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Machine learning approaches for predicting compressive strength of concrete with fly ash admixture

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Abstract

As worldwide environments differ from place to place, the cementitious composites change their initial characteristics. That's why it's crucial to understand their mechanical qualities for protection. In the case of concrete, the Compressive strength (C.S) is among the most crucial properties. Nowadays Machine learning (M-L) methods have been significant tools to predicting the C.S of concrete rather than traditional methods. In this study, the experimental investigation is compiled and M-L approaches are used to predict the C.S of fly ash-containing concrete. All of the materials in this research were analyzed for their chemical and physical characteristics and supervised machine learning techniques are the focus for predicting concrete C.S. Outcome prediction techniques like Artificial neural networks (A N N), Gene expression programming (G E P), and Decision trees (D-T) were studied. To run the models with proper datasets, concrete samples (cylinders) with varying mix ratios were cast and evaluated at different ages. The 07 input elements (Cement, fly ash, superplasticizer, coarse aggregate, fine aggregate, water, and curing days) were used to forecast the output element C.S. A total of 100 data points were used to predict CS. Furthermore, the experimental evidence is validated by study of Root mean error (RME), Root mean Square error (R M S E). and k-fold Cross validation (R^2), The statistical tests were included to see how well the adopted model was performed. The bagging algorithm method outperforms GEP, ANN, and DT in terms of prediction accuracy, as shown by an R^2 value of 0.97 vs 0.82, 0.81, and 0.78, respectively.

1. Introduction

Concrete is perhaps the tremendously used materials for constructing buildings of every kind, and it can be used in a myriad of different ways across the construction sector. The main components of regular concrete are cement, water, and various sizes of rocks and gravel [1-3]. Globally, cement manufacturing and usage in building projects are the leading causes of greenhouse gases (GHG) [4]. Cement industries are a major CO_2 emitter, Have a significant influence on the environment [5]. As four billion tonnes of cement production are generated per year, the equal amount of CO2 released in the surrounding region [6]. To limit this impact with using discarded or recycled material is recommended [7]. Not just reduce the need for concrete but its deterioration of the environment will stop [8]. Cement may be replaced by many industrial operational residues (e.g. G G B S, Granite Powder, Fly Ash (F-A) [9]. These additional raw resources will enhance the Hardened concrete and flawlessly reduce carbon footprint upto 80%.

When it comes to the design and research of concrete buildings, the concrete compressive strength (also known as C C S) is considered to be one of the most essential characteristics. The fundamental components of concrete may be enhanced by adding supplementary components like chemical or mineral admixtures, either before or after

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the concrete has been set. Cementitious mixtures affect concrete quality [10]. Every project requires a lab strength study to determine concrete quality [11]. Predicting concrete strength is a major difficulty in concrete manufacturing units. For heterogeneous construction, the strength is an essential criterion since ancient time [12]. The mineral admixture added to concrete has a key role in the environment due to global requirements and sustainability [13]. Sustainable materials like fly ash are a reliable alternative for cement in retrofitting, repairs, and big construction. It improves concrete's mechanical and rheological qualities [14].

Because the compressive strength (C.S) of concrete requires a lot of time and effort, It's not easy to find a balance between cost and quality when deciding how much of each appropriate concrete material to use. To save time and money in the lab, scientists have invested more than one decade developing artificial methods for choosing the best strength prediction techniques [15]. It's hard to find or forecast concrete's C.S of complicated mix-ups. Concrete's C.S is evaluated in the lab by breaking the cylinders and standard-sized cubes for a certain amount of time after casting the specimens [16]. The use of this technique has been universally adopted. However, performing testing in a laboratory is likely to be time consuming and money consuming. The traditional accepted lab methods involve lots of time and money for machinery setup and actual specimen testing.

In recent years, aids of advance technologies like artificial intelligence (A-I) and Machine learning (M-L) have been focused into predictive scenario of several mechanical characteristics in concrete [15,17]. M-L approaches such as supervised learning (regression, classification), Unsupervised learning, clustering, and reinforcement learning can be useful to estimate the many other parameters with varying degrees of effectiveness, and they can also assist in predicting the C.S with exact accuracy [22].

2. Machine Learning Overview

The most advanced kind of A-I is machine learning, which has the highest creation of predictive algorithms should be the primary emphasis. This is as a result of the objective recognition of a variety of patterns present in massive datasets for a specific activity that must be completed. This man-made region is designated as Intelligence enables computers to carry out those difficult and complex tasks. Complicated jobs that required a fine level of precision from the robots. These algorithmic processes developed an algorithm that, rather than manually identifying patterns, could learn them from the data. These algorithms individually learned logics from available data, so it perform better than human program interference. These algorithms are built on computer training, which allows learning attributes to make the data point for interpret knowledge and easily create solutions of other accessible datasets. If an algorithm is taught to distinguish benign from malignant lesions on imaging, it may be used with additional image data to malignant based on learned criteria.

The A-I subfields are organized hierarchically as shown in Fig 1. The following is a list of general categories that may be applied to M-L models. Similarly, the M-L branches are categorized in various ways. It is mainly divided into three category namely Supervised Learning, Unsupervised learning and reinforcement learning.

The model presentation in supervised learning-based tasks starts with the annotated data collection (also known as a feature vector) to imply that datasets include instances of observations and based on what they were anticipating. In order for these models to generate a result of inferring a function that translates feature vectors to label vectors. Standard and well-liked methods of supervised machine learning include the decision tree, boosting, S V M, AdaBoost, bagging, artificial neural networks, and manipulation of gene expression.

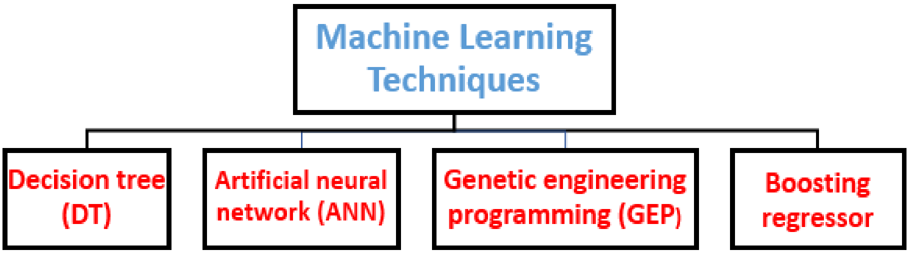


Fig. 1 Artificial intelligence's hierarchical structure and the several subfields

For unsupervised learning, the available datasets are often quite limited for the output labels are scant or nonexistent in several cases. The purpose of these models is rather to determine the interrelationship and/or expose the dormant parameters based on the findings.

3. Literature Review and Machine Learning Techniques

For forecasting of a variety of scientific issues, the hottest trends in machine learning technology commonly used are A N N, G E P and D-L (deep learning)[23-24]. S V M is built to handle nonlinear regression situations better, which helps it overcome the limitations of other methods [25]. It is capable of a superior global optimum solution and has excellent generalizability. In spite of the fact that the Decision tree (D-T) and Random forest (R-F) is structured like a tree and employs nodes and roots to distribute data. the outcomes of the prediction [26]. DT makes use of an exhaustive database that contains the variable that is of interest to it, while the selection of unique particulars within the factors that create the trees used for prediction in R-F is based on randomization. After then, a correct forecast is shown by connecting the averaged prediction with as many voters as possible. One of the most recent machine learning (M-L) computer algorithms, GEP, was developed by imitating the Darwinian evolutionary process [27]. It does it by expressing the non-linear nature of the connection via an expression tree. Methods that are associated with machine learning (M-L) are often used in order to extract undiscovered trends, necessary data, and relationships from a huge database. Despite this, the procedure makes use of database systems, in addition to machine learning and statistical investigation. Both modeling and prediction may be accomplished via the use of two distinct methods. One among them is a conventional method that is based on a solitary model all on its own, while the other is a methodology that is recognized as the ensemble algorithm method [28]. Early literature on these algorithms suggests that ensemble strategies appear to be more precise when compared to the standard standalone ML models [29]. All weak learners in ensemble learning models are first trained with the use of training data, and then combined these weaker/Slow learners with other learners to form a perfect learner [30].

Though many years ago, numerous machine learning algorithms have been used for the purpose of predicting the performance of different factors. Despite this, there has been a discernible shift toward a greater use of them in the field of civil engineering over the time of the last several years. It is owing to the great level of precision that they possess in their forecasting of properties (mechanical). The working theory of M-L is quite similar to that of traditional algorithms; however, since nonlinear behaviour is more accurate than linear behaviour, the working principle of ML is exactly the same. Evaluation of tangible mechanical properties frequently makes use of A N N, decision tree algorithm D-T, support vector machines S V M, R-F, G E P, and D-L [31]. Researcher [32] took 11 different algorithms in order to determine the shear strength in the steel fibres reinforced concrete beams. In order to make an accurate prediction of the mechanical characteristics of silica fume concrete, Researcher [33] employed ANN in conjunction with multi-objective grey wolves optimizer. Researcher [34] used D-T, A N N and S V M in order to estimate the C.S of concrete.

Researcher [35] evaluated the C.S and tensile strength of waste concrete using an ANN algorithm. The concrete C.S in marine environments was predicted [36] by using SVM, and the results were compared to those obtained by utilising ANN and DT models. Using a variety of different machine learning algorithms, [37] were able to forecast the strength properties of lightweight foamed concrete. Researcher [38] made use of a machine learning approach for finding durability property in reinforced concrete. The use of machine learning helped Suguru. [39] to construct an automated detector of fractures in concrete structures. For the purpose of gathering research data, images of the concrete were employed, whereas the use of deep learning was used for the crack detection. Researcher [40] determine the degree of precision achieved by the machine learning models. To make their prediction of the interfacial bond, [41] employs M L R, S V M, and A N N. comparison between fiber-reinforced polymers (FRPs) and concrete in terms of strength.

An A N N, which are effective methods for addressing heterogeneity in the testing model [42]. Many scholars are in favor of the widespread use of A N N in C.S prediction. The input, hidden, and output layers are all components of the feed forward ANN class, which is often referred to as multilayer perception (M L P). These conventional kind of neural nodes are simpler to work with in the power prediction model [43-44]. This study incorporates a number of categorical criteria for the purpose of predicting the C.S of fly ash concrete mixes. This is done in order to facilitate the development of a unified M-L model that can account for a wide variety of mixture features. In addition, rather than relying on the findings of previous research, the models will make use of a variety of Fly Ash concrete combinations. Since a cemented composite is intended to be used mainly for compression as a building material, the mechanical strength of the material is considered to be the most important feature it possesses. In the research that was done, typical compressive strengths were found to range from around 25 to 115 MPa [45-49].

4. Research Significance

The computational methods have been more productive in the recent decade and minimizes physical efforts due to their time saving techniques. This era of interdisciplinary domain use is emerging field having less validations available in the civil engineering hands. The minute research work available on the ANN tactics and its use in the field of C.S prediction. The Advanced M-L technics can effectively save laboratory handmade workouts and excessive material costing. Aspects of this study's is very significant and innovative due to following reasons (a) originality (b) relevance include its ASTM's experimental works for fly ash concrete (FAC) (c) developing a FAC model with the use of machine learning (M-L) algorithms.

This study focuses on strength predictions by using M-L (DT, ANN, boosting) approaches. Fly ash mixed concrete considered for whole experimental program. M-L was used to predict and compare actual results. Relevance of this quality of the results produced by different M-L algorithms. Another thing that this study does provides a method for contrasting individual and ensemble M-L methods and the outcomes of the experimentation. Each Statistical checks and kfold performance model assessed for cross-validation. The goal of this study is to investigate the relationship between the input parameters and the precision of the predicted output. Applications like this were used to make comparisons the accuracy with which various methods make predictions.

Table 1. Trends of adopting M-L techniques for the prediction of various mechanical properties

Sr No	Reference and Year	Algorithm and Method adopted by Researchers	Dataset Used	Output (Prediction Parameter)	alternative mineral admixture used)
1	Researcher [50]	Convolutional Neural Network Regression (CNN), Ensemble Regression models	345	Compressive Strength (C-S)	sludge-cement
2	Researcher [51]	A N N, G E P, and Gradient boosting tree (GBT) models	232	C-S	demolition waste
3	Researcher [52]	support vector regression (SVR), grid search (GS) optimization algorithm,	559	C-S	Not Used
4	Researcher [53]	ensemble deep neural network models	270	C-S	Fly ash
5	Researcher [54]	Back propagation neural network (BPNN), multivariate adaptive regression spline (MARS), Relevance vector machine (RVM)	629	C-S	Not Used
6	Researcher [55]	Individual and ensemble algorithm (GEP, DT and Bagging)	270	(C-S)	Fly ash
7	Researcher [21]	Individual and ensemble modelling (A N N, bagging and boosting)	1030	C-S	Fly ash
8	Researcher [18]	Individual algorithm (A N N, GEP, D-T)	642	Chloride Concentration	Fly ash
9	Researcher [56]	Data Envelopment (DEA)	114	C-S, Slump Value, L-box and V-funnel test	Fly ash
10	Researcher [57]	Multivariate (MV)	21	C-S	Crumb Rubber
11	Researcher [58]	Support vector machine (S V M)	25	C-S	Fly Ash
12	Researcher [59]	SVM	115	Slump Value, L-box and V-funnel test	Fly Ash
13	Researcher [60]	Adaptive neuro fuzzy inference system (ANFIS-ANN)	7	C-S	POFA
14	Researcher [20]	Gene expression programming (GEP)	277	Axial Capacity	Not Used

Table 1 (Cont.) Trends of adopting M-L techniques for the prediction of various mechanical properties

Sr No	Reference and Year	Algorithm and Method adopted by Researchers	Dataset Used	Output (Prediction Parameter)	alternative mineral admixture used)
15	Researcher [61]	G E P	357	C-S	Not Used
16	Researcher [62]	R-F and G E P	357	C-S	Not Used
17	Researcher [63]	A N N	205	C-S	Fly Ash, GGBFS, SF, RHA
18	Researcher [64]	Intelligent rule enhanced multiclass SVM and fuzzy rules (IREMSVM-FR)	114	C-S	Fly Ash
19	Researcher [65]	R-F	131	C-S	Fly ash, GGBFS
20	Researcher [66]	M A R S	114	C-S, Slump value, L-box test	Fly ash
21	Researcher [67]	Random Kitchen Sink Algorithm (RKSA)	40	C-S, Slump value, V-funnel and J-ring test	Fly Ash
22	Researcher [68]	Adaptive neuro fuzzy inference system (ANFIS)	55	C-S	Not Used
23	Researcher [69]	A N N	114	C-S	Fly Ash
24	Researcher [70]	A N N	69	C-S	Fly Ash
25	Researcher [71]	A N N	169	C-S	Fly Ash, GGBFS, RHA

5. Experimental Program

The basic concrete making elements such as water, cement, fly ash, sand, coarse aggregate priory examined with IS Code and ASTM standards. Type-1; 53Grade cement (Ordinary Portland) was used for experimental study. The standard specification stated as per ASTM C150 has been considered for cement used and research work. To avoid effect of surrounding moisture the cement bags were covered with air tight polythene sheets. The fly ash and cement physical-chemical properties are mention in the Table 2 and Table 3.

In order to establish the fine aggregate's qualities, testing was conducted in accordance with the ASTM standard. The concrete mix that was prepared in accordance with ASTM requirements included coarse aggregates that were readily accessible in the surrounding area and had a maximum nominal size of 20 mm. Table 4 includes the physical properties of Coarse Aggregate (CA) and Fine Aggregate (Fa).

The various mix proportions conducted for examination are tabulated in Table 5(a,b,c). The cylindrical Specimen size of 100mm dia and 200 mm height were casted for w/c ratio 0.4 to 0.6. The curing of specimens done at room temperature 27 degree Celsius for period of 3,7,14, 28, and 90days. After proper curing, the C.S carried out according to

ASTM C39. The hit and trial method considered with superplasticizer dose to fulfill desire workability property of mix. The glimpse of laboratory work shown in Fig. 2.

Fig. 2 shows a glimpse of experimental work that were subjected to compressive testing

Table 2. Physical properties of cement and fly ash used

Sr No	Material	Property	Measured Unit	Obtained Value
1	Cement	Specific surface area	Cm2/gm	8299
2	Cement	Specific Gravity	gm/cm2	3.1
3	Cement	Insoluble residue	Percent	0.5
4	Cement	Particle Size	µm	1.65
5	Cement	Loss of Ignition	Percent	2.29
6	Fly Ash	Retention on 45 micron Sieve	Percent	33
7	Fly Ash	Lime Reactivity	N/mm2	7
8	Fly Ash	Soundness test using Autoclave Expansion	Percent	0.06
9	Fly Ash	Drying Shrinkage	Percent	0.05
10	Fly Ash	C.S compare to cement mortar cube	Percent	81

Table 3. Chemical properties of fly ash and cement

Sr No	Chemical Compound	Cement	Fly ash
1	Calcium Oxide-(CaO)	65.82	2.35
2	Iron Oxide-(Fe_2O_3)	3.63	26.87
3	Silica-(SiO_2)	18.99	50.9
4	Alumina-(Al_2O_3)	6.94	4.27
5	Magnesium Oxide -(MgO)	1.98	1.52
6	Sodium Oxide-(Na_2O)	0.10	0.11
7	Potassium Oxide- (K_2O)	0.45	1.47

Table 4. Physical properties of Coarse Aggregate (CA) and Fine Aggregate (Fa)

Sr No	Aggregate Type	Property	Measured Unit	Result	Standards Followed
1	CA	Bulk Specific Gravity	No Unit	2.75	ASTM C128, C127
2	Fa	Bulk Specific Gravity	No Unit	2.65	ASTM C128, C127
3	CA	Moisture Content	Percent	0.75	ASTM C566
4	Fa	Moisture Content	Percent	1.10	ASTM C566
5	CA	Moisture Absorption	Percent	1.40	ASTM C128/ C127
6	Fa	Moisture Absorption	Percent	1.10	ASTM C128/ C127
7	CA	Fineness Modulus	No Unit	-	ASTM C136
8	Fa	Fineness Modulus	No Unit	2.45	ASTM C136
9	CA	Nominal Maximum Size	mm	20	-
10	Fa	Nominal Maximum Size	mm	4.70	-
11	CA	Rodded Unit Weight	kg/m^3	1580	ASTM C29
12	Fa	Rodded Unit Weight	kg/m^3	-	-

Table 5a. Mix proportions conducted of specimens (sr. no 1 to 33)

Sample no	Cement (kg/m³)	Flyash (kg /m³)	Water (kg/m³)	Superplasticizer (Kg/m³)	Coarse aggregate (kg/m³)	Fine aggregate (kg /m³)	Curing Period (days)	CS (N/mm²)
1	185.5	102	166.6	7.7	1009.5	908.5	90	39.4
2	170.5	127.9	161.5	8	1093.1	801.6	3	18.23
3	180.5	127.9	165.8	8	1093.1	801.7	14	24.46
4	160.5	127.9	161.8	8	1093.1	807.1	28	28.53
5	241.9	126.1	184	5.9	1060.7	782.4	14	23.03
6	211.9	126.1	183.9	5.9	1060.7	782.4	28	22.93
7	211.9	125.1	183.9	5.9	1060.7	782.4	56	34.33
8	239.8	118.8	191.6	4.8	1032.5	761.7	90	33.43
9	195.1	124.7	160.5	10.1	1091.2	805.7	3	10.61
10	190.5	124.7	161.6	10.1	1091.2	805.7	14	24.22
11	167.9	168.8	172.1	4.7	1061.7	783.2	3	12.9
12	135.9	163.8	176.2	4.7	1061.7	783.2	14	28.61
13	165	161.8	172.1	4.7	1061.7	783.2	28	26.32
14	230.4	118.7	194.9	6.3	1031.2	760.7	3	16.59
15	228.5	119.7	191	6.3	1031.2	760.7	14	22.43
16	229.5	118.7	194.9	6.3	1031.2	760.7	90	43.49
17	247.9	94.6	186.4	7.2	953	850.1	3	22.55
18	237.9	92.6	188.4	7.2	953	850.1	14	27.72
19	247.9	92.6	186.4	7.2	953	850.1	90	48.95
20	250.3	96.2	187.1	5.7	960	864.3	3	13.9
21	250.8	96.2	186.2	5.7	960	864.3	14	28.52
22	212.3	125.4	158.7	8	1088.5	802.6	3	19.54
23	212.4	125.2	181.6	6	1031.5	760.8	14	32.04
24	251.6	124.7	188.2	6.6	1031.5	813.8	56	36.02
25	251.7	123.3	181.3	6.6	1031.5	760.8	90	46.32
26	181.6	123.3	169.3	7.8	1058.7	813.8	3	15.73
27	181.6	123.3	170.3	7.8	1058.7	813.8	14	24.05
28	181.6	123.3	169.3	7.8	1058.7	780.9	28	29.91
29	182.3	124.9	170.3	7.8	1058.7	780.9	56	38.89
30	181.2	122.3	169.3	7.8	1058.7	780.9	90	47.89
31	249.9	125.3	168	9.6	964.3	868.1	90	47.11
32	229.9	125.3	160.3	12	977	878.7	3	23.23
33	220.6	125.3	145.8	12.6	1009.1	902.9	28	32.86
34	210.6	125.3	143	12.2	1089.9	804	56	63.67
35	220.6	125.2	140.8	12.2	1089.9	804	90	63.44
36	213.5	125.2	154.5	10.4	1056.6	779.5	28	44.27
37	213.5	125.3	154.7	10.4	1056.6	779.5	56	48.26
38	213.5	125.3	154.5	10.4	1056.6	779.5	90	55.21
39	213.3	125.3	155.3	11.9	1055.4	778.6	3	20.76
40	213.3	125.3	154.3	11.9	1055.4	803.1	14	38.1

Table 5b. Mix proportions conducted of specimens (sr. no 34 to 66)

Sample no	Cement (kg/m^3)	Flyash (kg/m^3)	Water (kg/m^3)	Superplasticizer (Kg/m^3)	Coarse aggregate (kg/m^3)	Fine aggregate (kg/m^3)	Curing Period (days)	CS (N/mm^2)
41	213.3	125.3	155.4	11.9	1055.4	803.1	28	43.56
42	213.3	125.3	154.3	11.9	1055.4	803.6	56	50.55
43	213.3	125.3	155.2	11.9	1055.4	803.1	90	59.52
44	218.7	125.3	158.2	11.5	1081.8	798	56	41.33
45	218.7	125.3	159.8	11.5	1081.8	798	90	46.37
46	375.8	125.3	216.4	0	1006.6	765.5	3	20.1
47	190.1	125.3	165.3	10.1	1082.1	802	14	21.34
48	164.8	125.3	163.5	0	1008.7	904	28	27.23
49	190.1	125.3	165	10.1	1082.1	802	28	27.79
50	249.8	125.3	192.5	5.5	952	860.3	28	29.33
51	213.3	125.3	158.9	11.9	1046.7	775	28	45.73
52	194.5	125.3	171.2	7.7	1001.1	904.9	28	40.39
53	251.2	125.3	192.6	6	1046.7	757.4	28	38.11
54	309.8	125.3	189.6	0	939.3	715.3	28	42.06
55	279.8	125.3	189.6	0	939.3	703.1	7	37.69
56	290	125.3	183.3	0	1072.3	757.4	7	24.3
57	252.3	125.3	186.4	0	1114.7	787.4	7	14.23
58	338.8	125.3	196.7	0	971.1	803.1	3	19.36
59	256.8	125.3	192.5	0	971.1	859.6	90	28.66
60	253.8	125.3	192.4	0	971.1	802.8	90	29.78
61	306.8	125.3	193.2	0	971.1	802.6	28	30.45
62	306.8	125.3	190.9	0	971.1	802.6	90	37.04
63	289.8	125.3	191.9	0	939.1	758.1	28	47.41
64	296.8	125.3	191	0	939.1	758.1	90	52.3
65	298.8	125.3	187	0	969.1	766.1	3	18.23
66	287.8	125.3	188.3	0	969.1	761.1	7	22.33
67	288.8	125.3	188.3	0	969.1	762.1	14	30.34
68	291.8	125.3	187	0	969.1	766.1	28	34.67
69	330.8	125.3	191.9	0	981.1	804.1	90	41.22
70	348.8	125.3	191.9	0	1050.1	809.1	3	17.71
71	294.8	125.3	185	0	1072.1	772.5	28	28.31
72	237.8	125.3	184.9	0	1121.1	792.1	28	17.96
73	295.8	125.2	191	0	1088.1	768.6	7	17.95
74	322.3	125.3	203.1	0	977.1	843.1	14	25.23
75	321.8	124.9	201.2	0	977.1	803.3	28	27.27
76	321.8	125.2	202.4	0	977.1	823.1	90	31.69
77	301.8	125.3	202.4	0	977.1	820.1	28	27.23
78	312.3	125.1	182.1	0	1043.1	737.1	28	41.2
79	316.8	125.3	192.2	0	939.1	724.1	3	27.41
80	209.8	125.3	142.2	0	899.1	899.1	7	50.53

Table 5c. Mix proportions conducted of specimens (sr. no 34 to 66)

Sample no	Cement (kg/m^3)	Flyash (kg/m^3)	Water (kg/m^3)	Superplasticizer (Kg/m^3)	Coarse aggregate (kg/m^3)	Fine aggregate (kg/m^3)	Curing Period (days)	CS (N/mm^2)
81	220.7	125.3	142.2	0	899.1	899.1	28	73.23
82	143.8	125.3	157.9	18.2	946.1	847.1	28	18.54
83	147.8	125.3	158.1	16.2	1005.1	833.1	28	21.07
84	325.8	125.1	198.8	11.2	804.1	795.1	28	40.9
85	289.8	125.3	220.2	11.2	901.1	716.1	28	10.71
86	299.6	125.3	211.2	10.1	881.3	730.7	28	26.93
87	147.9	125.1	158.9	16.3	1004.9	833.2	28	20.1
88	326.3	125.3	193	11	804.2	795.6	28	36.73
89	276.2	125.3	217.1	11.2	900.8	716	28	10.67
90	150.5	125.3	164.3	15.8	1077.6	690.1	28	16.56
91	190.6	125.3	184.8	11.3	982.6	814.1	28	16.33
92	190.7	125.3	167.9	11.8	994.3	787.1	28	19.78
93	188.5	125.3	182.1	11.9	1026.4	735.1	28	21.13
94	297.9	125.1	189.1	6.3	882.1	818.1	28	42.76
95	318.7	125.3	212.4	5.9	863.6	728.1	28	37.21
96	355.7	125	196	11.2	804.5	772.1	28	37.39
97	199.6	125.3	185.1	12.8	852.4	859.6	28	19.13
98	278.5	125.3	170	10.3	928.4	785.1	28	42.28
99	305.5	125	217	10.6	942.2	796.3	28	42.89
100	318.5	125.3	196	11.2	856.3	736.5	28	43.6

The modeling work performed according to 07 input parameters and 01 output (i.e. C.S). These input dataset consists various variables, which mentioned in the Table 6. The details of frequency distribution also presented in the Table 6 and statistical distribution mentioned in Table 7. The concentration used for computing the C-S is graphically represented by using Histogram as shown in fig. 4.

Table 6. Dataset properties for Input- output variables

Parameter	Min value	Max value
Cement (kg/m^3)	135.9	375.8
Water content (kg/m^3)	141.4	220.9
Fly ash (kg/m^3)	92.6	168.8
Superplasticizer (% by mass)	0	18.2
Fine Aggregate (kg/m^3)	690.1	908.5
w/c ratio	0.4	0.6
Curing period (days)	3	90
Course Aggregate (kg/m^3)	804.1	1121.1
C.S (MPa)	10.6	73.23

The models were executed via the usage of the anaconda programme. The detail names of algorithms used to compute C.S are i) boosting algorithm, ii) Artificial neuron network (A N N), iii) Genetic engineering programming (G E P), and iv)Decision tree (D-T). The simple algorithm flowchart of D-T and A N N Technique in schematic form is mentioned in Fig.3

Table 7. Details of parameters study

Sr. No.	Parameters	Cement kg/m^3	Fly Ash kg/m^3	Water kg/m3	Super Plasticizer kg/m^3
1	Mean or Avg	241.2	123.854	178.77	6.426
3	Median	230.35	124.8	184.2	7
2	Std. Deviation	55.62	10.13	18.01	4.94
2	Std. Error	5.62	1.02	1.82	0.50
4	Mode	213.5	124.8	191.3	0
6	Sample Variance	3093.85	102.65	324.33	24.44
7	Kurtosis	-0.8	9.8	-0.6	-1.1
8	Skewness	0.27	0.55	-0.08	-0.02
9	Maximum	376	168.3	220.5	18
10	Minimum	136.1	92.1	141.1	0
11	Range	239.9	76.2	79.4	18
12	Sum	24120	12385.4	17877.1	642.6
13	Count	100	100	100	100

