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Research Article

Estimation Of Strength Properties Of Self Compacting Concrete By Using Artificial Intelligence And Machine Learning Techniques

M.R. Rajagopal[1*], K. Malarvizhi[2], Sahana T Swamy[3], Dr. Ghanasham C. Sarode[4], Swapnil Balakrishna Gorode[5], E.S. Karthic[6]

[1]Associate Professor, Department of Civil Engineering, CVR College of Engineering, Hyderabad 501510, India.
[2]Assistant Professor, Department of Computer Science and Engineering, Akshaya College of Engineering and Technology, Kinathukadavu, Coimbatore, Tamil Nadu, India.
[3]Assistant Professor, Department of Civil Engineering, CMR University (Lakeside Campus), Off, Bagalur Main Rd, near Kempegowda International Airport, Chagalahatti, Bengaluru 562149, India.
[4]Associate Professor, Department of Civil Engineering, Dr.D.Y.Patil Institute of Technology, Pimpri, Pune 411018, Maharashtra, India.
[5]Assistant Professor, Department of Civil Engineering, Pimpri-Chinchwad college of Engineering, Pune, Maharashtra, India.
[6]Assistant Professor, Department of Civil Engineering, Rajalakshmi Engineering College, Chennai-602105, Tamil Nadu, India.

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ARTICLE INFO | **ABSTRACT**

Replacing a portion of concrete with Class F fly ash aids sustainable development and reduces the greenhouse effect. Developing an accurate predictive model for the compressive strength of self-compacting concrete (SCC) using Class F fly ash is crucial. This study evaluates various machine learning models using a dataset of 327 samples. Models include regression trees, support vector regression, Gaussian process regression, and artificial neural networks (ANNs). The ensemble of ANNs exhibits the highest accuracy, with a mean absolute error of 4.37 MPa and a correlation coefficient of 0.96. Additionally, simpler models like multi-genetic programming and individual regression trees perform comparably well. Self-compacting concrete, Class F fly ash, compressive strength, machine learning, artificial neural networks, regression trees, and Gaussian process regression are key terms in this study.

Keywords: self-compacting concrete; Class F fly ash; compressive strength; machine learning; artificial neural networks; regression trees; Gaussian process regression

1. Introduction

The huge creation of Portland concrete prompts the emanation of significant carbon dioxide, and subbing concrete with fly debris is a viable method for lessening these ozone depleting substance discharges, accordingly advancing practical turn of events. As per ASTM C618, fly debris utilized in concrete is grouped into two classes: Class F, which has low calcium content, regularly got from consuming anthracite or bituminous coal, and Class C, which has high calcium content, normally got from consuming lignite or somewhat bituminous coal. The ASTM C618 standard layouts the physical, synthetic, and mechanical properties of these fly debris class. Typically, Portland cement contains 65 percent lime, some of which is released during hydration [1].
Blending it in with Class F fly debris, a pozzolanic material, shapes new covers, improving numerous properties of the subsequent cement. Utilizing fly ash in concrete has the potential to improve the material's workability, strength, water demand, permeability, chloride ion penetration, heat of hydration, sulfate resistance, alkali reactivity resistance, and drying shrinkage. SCC (self-compacting concrete), an elite presentation concrete, is portrayed by its liquid and thick consistency, permitting it to move through thickly supported structures without the requirement for outer compaction energy. This property can be accomplished utilizing corresponding cementitious materials like Class F fly debris, whose particles carry on like smaller than usual metal balls, giving a greasing up impact. Fly debris expansion brings about a slower response and less intensity age per unit time contrasted with Portland concrete, which is favorable for enormous substantial designs. As of late, there has been an expanded utilization of AI (ML) strategies and calculations to foresee the compressive

