets so that future outputs can be anticipated with higher accuracy. Unsupervised learning, in which covered up patterns or inborn structures are found in available input data sets without being labelled. Common calculations for performing classification incorporate support vector machine(SVM). k-nearest neighbor naive bayes, calculated relapse and neural systems.

Reinforced learning works on the principle of feedback wherein the user feedback is used to improve the output accuracy.

BPNN is an ANN based capable device which is utilized for apprehension of the incursion action. The neuron is the Fundamental component of BPNN that stores and processes information. The back propogation neural network (BPNN) was created by Rumel hart as a arrangement for the issue of planning multi-layer perceptrons. The basic advances interpreted by the BPNN were the consideration of a differentiable exchange function at each node of the framework and the utilization of error backpropogation to modify the internal system loads after each training span. BPNN can be utilized for both direct as well as non straight classification.

3. OBJECTIVES OF THE STUDY

a. To verify the capability of Back Propagation Neural Network (BPNN).

b. To make a comparative study of BPNN

c. To compute various statistical analysis.

4. AVAILABLE METHODS

4.1. Experimental Methods

4.1.1. UTM TEST

Compressive strength is the property of concrete due to which the concrete resist the loads without failing. UTM (universal testing machine) test is a destructive test in which the average of 3 cubes is taken to evaluate the valve of compressive strength just before failure under the load in the machine. Concrete of specified grade is prepared and filled in 3 cubical moulds of size 150x150x150 mm' or cylinders of 150mm diameter and 300mm high if size of aggregate is greater than 20mm. For size less than 20mm moulds of size 100 100 100 mm^2 are used. The concrete is placed in 3 equal layers of 50mm and compacted with tamping rod 35 times before the next layer in placed. The cubes are placed at standard room temperature i.e 27+3 for 24 hours 30minutes which starts the moment water is added to the mixture while making concrete. The samples are then taken out and placed in water and are removed only before testing. The samples are placed in UTM and load is applied and gradually increased to 14Mpa per minute and continued till the sample is crushed and highest applied load just before failure is measured.

FIG. 4.1: CUBE UNDER TEST IN UTM

4.1.2. Rebound Hammer Test

This test was developed by Schmidt in 1948 and is most commonly used non destructive test.This is a test of non destructive nature which is used to predict compressive strength. Since it is not possible to calculate compressive strength without destruction of the cubes therefore the strength is calculated indirectly by calibrated scale. The rebound hammer test is an easy test that takes less time than destructive test. The hammer is pulled against the specimen under test and the based on the strength of the wall under test the spring attached to rider along with guide scale is driven back which gives a number on the scale called rebound number. This test can be carried out at any angle but for each angle the results are different hence for every angle separate calibration is needed which is one of the drawbacks of this method.

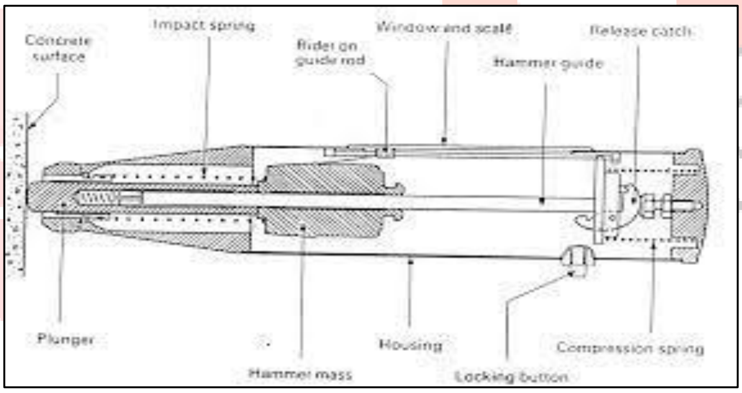

Fig. 4.2 : sectional view of rebound hammer test

The above experimental methods have following disadvantages:

- Wastage of concrete.
- Complex method for determining compressive strength.
- Flaws can not be determined with accuracy.

4.2. Analytical Methods

4.2.1. Genetic Programming

Genetic programming could be a bunch of directions and a wellness procedure to decide how efficiently a machine has played out a specific undertaking.

It may be a procedure utilized to enhance occupants of PC program in a line with a reasonable site controlled by a program's capacity to complete prearranged computational condition.

4.2.2. BPNN (Back Propagation neural network)

To defeat the confinement of recognition Rumelhart et al. in the year 1986 had portrayed another managed learning framework known as Back Engendering Neural Network (BPNN).

BPNN (Back propogation neural systems) is an Artifical neural framework (ANN) based ground breaking method which is utilized for location of the interruption action. Fundamental part of BPN might be a neuron, which stores and procedures the information. Part begins with organic model of neuron trailed by computational demonstrate of neuron which begins from normal model.

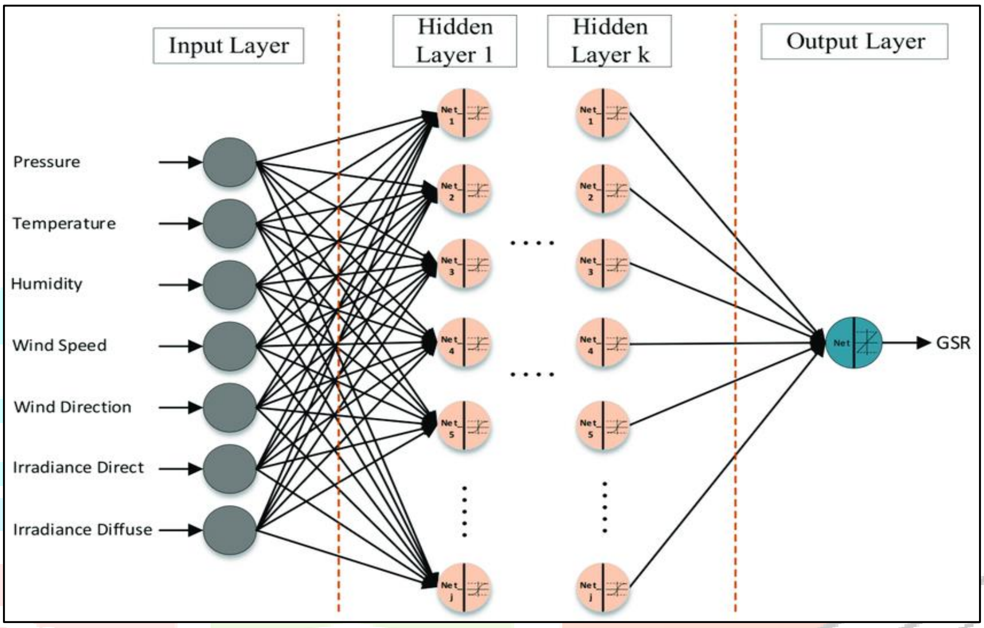

Fig. 4.3 : Structure of BPNN

Advantages of BPNN :

1. BPNN requires less labour work.
2. BPNN takes less time in calculation.
3. BPNN gives us the approx.(nearest value) result of given input.
4. BPNN(Back propagation neural networks) is an Artificial neural network (N) based astonishing strategy that is utilized for identification of the interruption movement.
5. It overcome the limitation of perception by another administered leaming methodology referred as Back Propagation Neural Network(BPNN).

