Prediction on Flexural strength of High Strength Hybrid Fiber Self Compacting Concrete by using Artificial Intelligence

Boppana Narendra Kumar[1], Pariyada Pradeep Kumar[2]

[1]Professor, Dept. of Civil Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India
[2]PG student, Department of Civil Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India

E- mail: [1]narendrakumar_b@vnrvjiet.in, [2]pariyadapradeep123@gmail.com

Abstract

The primitive focus of this research work is about the artificial intelligence methods engaged for creating an outlook for flexural strength of High Strength Hybrid Fiber Self Compacted Concrete (HSHFSCC), which is considered to be a special concrete in order to tackle both workability and durability without disturbing the strength of the concrete. It possesses not only the good deformability during fresh state but also put forward high aversion to segregation resulting in superior homogeneity and increase in productivity by altering the period of construction. While incorporating various fibers like glass, steel, carbon, synthetic, and quartz powder in plain concrete, directs in the enhancement of post-cracking, toughness, ductility and limits the detrimental effect of shrinkage. The current work is classified into two stages. 1) Development of HSHFSCC and High Strength Self Compacting Concrete (HSSCC). 2) Engaging different Machine Learning (ML) models to divide the obtained information into Train, Test and Validation followed by 19 types of different ML regression models accompanied with Artificial Neural Network for engaging the function to appropriate the flexural strength of HSHFSCC and HSSCC. The boundary conditions discussed as input includes Setting time, percentage of quartz and river sand. Total 25 number of datasets are used for 5-fold cross validations by adopting MATLAB ML and Deep learning toolkit and Python is adopted to validate the optimized models. The evaluation factors like R-square and Root mean square show a great level of accuracy and reliability of the model.

Keywords: Artificial Neural Networks (ANN), flexural strength, HSSFCC, HSHFSCC, modeling, MATLAB

DOI: https://doi.org/10.36548/jaicn.2022.1.001
Received: 05.12.2021, received in revised form: 03.01.2022, accepted: 10.01.2022, published: 20.01.2022

1. Introduction

Self-Compacting Concrete (SCC), when compared to normal concrete, is more brittle under the application of load. The tensile stresses which are caused due to environmental conditions and imposed loads are intensified at the boundary junction of cement matrix and aggregates. The development of minute cracks occurs due to the brittleness of SCC, which is also responsible for the enhancement of their size as well as number [1, 7, 9]. These minute cracks propagate into the concrete matrix thereby giving rise to macro cracks. These macro and micro-cracks can be minimized by the addition of arbitrarily distributed short fibers [2, 3, 12]. These types of concretes are currently being utilized in constructions such as rock slope stabilization, linings of tunnels, in Reinforced Cement Concrete (RCC) buildings, etc [4, 6, 12, 14]. Machine learning is considered as the execution of Artificial Intelligence (AI) which helps to provide the systems and to learn and enrich from experience without being express programmed [5, 6, 8]. The learning process begins by the observation of datasets to seek help from the previous patterns and make better predictions for the subsequent samples. This process is categorized into supervised and unsupervised learning methods. Supervised machine learning methods use samples of input and output to train the model. This model is then used to perform predictions on future data. Regression algorithms used in this approach, fall under this category [7, 8]. Regression analysis helps in estimating associations amidst variables, helping to enquire about the key patterns in large and diverse data sets and how they compare with each other [9-11,13]. An ANN is a system that can be learnt by utilizing the neurons enabled from a structure layered such as to identify and classify the given data.

2. Data collections and experiments

The experimental investigation is focused on understanding the performance of the material and structural behavior**.** To develop HSSCC mixes river sand is substituted by quartz sand in proportions of 0, 20, 40, 60, 80, and 100 [7, 9, 12, 15-17]. The hardened properties and fresh properties of the above mixes are determined to obtain optimized mix proportions [14]. By using this optimized mix proportion, and by working on differencing dosages of glass fibers and steel fibers the optimum fibrous powder content is determined [15, 18]. It is noted that a dosage of 1.5% (0.75% glass fibers+ 0.75% steel by weight) satisfies the fresh and hardened properties [4, 7, 8]. After finalizing HSHFSCC and HSSCC mixes stress-strain of mixes are obtained. Moreover, flexural strength is determined including fresh properties.

2.1 Mix proportions of HSSCC and HSHFSCC

Table 1 expresses the mix proportions of the mixes of HSSCC and HSHFSCC with varied range of steel and glass percentage incorporated in each mix.