strength (CS) of SCC. The most well-known approach has been the utilization of counterfeit brain organizations (ANN) [2].
Siddique et al. fostered an ANN model to anticipate the CS of SCC at different ages, utilizing standards like MAE, RMSE, and connection coefficient for precision. Based on 169 samples, Asteris et al. investigated the use of ANN to predict the CS of SCC with fly ash after 28 days. Douma et al. also used ANN to model the properties of SCC with fly ash. They looked at models using the MSE, coefficient of determination, and MAPE criteria, and they recommended an ANN model with 17 neurons in a hidden layer. Different scientists, for example, Saha et al., investigated help vector machines (SVM) with various part works to anticipate new and solidified substantial properties with fly debris. Azimi-Pour et al. inspected the properties of high-volume fly debris substantial utilizing SVM models, finding that a RBF portion capability gave higher precision. Zhang et al. used the random forest (RF) and the beetle antennae search algorithm (BAS) to predict the CS of fly ash-based lightweight SCC. Regression trees (RT), artificial neural networks (ANNs), genetic programming, and boosting regressors were all examined by Song et al., and ensemble algorithms were recommended for accuracy. Hadzima-Nyarko et al. explored the utilization of elastic and fly debris added substances in SCC, using different Gaussian cycle relapse (GPR) models, which demonstrated compelling for anticipating CS, affirmed by SEM pictures [3].
Kovacevic et al. directed comparable examinations, presuming that GPR models were ideal. Farooq et al. tested ANNs, SVMs, and gene expression programming (GEP), recommending GEP as the best model, while Pazouki et al. optimized ANN models by employing the firefly algorithm to predict CS. De-Prado-Gil et al. utilized outfit techniques like RF, KNN, ERT, XGB, GB, LGBM, CB, and GAMs, viewing RF models as profoundly powerful in foreseeing the CS of SCC with reused totals. The curiosity of this exploration lies in the broad utilization of cutting-edge ML strategies on an enormous arrangement of exploratory information, giving a point-by-point examination and improvement of model hyperparameters. This incorporates MGGP models, relapse tree-based models, SVM models with different piece capabilities, GPR models, ANN models, and groups. Moreover, this paper investigates GPR strategies with programmed pertinence assurance (ARD) covariance capabilities for demonstrating the CS of SCC with Class F fly debris, a first in this examination region [4].

2. Methods

AI (ML) is a part of man-made reasoning and incorporates techniques for preparing calculations to such an extent that they can gain from information and decide and expectations, which can be applied in the displaying of the way of behaving of designs and materials. The strength of ML strategies lies in the way that these techniques can address an overall relationship or capability straightforwardly from exploratory information to display the way of behaving of complicated frameworks with various impact factors, whose impacts, both individual and synergistic, are obscure or hard to foresee. Additionally, these techniques are able to process a large amount of data that includes both "noise," which is an essential component of experimental data, in addition to complex information about the observed phenomenon. The use of ML techniques has become more articulated as of late because of the rising measure of information accessible as well as because of huge advancement in the field of figuring.

2.1. Multi-Gene Genetic Programming (MGGP)

MGGP, a method for machine learning that draws inspiration from biological processes, is used in symbolic regression to predict continuous output variables from input variables. Not at all like conventional relapse techniques, MGGP doesn't assume the model construction in advance; all things being equal, it permits the observational information to shape the model design. MGGP creates a different arrangement of models addressed by trees, each better through cycles utilizing transformative techniques. These models, made out of individual trees or qualities, go through hybrid, change, and duplicating to shape the future. Random sections can be exchanged between parent individuals during cross-pollination, which can occur at the gene or tree level. Mutation alters a single node within a gene at the level of a single gene. The expectation of result depends on a direct blend of nonlinear changes of information factors, still up in the air by least squares assessment. The wellness capability, normally root mean square mistake (RMSE), guides model improvement in progressive ages, with people chosen through competition determination in light of RMSE and expressional intricacy. Based on the number of nodes in trees and their possible subtrees, expressional complexity favors flatter trees over deeper ones [5].

2.2. Regression Tree Ensembles

Grouping tree techniques are flexible, material to both relapse and order undertakings. The development of a tree follows a covetous methodology, where the space is separated into subsets in view of the best parted variable and not set in stone by limiting a particular model. This interaction proceeds recursively until a halting model is met. The model result for a given test perception is the mean worth of perceptions in the locale to which the test has a place. At the point when a solitary tree model displays unfortunate speculation on the test set, group methods like sacking, irregular woodland (RF), and helping can be utilized to conquer this issue. Packing includes making various models utilizing bootstrap inspecting or testing with substitution, each prepared on an alternate subset of the information. In RF, relapse trees are framed utilizing a bootstrap technique, with just a subset of factors haphazardly chose for each split. The last model in packing and RF is acquired by averaging the forecasts of every individual model. Slope helping constructs a troupe by successively adding models, with each new model prepared to make up for the shortcomings of the ongoing outfit. Gradient optimization techniques, in which subsequent models approximate the residuals of previous models by minimizing the gradient of the loss function, serve as inspiration for this strategy [6-7].

