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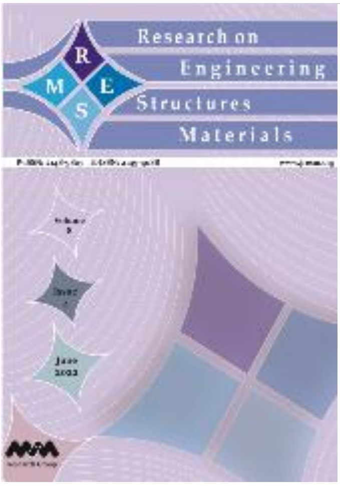

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Research Article

Predicting strength of concrete by ensemble technique

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Abstract

The developing countries share similar attributes at all the regions. Still 43% of urban population did not escape from slums live hoods. As many developing countries focuses on the infrastructural development and try to improve people living standards. This infrastructural built-up activity consumes lots of concrete and other construction materials. These construction materials possess different properties from place to place. Cementitious composites undergo transformations in their fundamental properties due to regional variations in environmental conditions. Therefore, their mechanical strength computing tools plays crucial role. When topic touches with concrete, one of the most important characteristics is the compressive strength. Predicting the strength of concrete has traditionally been done with using mechanical means, but in recent years few soft computing methods have become important tools. In this research, we apply two methods to compute the Compressive strength of fly ash concrete based on the results of our own experimental findings. To anticipate concrete strength., this study investigated the properties of all the materials involved. The ensemble methodology and the decision tree were two of the success-forecasting methodologies that were investigated, and comparative assessments were made on them. The R^2 value for the ensemble methodology was determined to be 0.96, which was much higher than the DT method's 0.76. In addition to k-fold Cross Validation, the findings of the trials are further supported by assessments of root mean square error (RMSE) and root mean error (RME). Ensemble approaches are good for minimizing model variance, improving prediction accuracy. Combining many models to make a single forecast from all their potential predictions eliminates variation.

1. Introduction

Concrete's strength, durability, resilience, and adaptability make it a go-to material for a broad range of building projects. This remarkable substance is put to use in the production of a broad variety of buildings, roads, and walkways. During building, concrete is employed for its strength, longevity, and adaptability. These superior qualities have made concrete the material of choice for both commercial and residential building projects because to its dependability and widespread application in the building trade. Standard concrete consists primarily of cement, water, and rocks and gravel of varying sizes [1-3]. Greenhouse gases (GHG) are mostly caused by the cement manufacturing process and huge incorporation in concrete infrastructure [4]. When it comes to CO_2 emissions, the cement industry is among the worst offenders [5]. If four billion tonnes of cement are produced per year, the same quantity of CO_2 pollutant is also discharged into the environment [6]. Making use of waste or repurposed materials is suggested to lessen this effect [7]. Reduced concrete use has further environmental benefits [8]. Many types of industrial waste

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products (e.g. G G B S, Granite Powder, Fly Ash (F) [9]) can be used as a cement substitute. Hardened concrete will benefit from these additional raw materials and, simultaneously, lower its carbon footprint by as much as 80 percent without sacrificing quality.

In the process of mix design, the compressive strength (C.S) is regarded as one of the most important qualities and study of concrete structures. Additives, such as chemical or mineral admixtures, can be added to concrete either before or after it sets to improve its basic components. The quality of concrete can be affected by the cementitious mixes used [10]. Lab tests of concrete's strength are necessary for every project [11]. Concrete factories have a hard time with strength prediction because of this. In ancient times [12], the strength became an important criterion for heterogeneous building. Due to worldwide standards and sustainable development, the mineral additives used for making concrete found key role in the environment [13]. Fly ash, a sustainable substance, can be used as a dependable substitute for cement in renovations, alterations, and major building projects. Concrete's mechanical and rheological properties are enhanced [14].