5. LITERATURE REVIEW

In this chapter various literatures on the prediction of compressive strength of concrete with various admixtures for solving problems in civil engineering have been surveyed, studied and following facts are reported briefly.

Hwang et al. (1998) analyzed the impact on the compressive strength of concrete due to replacement of fine-aggregate by flash. It was found out that strength and carbonation rate in concrete with water cement ratios of 0.3, 04 and 0.5. increased when fine aggregate was substituted by fly ash upto 1/4th and 1/2 by weight.

Siddique (2003) determined that with increase in fly ash replacing fine aggregate compression strength in concrete increases upto a certain limit only after which it goes on decreasing. Further when fine aggregate was replaced by 50% compression strength increased upto 51% for 281 days and 67.1% for 365 days.

Alvin Harison et al. (2014) researched the increase and decrease of strength of concrete with change in percentage of amount of fly ash for 1 week. 4 week and 8 weeks strength. They found that by using fly ash the I week strength was lesser than unsubstituted concrete but the strength went on increasing after 4 weeks. Upto 30% the strength increased fairly and decreased beyond that The increase was more prominent 20% substitution.

Nurcihan Ceryan (2014) used prediction models SVM (support tor machine) and RVM (relevant vector machine) and compared their results with ANN to predict the Uniaxial Compressive Strength of volcanic rocks which normally is determined by tests which are expensive, destructive and time consuming in nature. The input parameters taken were porosity and P-durability. The above mentioned methods were successful as compared to ANN in areas of statistical performance criterion for training and testing data which are R^2, RMSE, MAPE, NMAPE, RSR, E. It was found that ANN produced very less accurate results and SVM, RVM performed with a great accuracy. These results are a way forward in use of prediction models. for determination of UCS of volcanic rocks in quick time without involving physical tests and destructive tests.

Vinay chandwani et al (2015) hybridized two main techniques of artificial intelligence which are ANN (artificial neural networks) and GA(Genetic Algorithm) for modelling the slump of Ready Mix Concrete(RMC) based of six input parameters i.e cement, sand, course aggregate, fly ash, admixtures and water cement ratio. The results of these hybrid techniques was compared with BPNN(back propagation neural network) model which is a subset of ANN. The accuracy of this hybrid model was very high and it can be used to forecast slump for a given mixed-design in short span without the need of performing different test with diverse design blend proportions.

Yeh (1998) used a modified BPNN for forecasting compression strength of concrete and used 7 input parameters viz water hinder ratio, cement, fine aggregate, coarse aggregate, grain size, and testing age. Logarithmic neurons and exponent neurons were added as input and output layer in BPNN. The accuracy in prediction of BPNN was checked in modelling compressive strength and the results showed that the logarithmic neurons and exponent neurons improved the accuracy in developing the compressive strength model.

SZ Khan et al (2015) used Functional Neural Networks for estimating the residual strength of clay. They used the existing available data for predicting the strength using FN and compared the results with Support Vector Machine (SVM) and ANN on the basis of statistical parameters like Co-relation factor. Nashsutcliff coefficient of efficiency (E), absolute average error, Maximum average error, and Root Mean Square Error (RMSE) based on the result of comparison of these parameters it was found that FNN was a better prediction model for the data. However valves of E and R were found to be less than SVM. From this research a prediction equation was developed for future use in this field.

6. METHODOLOGY

6.1. GENERAL

This part comprises of technical details of the utilized machine learning methods to predict the compressive strength of concrete with admixtures. The following figure is a flowchart which briefs the technical steps required to achieve the objective.

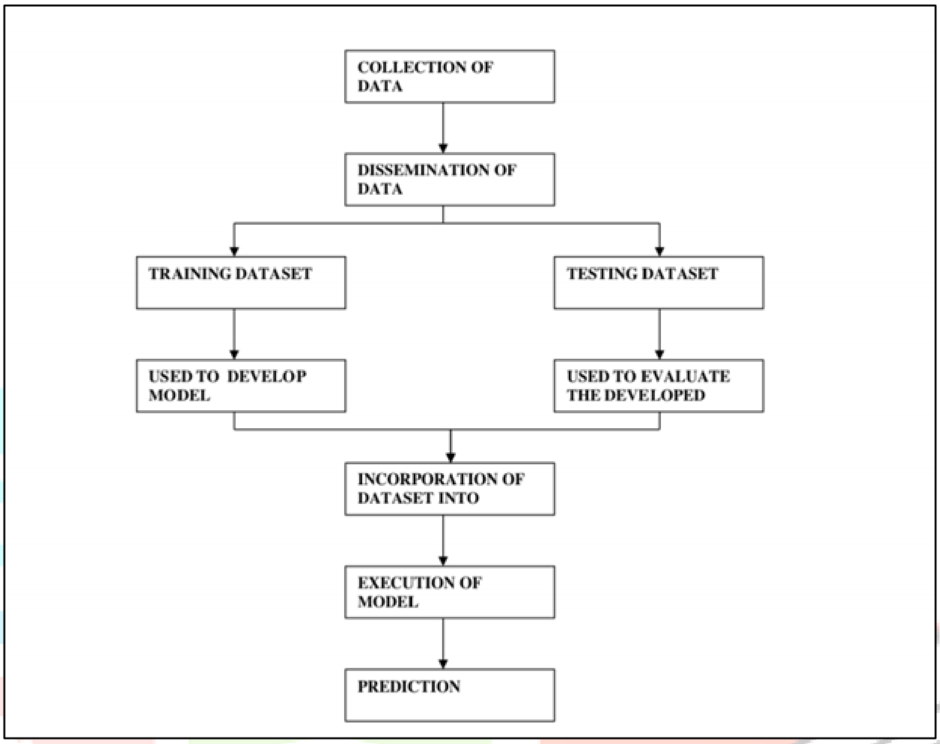

Fig – 6.1 METHODOLOGY FOR THE ADOPTED TECHNIQUE

Brief description of methodology flow chart:

1. First the data is collected and it is given as input. There are 6 input parameters here viz cement, water content, coarse aggregate, fine aggregate, fly ash and water cement ratio.