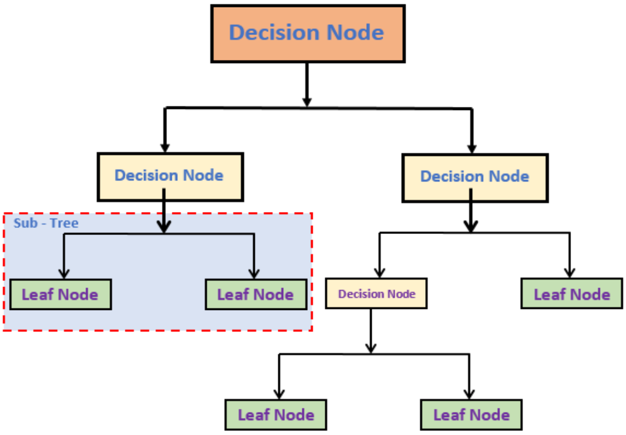
Table 7(Con.). Details of parameters study

Sr. No.	Parameters	Coarse Aggregate kg/m^3	Fine Aggregate kg/m^3	Days	Comp. Strength MPa
1	Mean or Avg	1001.3	793.273	33.67	30.49
3	Median	1006.2	794.9	28	27.52
2	Std. Deviation	71.36	48.00	28.81	13.00
2	Std. Error	7.21	4.85	2.91	1.31
4	Mode	1055.6	800	28	17.11
6	Sample Variance	5092.88	2304.07	830.20	169.06
7	Kurtosis	0.3	0.7	-0.1	0.2
8	Skewness	-0.77	0.17	1.06	0.67
9	Maximum	1118	905.4	90	72.11
10	Minimum	801	650	3	9.49
11	Range	317	255.4	87	62.62
12	Sum	100130	79327.3	3367.0	3049.3
13	Count	100	100	100	100

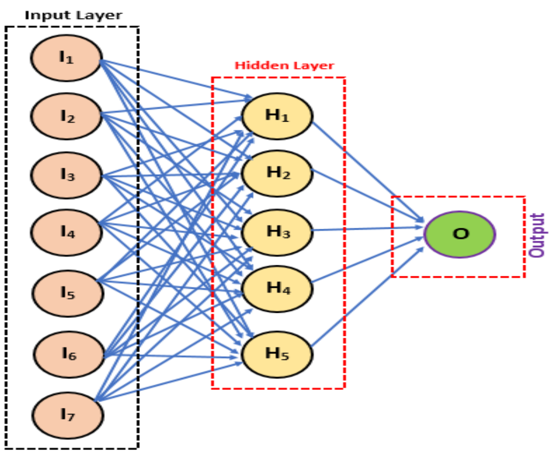
The decision tree is widely recognised as both one of the most simple and effective classification methods. It is a model that resembles a tree that divides data points into a variety of classes based on whether or not the data points fulfil a set of predetermined criteria. D-T manages the categorization job based on criteria derived from the characteristics of the incoming data. The behaviour of the decision tree is designed for no similarities whatsoever in the classification and regression trees.

Artificial neural systems (A N N's), on the contrary hand, are capable of learning similar to the human brain. Artificial intelligence (A-I) relies on A N N as its backbone in order to effectively address difficult issues. ANN has the ability to improve its output via a learning process that it can carry out on its own. Back propagation is a standard set of training rules used by ANNs, just as humans need standard specifications or guidelines to arrive at the correct result or output. For this ANN analysis, hidden layer size taken as (20 nos , 20 nos). The activation function intentionally relu was used and solver kept Adam with alpha-value 0.0001.

The concept of genetic programming was firstly introduced by Ferreira [72]. In comparison to earlier generations of genetic algorithms, Gene expression programming (G E P) can quickly gather massively increased data. Since genetic operators are directly affecting the chromosome, the process is more open. It all starts off with the first population's chromosomes, which are created at random. After the chromosomes are uncovered, fitness cases are used to determine each person's starting point for strength. They are picked out based on how well they can be reproduced and altered. Synthesis of the genomes finally replication with alterations until appropriate results are obtained are all applied to the new chromosomes. The first chromosomes for the population are generated at random. Once a person's chromosomal makeup has been determined, a fitness case is utilised to provide a baseline for their physical ability. Selection criteria include ease of duplication and tampering potential. The new chromosomes go through synthesis, conflict with the selection environment, selection, and eventually replication with changes until the desired outcomes are achieved [72].



(a)



(b)

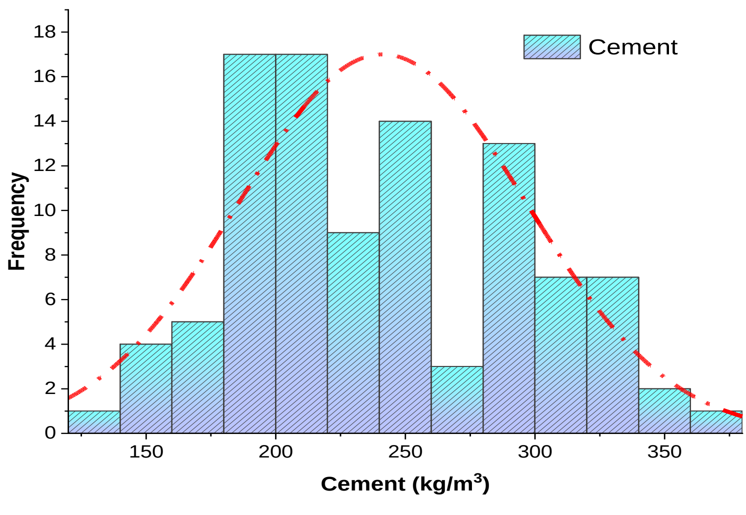
Fig .3 Flow Chart of Decision Tree Technique (D-T) and Artificial Neural Network Technique (A N N)

6. Results and Discussion

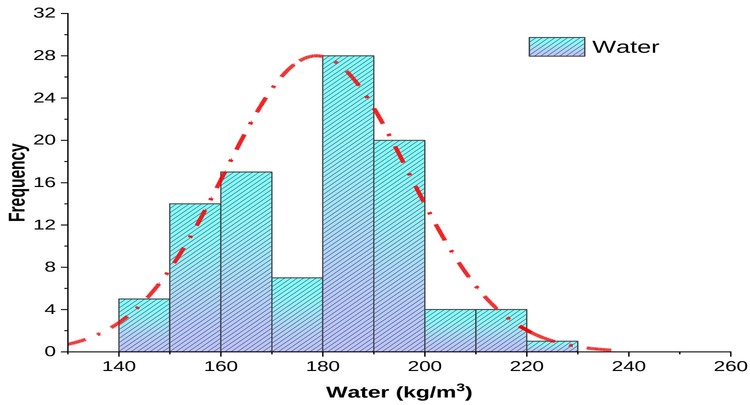
Figure 5 depicts the findings of the predictive model of fly ash Binder concrete with the help of a decision tree. According to Fig. 5(a), the DT provides a more improved coefficient of correlation R2 = 0.76 when predicting the concrete C-S. In addition, the modelled error distribution indicates value of the average error found 4.22 MPa, with the range 0.001 MPa to 21.40 MPa. In addition, the performance of the model can be evaluated based on its output results. It reveals that the majority of a data points are found within 7 MPa, with a precision of 2/3 results; 1/3 percent of the data is located within the range of 7MPa to 10 MPa; and one data point reveals that space exists more than 20Mpa.