It is not easy to strike a balance between cost and quality when considering the quantity of each suitable concrete material to use, as determining the C.S of concrete takes a lot of time and work. Scientists have spent the better part of a decade creating artificial methods for picking the most effective strength prediction techniques [15] to help them save time and money in the lab. Complex concrete mixtures are difficult to locate and predict. The C.S of concrete is determined in the laboratory by breaking cylinders and conventional cubes after they have been cast for a specified period of time [16]. This method's application has reached a plateau of near-universal acceptance. However, laboratory testing will certainly be expensive and time-consuming. It takes a lot of time and money to set up apparatus and conduct tests on specimens using the conventional, established laboratory methods.

Recently, researchers have been putting a lot of effort into developing prediction scenarios for a variety of mechanical features in concrete with the use of tearing technologies like artificial intelligence (AI) and machine learning (ML) [15,17]. Using methods such as supervised learning, it is possible to estimate a great many parameters (W/C, SCBA%, FA, CC, CA), although with varying degrees of accuracy in the regression, classification, clustering, and reinforcement learning [22].

2. Machine Learning [ML] Overview

The primary focus should be placed on the development of prediction algorithms for machine learning, the most sophisticated kind of AI. This is due to the fact that several patterns in large datasets can be objectively recognized in order to carry out a certain task. This artificial zone, labelled Intelligence, is what gives computers the ability to perform the intricate and laborious activities that would otherwise be impossible for them to do. Tasks that tested the robots' precision and difficulty. Through a series of computational procedures, we were able to create a programme that, rather than having to be explicitly programmed to recognize patterns, could infer them automatically from the available data. These algorithms outperform human-written code because they have independently learned logics from the data at hand. These algorithms are the product of computational learning theory, which permits the acquisition of data-point-specific properties necessary for the interpretation of knowledge and the rapid generation of solutions from any number of publicly available datasets. It is possible to employ extra image data in conjunction with an algorithm that has been trained to distinguish between benign and malignant lesions on imaging.

As can be seen in Fig. 1, the AI subfields are structured in a hierarchical fashion. A few broad classifications for ML models are provided below. The ML phylogenetic trees can be broken down into several distinct groups. The ML are known as Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

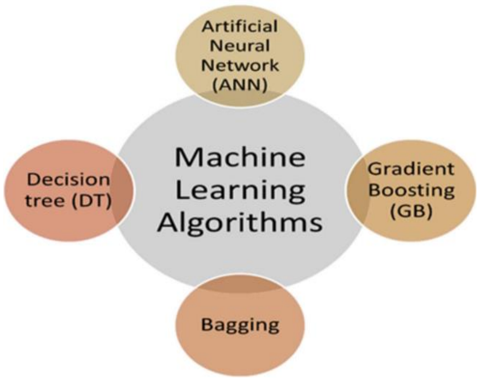


Fig. 1 AI's subfields

Popular and widely used approaches to supervised machine learning include the decision tree, boosting, S V M, AdaBoost, bagging, ANNs, and gene expression modulation. 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

Ensemble techniques are a kind of statistical and numerical learning approach that mimics the human interpersonal learning behavior of polling a group of experts before reaching a major decision. To improve the accuracy and reliability of their recommendations in supervised and unsupervised learning situations, ensembles integrate the judgements, learning algorithms, perspectives on the data, and other features of several learning machines. A N N, G E P, and deep learning are now popular developments technology utilized for predicting a wide range of scientific issues [23, 24]. Specifically, S V M is more robust in nonlinear regression settings than other approaches [25]. It has high generalizability and may provide better global optimal solutions. Despite having a tree-like form and using nodes and roots to distribute data, the results of the prediction [26] differ from the Decision tree (D-T) and Random Forest (R-F). While R-F relies on a randomized sampling of unique particulars among the elements that build the trees used for projection, DT makes use of an extensive database that includes the variable of interest to it. The next step is to prove that the mean prediction is right by tying it to as many votes as feasible. Using inspiration from Darwinian evolution, GEP, a cutting-edge M-L computer algorithm, was created [27]. It achieves this by using an expression tree to depict the connection's non-linearity. Machine learning (ML) techniques are often used to glean previously unknown patterns, data points, and connections from a massive repository of information. Despite this, the process employs databases, machine learning, and statistical analysis. There are two unique techniques that may be used for both modelling and prediction. For one, there is the time-honored, single-model approach; for the other, there is the ensemble-algorithm technique [28]. Evidence from the first studies of these methods shows that, relative to solo ML models, ensemble procedures improve accuracy [29]. With the use of the training data, ensemble learning models first perfect the weaker/slower learners, and then merge them with the stronger/faster learners to create a perfect learner [30].

Several machine learning techniques have been utilized for performance prediction over a wide range of criteria for quite some time. However, throughout the course of the last several years, a clear trend toward a larger usage of them in engineering field has emerged. Because of the high accuracy with which they predict property values (mechanical). Since nonlinear behavior is more accurate than linear behavior, the underlying theory of ML is identical to that of conventional algorithms. Statistical methods such as A N N, the decision tree algorithm D-T, support vector machines S V M, R-F, G E P, and D-L, and others are extensively used in the evaluation of perceptible mechanical qualities [31]. To compute the shear strength of concrete beams, the study by [32] used 11 distinct methods. Study [33] used ANN in tandem with the multi-objective grey wolves optimizer to forecast the mechanical properties of silica fume concrete with high precision. C.S estimates for concrete were calculated using D-T, A N N, and S V M by the researcher [34].

Utilizing an ANN system, researcher [35] determined the C.S and tensile strength of discarded concrete. Concrete C.S was estimated [36] using SVM, and outcomes were contrasted to those obtained using ANN and DT models in coastal situations. To foretell the durability of lightweight foamed concrete, Researcher [37] used a number of machine learning techniques. One study [38] used a machine learning technique to identify a reinforced concrete durability feature. Suguru. [39] used machine learning to create a robotic system for detecting cracks in concrete. Images of the concrete were utilized for data collection, and deep learning was put to use to spot the cracks. Accuracy of machine learning models is evaluated by researchers [40,41] .

There is a lot of variability in the testing model, and one way to deal with it is via an A N N [42]. The broad use of A N N in C.S prognosis has received support from many academics. The feed forward ANN classification (multilayer perception), consists of 03 layers: Input, hidden, and output (M L P). For the power prediction model, these more traditional neural nodes are more convenient to operate with [43, 44]. For the objective of foretelling the C.S of fly ash concrete mixes, this research makes use of a variety of categorical criteria. The goal is to make it easier to create a universal M-L model that can capture a broad range of mixture characteristics. In furthermore, the models will use a wide range of Fly Ash concrete mixtures rather than only using the results of earlier studies. Since a cement composite's primary function as a construction material is compression, its mechanical strength is prized above all others. Studies have shown that ordinary compressive strengths are within the range of 25 to 115 MPa [45-49, 72]. Generative ensemble approaches, on the other hand, produce groups of base learners that manipulate the base supervised learning or the data frame structure to enhance the base learners' variety and performance. In this situation, the fundamental problem with the ensemble method is not the mixing approach, but rather the manner in which various base learners are generated. Methods such as resampling, which divide the input space and train base learners on bootstrap samples reproduces of the data; random subspace algorithms, which produce diversified base learners by using varying random selection sub-sets of features; and combination of experts methods, which divide the input space and train an ensemble of neural networks to conduct an impactful estimation at each assigned territory separately, are all examples.

Table 1. Trends of adopting soft computing techniques for the prediction of various terms

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]	(BPNN), (MARS), (RVM)	629	C-S	Not Used
6	Researcher [55]	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	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	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
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	Fly ash
21	Researcher [67]	Random Kitchen Sink Algorithm (RKSA)	40	C-S, Slump value, V-funnel	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]	ANN, DT, GEP	100	C-S	Fly Ash

4. Research Significance

Since the turn of the century, computer technologies have become more efficient, reducing the need for laborious manual labor. There are fewer validations at civil engineers' disposal in this burgeoning sector of transdisciplinary domain utilization. The little literature on ANN strategies and their application to C.S. prediction. Through the use of cutting-edge ML techniques, costly manual labor in the lab and expensive raw materials may be avoided. This study's significance and novelty stem from (a) its novelty and (b) its applicability to current issues, such as the ASTM's experimental works for fly ash concrete (FAC) (c) using ML methods for FAC model development.

This research focuses on ML (discrete-event neural network) and boosting techniques for making predictions of strength. The use of concrete that contains fly ash was explored during the whole experimental procedure. Actual results were predicted and compared using ML. Quality of these findings provided by various ML algorithms and their applicability. This research also gives a means of comparing and evaluating the results of experiments conducted using individual and ensemble ML approaches. Both statistical tests and k-fold performance models were evaluated for cross-validation [71]. The purpose of this analysis is to look at how different inputs affect the reliability of the expected output. Such applications were utilized to evaluate the predictive efficacy of different approaches.

5. Experimental Program

The fundamental components of concrete have been thoroughly analyzed in accordance with IS Code and ASTM standards. Experiments were conducted using Type-1; 53Grade cement (Ordinary Portland). For both the cement utilized and the studies conducted, the standard specifications indicated by ASTM C150 were taken into account. Cement bags had airtight polythene coverings placed on top of them to prevent the bags from absorbing moisture from the air. Table 2 and Table 3 provide the chemical and physical characteristics of fly ash and cement, respectively.

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

The fine aggregate's quality was determined by testing that met the requirements of the ASTM standard. Coarse aggregates with a standard thickness of less than 20 mm were sourced locally and used into the fresh concrete that was formulated to meet ASTM standards. Coarse Aggregate (CA) and Fine Aggregate (FA) physicochemical parameters are listed in Table 4. (Fa).

Table 2. Physical Analysis of cement (C)and fly ash (F)

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

Table 5 summarizes the results of the tests performed on the different mix proportions (a, b, c). Specimens with a diameter of 100mm and a height of 200mm were cast with a w/c of 0.4 - 0.6. the specimens were cured at 27 degrees Celsius for 3, 7, 14, 28, and 90 days. The C.S. performed to ASTM C39 standards after curing properly. To achieve the desired mix workability attribute, the hit-and-trial approach was examined with the superplasticizer dosage. Fig. 2 is a view inside laboratory procedures.

Table 3. Chemical Analysis of fly ash (F) and cement (C)

Sr No	Chemical Compound	C	F
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 Analysis of Coarse Aggregate (C-a) and Fine Aggregate (F-a)

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

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

Sample no	Cement (kg/m^3.)	Fly Ash (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)
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.)	Fly Ash (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/m³.)	Fly Ash (kg /m³.)	Water (kg/m³.)	Superplasticizer (Kg/m³.)	Coarse aggregate (kg/m³.)	Fine aggregate (kg /m³.)	Curing Period (days)	CS (N/mm²)
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 modelling was carried out using a total of seven inputs and one result (i.e. C.S). Table 6 lists the individual variables that make up this input dataset. Table 6 presents the frequency distribution information, while Table 7 describes the statistical distribution. Using a histogram, figure 4 depicts the intensity that was included into the C-S calculation.

Table 6. Dataset properties for Input- output variables

Parameter	Min value	Max value
C (kg/m^3)	135.9	375.8
Water content (kg/m^3)	141.4	220.9
F (kg/m^3)	92.6	168.8
Superplasticizer (% by mass)	0	18.2
Aggregate F-a (kg/m^3)	690.1	908.5
Curing period (days)	3	90
Aggregate C-a (kg/m^3)	804.1	1121.1
C.S (MPa)	10.6	73.23

There are a number of techniques that may be used to calculate C.S., some of which are listed below: i) boosting algorithm; ii) Decision tree (D-T). Fig.3 shows a simplified schematic flowchart of the algorithms for the D-T . The anaconda software was used to run the models. schematic flowchart of the algorithms for the D-T . The anaconda software was used to run the models.

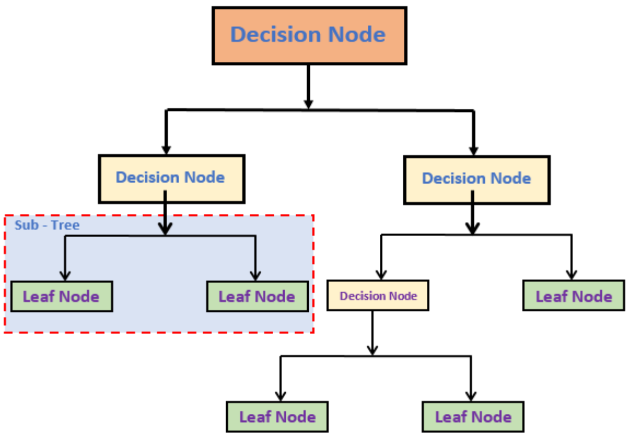
Table 7. Details of parameters study

Sr. No.	Parameters	Cement kg/m^3	Fly Ash kg/m^3	Water kg/m^3	Super Plasticizer kg/m^3
1	Mean or Avg	241.2	123.8	178.7	6.4
3	Median	230.35	124.8	184.2	7
2	Std. Deviation	55.62	10.13	18.01	4.9
2	Std. Error	5.62	1.02	1.82	0.5
4	Mode	213.5	124.8	191.3	0
6	Sample Variance	3093.8	102.65	324.33	24.4
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	793.27	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 well-known as an efficient and straightforward approach to categorization. It's a model that looks like a tree and uses a set of specified criteria to sort data into several classifications. D-T oversees the classification process using criteria determined from the nature of the incoming data. The decision tree's behavior is planned such that the classification and regression trees share no characteristics at all.



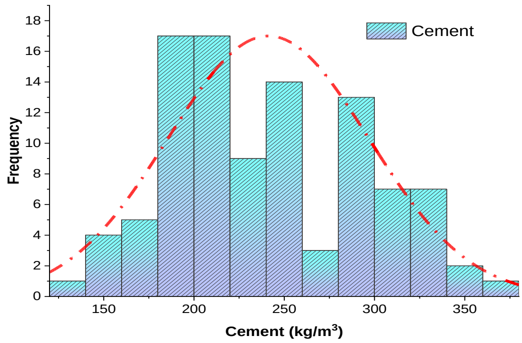
(a)

Fig .3 Flow Chart of Decision Tree Technique (D-T)

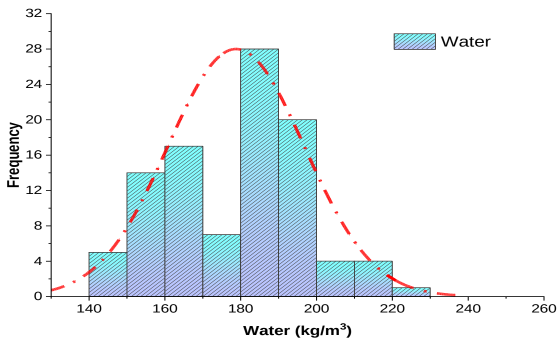
In contrast to artificial neural networks (ANNs), the usage of a structure that is based on decision trees gives explicitness. Because the process of decision tree clustering imitates the process of human thought, it is easy for even communities who are not technically oriented to grasp the behavior. However, in comparison to the simple decision tree, the majority of more sophisticated tree-based designs are relatively complicated. Despite this, every single tree-based model that was used in this investigation was a decision tree-based model. Because of this, it is very necessary to explain the process that a decision tree regressor goes through.

6. Results and Discussion

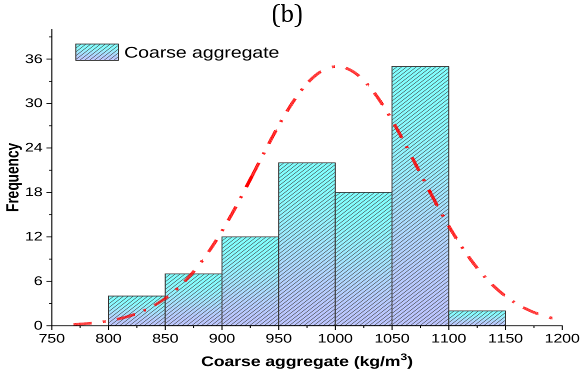
The results of the decision tree fly ash binder concrete prediction model are shown in Figure 5. Figure 5(a) shows that the DT has a higher $R^2 = 0.76$ when projecting the concrete C-S. The limit of the modelled error ranges from 0.001 MPa to 21.40 MPa, even with average error observed to be 4.22 MPa. Furthermore, the output results and model's performance corelated with each other's. Two-thirds of the findings show that the data lies within 7 MPa, with high accuracy; one-third of the results show that the data found between value 7 MPa to 10 MPa, with low precision; and one result shows that space exists at a pressure higher than 20 MPa, with low precision.



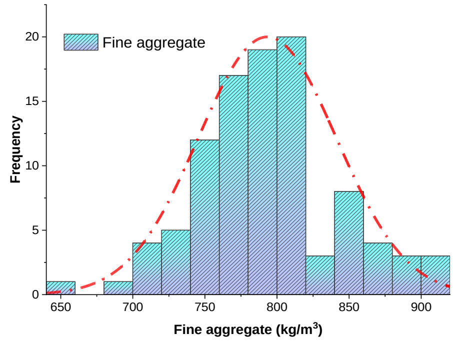
(a)



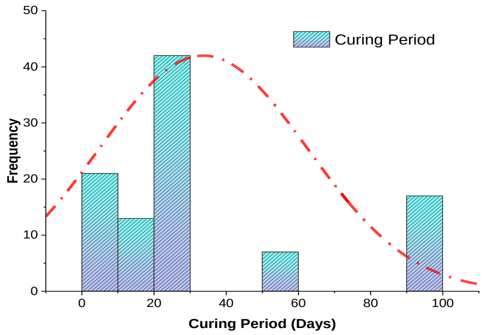
(b)



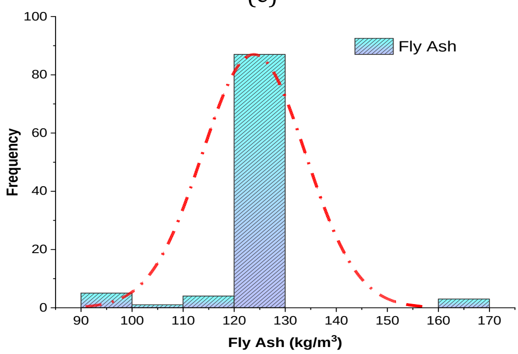
(c)


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

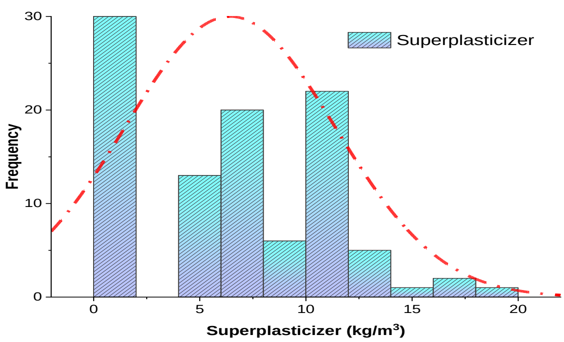
(d)


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

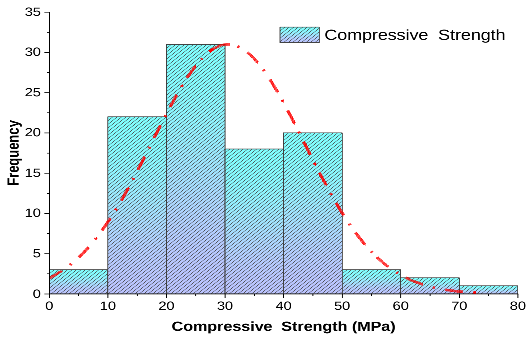
(e)


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

(f)


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

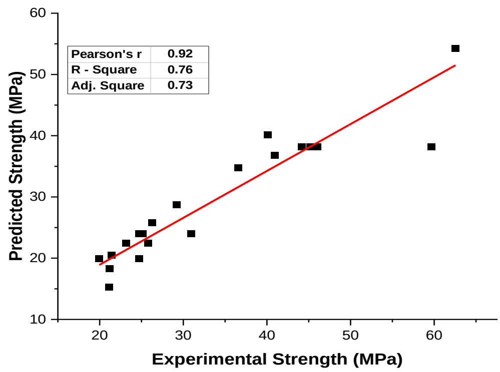
(g)



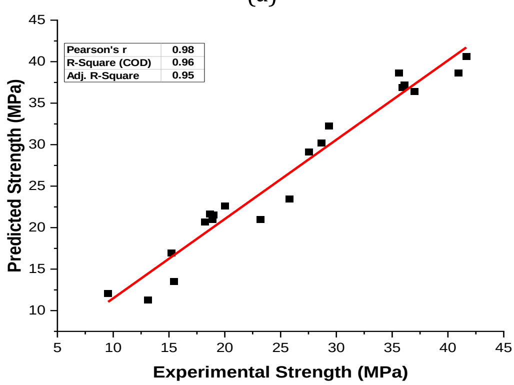
(h)

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

The effectiveness of the ensemble (boosting) algorithm often used estimate the C.S of concrete was substantially higher when compared here to other machine learning techniques employed for this study. You may get a sense of its efficiency by looking at Figure 5(a), which shows the relationship between the actual and ideal output. The estimated standard deviation is 2.0 MPa, with a range of 0.57 to 3.0 MPa, as shown in Fig. 5(b). Furthermore, the fact that all error data found less than 4 MPa demonstrates the reliability.



(a)



(b)

Fig. 5 (a) Performance of DT algorithm (b) Boosting Regressor algorithm

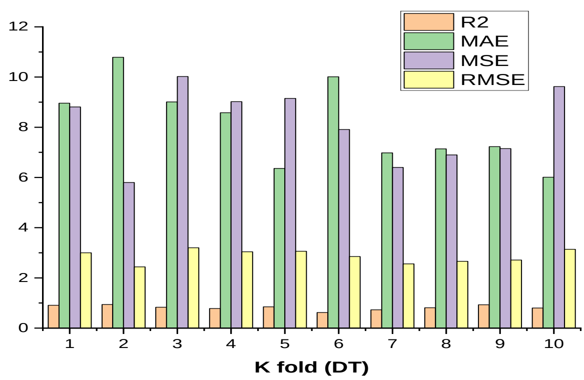
6.1 K-fold Cross validation

Multiple tasks may benefit from the use of the J. knife test and the K-fold cross validation algorithm test, including reducing the impact of bias in a random training data selection, excluding less-representative examples from the data collection, and reducing the severity of overfitting issues. The stratified 10-fold validation method has been proven reliable and is often used to maximize productivity with minimal hardware and software requirements. Similarly, this study employs a ten-fold analysis, albeit it does so by splitting the data into k distinct subsets.

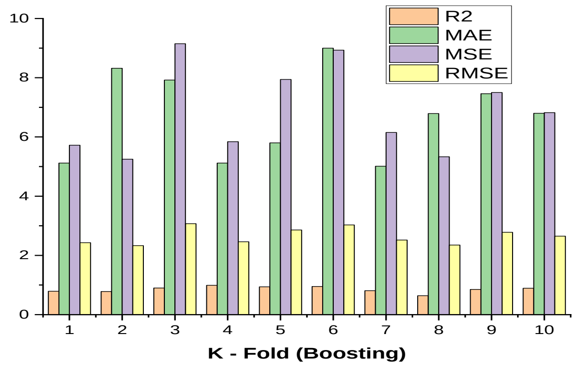
The collected information may be partitioned into distinct categories, of which several are required for the analysis. It is not feasible to validate the model by using more than one data subset in the verification process. separate attempts at the procedure are required to get a result that is representative of the norm. The statistical tests' findings were also used into an evaluation of the models' performance. Evidence for the model's efficacy was derived from the formulations that were created in accordance with the underlying study.

The attempted approach of k-fold cross validation is employed to ascertain how much the bias and variance of the testing set have been reduced. But there is noticeable variation in the results produced by each of learning methods. The BR model has a substantially better R^2 value and far fewer mistakes compared to decision tree models. Further, as can be shown in Fig. 6(a), the Decision tree (D-T) model has an average R^2 value of 0.78, with values as high as 0.90 and as low as 0.58. Validation error rates that drop indicate that the models have been improved. Values of 8.08 MPa, 8.04 MPa, and 2.82 MPa may be seen in the decision tree shown in Figure 6(a). As can be seen in Fig. 6(b), the average R^2 for the boosting regressor ranges from 0.82 to 0.62, with a maximum of 0.97. The lowest mean absolute errors (MAE), mean standard errors (MSE), and root mean squared errors (RMSE) for BR are shown in 6(b) as 6.714% MPa, 6.806% MPa, and 2.59% MPa, respectively.

More so, statistical tests conducted on the dataset showed that the ensemble ML approach had lower error rates than the other methods used (D-T). The findings for the bagging regressor (B-R) reveal an error of 3.69 MPa (mean absolute error), 24.76 MPa (mean standard error), and 4.79 MPa when statistical tests are done (root mean squared error). Coefficient of determination (R^2) is directly related to this test; higher R^2 value once again for model corresponds to lower R^2 value due to less error.



(a)



(b)

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

6. Conclusion

- Ensemble approaches are good for minimizing model variance, improving prediction accuracy. Combining many models to make a single forecast from all their potential predictions eliminates variation.
- The foundation of this research is a thorough analysis of M-L algorithms used on fly ash-based concrete. Decision tree (D-T), and bagging regressor (B-R) were some of the supervised machine learning methods analyzed for their ability to predict the C.S of fly ash-mixed concrete. In addition, the performances of the individual machine learning algorithms were compared to those of the ensemble machine learning method.
- There is less discordance between observed and predicted outcomes when using distinct machine learning techniques. In contrast to regression, it may accommodate several answers and outputs at once. The field of research known as "machine learning" is dedicated to understanding how to duplicate and implement certain cognitive features of the machine learning tool in order to create technological products and build relevant hypotheses.
- Nonetheless, the ensemble was found to be a fairly strong and significantly reliable way, as demonstrated by the value of its coefficient correlation (R^2), which was equal to 0.96 when compared to the total accuracy of the independent ML techniques. This was accomplished by using a bagging regressor. There is an average R^2 value 0.76 for the D-T.
- Mean absolute error (3.6 MPa), mean squared error (24.6), and root mean squared error (4.9) are all less than they are when using other methods, further demonstrating the superior accuracy of the bagging regressor.
- The model's accuracy was confirmed using the K-fold cross validation method, which corroborates the bagging regressor's usefulness.
- Statistical analysis done on the dataset showed that the ensemble ML approach yields lower error rates than the other individual methods used (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 found that ensemble machine learning methods are an effective and helpful tool for addressing a broad range of structural engineering issues, and it is

anticipated that the usage of these algorithms will rise over the duration of the subsequent years.

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