3. Dataset

To shape a CS expectation model for various periods of SCC tests with the expansion of Class F fly debris, framing an adequately enormous arrangement of test information of such concrete is important. A database of SCC sample tests from the published literature was used in this instance. The all-out number of tried examples utilized for displaying comprised of a sum of 327 tried examples with various times of the tried example from 1 day to 365 days. Substantial constituents were investigated as information factors: concrete (C), water (W), Class F fly debris (A), coarse total (CA), fine total (FA), superplasticizer (SP), and the time of tests (AS). The strength of this concrete at a cylinder pressure of 100 mm 200 mm, expressed in MPa, was the output variable. As Supplementary Materials (Supplementary Materials S1), the entire database is available. According to the value of the correlation coefficient, there is an intercorrelation between the input variables (such as the ratio of superplasticizer to fine aggregate, the ratio of fly ash to cement, etc.) in addition to a certain correlation between compression strength as an output variable and some input variables (such as cement, sample age, etc.). The use of AI techniques is very viable in demonstrating simply such issues with intercorrelation. Furthermore, histograms organized along the principal inclining show the equilibrium of the dataset. Using the attached dataset and the built-in function corrplot (Matlab 2020a), all diagrams are generated automatically. It is essential to be familiar with the statistical indicators of the data that are being used when applying various machine learning algorithms to the definition of prediction models. The models that are being framed sum up inside the information on which the model preparation was performed. The built-in randperm function of the Matlab program was used to mix the entire dataset with random permutations of samples, then randomly selecting 80 percent of the samples for model training and 20 percent for model testing. This 80:20 division of information is a standard strategy in AI. The accuracy of the model was evaluated using the criteria root mean square error (RMSE), mean absolute error (MAE), Pearson's linear correlation coefficient, and mean absolute error (MAE). All of the analyzed models were trained on the same training set [8-11].

Table 1. Statistical properties of variables used for modelling.

Constituent	**Max.**	**Min.**	**Mean**	**Mode**	**Count**
Cement (C) (kg/m^3)	505	62.00	293.08	249.00	325
Water (W) (kg/m^3)	390.50	132.50	197.00	181.00	325
Fly ash (A) (kg/m^3)	372.00	20.00	170.23	161.00	325
Coarse aggregate (CA) (kg/m^3)	1195.00	590.00	828.34	831.00	325
Fine aggregate (FA) (kg/m^3)	1105.00	434.00	807.47	912.00	325
Superplasticizer (SP) (%)	4.50	0	0.980	0.80	325
Age of samples (AS) (days)	325	1	44.31	29.00	325
Compressive strength (MPa)	95.60	4.44	36.45	13.00	325
Statistical analysis of input and output parameters for **Training set**					
	Max.	Min.	Mean	Mode	Count
Cement (C) (kg/m^3)	505	62.00	292.57	250.00	260
Water (W) (kg/m^3)	395.39	133.25	197.83	180.00	260
Fly ash (A)(kg/m^3)	375.00	20.05	169.40	160.00	260
Coarse aggregate (CA) (kg/m^3)	1195.00	590.05	825.08	837.00	260
Fine aggregate (FA) (kg/m^3)	1119.00	434.05	811.44	910.00	260
Superplasticizer (SP) (%)	4.50	0	0.98	0.50	260
Age of samples (AS) (days)	363	1.1	43.86	28.00	260
Compressive strength (MPa)	90.50	4.92	36.55	12.00	260
	Statistical analysis of input and output parameters for Test set				
Cement (C) (kg/m^3)	505	62.00	295.11	295.11	68
Water (W) (kg/m^3)	279.50	132.00	193.68	193.68	68
Fly ash (A)(kg/m^3)	336.00	20.00	173.56	173.56	68
Coarse aggregate (CA) (kg/m^3)	1190.00	590.00	841.48	841.48	68

Fine aggregate (FA) (kg/m^3)	1109.00	434.00	791.43	791.43	68
Superplasticizer (SP) (%)	4.60	0	0.98	0.98	68
Age of samples (AS) (days)	365	1	46.09	46.09	68
Compressive strength (MPa)	72.61	4.44	36.02	4.44	65