2. Segregation of data. The data is randomly segregated into 70% and 30% as there is no thumb rule for it.

3. The 70% segregated data used as training dataset to construct the model.

4. The 30% segregated data is used as testing dataset to evaluate the datasheet.

5. Both the training and testing data is incorporated into the Al model.

6. Based on the inputs used the compressive strength can be predicted by the used model. 7. Statistical parameters like R. R2, RMSE, WAP, VAF. PI, NMBE%, NS. RSR are used to justify the model.

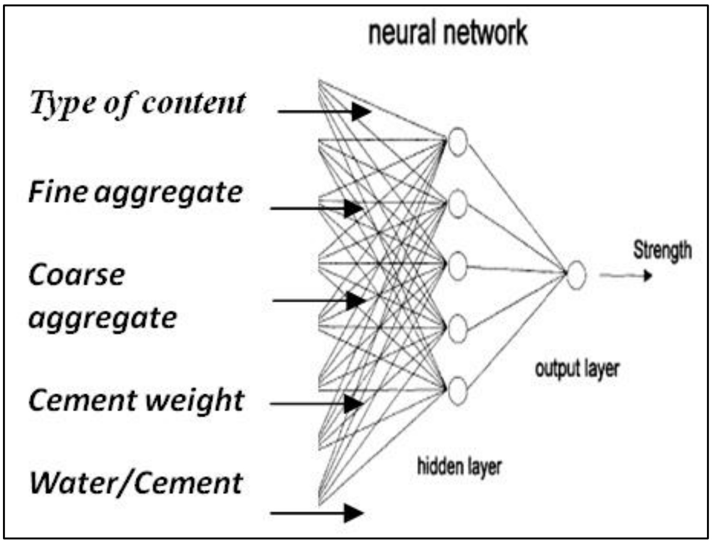

FIG. 6.2 : TYPICAL BPNN ARCHITECTURE

In the above figure, totally six inputs are considered for accomplishing the target of compressive strength prediction for 28 days. The next layer is the unrevealed layer where the real work of this model held which was boosted by activation functions.

Back Propagation: Back propagation neural network is the subset of artificial neural networks to compute a gradient that's needed within the calculation of the weights to be utilized in the network. Simply BP refers to the "the backward propagation of errors," because if flaws are detected in the outcome it is disseminated behind beyond the network layers. It's very typically accustomed to practice the deep neural networks, a term bearing on neural networks with quite one hidden layer BPNN has the necessity of using the loss function with the allusion of the loss function to the output neuron to be revealed and it does not imply the required target value. It has the cause that the BPNN is to be for the supervised learning model for the generalization. However BPNN is also utilized in some unsupervised networks like auto-encoders.

Back propagation neural network is additionally happened according to the rule of delta to the multi pronged layered feed forward networks which is used to the chain norms for the individual layers. BPNN almost associated with the Gauss-Newton algorithm and is an element of constant investigates for the rear propagations. The weight associated with the function which can be activated by the neurons for stimulating the each and every neuron for its vectorizations. The BPNN could be a multi layered feed forward neural network and it is too distant which was utilized more extensively. It's also reviewed the global way of induce the activation function from the bias to the précised neuron for the succinct libraries and implementing the matrix functions.

BPNN operates by getting closer of the non linear kinship among the input and outcome by stimulating the internal values In addition, the generalized input data for the cost function and its quadratic cost and the single training samples for the weights and bias. The Back Propagation Neural Network has two platforms as training and testing dataset. In the course of the training the network nurtured with the compiled input data and the respective output of the nurtured inputs.

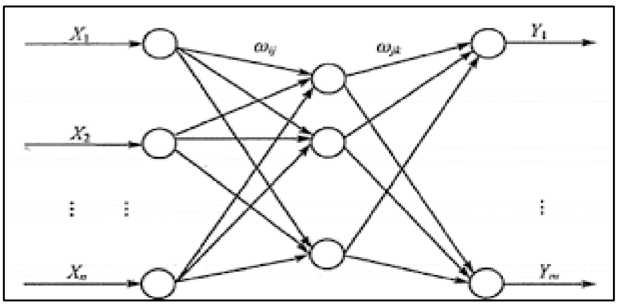

FIG. 6.3: TOPOLOGY OF BACK PROPAGATION

The above figure shows the topology of the Back propagation neural network which comprises of input layers, hidden layers and the output layers along with the bias and the activation function. The execution of the BPNN involves in the static mapping of the input to the issues of the bias for the feed forward network which ensembles the recognition of patterns. In the recurrent propagation the flaws are determined and propagated in the rear end. The sensitivity of the noisy data can be considered as the con of this adapted method; however it can able to simplify the network pattern by diffusing the weighted links which has the least effect on the practiced network. The partial derivatives of the cost function calculate the intermediate quantity which is considered as the error from the earlier neuron in order to execute the propagations from the backward. These derived cost functions will lead the neurons to determine the error from the layered neuron so that the output by the activation function makes the each layer under propagation. There are four fundamental equations for the BPNN which are errors, gradients of the cost function. performances and the number of iterations. The working methodology of the back propagation totally depends on the input data. The second neuron determines the rate at which the activation function is changing. In case of quadratic cost the vector which has partial derivatives as expressing the rate of variations of variables with respect to the activation function.

6.2. DATASET

The dataset used for determining the compressive strength of concrete with various admixtures was obtained from various research works-from PK Mehta et al (1982), Ravina et al (1988), L. Lam et al (1998), Cengiz Duran Atiş (2003), Liu M et al (2011) and Palika et al (2016). The dataset consists of 6 parameters cement, fine aggregate, coarse aggregate, water content and fly ash and water cement ratio. In machine learning it is important to perform normalization on data. The need for normalization arises due to large difference in range of data which could affect the accuracy of the model. The primary aim is to reduce to numerical valves in data to a common scale with small difference in range of valves, however in machine learning dataset with small range of differences does not need to be normalized. The compressive strength is normalized between 0 and I because the valves have a different range. It is done without distorting the difference in range of valves.