Table 1. Mix Proportions

Designation of Mix	Cement (kg/m^3)	Micro Silica(kg/m^3)	Quartz powder (kg/m^3)	Quartz Sand (kg/m^3)	Coarse aggregate (kg/m^3)	SP% of Powder content	VMA% of Powder content	W/P ratio	Fibres % of Powder content	
									Steel	Glass
HSSCC	640	64	160	910	800	1.5	0.5	0.21	---	---
HSHFSCC	640	64	160	910	800	1.5	0.5	0.21	1.5	---
HSHFSCC 1	640	64	160	910	800	1.5	0.5	0.21	1.35	0.15
HSHFSCC 2	640	64	160	910	800	1.5	0.5	0.21	1.20	0.30
HSHFSCC 3	640	64	160	910	800	1.5	0.5	0.21	1.05	0.45
HSHFSCC 4	640	64	160	910	800	1.5	0.5	0.21	0.90	0.60
HSHFSCC 5	640	64	160	910	800	1.5	0.5	0.21	0.75	0.75
HSHFSCC 6	640	64	160	910	800	1.5	0.5	0.21	0.60	0.90

2.2 Fresh properties of HSSCC and HSHFSCC

According to the EFNARC guidelines for testing SCC fresh properties, test methods like V Funnel test, L Box test and Slump Flow test, are used to characterize the workability nature and for justifying the SCC mix proportions [2005].

Figure 1. Flow Table Test

Figure 2. L-Box Test

Table 2 shows the fresh properties with values of flow table, V funnel and L box for all the 8 mixes of HSSCC and HSHFSCC.

Table 1. Fresh Properties of HSHFSCC and HSSCC

Designation of Mix	Flow Table data		V Funnel data		L box Ratio
	Diameter (mm)	T_{50} (in sec)	T_f (in sec)	T_{5min} (sec)	
HSSCC	744	3	7	9	0.98
HSHFSCC	738	3	7	11	0.98
HSHFSCC-1	733	3	7	11	0.96
HSHFSCC-2	731	4	9	12	0.95
HSHFSCC-3	729	4	9	12	0.93
HSHFSCC-4	725	4	12	14	0.88
HSHFSCC-5	719	5	13	16	0.86
HSHFSCC-6	704	6	14	17	0.83

2.3 Flexural strength of HSSCC AND HFHSSCC

In this study, six specimens of 500 mm × 100 mm × 100 mm are placed in flexural testing machine and subjected to three points loading until the specimens failed at 7, 28 & 90 days [11,15]. Table 3 shows the flexural strength for all the HSSCC and HSHFSCC specimens for 7, 28, 90 & 180 days respectively [12, 14].

Table 2. Flexural Strength of HSSCC & HSHFSCC

Mix Designation	Flexural Strength (MPa)			
	7 DAYS	28 DAYS	90 DAYS	180 DAYS
HSSCC	7.32	10.44	11.05	11.21

HSHFSCC	7.44	10.64	11.24	11.49
HSHFSCC-1	7.58	10.85	11.59	11.84
HSHFSCC-2	7.77	11.12	12.05	12.29
HSHFSCC-3	8.03	11.46	12.39	12.73
HSHFSCC-4	8.32	11.84	12.87	13.17
HSHFSCC-5	8.61	12.37	13.62	13.98
HSHFSCC-6	8.23	11.47	12.41	12.97

2.4 Modelling methods

MATLAB Machine Learning and Deep Learning toolkit provide many algorithms for regression which include linear regression models, regression trees, Support Vector Machine (SVM), Gaussian process regression models and ensembles of trees [6]. 5-fold cross-validation was performed on the models that were trained to find various efficiency parameters which include R-squared error, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Square Mean Error (RSME).

2.5 Function approximation of flexural strength of HSSCC and HSHFSCC by MATLAB

Table 4 shows that the assessment parameters including R-squared and RMSE of fine tree and Artificial Neural Networks, show higher level of reliability and accuracy of the model.

Table 3. Performance of various models for HSSCC and HSHFSCC in MATLAB

Model	RMSE		R-Squared		MSE		MAE	
	HSHF SCC	HS SCC	HSHF SCC	HS SCC	HSHF SCC	HS SCC	HSHF SCC	HS SCC
Linear Regression (LR)	1.13	1.25	0.53	0.32	1.82	1.57	1.22	1.11
Interactions L. R	1.79	1.52	0.17	0	3.21	2.31	1.59	1.3
Robust L. R	1.36	1.26	0.52	0.31	1.85	1.6	1.22	1.11
Stepwise L. R	1.31	1.19	0.55	0.39	1.73	1.42	1.19	1.06
Medium Tree	1.45	1.52	0.45	0	2.11	2.32	1.26	1.24
Coarse Tree	1.96	1.52	0	0	3.86	2.32	1.6	1.24
Linear SVM	1.6	1.29	0.33	0.28	2.58	1.68	1.17	0.8
Fine Tree	0.81	0.47	0.83	0.90	0.65	0.22	0.70	0.40
Quadratic SVM	1.24	1.31	0.6	0.26	1.54	1.72	0.98	0.94
Cubic SVM	1.2	1.41	0.62	0.14	1.45	1.99	0.98	1.1
Fine Gaussian SVM	1.86	1.68	0.1	0.21	3.46	2.82	1.43	1.35