4. Results

To shape a CS expectation model for various periods of SCC tests with the expansion of Class F fly debris, framing an adequately enormous arrangement of test information of such concrete is important. A database of SCC sample tests from the published literature was used in this instance. The all-out number of tried examples utilized for displaying comprised of a sum of 327 tried examples with various times of the tried example from 1 day to 365 days. Substantial constituents were investigated as information factors: concrete (C), water (W), Class F fly debris (A), coarse total (CA), fine total (FA), superplasticizer (SP), and the time of tests (AS). The strength of this concrete at a cylinder pressure of 100 mm 200 mm, expressed in MPa, was the output variable. As Supplementary Materials (Supplementary Materials S1), the entire database is available.
According to the value of the correlation coefficient, there is an intercorrelation between the input variables (such as the ratio of superplasticizer to fine aggregate, the ratio of fly ash to cement, etc.) in addition to a certain correlation between compression strength as an output variable and some input variables (such as cement, sample age, etc.). The use of AI techniques is very viable in demonstrating simply such issues with intercorrelation. Furthermore, histograms organized along the principal inclining show the equilibrium of the dataset.
Using the attached dataset and the built-in function corrplot (Matlab 2020a), all diagrams are generated automatically. It is essential to be familiar with the statistical indicators of the data that are being used when applying various machine learning algorithms to the definition of prediction models. The models that are being framed sum up inside the information on which the model preparation was performed. The built-in randperm function of the Matlab program was used to mix the entire dataset with random permutations of samples, then randomly selecting 80 percent of the samples for model training and 20 percent for model testing. This 80:20 division of information is a standard strategy in AI. The accuracy of the model was evaluated using the criteria root mean square error (RMSE), mean absolute error (MAE), Pearson's linear correlation coefficient, and mean absolute error (MAE). All of the analyzed models were trained on the same training set.

Table 2. Comparative analysis of results of different machine learning models.

Model	**RMSE**	**MAE**	**R**
MGGP	7.2	5.7	0.9
Decision tree	8.9	6.7	0.8
TreeBagger	7.2	5.6	0.91
Random forest	6.8	5.6	0.93
Boosted tree 1	5.8	4.9	0.95
Boosted tree 2	6.5	4.6	0.92
SVM linear	12.6	10.3	0.74
SVM RBF	5.7	4.4	0.92
SVM sigmoid	12.77	10.5	0.75
GP exponential	6.8	5.4	0.93
GP Sq.exponential	6.6	5.2	0.94
GP Matérn 3/2	6.4	4.8	0.94
GP Matérn 5/2	6.5	4.6	0.94
GP Rat. quadratic	6.6	4.9	0.94
GP ARD exponential	5.8	4.5	0.95
GP ARD Sq. exponential	6.3	4.5	0.95
GP ARD Matérn 3/2	6.3	4.6	0.94
GP ARD Matérn 5/2	6.5	4.3	0.94
GP ARD Rat. quadratic	6.3	4.8	0.94
ANN	8.9	6.9	0.89
Ensemble ANN	**5.6**	**4.3**	**0.95**

5. Conclusions

For the purpose of predicting the compressive strength (CS) of self-compacting concrete (SCC) with the addition of Class F fly ash, this research investigates a variety of cutting-edge machine learning approaches. Strategies like MGGP, RT, and troupe methods in light of RTs, TreeBagger, irregular woods, supported tree models, SVM models with various bits, GPR models, individual ANN models, and gatherings of ANN models are talked about. The paper gives a point-by-point method to improving boundaries for every single broke down model and assesses their exactness utilizing RMSE, MAE, R, and MAPE standards. It underlines the significance of individual information factors and the positive effect of fly debris on substantial strength. Individual and ensemble models are examined for accuracy using a comprehensive database of literature tests. The effectiveness of ensemble models made up of GPR models and neural networks, which were not extensively discussed in previous research, is highlighted in this study. Furthermore, less precise yet more interpretable individual models like MGGP and RT are contrasted with usually utilized ANN models. Both MGGP and RT models offer bits of knowledge into the connection between substantial constituents and compressive strength, with MGGP giving a condition-based relationship and RT offering a straightforward tree structure, pivotal for functional execution at times.
The discoveries empower ventures to demonstrate their substantial blend all the more proficiently, without huge speculation. Among the assessed models, the outfit of ANNs arises as the ideal decision with acceptable exactness for anticipating substantial strength across different ages. The use of bootstrap conglomeration prominently further develops precision contrasted with individual ANN models, and growing the data set could additionally upgrade model execution. Although GPR models with an ARD exponential function have a slightly lower accuracy, they are able to determine the impact that each variable has on prediction accuracy. Compared to the optimal ensemble ANN model, the MGGP model stands out for its explicit expression, making it easier to make concrete predictions across ages with slightly lower accuracy. The easier RT model accomplishes equivalent precision to the best individual ANN model, making it a helpful other option.

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