Table 6.1 Dataset of compressive strength of admixtures in concrete

Cement (component 1) (kg in a m^3 mixture)	Blast Furnace Slag (component 2) (kg in a m^3 mixture)	Fly Ash (component 3) (kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5)(kg in a m^3 mixture)	Coarse Aggregate (component 6) (kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	Concrete compressive strength(MPa, megapascals)
167.95	0.02	163.83	121.75	5.72	1058.7	780.11	24.24197616
213.72	11	24.51	181.71	6.86	1065.8	785.38	45.70536404
213.76	13.61	24.52	181.74	6.65	1066	785.52	40.2309246
182.04	15	121.97	170.21	8.19	1059.4	780.65	31.2677366
168.88	15	124.25	158.33	10.83	1080.8	796.15	31.11605188
277.19	17.2	24.46	160.7	11.19	1061.7	782.46	63.14221208
218.23	17.5	123.78	140.75	11.91	1075.7	792.67	55.50971276
214.9	17.6	121.89	155.63	9.61	1014.3	780.58	52.20022796
397	19	158	167	20.8	967	633	55.64760796
333	19	163	167	17.9	996	652	47.27736932
334	19	158	189	15.3	967	633	44.32641204
145	19	119	184	5.7	833	880	29.15794004
160	20	122	182	6.4	824	879	39.39665864
250	20	95	159	9.45	860	800	67.86512268
275	20	120	162	10.35	830	765	76.23536132
165	22	143.57	163.81	0	1005.6	900.9	26.200088
165	22	132.1	175.06	8.08	1005.8	746.6	46.38794528
178.03	24	118.6	179.94	3.57	1007.3	746.8	39.1622368
167.35	24	128.62	175.46	7.79	1006.3	746.6	41.20308576
172.38	24	172.37	156.76	4.14	1006.3	856.4	33.68779736
173.54	24	173.53	164.77	6.47	1006.2	793.5	38.20386516
167	26	167	164.03	7.91	1007.3	770.1	41.40992856
173.81	26	159.9	172.34	9.73	1007.2	746.6	37.81086384
446	42.08	79	162	11.61	967	712	57.02655996

446	42.22	79	162	11.64	967	712	44.42293868
446	45.21	79	162	11.64	967	712	51.021224
446	50.05	79	162	10.3	967	712	53.38612668
387	53.8	94	157	14.32	938	845	50.23522136
387	54.64	94	157	13.93	938	845	46.68441996
387	75.4	94	157	11.61	938	845	46.68441996
355	86	97	145	13.13	967	871	44.02993736
355	91.7	97	145	12.25	967	871	55.45455468
491	92	123	210	3.93	882	699	55.55108132
491	93.37	123	201	3.93	822	699	57.915984
424	97	132	178	8.48	822	750	62.05284
424	97.1	132	168	8.92	822	750	72.09850532
202	97.82	141	206	1.72	942	801	21.96670536
284	98.05	141	179	5.46	842	801	43.73346268
359	98.06	141	154	10.91	942	801	62.93536928
359	98.8	141	154	10.91	942	801	59.49488404
273	99	82	210	9	904	680	37.16965116
162	100	148	179	19	838	741	33.75674496
154	100.5	112	220	10	923	658	16.49916068
147	100.6	89	202	9	860	829	19.98790924
152	101	139	168	18	944	695	36.34917472
310	105	111	168	22	914	651	33.68779736
159	105	116	175	15	953	720	27.67556664
142	105.1	130	174	11	883	785	44.6090972
298	110.5	107	201	6	878	655	53.52402188
280	111	100	172	9	825	805	52.82075636
252	111	76	194	8	835	821	33.39821744

160	111	146	203	11	829	710	32.83974188
287	112	94	188	9	904	696	41.94082508
132	112.3	161	179	5	867	736	33.3016908
140	114.6	128	237	6	869	656	35.22532884
265	115	86	195	6	833	790	41.540929
276	116	90	180	9	870	768	44.27814872
149	116	109	193	6	892	780	23.69039536
261	116	78	201	9	864	761	32.39847724
237	116.8	71	247	6	853	695	28.62704352
153	117	113	178	8	1002	689	25.55887532
140	117.6	103	200	7	916	753	36.4388066
153	118	113	178	8	867	824	26.22766704
262	120.5	86	195	5	895	733	33.7153764
149	121	92	183	7	953	780	23.51802636
143	128	143	191	8	967	643	29.72331036
260	128.5	78	171	10	936	763	49.77327244
144	128.9	133	192	8	814	805	29.86810032
266	129	87	178	10	910	745	39.41734292
314	129.8	113	179	8	869	690	46.2293658
144	129.9	106	178	7	941	774	26.14492992
277	132.6	91	191	7	946	666	43.5748832
155	133	143	194	9	880	699	28.98557104
136	136	126	172	10	923	764	29.06830816
255	136.3	77	189	6	919	749	33.79811352
162	137	172	216	10	822	638	39.84481804
136	137.2	98	199	6	847	783	26.96540636
164	139	128	197	8	961	641	27.234302

162	139.4	164	202	10	820	680	30.6472082
157	142.8	152	200	9	819	704	33.05347944
149	143	194	192	8	935	623	24.5798194
135	144	193	196	6	965	643	21.91154728
159	144.2	161	201	7	848	669	30.88163004
144	145	195	176	6	1021	709	15.340841
154	145	185	228	7	845	612	24.3385028
167	145	195	185	7	898	636	23.8903434
184	145	190	213	6	923	623	22.93197176
156	145	187	221	7	854	614	29.41304616
236.9	145.3	71.5	246.9	6	852.9	695.4	28.62980142
153.1	148.9	113	178.5	8	1001.9	688.7	25.5595648
139.9	149	103.3	200.3	7.4	916	753.4	36.44363293
153.1	153	113	178.5	8	867.2	824	26.23318285
261.9	161.6	86.1	195.4	5	895.2	732.6	33.71882378
149	162	91.7	182.9	7.1	953.4	780.3	23.52423164
143	163	142.7	190.7	8.4	967.4	643.5	29.72606826
259.9	163.9	78.4	170.6	10.4	935.7	762.9	49.77327244
143.7	164	132.6	191.6	8.5	814.1	805.3	29.87085822
266.2	166.6	87.5	177.9	10.4	909.7	744.5	39.42147978
314	167	113.2	178.9	8	869.1	690.2	46.23419213
143.8	169	106.2	178.1	7.5	941.5	774.3	26.14768782
277	169.4	91	190.6	7	946.5	665.6	43.57833058
155.2	170	143.2	193.8	9.2	879.6	698.5	28.99108685
136.4	170.2	125.8	171.6	10.4	922.6	764.4	29.07313449
255.3	174	77	188.6	6.5	919	749.3	33.798803
272.8	178	81.8	209.7	9	904	679.7	37.17103011