Medium Gauss SVM	1.6	1.48	0.33	0.05	2.57	2.2	1.1	1.07
Coarse Gaussian SVM	1.65	1.36	0.29	0.2	2.74	1.87	1.12	0.83
Boasted Trees	1.5	1.24	0.41	0.33	2.26	1.55	1.26	1.06
Bagged Trees	1.08	1.07	0.69	0.5	1.18	1.16	0.92	0.88
Squar1edExponential	1.27	1.26	0.58	0.31	1.63	1.59	1.01	0.96
Matern 5/2 GPR	1.29	1.26	0.56	0.37	1.68	1.59	1.03	0.97
Exponential GPR	1.39	1.34	0.49	0.23	1.95	1.79	1.08	1.05
Rational GPR	1.27	1.26	0.58	0.31	1.63	1.59	1.01	0.96
ANN	0.34	0.004	0.97	0.99	-	-	-	-

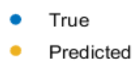
3. Graphs between the flexural strength and input variables

Regression analysis is performed between flexural strength and input variables. Thus, the output is obtained as a graph between flexural strength and input variable. Input variables lie on X-axis and Flexural strength lies on Y-axis. Input variables for HSSCC are the quantity of river sand, the quantity of quartz sand, and setting time of concrete whereas input variables for HSSCC are the quantity of steel, the quantity of glass fiber and setting time of concrete [7,8]. Function approximation is performed. The points with true and predicted values are clearly shown where, blue point denotes the true value and orange point denotes the predicted value.

3.1 Function approximation of flexural strength of HSHFSCC and HSSCC in MATLAB

The below graphs depict the values to be predicted (flexural strength) on the Y axis and the input parameters (river sand, quartz sand, steel, glass and time) on the X axis for both HSSCC and HSHFSCC.

