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Comparative analysis of machine learning techniques in the prediction of the strength of structural concrete

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ABSTRACT

Compressive strength is one of the important parameters in the assessment of the mechanical performance of concrete. Advanced and precise estimation or methods can save up a lot of time, cost and also diminish environmental related problems. In this study, various Machine learning (ML) techniques are used to predict the concrete compressive strength. The various algorithms are implemented using a 1066 dataset having different mix designs collected and various ML investigations were made. The compressive strength was modeled as a function of various input parameters like cement content, blast furnace slag, fly ash, superplasticizer, water, coarse aggregate, fine aggregate, and age. The various ML models inclusive of decision tree classifier (DT), Random Forest (RF), support vector machine (SVM), naïve bayes (NB), gradient boosting (GB), K nearest neighbour (KNN), and artificial neural network (ANN) were developed using python programming executed using Google Colab platform. Further, the performance of the developed ML models was analysed through the accuracy, confusion matrix, precision, recall, F1-score and, Receiver Operating Characteristic (ROC) results. The results revealed that, amongst all the ML tools, the NB and SVM algorithms could predict the concrete compressive strength with better accuracy when compared with the other algorithms. Thus, the outcomes from the present research investigation can provide a reference for the accurate estimation of the concrete compressive strengths, which would further benefit the engineering fraternity in managing the projects with ease. The application of this study would definitely leads to reduce the time taken for manual work and also the time consumed in the laboratory trials pertaining to concrete mixes.

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1. Introduction

Concrete is one of the most important materials in the civil engineering field. It is also considered the second most important universal material following water. The real concrete compressive strength is unspecified in the early age of structure[1,2]. Coarse aggregates, fine aggregates, binder materials, water, and other raw materials are mixed to generate concrete. Concrete mix is vastly used across the world. Concrete compressive strength plays a very important role in the design of any structure. To obtain the desired mix proportions of the concrete, desired strength of the concrete is to be selected. The process must undergo a few stipulated standard manual processes in finding the optimum mixes for the design strength requirements. The desired mixes are to be prepared in standard fashion, cured and the compressive strength has to be determined in the laboratory. This results in the wastage of resources like workmanship and materials for every trial [34]. Also, casting concrete specimens using laboratory processes and experimental progress to find their properties is a time engaging task[5–7]. Hence, researchers are in a search of few faster and accurate techniques which would help in the determination of the concrete compressive strength at a faster pace. This accurate predictive determination of compressive strength would definitely

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help in determining the welfare of concrete structures [8]. Various researches have looked into the parameters that affect the value of compressive strength of concretes [9–13]. Different types of methods are implemented to predict a better concrete compressive strength. Moreover, researchers are continually finding a method that is suitable for making the progress simple. In such cases the use of machine learning techniques plays a major role. Machine learning helps to adapt and learn the dataset, by use of certain algorithms. Machine learning is a self-learning system, which is also a subset of artificial intelligence (AI). AI is the ability which can learn and understand in a similar course of action as one found naturally in the human brain. All the machine learning is counted under the AI. Machine learning has three different types of classification which can be named as - supervised learning, unsupervised learning, and reinforced learning. In this paper, both the supervised and the unsupervised learning methods were adopted for the research. The supervised learning is further categorized as decision tree classifier (DT), Random Forest (RF), support vector machine (SVM), naïve bayes (NB), gradient boosting (GB), K nearest neighbour (KNN) and artificial neural network (ANN). Whereas, under unsupervised learning, the K Mean (KM) method is considered for the investigations.

The various models are built by giving a certain amount of dataset and allowing the algorithm to predict the classes assigned [14]. A machine learning algorithm can be said to under fitted when it is not possible for it to entrap the basic trend data. Under-fitting can happen when there is insufficient data, when a model gets feuded with large amounts of data or inaccurate data it shows the overfitting. Performance metrics in machine learning classification models help to know the efficiency or the performance of methods used. In this study, the classification models are used which give the discrete values as output. Accuracy, confusion matrix, precision and recall, F1 score, Area under receiver operating curve are some of the performance metrics used under the scope of the research. Several researchers have worked on the various methods of ML; a few key outcomes were presented in the following sections.