162	178	148.1	178.8	18.8	838.1	741.4	33.76226077
153.6	178.1	112.3	220.1	10.1	923.2	657.9	16.50398701
146.5	180	89.3	201.9	8.8	860	829.5	19.98790924
151.8	180	138.7	167.5	18.3	944	694.6	36.3498642
309.9	183.9	111.2	167.8	22.1	913.9	651.2	38.21558625
158.6	184	116	175.1	15	953.3	719.7	27.68108245
141.9	187	129.7	173.5	10.9	882.6	785.3	44.6118551
297.8	188	106.9	201.3	6	878.4	655.3	53.52471136
279.8	188	100.4	172.4	9.5	825.1	804.9	52.82696164
252.1	190	75.6	193.8	8.3	835.5	821.4	33.39959639
160.2	190.1	146.4	203.2	11.3	828.7	709.7	35.31427124
287.3	196	93.9	187.6	9.2	904.4	695.9	43.79827342
132	206.5	160.9	178.9	5.5	866.9	735.6	33.30651713
139.7	207	127.7	236.7	5.8	868.6	655.6	35.22532884
264.5	207	86.5	195.5	5.9	832.6	790.4	41.54230795
276.4	209	90.3	179.6	8.9	870.1	768.3	44.284354
148.5	214	108.6	192.7	6.1	892.4	780	23.69660064
260.9	214	78.3	200.6	8.6	864.5	761.5	32.40123514

7. RESULTS

The capability of the developed BPNN model can be assessed by Pearson's Coefficient of Correlation (R) and it computes the statistical relationship among the variables. The correlation between observed and the forecasted values was rely upon the value of R, however if the relationship is non-linear it may give biased results. It's a known fact, when R is close to unity. then the adopted predictive model is good. In the present study six different statistical parameters have been employed for judging the performance of the trained ANN models. The parameters include: root mean square error (RMSE). mean absolute percentage error (MAPE), coefficient of correlation (R). coefficient of efficiency (E), root mean square error to observation's standard deviation ratio (RSR) and normalized mean bias error (NMBE). The above performance statistics were evaluated using:

$$R = \left(\frac{\sum_{i=1}^{N}((T_i - \overline{T})(P_i - \overline{P}))}{\sqrt{\sum_{i=1}^{N}(T_i - \overline{T})^2 \sum_{i=1}^{N}(P_i - \overline{P})^2}} \right)$$

$$E = 1 - \frac{\sum_{i=1}^{N}(T_i - P_i)^2}{\sum_{i=1}^{N}(T_i - \overline{T})^2}$$

$$RSR = \frac{RMSE}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - \overline{T})^2}}$$

$$NMBE(\%) = \frac{1/N\sum_{i=1}^{N}(P_i - T_i)}{1/N\sum_{i=1}^{N}T_i} \times 100$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - P_i)^2}$$

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|T_i - P_i|}{T_i} \times 100$$

where Ti, and Pi, denote the target or observed values and ANN predicted values and T and P represent the mean observed and mean ANN predicted values, respectively. N represents the total number of data.