A) Decision tree Regressor (Fine tree) of HSSCC



ISSN: 2582-2012

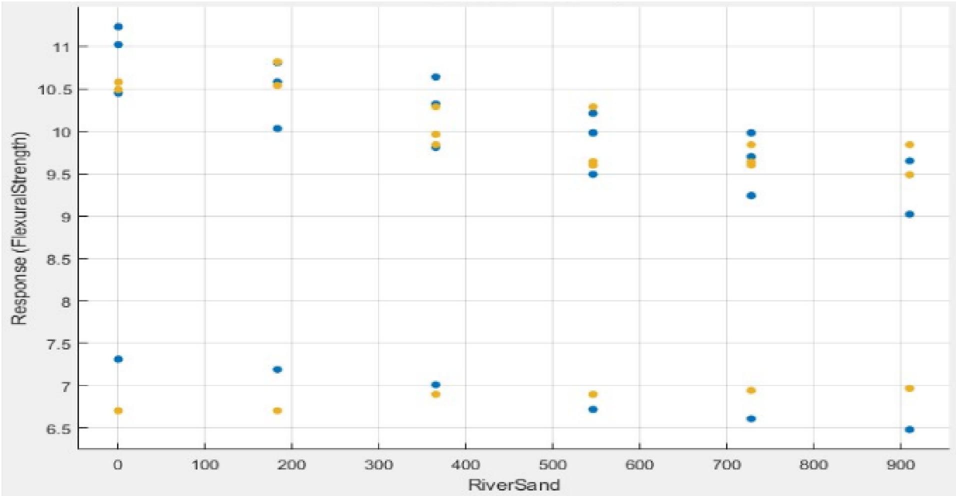


Figure 3. Graph between Flexural strength and quantity of River sand

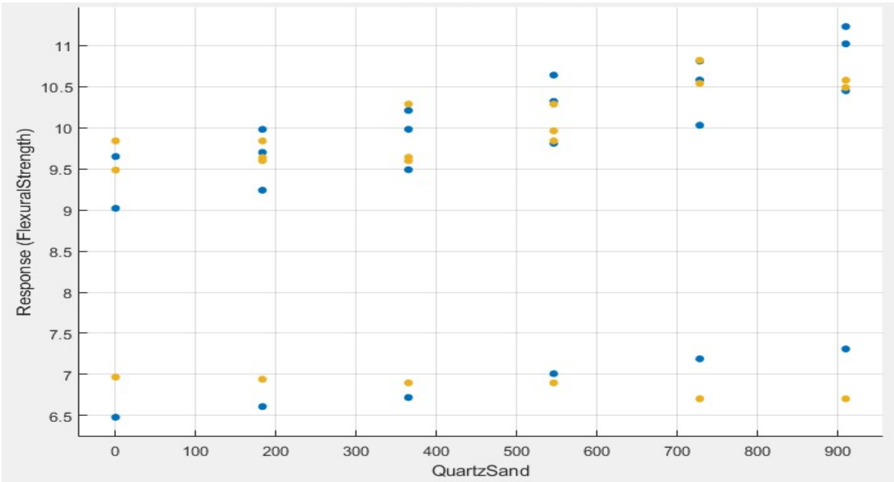


Figure 4. Graph between Flexural strength and quantity of Quartz sand

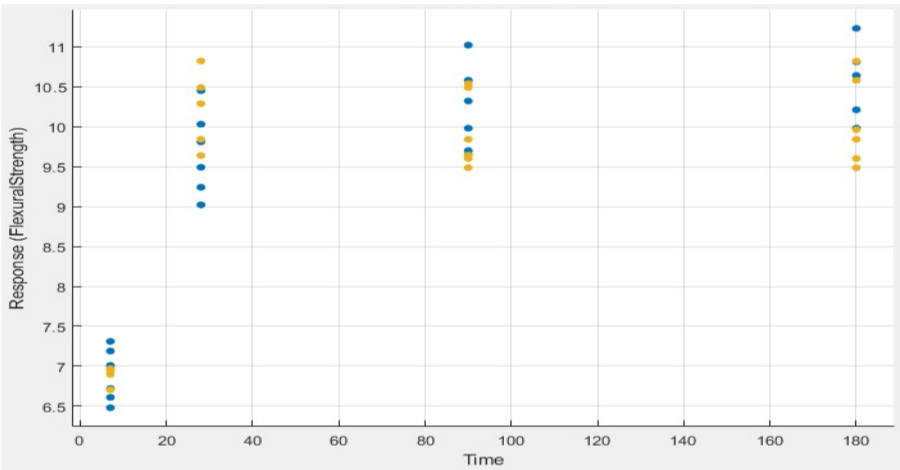


Figure 5. Graph between Flexural strength and setting time

B) Decision tree regressor (fine tree) of HSHFSCC

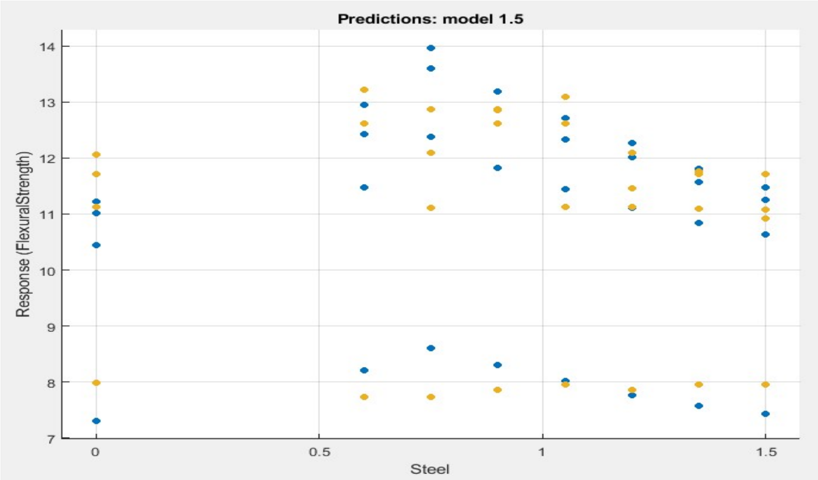


Figure 6. Graph between Flexural strength and percentage of steel

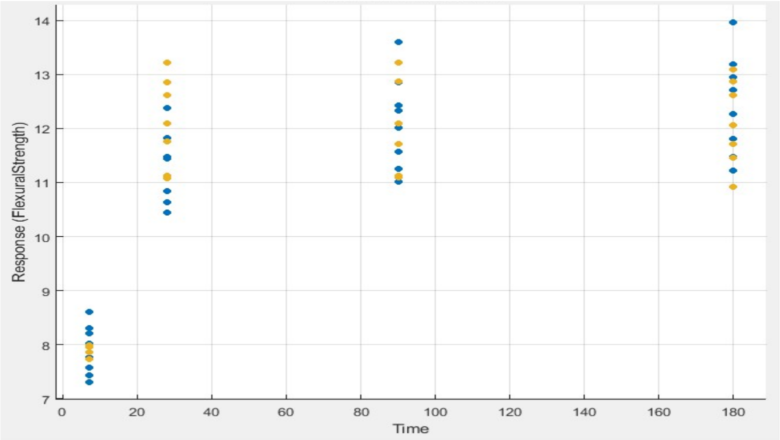


Figure 7. Graph between Flexural strength and setting time

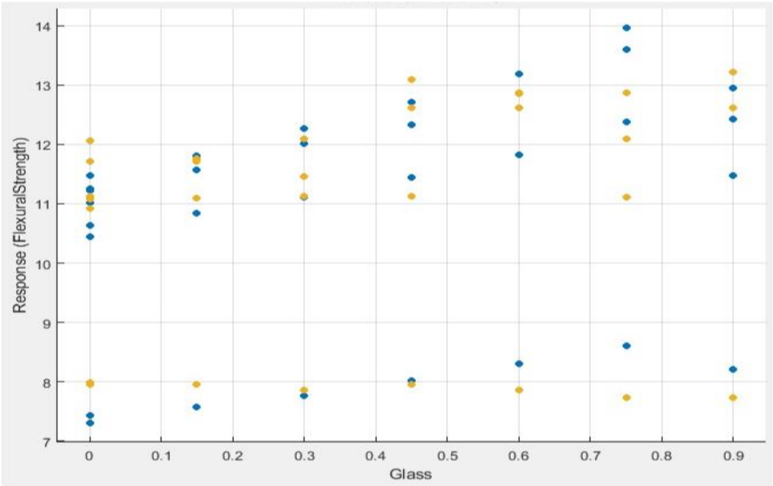


Figure 8. Graph between Flexural strength and percentage of glass

C) Artificial neural network (plot fit) of HSSCC

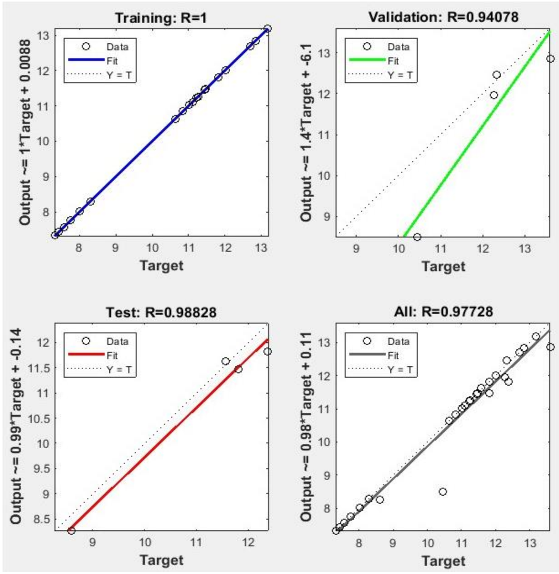


Figure 9. Graph between real values and predicted fit for Flexural strength

Figure 9 gives us a contrast between the actual values obtained through experiments and the predicted values using various prediction models in MATLAB, for HSSCC and HSHFSCC.

3.2 Function approximation of flexural strength of HSHFSCC and HSSCC in PYTHON

Approximation in python is also performed on the same models. From table 5, it is observed that Fine tree regressor and Artificial Neural Networks (ANN) yield the best results.

Table 5. Performance of models in Python

Algorithms	RMSE		R-Squared	
	HSHFSCC	HSSCC	HSHFSCC	HSSCC
Decision Tree Regression	0.4913	0.2916	0.945	0.945
Neural Network	0.2489	0.1861	0.984	0.990

The below graphs depict the predicted values of flexural strength for HSHFSCC and HSSCC using two models i.e Decision Regressor and Artificial Neural Network by giving input parameters such as percentage of steel, percentage of glass, and setting time.