As can be seen in Figure 5 (b), the ANN algorithm's prediction of the C.S produces a value that has a very strong association both with the experimental value and with the value that was anticipated. The model found an R2 value equal to 0.88 and seen a low error. While the smallest and highest errors were found to be 0.0 MPa (Zero) and 21.4 MPa, respectively. Similarly, one value of distribution error values of model found above 20 MPa and remaining 95 percent as depicted less than 10MPa.

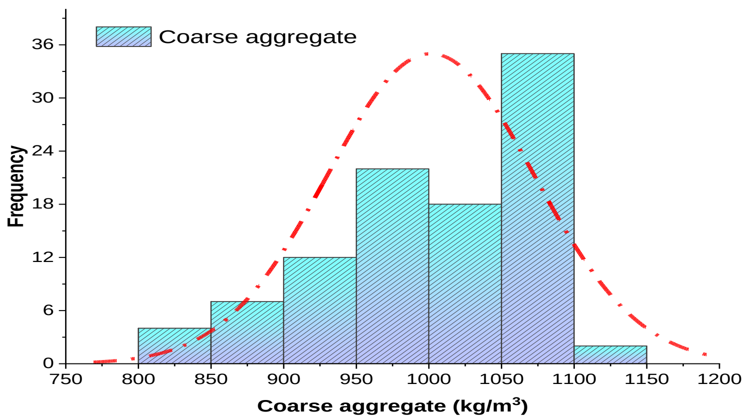
Figure 5 (c) is an illustration of the impact that the factors have on the linear regression model used. The GEP succeeded more correctly than the earlier algorithms by displaying a better values for the coefficient of determination with R square equal to 0.86. Otherwise stated, the GEP outperformed the earlier algorithms. The lowest value of errors is close to 0.77 MPa, average distribution value close to 3.353 MPa and the highest value of errors is equivalent to 5.99 MPa. In addition, the conclusion of the expected error reveals that one hundred percent of the datasets are below 5.99 MPa, demonstrates that the model is accurate.



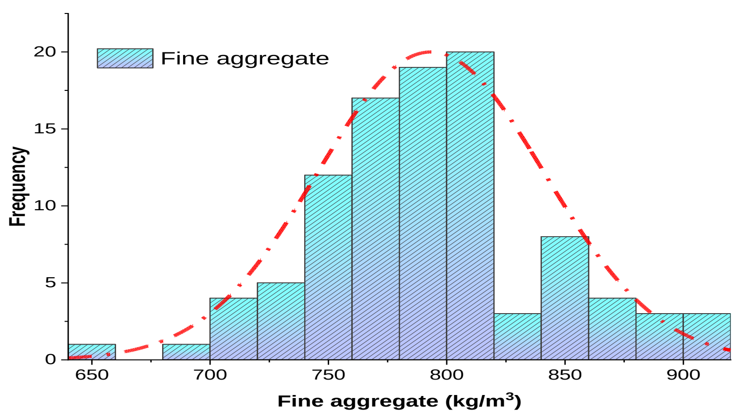
(a)


Water
Frequency
0
4
8
12
16
20
24
28
32
140
160
180
200
220
240
260
Water (kg/m3)

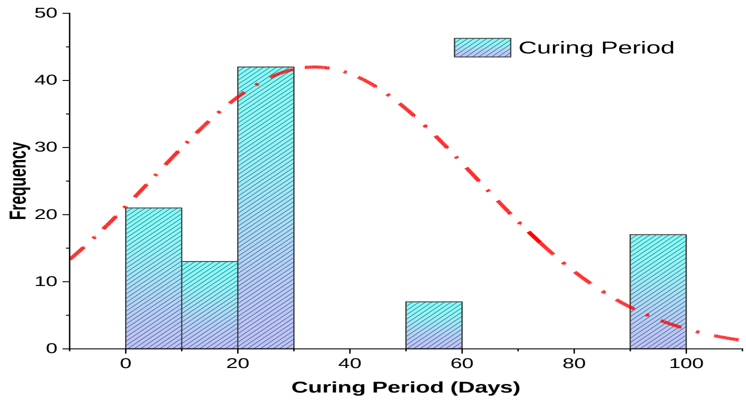
(b)


Coarse aggregate
Frequency
0
6
12
18
24
30
36
750
800
850
900
950
1000
1050
1100
1150
1200
Coarse aggregate (kg/m3)

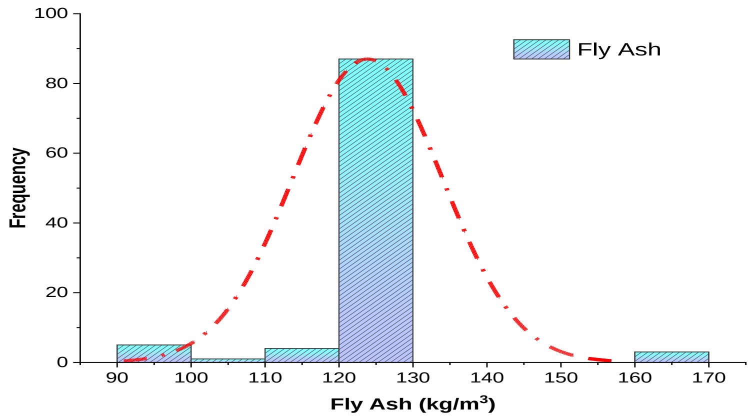
(c)


Fine aggregate
Frequency
0
5
10
15
20
650
700
750
800
850
900
Fine aggregate (kg/m3)

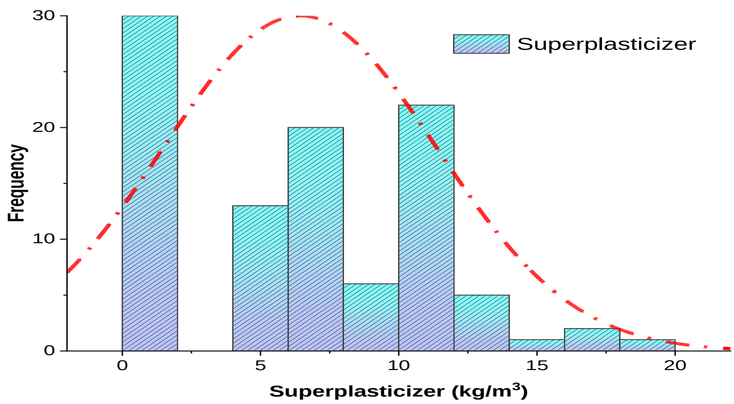
(d)


Curing Period
Frequency
Curing Period (Days)
0
10
20
30
40
50
0
20
40
60
80
100

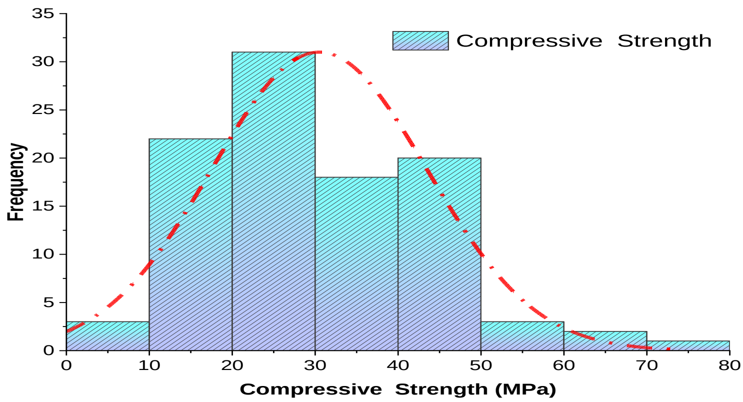
(e)


Fly Ash
Frequency
Fly Ash (kg/m³)
0
20
40
60
80
100
90
100
110
120
130
140
150
160
170

(f)


Superplasticizer
Frequency
Superplasticizer (kg/m³)
0
10
20
30
0
5
10
15
20

(g)



(h)

Fig. 4 Histogram of concentration used for computing the C-S

When compared to the individual machine learning strategies that were used for this research, the performance of the ensemble (boosting) machine learning algorithm that was used to predict the C.S of concrete was much superior. Figure 5(d), which depicts the correlation between the actual and desired output, provides a glimpse of its performance. While Fig. 5(d) provides details concerning the error distribution, which indicates that the highest and lowest values of the error are equal to 3.0 MPa and 0.57 MPa, respectively, including an average error of estimated 2.0 MPa. In addition, the fact that one hundred percent of the error data are below 4 MPa proves how accurate the model is.

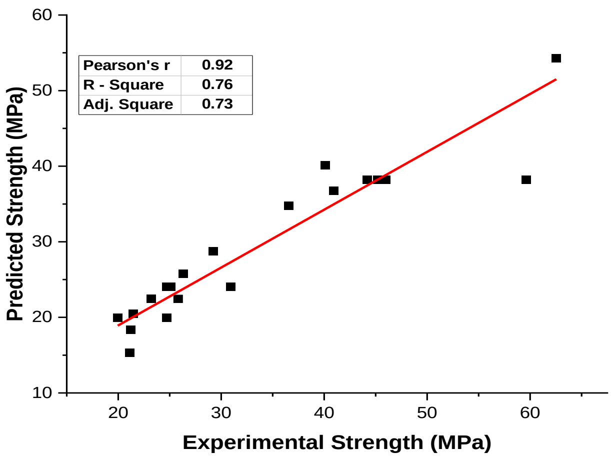
6.1 K-fold Cross validation

The J. knife test and K-fold cross validation algorithm test can be applied for a variety of purposes, such as the lesser of biases in a random training data selection, the attempting to hold out of the data set, and the minimization of the overfitting problems. The stratified 10-fold validation technique is recognised as accurate and is often used for the purpose of achieving the most efficient use of computer resources. The same ten-fold analysis is also used in this research, but it does so by dividing the data into k-groups. It then takes nine out of ten of those subgroups to analyse the data, thus the total number of subsets is ten. The model can only be validated using a single subset of data. This procedure must be carried out a total of 10 times before an average result can be determined. In addition to this, the results of the statistical checks were used to assess the response of the models that were implemented. The evidence on the model's performance was obtained by the use of the formulae, which were developed in line with the relevant research.

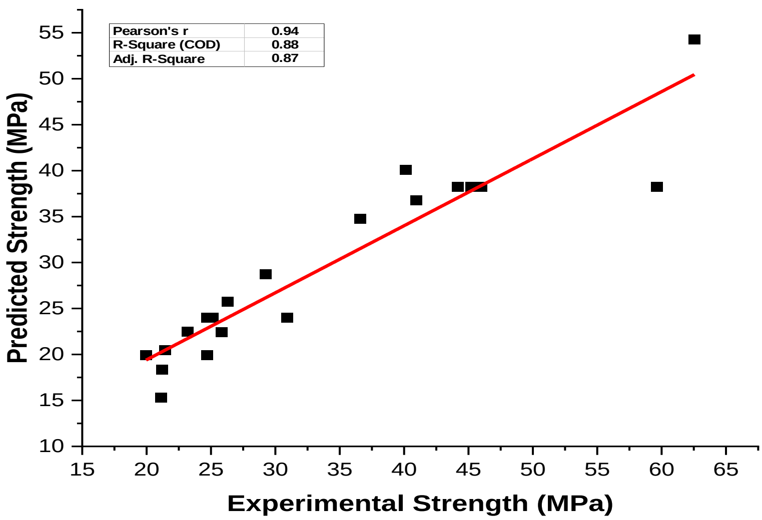
In order to investigate whether or not the bias as well as variance of the test set have decreased, the tried-and-true method of k-fold cross validation is being used. In contrast, the output of each of the machine learning algorithms demonstrates some level of variability. In contrast to the A N N and decision tree models, the G E P model has much less errors and a significantly higher R^2 value. Based on the range shown in Fig. 6 (a), the average R^2 value for G E P modelling is 0.82, with values ranging from 0.95 to 0.65. In contrast, the A N N model delivers an average R^2 value of 0.81 over 10 folds, with highest and lowest scores of 0.92 and 0.66. Moreover, as shown in Fig. 6(c), the average R2 value for the Decision tree (D-T) model is 0.78, whereas the highest and lowest values are 0.90

and 0.58, respectively. Reduced error rates in validation are a reflection of improved models. Results from the validation indicators show that the GEP has an average MAE, MSE, and RMSE of 7.89 MPa, 7.80 MPa, and 2.78 MPa, respectively (see Fig. 6 (a)).

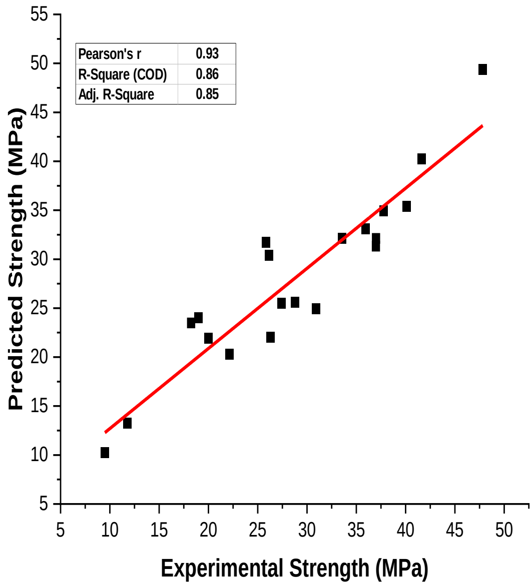
The figures 6 (b) for ANN's mean absolute error, mean standard error, and root mean squared error averages are 8.24 MPa, 8.17 MPa, and 2.854MPa, respectively. Similarly, Figure 6 (c) shows the decision tree values of 8.08 MPa, 8.04 MPa, and 2.82 MPa, respectively. While Fig. 6(d) shows that the highest possible value of average R^2 for the boosting regressor is 0.82, the lowest possible value is 0.62, and the max value is 0.97. As can be seen in 11(d), the lowest average values for BR's MAE, MSE, and RMSE were consecutively 6.714 MPa, 6.8 MPa, and 2.59 MPa. The statistical indicator were performed for K-fold cross-validation may be seen shown in Figure 6 (a) to (d).



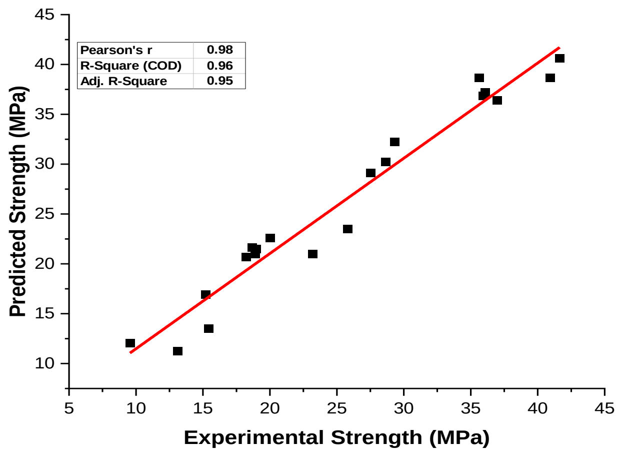
(a)



(b)



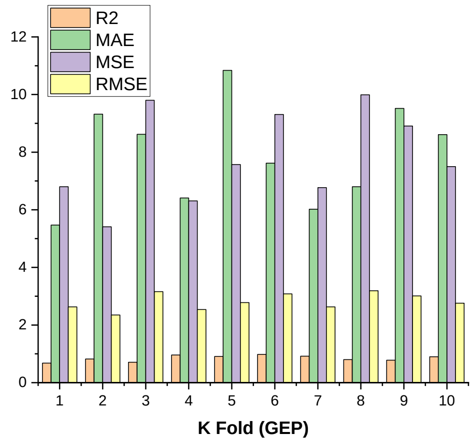
(c)



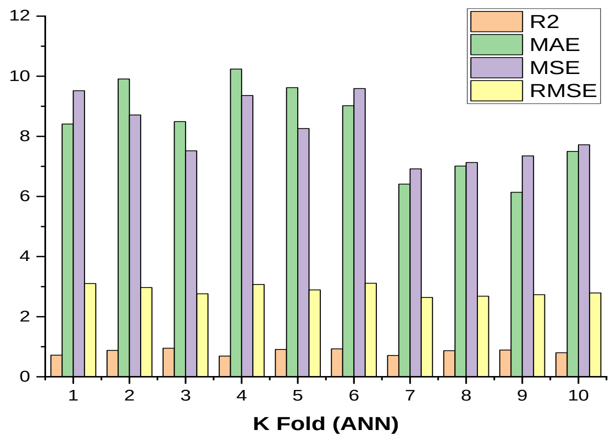
(d)

Fig. 5 (a) Performance of DT algorithm (b) ANN algorithm (c) GEP algorithm (d) Boosting Regressor algorithm , Relation between the predicted and experimental values of the compressive strength

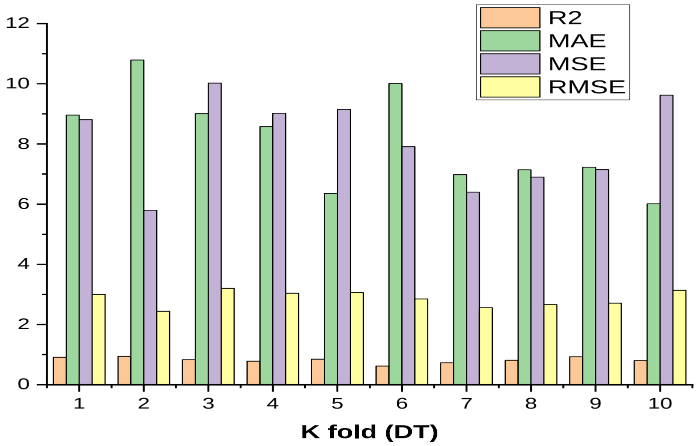
In moreover, statistical tests that were performed on the dataset revealed that the ensemble ML method has lower error rates compared to the other three individual algorithms that were implemented (G E P, A N N, and D-T). The mean absolute error, the mean standard error, and the root mean squared error for the bagging regressor (B-R) come to 3.69 MPa, 24.76 MPa, and 4.79 MPa, respectively, when statistical tests are performed. In contrast to one another, the G E P, A N N, and D-T all display pattern vice with a lower degree of deviation among themselves. This check has a direct connection to the coefficient of correlation (R^2); a lower error value indicates a highest R^2 value again for model.



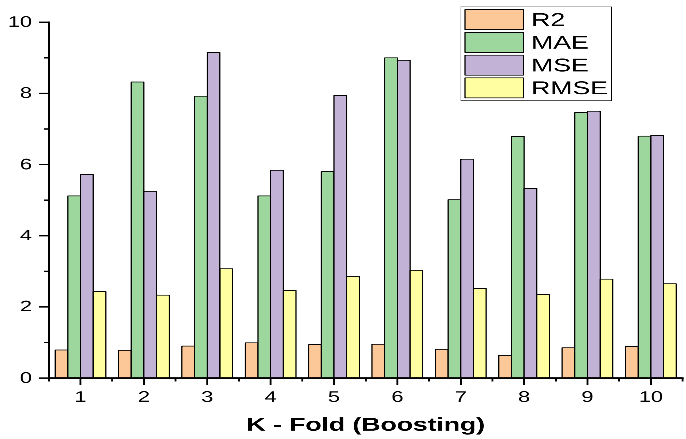
(a)



(b)



(c)



(d)

Fig.6 “K-fold” cross-validation; (a) ANN model and (b) GEP model cross-validation (c) DT model and (d) Boosting regressor

6. Conclusion

This study is predicated on a comparative evaluation of M-L algorithms applied to concrete made with fly ash as its primary component. For the purpose of predicting the C.S of fly ash-mixed concrete, supervised machine learning techniques such as decision tree (D-T), artificial neural network (A N N), genetic engineering programming (G E P), and bagging regressor (B-R) were examined. In addition, the individual machine learning algorithms were contrasted with the ensemble machine learning technique in order to get a deeper comprehension of their capabilities.

- The individual machine learning algorithms demonstrate improved performance, with a less amount of variation between the real and expected results. In comparison to regression, it has the ability to handle many outputs and responses, while regression models can only handle one response at a time.

The purpose of this discipline is to study how to replicate and apply some of the cognitive functions of the machine learning tool, so that people may produce technological goods and establish applicable theories.

- However, when the overall accuracy of the independent ML techniques was compared with that of the algorithm employed by the ensemble (bagging regressor), the ensemble was found to be a relatively strong and much more accurate method, as indicated by the value of its coefficient correlation (R^2), and this was equal to 0.97. The G E P, A N N, and D-T each have average R^2 value of 0.82, 0.81, and 0.78, respectively.
- The lower values of the errors, including the mean absolute error (3.6 MPa), the mean squared error (24.6), and the root mean squared error (4.9), further support the excellent accuracy of the bagging regressor, while alternative techniques exhibit greater values for these misjudgments.
- The K-fold cross validation technique, which was used to verify the correctness of the model, also demonstrates that the bagging regressor was beneficial.
- Statistical tests that were performed on the dataset revealed that the ensemble ML method has lower error rates compared to the other three individual algorithms that were implemented (G E P, A N N, and D-T)
- The use of statistical checks additionally verifies that bagging regressor shows an improvement in model performance by reducing the amount of error that exists between the outcomes that were sought and those that were predicted.
- It has been shown that ML algorithms are an effective and practical tool for tackling many structural engineering issues and are predicted to continue to be used in the future.

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