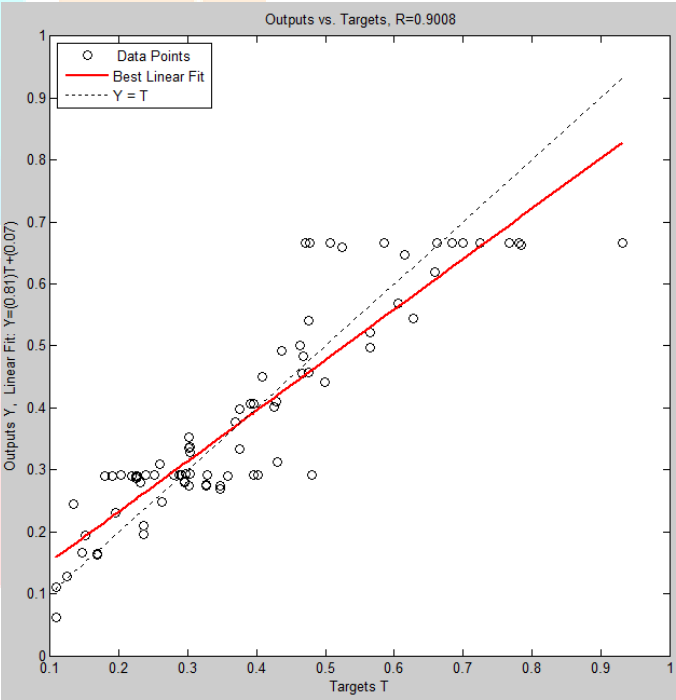

FIG. 7.1 : TRAINING CAPACITY OF BPNN MODEL

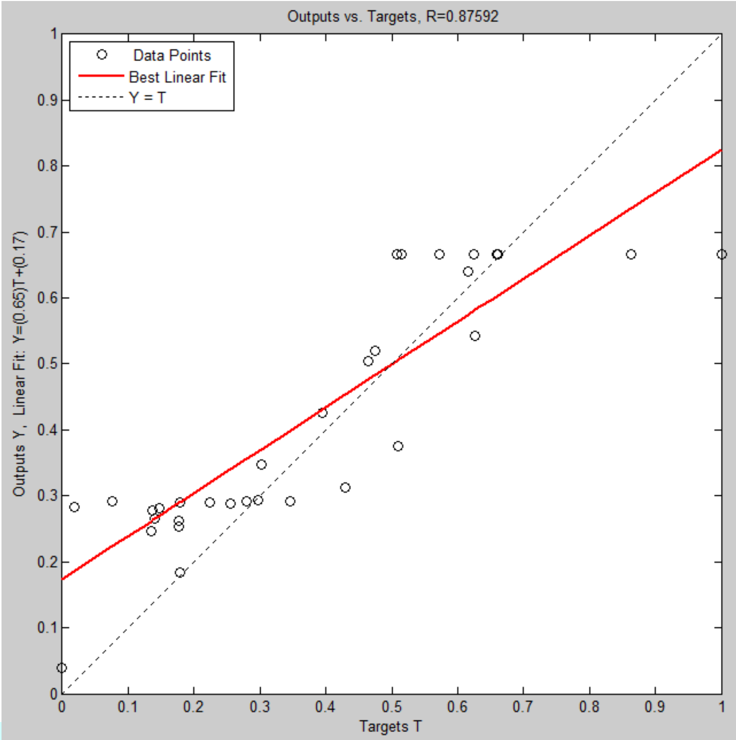

FIG. 7.2 : TESTING CAPACITY OF BPNN MODEL

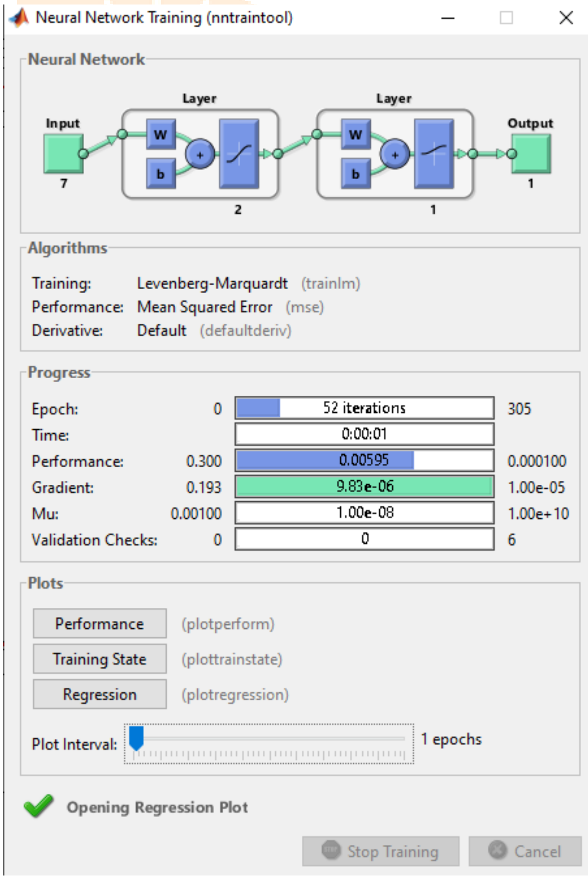

FIG. 7.3 : NEURAL NETWORK TRAINING

The determined values of the statistical approaches for BPNN have been depicted in the table.

TABLE 7.1 : STATISTICAL PARAMETERS FOR BPNN

	Training	Testing
RMSE	0.0771301	0.130910614
RSR	0.184496	0.309327
R^2	0.8114406	0.767235846
MAPE	0.1701078	1.200029
E	0.965961	0.904317
NMBE	-0.00051	0.142549

There are other measures like cumulative dissemination and probability density function also considered for scrutinizing the models. If this dissemination is near to the unity, then it can be decided as the good model. The ratio of predicted value and the measured values are determined and its lognormal disseminations have to be computed. Those can be plotted in the following figures.

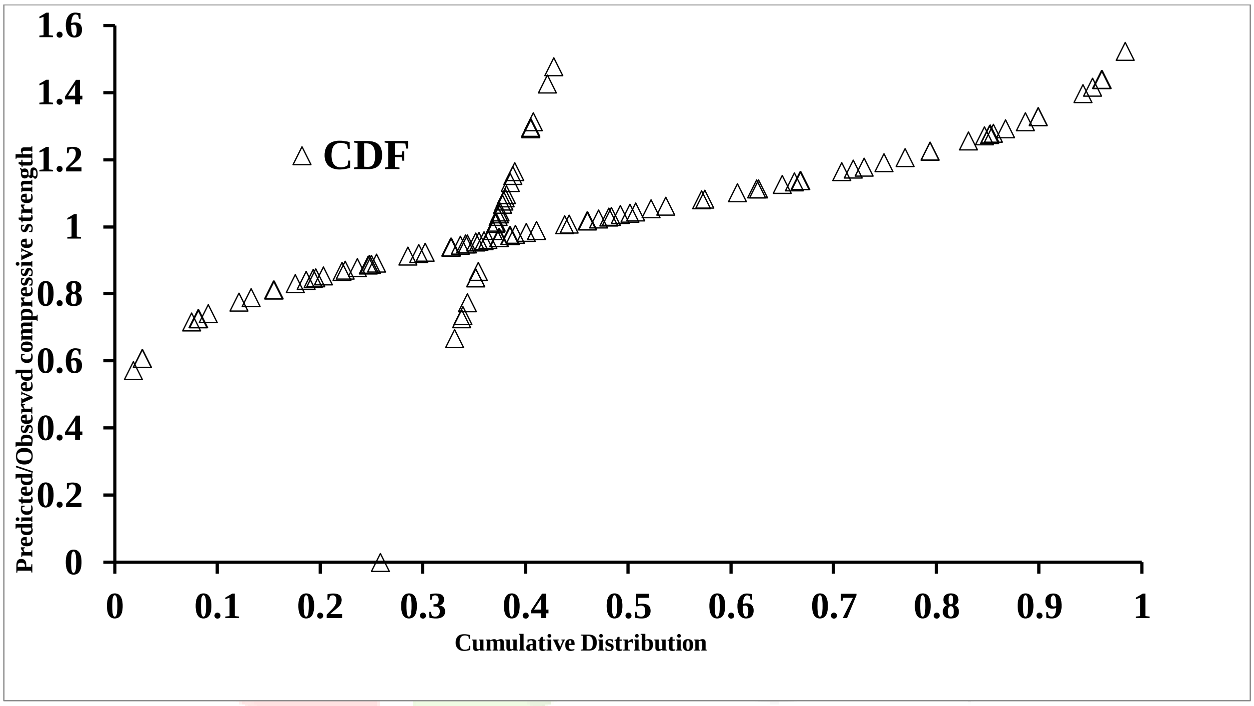

FIG. 7.4 : CDF PLOT OF PREDICTED VS OBSERVED COMPRESSIVE STRENGTH

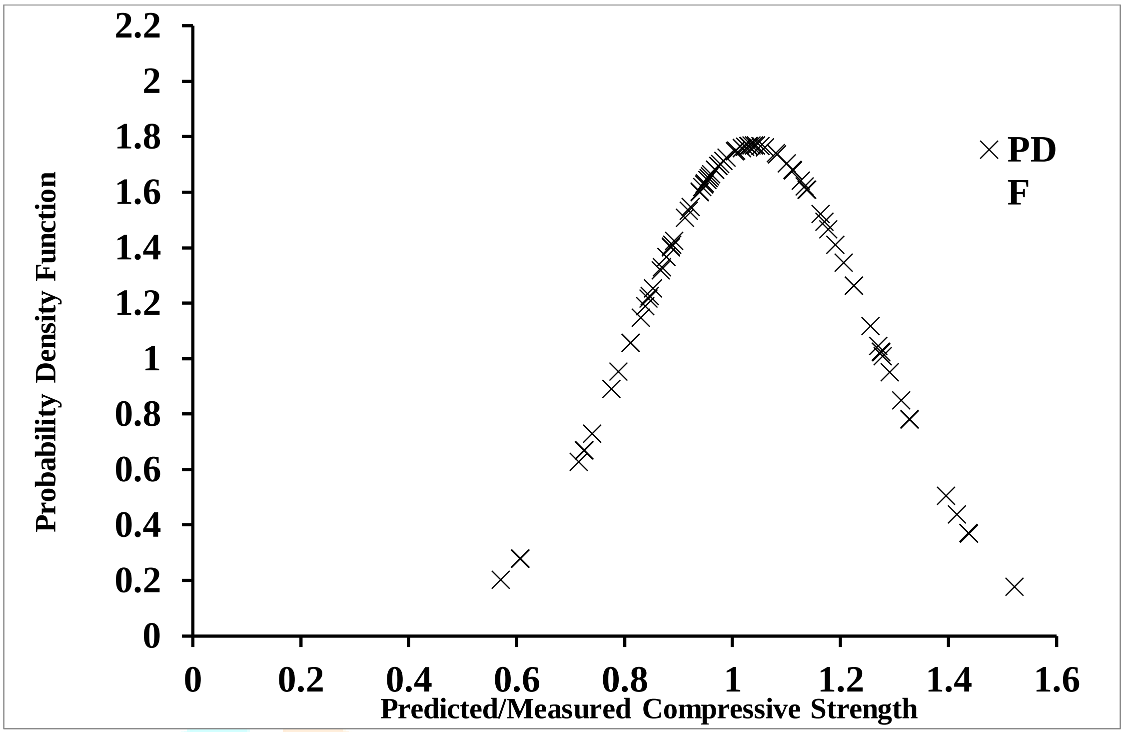

FIG. 7.5 : PDF PLOT OF PREDICTED VS OBSERVED COMPRESSIVE STRENGTH

The above determined R values, statistical error calculations, Cumulative Distribution Function and Probability Density Function were determined and exposed in the form of tables and figures.

8. DENORMALIZED DATA

The results obtained from BPNN model is in normalized form so denormalization is required to make it convenient to compare the results obtained. Following table shows the comparison of actual compressive strength with the predicted compressive strengths.

TABLE 8.1: DATA OF DENORMALIZED COMPRESSIVE STRENGTH FROM BPNN MODEL

Cement (component 1) (kg in a m^3 mixture)	Blast Furnace Slag (component 2) (kg in a m^3 mixture)	Fly Ash (component 3) (kg in a m^3 mixture)	Water (component 4) (kg in a m^3 mixture)	Superplasticizer (component 5) (kg in a m^3 mixture)	Coarse Aggregate (component 6) (kg in a m^3 mixture)	Fine Aggregate (component 7) (kg in a m^3 mixture)	Concrete compressive strength(MPa, megapascals)	Predicted Compressive strength (BPNN)
50.3562	42.08	163.83	121.75	5.72	1058.7	780.11	24.24126	25.43645
112.787	98.05	24.51	181.71	6.86	1065.8	785.38	45.70494	42.24357
112.8416	98.06	24.52	181.74	6.65	1066	785.52	40.23043	42.74291
69.57512	45.21	121.97	170.21	8.19	1059.4	780.65	31.26712	30.44205
51.62473	42.22	124.25	158.33	10.83	1080.8	796.15	31.11543	34.13231
199.3608	97.82	24.46	160.7	11.19	1061.7	782.46	63.14203	55.7258
118.9387	54.64	123.78	140.75	11.91	1075.7	792.67	55.50943	53.08903
114.3965	53.8	121.89	155.63	9.61	1014.3	780.58	52.1999	49.9651
362.783	17.2	158	167	20.8	967	633	55.64732	55.95112
275.4862	17.5	163	167	17.9	996	652	47.27697	55.45786
276.8503	17.6	158	189	15.3	967	633	44.32597	43.20572
19.05214	116	119	184	5.7	833	880	29.15729	33.01183
39.51231	128	122	182	6.4	824	879	39.39615	33.13971
64.10543	129.8	118.6	179.94	3.57	1007.3	746.8	39.16172	40.13659
49.53779	129.9	128.62	175.46	7.79	1006.3	746.6	41.2026	39.77731

56.39877	13.61	172.37	156.76	4.14	1006.3	856.4	33.68721	32.08013
57.98102	50.05	173.53	164.77	6.47	1006.2	793.5	38.20334	39.59462
49.06039	75.4	167	164.03	7.91	1007.3	770.1	41.40945	40.33755
58.34931	93.37	159.9	172.34	9.73	1007.2	746.6	37.81033	38.34018
429.6195	24	79	162	11.61	967	712	57.02629	55.95112
429.6195	24	79	162	11.64	967	712	44.4225	55.95112
429.6195	24	79	162	11.64	967	712	51.02088	55.95112
305.4945	19	97	145	13.13	967	871	44.02949	55.96939
491	26	123	201	3.93	822	699	57.91573	55.95721
399.6113	22	132	178	8.48	822	750	62.05264	55.9633
399.6113	22	132	168	8.92	822	750	72.09845	55.9633
96.80078	11	141	206	1.72	942	801	21.96596	22.08112
208.6497	15	141	179	5.46	842	801	43.73301	43.09002
310.9505	19	141	154	10.91	942	801	62.93519	55.93894
310.9505	19	141	154	10.91	942	801	59.49465	55.93894
193.6456	105	82	210	9	904	680	37.16911	33.05446
42.24033	190	148	179	19	838	741	33.75616	33.16407
244.114	143	111	168	22	914	651	33.68721	35.75821
38.1483	149	116	175	15	953	720	27.6749	33.091
14.96011	167	130	174	11	883	785	44.60866	33.10927
227.7458	137	107	201	6	878	655	53.52371	48.44881
203.1936	129	100	172	9	825	805	52.82043	54.7941
165.0013	97	76	194	8	835	821	33.39763	33.20061
39.51231	188	146	203	11	829	710	32.83914	33.15189
212.7417	121	94	188	9	904	696	41.94035	45.3127
1.32	207	161	179	5	867	736	33.3011	32.3907
12.23209	164	128	237	6	869	656	35.22476	32.17757
35.42028	214	152	200	9	819	704	33.05288	33.13971
24.50819	153	194	192	8	935	623	24.57911	27.12934
5.412033	105	193	196	6	965	643	21.9108	19.09115
177.2774	100	78	201	9	864	761	32.39787	33.15189
144.5412	92	71	247	6	853	695	28.62639	32.98748
29.96423	145	113	178	8	1002	689	25.55818	25.2903
12.23209	133	103	200	7	916	753	36.43826	31.71476
29.96423	145	113	178	8	867	824	26.22698	33.04837
178.6414	111	86	195	5	895	733	33.71479	36.85433
175.9134	101	78	171	10	936	763	49.77291	47.13347
17.68813	170	133	192	8	814	805	29.86746	33.13362
7.321649	161.6	125.8	171.6	10.4	922.6	764.4	29.07248	32.85351
169.5026	98.8	77	188.6	6.5	919	749.3	33.79822	35.31977
193.3728	105.1	81.8	209.7	9	904	679.7	37.17049	33.04837
42.24033	190.1	148.1	178.8	18.8	838.1	741.4	33.76167	33.16407
199.1016	117	91	191	7	946	666	43.57443	45.84858
32.69226	184	143	194	9	880	699	28.98492	32.95703
6.776045	162	126	172	10	923	764	29.06766	32.78652
169.0934	99	77	189	6	919	749	33.79753	35.86174
42.24033	207	172	216	10	822	638	39.84432	33.12754
72.24858	86	190	213	6	923	623	22.93124	23.16505
34.05627	178	187	221	7	854	614	29.4124	32.31763
144.4048	91.7	71.5	246.9	6	852.9	695.4	28.62914	32.98748
30.10064	145	113	178.5	8	1001.9	688.7	25.55886	25.38773
12.09569	132.6	103.3	200.3	7.4	916	753.4	36.44308	31.99488
16.32412	169.4	142.7	190.7	8.4	967.4	643.5	29.72543	28.11585
175.777	100.6	78.4	170.6	10.4	935.7	762.9	49.77291	45.58064

17.27893	170.2	132.6	191.6	8.5	814.1	805.3	29.87022	33.13971
42.24033	214	164	202	10	820	680	30.64658	33.1458
184.3703	112.3	87.5	177.9	10.4	909.7	744.5	39.42097	40.1305
249.57	145.3	113.2	178.9	8	869.1	690.2	46.23378	55.89631
243.9776	142.8	111.2	167.8	22.1	913.9	651.2	38.21506	35.62424
37.6027	148.9	116	175.1	15	953.3	719.7	27.68041	33.08491
14.82371	166.6	129.7	173.5	10.9	882.6	785.3	44.61142	33.10318
16.32412	169	143	191	8	967	643	29.72267	27.28158
6.776045	196	98	199	6	847	783	26.96473	33.04228
44.96836	163	128	197	8	961	641	27.23363	29.35202
11.82289	163.9	127.7	236.7	5.8	868.6	655.6	35.22476	32.02533
182.0515	111	86.5	195.5	5.9	832.6	790.4	41.54183	34.35153
198.2832	116	90.3	179.6	8.9	870.1	768.3	44.28391	48.26612
24.50819	118	92	183	7	953	780	23.5173	30.24718
39.78511	188	146.4	203.2	11.3	828.7	709.7	35.31371	33.15189
213.1509	120.5	93.9	187.6	9.2	904.4	695.9	43.79783	44.81944
1.32	206.5	160.9	178.9	5.5	866.9	735.6	33.30592	32.51249
184.0975	112	87	178	10	910	745	39.41683	41.26924
249.57	145	113	179	8	869	690	46.22895	55.89631
17.68813	136	106	178	7	941	774	26.14424	30.74653
38.1483	209	161	201	7	848	669	30.881	32.9144
162.2733	180	95	159	9.45	860	800	67.86501	55.90849
196.3736	180	120	162	10.35	830	765	76.23536	55.93894
46.33237	0.02	143.57	163.81	0	1005.6	900.9	26.1994	26.53866
46.33237	128.5	132.1	175.06	8.08	1005.8	746.6	46.38753	38.17576
429.6195	24	79	162	10.3	967	712	53.38581	55.92676
349.1428	20	94	157	14.32	938	845	50.23486	55.96939
349.1428	20	94	157	13.93	938	845	46.68401	55.96939
349.1428	20	94	157	11.61	938	845	46.68401	55.96939
31.32825	144	112	220	10	923	658	16.49834	32.56121
21.78017	115	89	202	9	860	829	19.98713	33.10318
28.60022	178	139	168	18	944	695	36.34862	33.15189
182.7335	111	86	195	6	833	790	41.54045	34.3698
197.7376	116	90	180	9	870	768	44.27771	47.0543
24.50819	139	109	193	6	892	780	23.68967	32.26282
23.82618	139.4	108.6	192.7	6.1	892.4	780	23.69588	32.28718
177.141	100.5	78.3	200.6	8.6	864.5	761.5	32.40063	33.15798
305.4945	19	97	145	12.25	967	871	55.45427	55.9633
491	26	123	210	3.93	882	699	55.5508	55.95721
17.68813	15	195	176	6	1021	709	15.34	17.77581
31.32825	174	185	228	7	845	612	24.33779	32.45769
49.06039	187	195	185	7	898	636	23.88962	31.47118
30.10064	145	113	178.5	8	867.2	824	26.23249	33.04837
178.505	110.5	86.1	195.4	5	895.2	732.6	33.71824	36.50723
24.50819	117.6	91.7	182.9	7.1	953.4	780.3	23.5235	30.33853
17.41533	136.3	106.2	178.1	7.5	941.5	774.3	26.147	31.2885
199.1016	116.8	91	190.6	7	946.5	665.6	43.57788	46.0069
32.96506	183.9	143.2	193.8	9.2	879.6	698.5	28.99043	32.9753
30.78264	144.2	112.3	220.1	10.1	923.2	657.9	16.50316	32.59166
21.09816	114.6	89.3	201.9	8.8	860	829.5	19.98713	33.091
28.32742	178.1	138.7	167.5	18.3	944	694.6	36.34931	33.15189
227.473	137.2	106.9	201.3	6	878.4	655.3	53.5244	48.41836
202.9208	128.9	100.4	172.4	9.5	825.1	804.9	52.82664	54.27649
165.1377	97.1	75.6	193.8	8.3	835.5	821.4	33.399	33.19452

9. CONCLUSIONS

In this project, the nature inspired computational techniques have been adopted to determine the 28 day compressive strength. In this project the heuristic approach has been executed for figuring out the functions and design values. Back-propagation Neural Network (BPNN) is framed and executed in MAT LAB, proving their efficiency in determining the values of compressive strength. This can act as an assistance platform in order to benefit the engineering people to effortlessly estimate the technical values This accuracy of our model proves that this methodology will nullify the elbow grease and minimize the time for the futuristic actions. The accessibility of the experimental data led to create a practicable tool for envisioning the compressive strength. But BPNN also has some drawbacks in which it takes some time for training and also the structure of BPNN is complex which do not provide any practical equations. On the analysis of BPNN, BPNN is more efficient and accurate as valve of R is 0.9008 for BPNN training and 0.87592 for testing. Higher the valve of co-efficient of co-relation (R) higher is the accuracy. Also the other parameters valves of RMSE, MAPE, RSR are low for BPNN. In statistics, the value of co-efficient of determination. $R^2 > 0.8$, then can be considered that the relation between the measured and the foreseen values of the adopted data. In the adopted models, the value of R^2 is greater than the ideal values; however BPNN has higher value.

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