A) Decision regressor (fine tree) of HSHSSCC

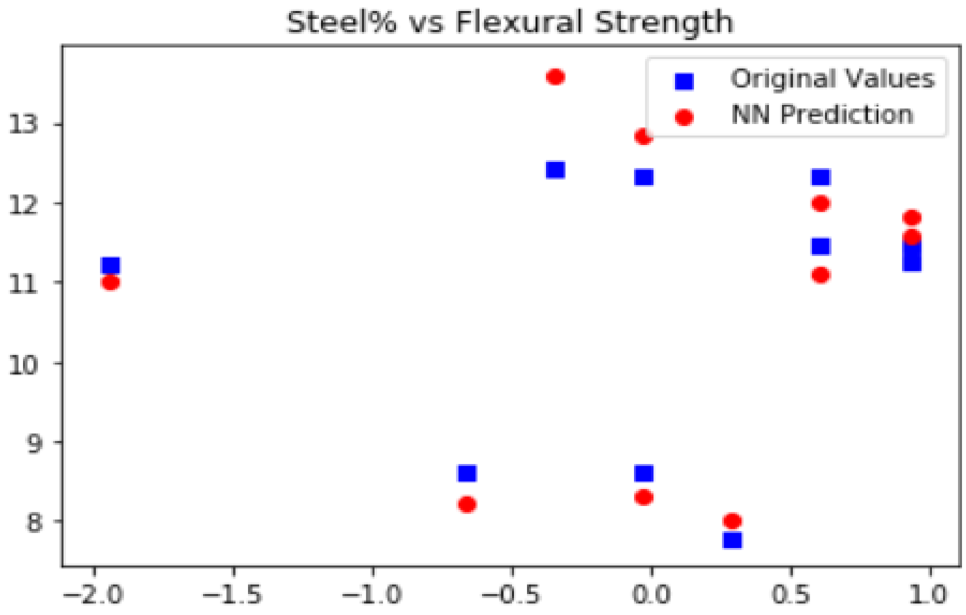


Figure 10. Graph between flexural strength and percentage of Steel

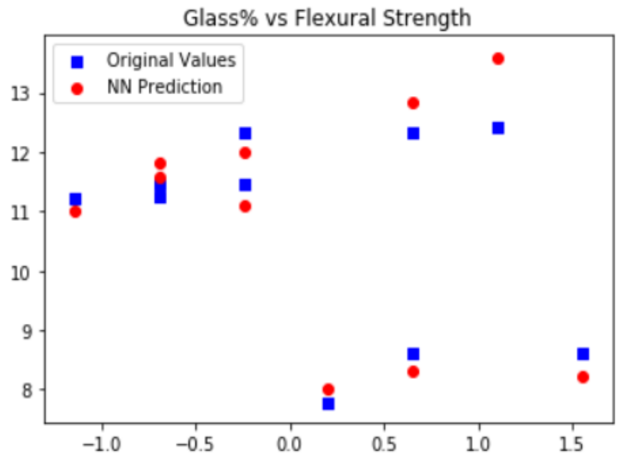


Figure 11. Graph between flexural strength and percentage of Glass

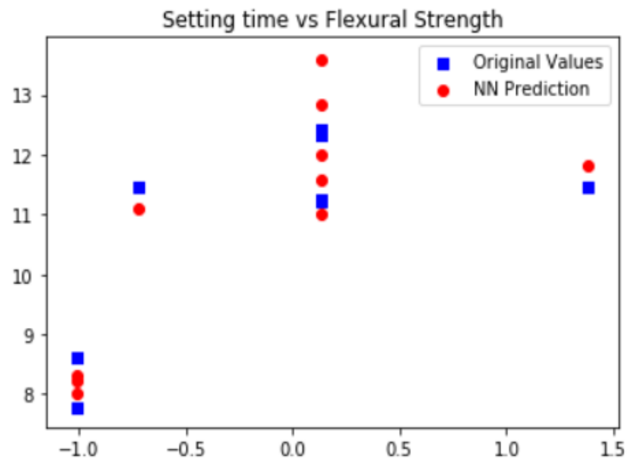


Figure 12. Graph between flexural strength and setting time

B) Decision tree regressor of HSSCC

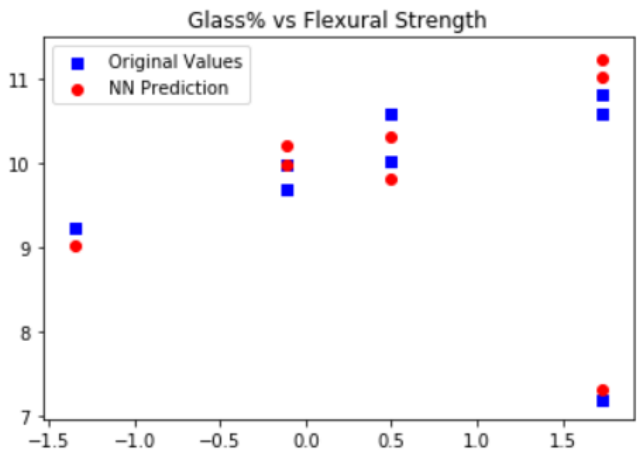


Figure 13. Graph between flexural strength and percentage of Glass

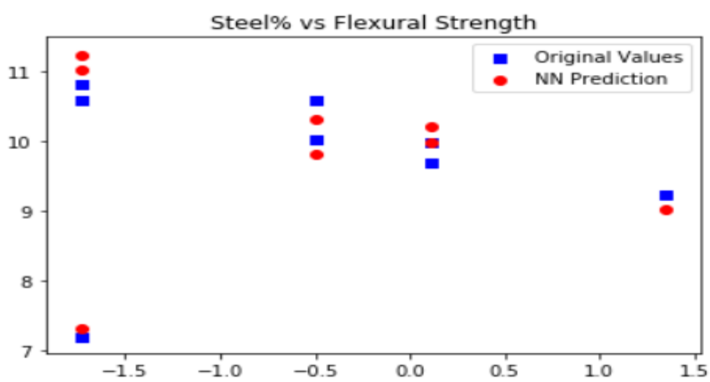


Figure 14. Graph between flexural strength and percentage of Steel

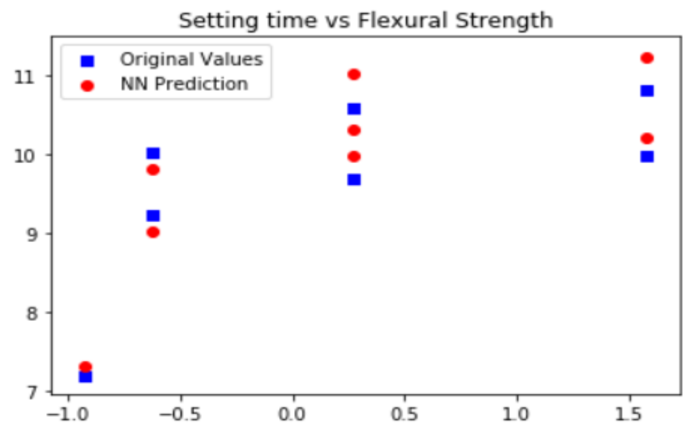


Figure 15. Graph between flexural strength and setting time

C) Artificial neural network of HSSCC

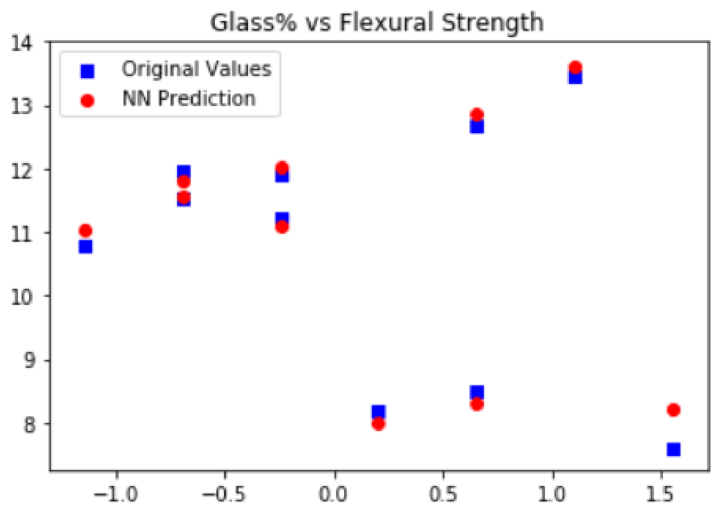


Figure 16. Graph between flexural strength and percentage of Glass

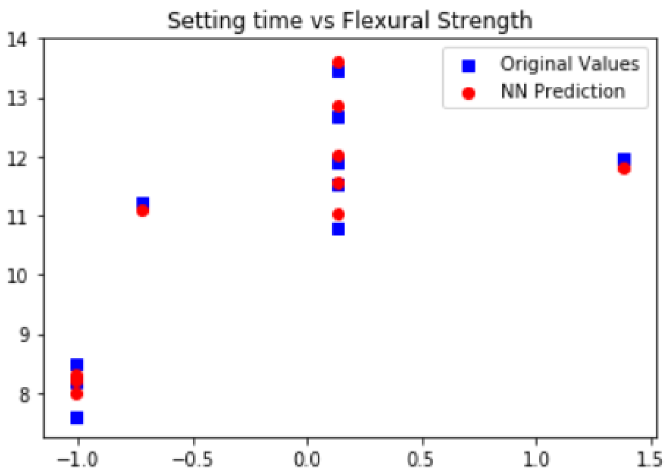


Figure 17. Graph between flexural strength and setting time

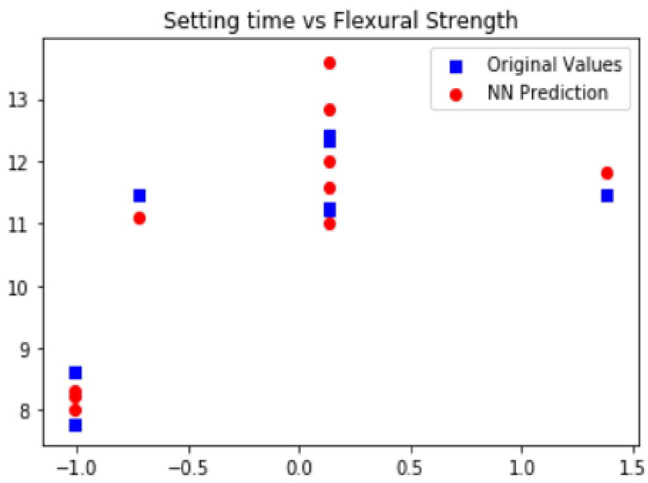


Figure 18. Graph between flexural strength and percentage of Steel

D) Artificial neural network of HSHFSCC

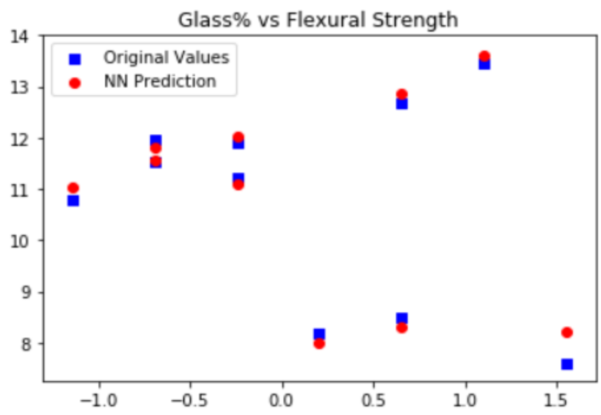


Figure 19. Graph between flexural strength and percentage of Glass

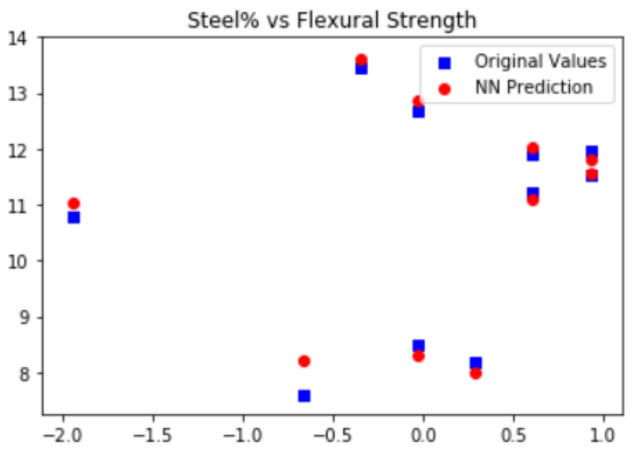


Figure 20. Graph between flexural strength and percentage of Steel

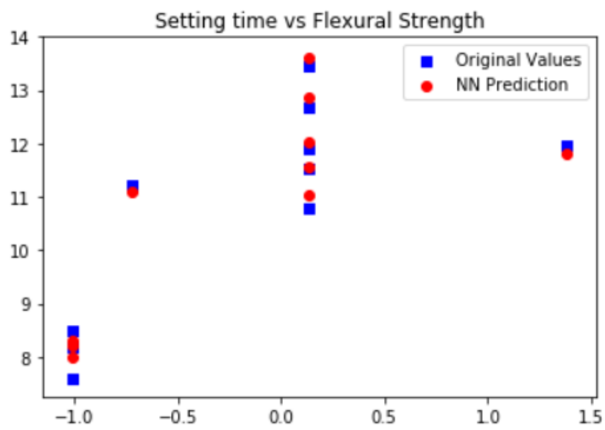


Figure 21. Graph between flexural strength and setting time

4. Results and Discussions