U.Atici. [3] used the ANN and multivariable regression analysis to predict the strength of mineral admixture based concretes, and the results obtained using the two methods are compared. In their research, the multiple regression analysis obtained more accurate results when compared with the results from the artificial neural network models, in predicting the compressive strength by using non-destructive testing values.Abobakr et al. [15] discussed the extreme learning machine (ELM) approach to predict the compressive strength of concrete, ELM model was generated with the laboratory data, and regression was applied, the data contained water, cement, fine aggregate, coarse aggregate, and superplasticizer as the input parameters. ELM was then compared with ANN which resulted in strong ELM potential to predict the compressive strength of high strength concrete.

Tuan et. al.[16] discussed the prediction of uni-axial compressive strength using the extreme gradient boosting (XGB) method which was also compared with SVM and ANN models. They revealed that the XGB models were performing better and could generate much more accurate result compared with the other methods.

HalilIbrahim[17], discussed the two level and hybrid ensembles for high performance concrete using DT models to predict the strength of concrete mixes. The proposed result used three ensemble approaches, and the obtained result showed that the DT models could predict the strengths accurately and also could generate a good correlation. The researcher concluded that the best models among the various eleven models were taken as GB-RS DT (R^2 = 0.9520), GB-GB DT (R^2 = 0.9456), and Bag-bag DT (R^2 = 0.9368).

Qinghuaetal.[18], used a RF algorithm to predict the compressive strength of high performance concretes, the study proposed two stages, simplify parameter settings and to predict the concrete compressive strengths. The result discussed that the proposed method was effective for input optimization and returned a better prediction than without variable optimization, considering the parameters must be set within a reasonable range. The models were then compared with the previously developed models, which revealed a strong generalization capacity for the prediction through the RF algorithm.BehrouzAhmadi-Nedushan[19], discussed about the estimation of compressive strength of concrete mixes using optimised instance based learning algorithm. The input variables of"water to binder ratio", "super-plasticizer" content, "water content", "fly ash content", etc. were considered. The K nearest algorithm was used as a ML tool for this research. Five models were developed for the investigation of the number of the neighbours. For each different model a modified version of the evolution algorithm was used and the optimal model parameter was found and reported. The result showed that, the optimized modes outperformed those of the derived standard k nearest algorithm, and this proposed model showed a better performance in comparison to generalised neural network models, stepwise regression and modular neural network models. UchennaAnyaoha [20], proposed soft computing in estimating compressive strength for high performance concrete with concrete composition appraisal, boosting smooth transition regression tree method was adopted, the result showed which was created with three sets of several analytic techniques at 28 days that boosting smooth transition regression tree dominance in the accuracy prediction over than other methods.

ZaherYaseenet. al., [21], proposed an extreme learning ML models for the estimation of compressive strength of lightweight foamed concretes using an extreme learning machine (ELM) which was validated with comparing multivariate adaptive regression spline (MARS), M5 tree models and also with SVR. The input parameters were taken as cement content, oven dry density, water binder ratio, and foamed volume. The result showed that ELM models would perform in a better accuracy than the other developed models. Vanessa Nilsenet. al., [4], discussed the prediction of concrete coefficient of thermal expansion and other properties using ML system, where linear regression and RF machine learning were applied, the results revealed that the RF models would give better accuracy than the other counterparts.

The literatures reveal that several types of "ML algorithms"were used for the prediction of the compressive strength of concrete, amid which the many researchers favoured the use of"ANN and SVM"methods. Specifically, Siddique et al., [13] adopted ANN methodin the self-compacting concrete (SCC)compressive strengths predictions which contained the bottom ash as one major ingredient. Further, Uysal and Tanyildizi [14] used a similar method to guesstimate the strength of SCC after subjecting it to a high temperature exposure. Dantas et al. [15] and Duan [16] adopted neural network based ML technique for the concrete containing recycled aggregates. Chou et al. [17,18] considered numerous"ML techniques" in predicting the strength, which included both "ANN and SVM" approach. Aiyer et al. [19] launched a sophisticated edition of SVM, i.e., "Least Square SVM" (LS-SVM). Motamedi et al. [20] continued the "SVM-based"ML prediction system to solve an additional complex problem, i.e., "Un-confined compressive strength" of cockle shell "cement-sand"blended concretes. Pham et al. [21] advanced the LS-SVM using the "metaheuristic optimization", and utilized the models to forecast the strength of "High-Performance Concretes". Omran et al. [22] evaluated the precision of various"data mining techniques" for forecasting the strength of eco-friendly concrete. Chithra et al. [23] reported the relevance of ANN in predicting the strength of ''nano silica'' and copper slag based concretes.

1.1. Contributions of the proposed work

Similar to the few key research outcomes specified above, several other researchers have also made some attempts in developing and comparing few AI/ML based models for the prediction of compressive strengths of various types of concretes. Most of the research works were focused on the two to three machine learning approaches and could suggest one of the best methods in order to predict the concrete strength parameters which in turn would result in obtaining the strength in an effortless manner. This, paper efforts were done to use 8 different Machine learning (ML) techniques on 1030 data sets collected from the literature [22] and various other 36 mixes (with their results) developed in the laboratory as per the standard code of practice. Based on various performance metrics, ML algorithms can be used to train and predict the data set. Under the present scope of work, an ML-based algorithm was developed to predict the data set of concrete compressive strength. This study includes a total of 1066 different mixed proportions. For developing these algorithms, 70% of the data was taken as training inputs and 30% was used for testing.

2. Methodology

2.1. Data collection, analysis andparameters

A Collection of a good dataset is a critical step in developing machine learning models in which execution is related strongly to the distribution of the training data and the testing data. To achieve good results, the collection of datasets plays a first step in the entire development of machine learning. In this research, a dataset of 1030 samples was collected from the various literature having different mix designs to determine the compressive strength of concrete [7,20,23–28], also in addition, the 36 samples were developed for a structural grade concrete based on the experiments conducted in the laboratory.The calculation of the given 1030 datasets in terms of percentile, mean and std values of the numerical values of the datasets is provided in Table 1.

The feature importance of the parameter used in the prediction of the strength of structural Concrete is shown by feature importance values. The dataset contains 8 different features namely, cement, blast furnace slag, fly ash, water,superplasticizer, coarseaggregate, fine aggregate, age, and its feature importance is measured based on training data. Table 2 shows the feature importance of the parameters.Among all features, cement contributes the highest with an importance of 0.269986 and fly ash contributes the least with an importance of 0.02619.

The input and output parameters taken from the model are the quantities of concrete mix [29]. The input parameters included cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age and the output parameters include compressive strength of respective concrete mixes. Once the dataset was collected and analysed, a data division was done where 70% of the data was taken for training and the remaining 20% was taken for testing [30]. The application of machine learning to an entire dataset may lead to over-fitting, hence the care must be taken while adopting the technique [16].

Table 2
Feature importance of the dataset.

Features	Feature importance score
Cement	0.269986
blast_furnace_slag	0.111588
fly_ash	0.026197
Water	0.070192
Superplasticizer	0.111924
coarse_aggregate	0.076974
fine_aggregate	0.085258
Age	0.247882

2.2. Classification of dataset

The dataset collected as discussed in section 2.1 was now normalized using Z-score normalization. The output variables of the dataset were labeled as LOW, MEDIUM, and HIGH. The compressive strength is classified as LOW where the strength ranges from 0 MPa to 40 MPa. The compressive strength ranging from 40 MPa to 71 MPa was classified as MEDIUM and compressive strength ranging from 71 MPa to 84 MPa was considered to be HIGH. After analysing the input parameters, the target variables were assigned with LOW, MEDIUM, and HIGH labels. Once the labeling was done, the labels were coded with numeric class as 0, 1, and 2 for determining further machine learning progress.

2.3. Applying machine learning algorithms

Several efforts were made to get a better result using machine learning, the concept behind applying the ML algorithms is that it can predict the target variable's class which in this research is the compressive strength value of concrete. The ML algorithm used in this work includes DT, RF, NB classifier, SVM, KNN, GB, ANN, and KM algorithms [8,14,31–34].The results obtained are considered on the basis of accuracy, confusion matrix, precision and recall, and F1-score.

3. Results and discussion

This research works on 1030 data sets taken from literature and 36 experimental values developed as per relevant standards, on which different algorithms were applied. Z-Score normalization is done in order to change all the data points to the same scale

Table 1
Descriptive statistics of the dataset.

	count	Mean	Std	min	25%	50%	75%	max
Cement	1030.0	281.167864	104.506364	102.00	192.375	272.900	350.00	540.0
Slag	1030.0	73.895825	86.279342	0.00	0.000	22.000	142.950	359.4
Ash	1030.0	54.188350	63.997004	0.00	0.000	0.000	118.300	200.1
Water	1030.0	181.567282	21.354219	121.80	164.900	185.000	192.000	247.0
Sp	1030.0	6.204660	5.973841	0.00	0.00	6.400	10.200	32.2
Ca	1030.0	972.918932	77.753954	801.00	932.000	968.000	1029.400	1145.0
Fine_aggregate	1030.0	773.580485	80.175980	594.00	730.950	779.500	824.000	992.6
Age	1030.0	45.662136	63.169912	1.00	7.00	28.000	56.00	365.0
Strength	1030.0	35.817961	16.705742	2.33	23.710	34.445	46.135	82.6

Table 3
Z-Score normalized values of random 6 samples taken from the dataset.

Cement (kg/m^3)	Blast furnace slag (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)	Age (days)	Concrete compressive strength (MPa)
−1.65	1.02	−0.84	1.02	−1.03	−0.44	0.94	−0.67	−2.00
−1.51	1.27	−0.84	1.02	−1.03	−0.18	0.33	−0.67	−1.94
−0.64	−0.85	1.88	−1.25	0.66	1.03	0.03	−0.27	0.25
−0.28	−0.85	1.00	0.53	−0.06	0.90	−0.21	0.86	0.25
0.40	2.42	−0.84	0.10	0.68	−0.38	−1.41	−0.27	2.34
2.30	−0.85	−0.84	−1.66	−1.03	−0.98	1.52	−0.27	2.32

so each feature is equally dominant. Hence, Z score normalizations were carried out for all 1066 (1030 + 36) datasets; here out of 1066 values, Table 3 shows the Z score normalized values of 6 samples parameters, 2 each from the category of LOW, MEDIUM, and HIGH using all the input and the output parameters.

Table 4 shows the results obtained from different ML techniques, respectively fromDT, RF, NB classifier, SVM, GB,KNN, and ANN algorithms for predicting the compressive strength. The results obtained are classified into LOW, MEDIUM, and HIGH classes. The performance was measured using Accuracy, Precision, Recall, and F1-score.

Visualization of the Decision tree obtained for the datasets to predict the compressive strength of cement is shown in Fig. 1.

Fig. 2 shows the value of k to be selected. The k value was taken as 3 before training the network. Results obtained showed that the performance metrics with k value of 3 could be used for the further analysis under the KNN algorithm.

Table 4 indicates that the accuracy of the results obtained from the DT algorithm as 87.69%; the accuracy from the RF algorithm as 87%. The best results were obtained for the NB and SVM algorithms which indicated an accuracy of 100%. The second-best algorithm to predict the compressive strength is the one developed by making use of the ANN technique as shown in Fig. 3, which indicates the accuracy of 90%. The other ML algorithms such as KNN and GB give accuracy to79% and 85% and do not possess the best outcome in terms of the ML experimental results for the given datasets when compared it with the other counterparts. A similar outcomes were obtained for the other parameters i.e., for precision, recall, and F1-score from the ML algorithms.

Figs. 4–10 shows the area under the curve of Receiver Operating Characteristic (ROC) of DT, RF, NB, KNN, GB, SVM and ANN which helps to predict the "compressive strength" of the concrete mixes.The X-axis gives the specificity and the Y-axis indicates the sensitivity. This is a well established and popularly known fact

Table 4
Comparison of Performance Measures (in percentage) for different classifiers.

Performance Measures	DT	RF	NB	SVM	KNN (k = 3)	GB	ANN
Classification Accuracy	87.69%	61.56%	100%	100%	78.68%	84.98%	90%
Sensitivity (Recall)	88%	87%	100%	100%	79%	85%	90%
Precision	88%	87%	100%	100%	78%	85%	90%
F1-Score	87%	87%	100%	100%	78%	85%	90%

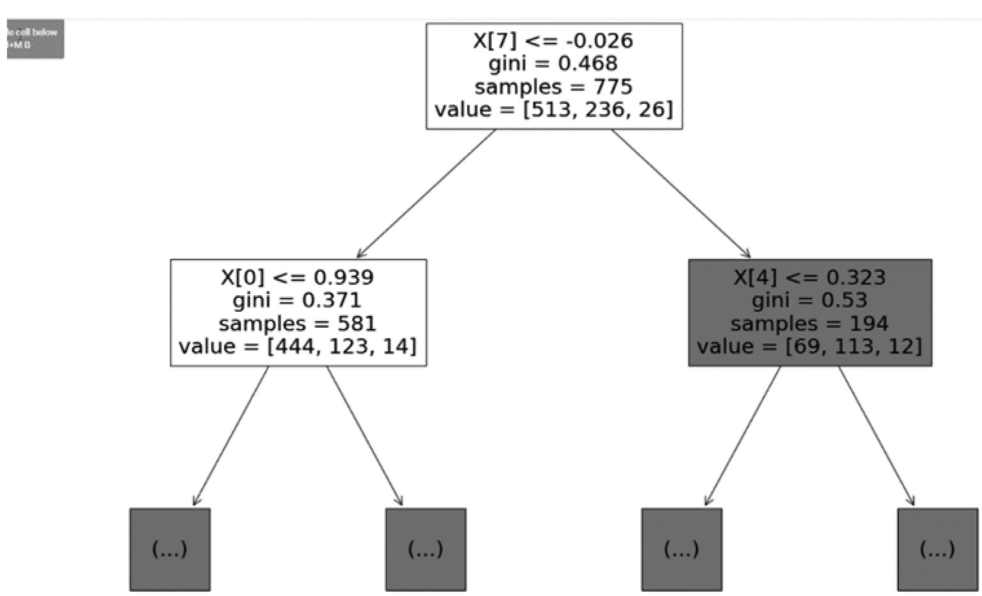

Fig. 1. Visualization of Decision tree to predict the compressive strength.

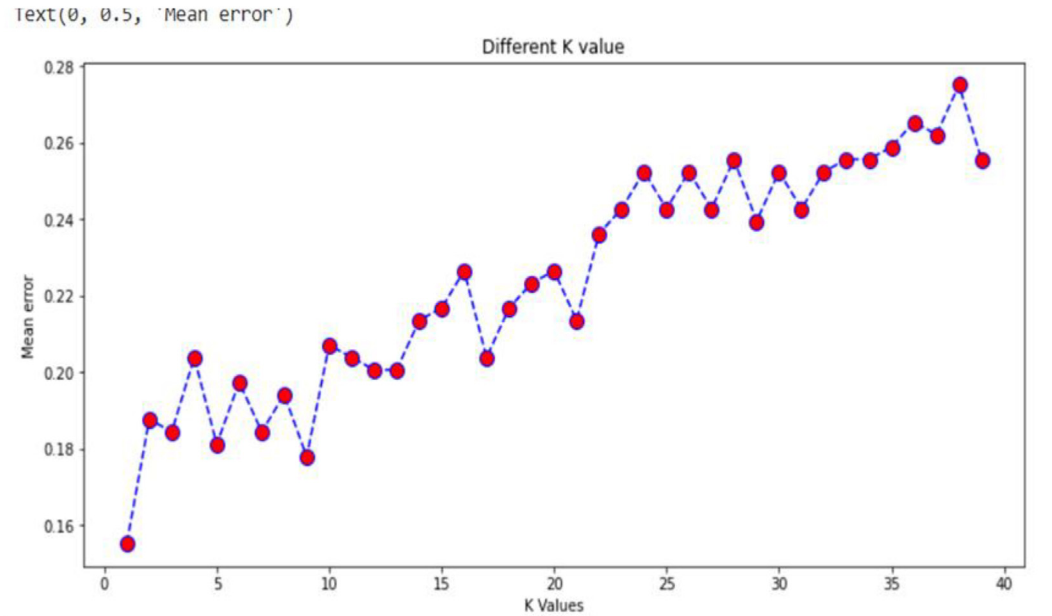

Fig. 2. Output obtained to justify the use of k = 3 from K nearest neighbour.

```
[[ 10   0   5]
 [  0 210   8]
 [  2  19  79]]
              precision    recall  f1-score   support

           H       0.83      0.67      0.74        15
           L       0.92      0.96      0.94       218
           M       0.86      0.79      0.82       100

    accuracy                           0.90       333
   macro avg       0.87      0.81      0.83       333
weighted avg       0.90      0.90      0.90       333
```

Fig. 3. Output obtained from Artificial neural network algorithm showing accuracy, confusion matrix, precision, recall, and F1-score.

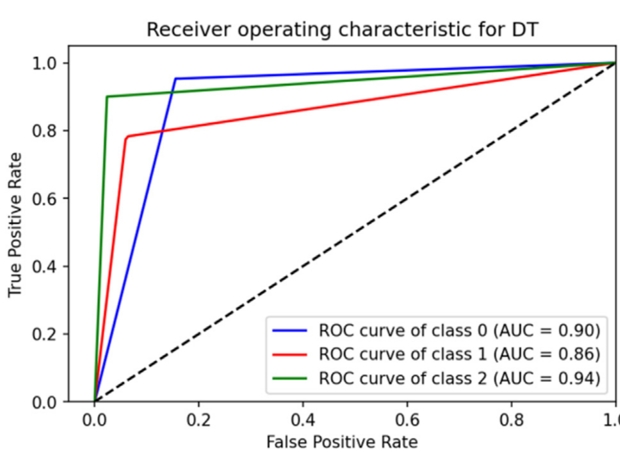

Fig. 4. ROC curve for predicting compressive strength of Concrete Mixes using decision tree(DT) algorithm.

from the basic knowledge of ML that, if the "Area Under Curve" (AUC) values tends to 1 it is considered to be a good classifier and AUC values less than 0.5 is considered a bad classifier. Hence, the presentation of ROC curve helps to indicate the significance of

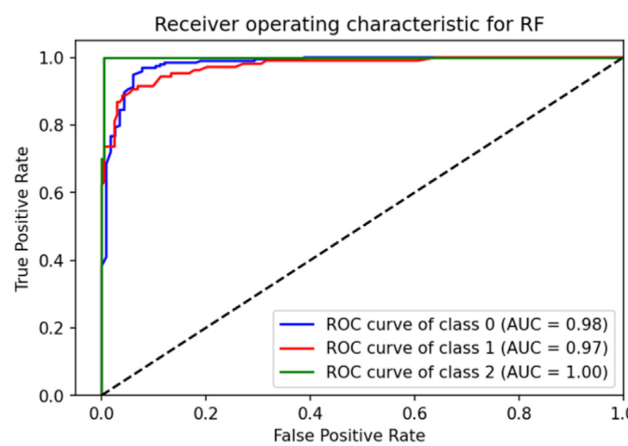

Fig. 5. ROC curve for predicting compressive strength using Random Forest(RF) algorithm.

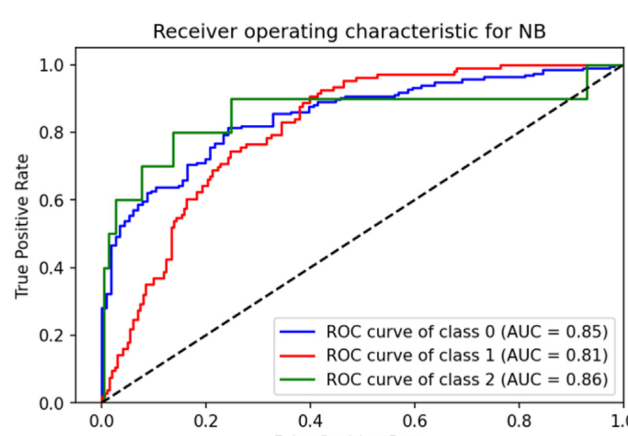

Fig. 6. ROCcurvefor predicting compressive strength using naïve bayes(NB) algorithm.

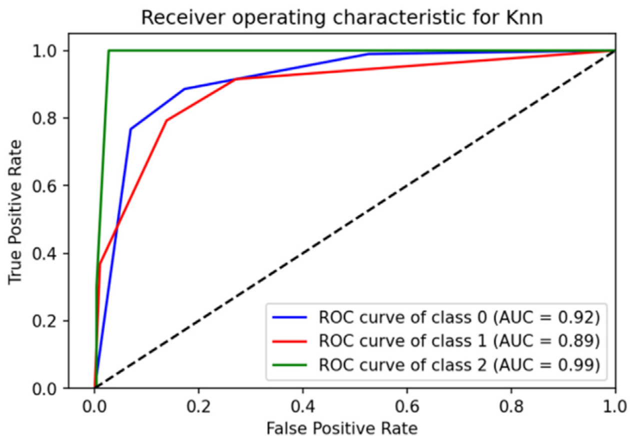

Fig. 7. ROCcurve for predicting compressive strength using k nearest neighbour (KNN) algorithm.

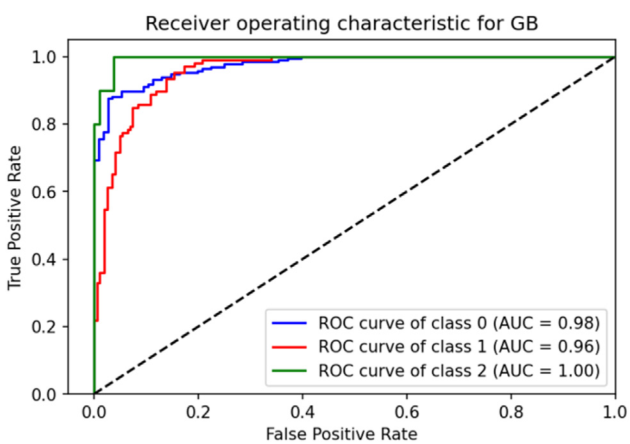

Fig. 8. ROC curve for predicting compressive strength using gradient boosting (GB) algorithm.

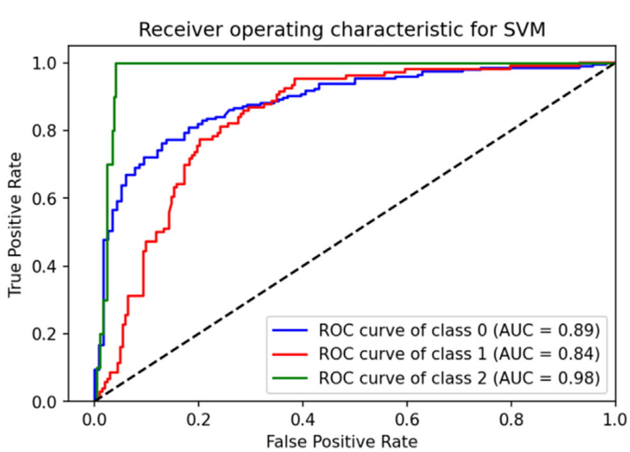

Fig. 9. ROC curve for predicting compressive strength using support vector machine (SVM) algorithm.

the obtained results from the ML algorithms. The ROC curve also signifies the trade-off true positive rate and false positive rate for various threshold settings of the model.The curve above the diagonal represents, the model is above chance level and is of good order. If the curve falls below the diagonal, the model is considered

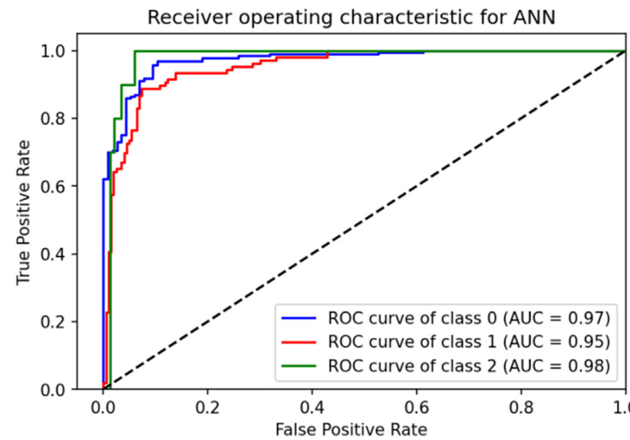

Fig. 10. ROC curve for predicting compressive strength using artificial neural network (ANN) algorithm.

to be bad.For all the types of algorithms, the output results represented from the Figs. 4–10 also indicates the ROC for all the three cases. The curve corresponds to "0″ represents ROC for "LOW" strength class; similarly, the results corresponds to "1″ and "2″ represents the ROC for "MEDIUM" and "HIGH" strength class respectively. For the reference, the diagonal line is represented in each figure which is called as "chance level" in ML language, and also the value of AUC is presented for all the ML algorithms.

From the analysis of the results of ROC presented from the Figs. 4-10, it can be revealed that all the outcomes from the ML tools could generate satisfactory results showing the multi-class ROC value of greater than 0.5, to be specific greater than 0.81, for the given dataset having all the defined three classes.Hence it can be confidently stated that the developed models could predict the compressive strength of the mixes with desired accuracy when the input mix design details were cautiously given.

Hence, from the combined analysis of various results obtained through the ML parameters, i.e., accuracy, precision, recall, and F1-score, the NB algorithm, and SVM algorithm stands as the best prediction tools for the determination of concrete compressive strength which is developed based on the 1066 mix details (i.e., 1030 mixes obtained from literature and 36 mixes obtained from experimental results). Further, ROC results would strengthen the ML models, which indicate the AUC value of greater than 0.50 with all the curves much ahead of the reference diagonal line i.e., "chance level". Thus, the developed models will definitely help to predict the very important parameter of concrete i.e., compressive strength to a level of experimental results.

Further, the Fig. 11 indicates the clustering of k-mean dataset for the unlabelled data. This kind of algorithm is used to determine behavioural segmentation, inventory categorization, sorting of sensor measurements, and various other aspects.

Lastly, in order to identify the parameter which does not contribute much to the development of the ML algorithms, feature importance of database study was carried out. Accordingly, Fig. 12 indicates the feature importance of the dataset which assigns certain scores to the input parameters based on their importance in contributing to the prediction of compressive strength. In this research, the input"super-plasticizer" attributes least for the prediction, which is indicated by the term "sp" from the output presented in the Fig. 12. This also means that this input parameter (super-plasticizer) can also be dropped out, and the existence of which does not affect the output parameters of the developed model. This result clearly indicates that even if this input variable is missing, the output (compressive strength) of the ML models does not show any significant changes.

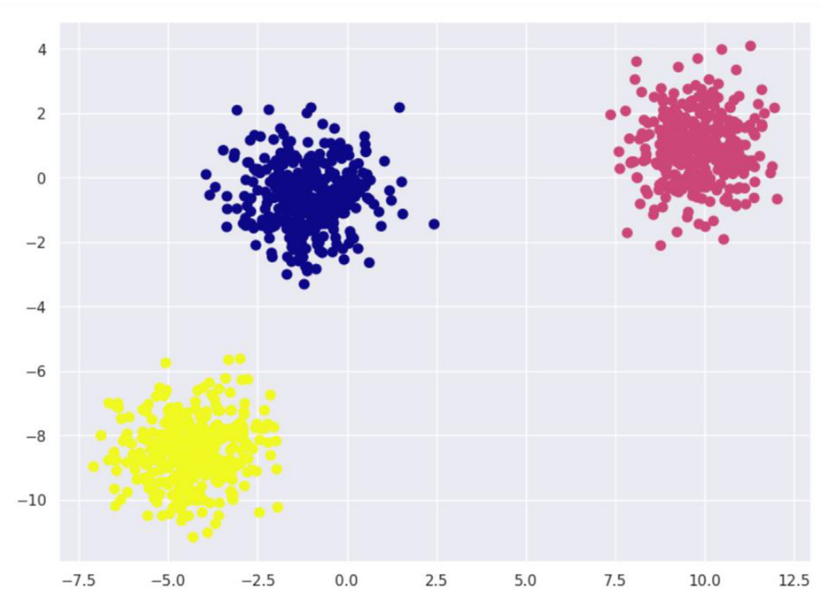

Fig. 11. Observation of K means cluster.

	cement	bf	fa	water	ca	fa.1	age
747	0.505540	-0.652483	1.622133	0.348068	-0.076124	-1.753399	-0.279597
718	1.400222	-0.305934	-0.846733	2.174405	-0.526262	-2.239829	3.551340
175	-1.391952	1.502146	-0.846733	0.193532	1.328306	-0.178114	-0.279597
828	0.853229	2.481523	0.846733	0.488555	0.554556	0.716929	0.701883

Fig. 12. Feature importance of the dataset.

4. Conclusions

In this research different machine learning algorithms were used to predict the compressive strength which is the target variable class label consisting of 1066 different mix designs input–output results. Before the application of the ML algorithm, the datasets were normalized using the Z-Score normalization technique. The proposed ML algorithms in this work were DT, RF, NB, KNN, GB, SVM, ANN, and K Means. Various performance metrics i.e., accuracy, confusion matrix, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) were obtained. From the results, the outcomes from the SVM (support vector machine) and NB (naive bayes) had shown the best performance metric value in terms of accurate compressive strength predictions. From the feature importance of database study, it was noticed that one of the input parameter (super-plasticizer) can also be dropped out without producing a considerable effect on the output of the developed ML model.

The overall outcomes from the present research investigation could be the accurate prediction of the concrete compressive strengths from the given input mix-design parameters, which would further benefit the engineering fraternity in reducing time, workmanship, and usage of laboratory equipment.

CRediT authorship contribution statement

Anisha P. Rodrigues: Writing – original draft, Writing – review & editing, Resources, Visualization, Validation. **Shriram Marathe:** Writing – original draft, Writing – review & editing, Resources, Visualization, Validation. **Roshan Fernandes:** Supervision, Conceptualization, Validation. **Arya Shikha:** Investigation, Methodology, Formal analysis. **Nidhi Shree:** Investigation, Methodology, Formal analysis.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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