In case of MATLAB maximum accuracy is obtained by two models:-, Fine tree R^2 value 0.90) and Artificial Neural Network (R^2 value = 0.99). Therefore, in MATLAB, the Artificial Neural Network model is considered as the best fit.

In the case of PYTHON, maximum accuracy is obtained by Decision Tree Regression (R^2 value = 0.945) and Neural Network (R^2 value a= 0.990). Hence with respect to PYTHON, Neural Network model is the best fit.

By considering both MATLAB and PYTHON, it is observed that both MATLAB by ANN model (R^2 value = 0.99) and PYTHON by Neural Network model (R^2 value = 0.99) are equally good for the best fit [4, 6, 9, 13].

In case of MATLAB Fine tree obtained R^2 value = 0.83 and Artificial Neural Network obtained R^2 value = 0.97. Therefore, in MATLAB, the Artificial Neural Network model is found to be the best fit.

In case of PYTHON, Decision Tree Regression has the R^2 value = 0.945 and Neural Network has R2 value = 0.984. Hence with respect to PYTHON, the Neural Network model is the best fit.

By considering both MATLAB and PYTHON, it is observed that, PYTHON by Neural Network model (R^2 value = 0.984) is the best fit.

The figures incorporated in the paper defines the flexural strength of concrete with different percentages of steel, glass. These figures are obtained by Machine Learning technique.

5. Conclusions

Artificial intelligence has impacted many domains today. Its capacity to perform high-level analysis on data shows that it can be very effectual for predictions, provided proper parameters that influence the prediction are given. In this study, three input parameters are considered to create the models and to evaluate the compressive strength of the concrete. 24 samples are used to perform the experiment which are further split as 16 samples for training and 8 samples for testing and validation. This is required to evaluate the performances of various models that are being tested. It is observed that Artificial Neural Network model in MATLAB might serve as the most sensible prediction tool for predicting the Flexural Strength of HSSCC and Neural Network mode in PYTHON might serve as the most feasible prediction tool for predicting the Flexural Strength of HSHFSCC. The performance of these models can be further increased by exposing them to larger datasets and fine-tuning the models for greater accuracy of prediction.

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Author’s biography

B. Narendra Kumar received his B. Tech in Civil Engineering, M. Tech in Structural Engineering and PhD at JNTU, Hyderabad. Presently, he is a Professor in the Department of Civil Engineering, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad. He holds a research interest on SCC and mix design. He plays a vital role in several Designs projects in relation with number of organizations and involved as a key person in Quality Control and Mix Designs. He has guided 20 M Tech projects and 60 B tech Projects. He has delivered invited lectures in other organizations and institutions. He is a member of ISTE, Member of ICI and Member of Institute of Engineers.

Pariyada Pradeep Kumar is an under-graduate in Civil Engineering and is currently undergoing postgraduation in Structural Engineering at VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad.