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# PREDICTING COMPRESSIVE STRENGTH OF STEEL FIBERS REINFORCED CONCRETE INCORPORATING SILICA FUME USING MACHINE LEARNING MODELS

***Aalia Faiz***

*Department of Building and Architectural Engineering, Bahauddin Zakariya University, Multan (Pakistan)*

***Fakhar Imam***

*Department of Civil Engineering, Institute of Southern Punjab, Multan, Pakistan*

***Shimza Jamil***

*Department of Building and Architectural Engineering, Bahauddin Zakariya University, Multan (Pakistan)*

***Wasif Zubair***

*Projects Planning and Asset Management Department, Sindh Engro Coal Mining Company*

***Ahmer Iqbal***

*Department of Civil Engineering, Quaid-e-Azam Educational Complex, Sahiwal*

***Corresponding author: Muneeb Ahmed (muneeb.gill@outlook.com)***

## Article Info



## Abstract

*Concrete is the most commonly used construction material around the world. As the compression strength of concrete goes up, the brittleness of the concrete matrix increases, hence terming it as a quasi-brittle material. This issue can be solved by the addition of steel fibers in the concrete mixture, which improve the post-peak load carrying mechanism of the concrete. Hence it becomes important to find the compressive strength of such improved concrete composites. In this study, a comprehensive dataset was developed by combining the findings from 17 research papers, which consisted of 8 participation variables, and compressive strength as the output variable. Three machine learning models were developed, i.e., Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Random Forest (RF). It was observed that ANN model exhibited the highest value of $R^2$ among the three models, i.e., $R^2$=0.9941. To check the issue of overfitting in the best performing model, K-Fold Cross Validation technique was applied with five folds, which returned the average value of $R^2$ as 0.9665, so validating the efficacy of the ANN model. In the last step, predictive equations were derived for the compressive strength calculation, as they eliminate the need for the model's foundation file and hence enhance the significance of the research project.*

**Keywords:** *Steel Fibers Reinforced Concrete, Machine Learning, Artificial Neural Network, K-Nearest Neighbor, Random Forest, K-Fold Cross Validation.*

## Introduction:

Concrete is a widely used material for construction purposes, owing to its inherent properties of high mechanical strength and excellent durability. Its application can be found in very diverse domains, like offshore construction, pavements, industrial buildings, etc. [1]. However, where high compressive strength of concrete is required, it is observed that brittleness of concrete increases [2]. Hence, under the application of tensile load, limited mechanical strength is achieved, along with the development of cracks at the initial stage of loading, hence terming it as a quasi-brittle material [3]. Due to these drawbacks, many researchers have tried to develop high strength concrete using supplementary cementitious materials, especially silica fume, as a partial replacement for cement [4]. This phenomenon has led to a decrease in the porosity of the concrete mixture, and the development of an enhanced micro-structure resulting in better packing density [5, 6]. For example, it was reported that along with the addition of quartz (silica) micro fillers in the concrete matrix, the incorporation of finely ground bagasse ash particles significate increased the pozzolanic activity of the cementitious mixture. The rate of hydration of the aforementioned mixture was found to be increased in the range of 10-75%, in comparison with the conventional reference mixture [7].

To tackle with the brittleness of cementitious composite with improved mechanical strength, steel fibers are commonly added in the concrete mixture [8]. This method has been seen as effective in case of lining of tunnels, industrial floor slab castings, and other related applications [9, 10]. The insertion of steel fibers in the concrete mixture differentiates it from normal concrete, due to its load carrying mechanism in the fractured stress zone [11]. It is observed that the stress-strain behavior of the concrete is greatly improved by steel fibers. Further the specifications of fibers, like length, diameter, ends, yield strength, etc., and the concrete mechanical strength also influence the load resisting mechanism of the concrete [12]. The addition of steel fibers to improve the post-cracking ductility, gives rise to the concept of steel fibers reinforced concrete used for special purposes.

In the past few years, there has been an increase in the use of artificial intelligence techniques in almost every field of engineering. For biomedical purposes, it has been used to increase the accuracy and process-time for diagnosis of imaging-intensive sub-domains, like radiology and pathology [13]. For generative content purposes, many large language models have emerged which may generate textual, as well as pictorial data. Hence upon their increasing popularity, the researcher working in the field of civil engineering have been inspired to use artificial intelligence to optimize the experimentation phase of research projects. Wasim Abbas et. al. used difference machine learning techniques to predict the mechanical strength, i.e. compressive, tensile and shear strength, the cement-based tile adhesive bonds to manufacture value-added product more efficiently [14]. Sadia Saif et. al. employed the artificial intelligence to optimize the production process of ceramic tiles by substituting the main raw material with various industrial waste ashes. The optimization was done and modelled to predict the temperamental results with confident accuracy [15]. Further, it was also used to detect the presence of heavy metals, like zinc, lead, arsenic, etc., in various industrial ashes to prevent the potential health related risks associated with their use [16].

Many researchers have specifically developed machine learning models to predict the compressive strength of various concrete composites using regression applications. Li et. al. modelled the compressive strength of concrete using supervised machine learning [17]. Support Vector Regression, Adaptive Boosting, and Bagging techniques were used to approximation the 28-days concrete's compressive strength, and was observed that the AdaBoost performed best among the three. Nguyen et. al. adopted various models to forecast the compressive strength of geopolymer concrete composites derived from green fly ash and compared the results with the experimental program [18]. The models developed included deep neural network and ResNet. Although, many similar examples of research can be found in the published literature, however there was a shortcoming about the development of machine learning models for steel fibers reinforced concrete with silica fume, and deriving the predictive equations in this regard.

Hence, the present investigation work was premeditated to develop the diverse machine learning techniques to forecast the compressive strength of steel fibers reinforced concrete containing silica fume, compare their perforce, and formulate the prediction equations for the best performing techniques. The analytical equations eliminate the need for the model source file, and hence make the findings widely usable for larger audience, thus increasing the significance of the current research work.

## Methodology:

The methodology adopted for the current research work consist of several distinct steps, as illustrated in Figure 1.

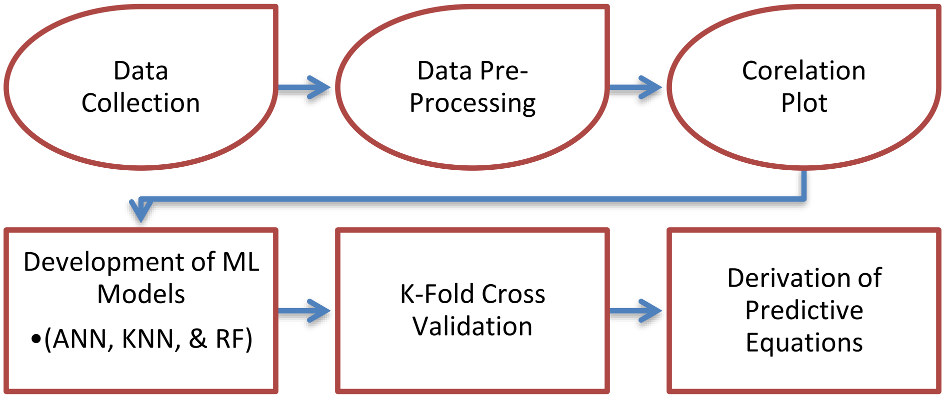



**Figure 1: Methodology for the research work**

### Data Collection

In this step, different research papers were studied on the topic of developing steel fibers reinforced concrete. The details about the mixture proportion and the compressive strength were noted and hence, a comprehensive dataset was developed consisting of a large number of data points.

### Data Pre-Processing

This is a very important step for the development of machine learning models. Data Pre-Processing refers to the preparation of dataset, on which various machine learning models are trained and tested. This technique includes several steps, like filling blank cells, removing null rows, etc. However, the most step in this technique is called 'Data Normalization'. Data Normalization refers to converting the entire dataset in a same range. This step is essential as it increases the efficiency of machine learning models to converge faster towards the desired output [19]. The normalization function used during the modelling is given by eq. (1):

$$\text{Normalization Function:} \quad Mi = \frac{(X_{max} - X_{min})(Y_i - Y_{min})}{(Y_{max} - Y_{\min})} + X_{min} \quad \textbf{(1)}$$

In this relation, $M_i$ refers to the scaled parameter, while $Y_{max}$ and $Y_{min}$ indicate the supreme and least values found within the actual dataset. $X_{max}$ and $X_{min}$ denote the supreme and least values within the scaled range, respectively, and $Y_i$ represents the limitation to be clambered.

### Correlation Plot

Correlation Plot is a vital figure to understand the relationship between variables. It defines either direct or inverse relation exists among input variables, as well as among input and output variable. This plot represents the coefficient of correlations of the dataset in the method of a high temperature plan. The straight relation among elements is presented by a positive coefficient, though a reverse relation is presented by a negative relationship [20].

## Development of Machine Learning Models

During this step, the normalized dataset was used to train three machine learning models, and the output data, i.e., the compressive strength of steel fibers reinforced concrete, was predicted. The general description of the developed machine learning models is given as follows.

### a) Artificial Neural Network (ANN)

ANN is a very effective technique for ML for predicting of mechanical durability of cementitious composites. This model is inspired by the working of neurons, a small processing unit, in the human brain, which are interconnected and work simultaneously [21]. During the training process, different values of weight and bias are assigned to each neuron. This value is responsible for the accuracy of the predicted output [22]. Hence the training process becomes very crucial, as it involves minimizing the error below a specified criterion.

### b) K-Nearest Neighbor (KNN)

*K*-Nearest Neighbors is a type of supervised machine learning technique, which is non-parametric in nature. It is utilized for addressing classification and regression challenges. During the training process, the distance between the data points and their corresponding *k* nearest neighbors is calculated by the model algorithm using *Euclidean Distance* formula [23]. The ideal value for k nearest neighbors is fundamental, as it balances a trade-off between bias and variance [24]. This technique is very popular, owing to its simplistic explanation and easy to implement algorithms.

### c) Random Forest (RF)

Random Forest is an ensembled supervised machine learning approach, which is very efficient for regression related tasks. By applying the law of large numbers, it greatly prevents the overfitting of data [25]. In comparison with the bagging technique, it introduces an extra layer of randomness to prevent overfitting and multi-collinearity in the dataset. Using these extra measures on the dataset, the accuracy of the regression output predicted data is greatly enhanced [26].

## K-Fold Cross Validation

This is a robust statistical technique which is used to analyze the performance and generalization of the developed ML model. In this strategy, the whole dataset was separated into k equally sized portions, also known as Folds. For validation purposes, the frequently used values of *k* are 5 or 10. During analysis, the model is trained using *k-1* Folds and the one remaining subset is used for testing purposes, and the resulting value of coefficient of determination is noted as a performance matrix [27]. The performance matrix is calculated for all the iterations, and the average estimate about the model's effectiveness is calculated at the end of the analysis. During this research project, the best ML model was selected on the basis of $R^2$ value, and the K-Fold cross validation approach was carried out on the best performing model only. The systematic diagram of K-Fold Cross Validation technique is given in Figure 2.

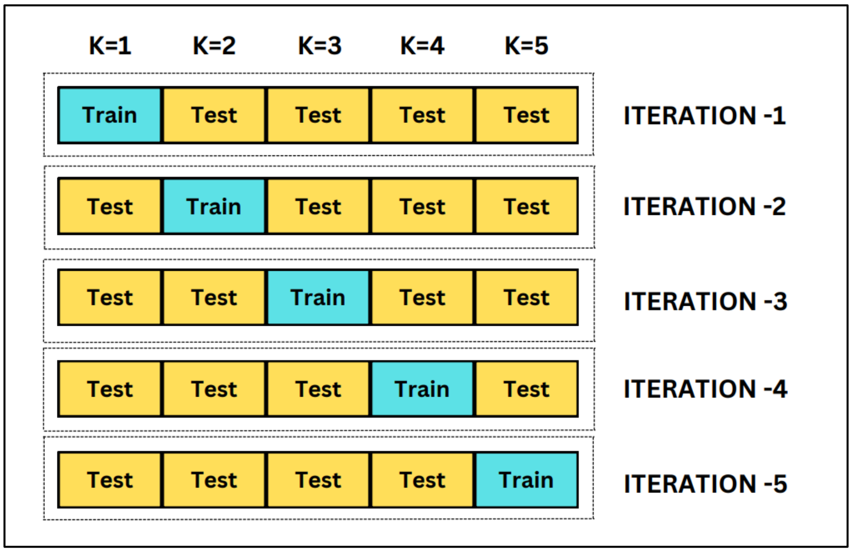



**Figure 2: Systematic Diagram of K-Fold Cross Validation Technique**

### Derivation of Predictive Equations

In the last step of this research project, the best performing model source file and model training constants were utilized to derive predictive equations. This is an essential step in ML, as it encompasses the elimination of the need for model's source file. Further, it also ends the need of advance IT skills, as the precative equations are very simple in nature, and can be modelled in excel spreadsheets [20]. Hence, considering these advantages, the predictive equations were derived for the best performing model.

## Results and Discussion:

### Preparation of Dataset

For this research project, the dataset included the findings reported by various researchers from 17 journal articles. The articles discussed various properties of steel fibers reinforced concrete, but for the sake of this research, only compressive strength data was obtained from the research papers, and their mix design was also noted. The overall dataset consisted of 156 data points, with 8 input variables and one output variable. The content of cement (C), water (W), sand (S), coarse aggregates (CA), superplasticizer (SP), silica fume (SF), steel fibers (ST) and their aspect ratio $(\frac{L}{D})$ were taken as input variables, while the compressive strength (CS) was treated as an output variable. Table 1 presents the descriptive statistics of the entire dataset.

**Table 1: Summary measure of dataset**

| | Cement (C) | Water (W) | Sand (S) | Coarse Aggregates (CA) | Super Plasticizer (SP) | Silica Fume (SF) | Steel Fibers (ST) | Aspect Ratio (L/D) | Compressive Strength (CS) |
|---|---|---|---|---|---|---|---|---|---|
| **Mean** | 454.51 | 172.78 | 786.53 | 929.96 | 0.92 | 6.37 | 0.87 | 64.03 | 60.90 |
| **Standard Error** | 8.20 | 2.45 | 12.63 | 20.92 | 0.15 | 0.96 | 0.05 | 1.41 | 1.78 |
| **Median** | 415 | 160 | 750 | 1050.50 | 0.12 | 0 | 1 | 64.52 | 61.20 |
| **Mode** | 400 | 152 | 835 | 1047 | 0 | 0 | 1 | 60 | 49.21 |
| **Standard Deviation** | 102.44 | 30.61 | 157.78 | 261.27 | 1.83 | 12.01 | 0.61 | 17.64 | 22.25 |
| **Sample Variance** | 10493.97 | 937.12 | 24893.81 | 68260.56 | 3.36 | 144.27 | 0.37 | 311.16 | 494.92 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Kurtosis** | 0.07 | 1.12 | 3.33 | 2.74 | 10.13 | 3.63 | -0.86 | 6.55 | -1.19 |
| **Skewness** | 1.01 | 1.11 | 1.61 | -1.80 | 3.04 | 2.15 | 0.31 | -2.31 | 0.12 |
| **Range** | 357 | 137 | 768 | 1170 | 9 | 43.00 | 2 | 85.71 | 73.10 |
| **Minimum** | 323 | 133 | 582 | 0 | 0 | 0 | 0 | 0 | 26.10 |
| **Maximum** | 680 | 270 | 1350 | 1170 | 9 | 43.00 | 2.00 | 85.71 | 99.20 |
| **Sum** | 70904 | 26954 | 122698 | 145073 | 144.18 | 994.48 | 135.45 | 9988.08 | 9499.78 |

### Data Pre-Processing

As discussed in the methodology section, this step involved the preparation of dataset ready for machine learning. It included filling the blank columns, deleting blank rows, removing duplicate data points, etc. Further, by using the *Normalization Function* given in eq. (1), the data was rescaled to lie within the **-1** to **+1** range for the modelling.

### Correlation Plot

In this step the coefficient of correlation plot was developed for the overall dataset, by presenting the coefficients of correlations in the form of a heat map. This plot is very helpful in understanding the relationship among different variables in the dataset. As stated earlier, the direct and inverse relations can be found by positive and negative coefficient values. Further, it is to be considered that the coefficient values greater than 0.5 may give rise to the issues of multi-collinearity in the dataset for modelling which is undesirable, however this might not be case in this dataset, owing to the independent nature of all the variables in the mixture design proportions [28].

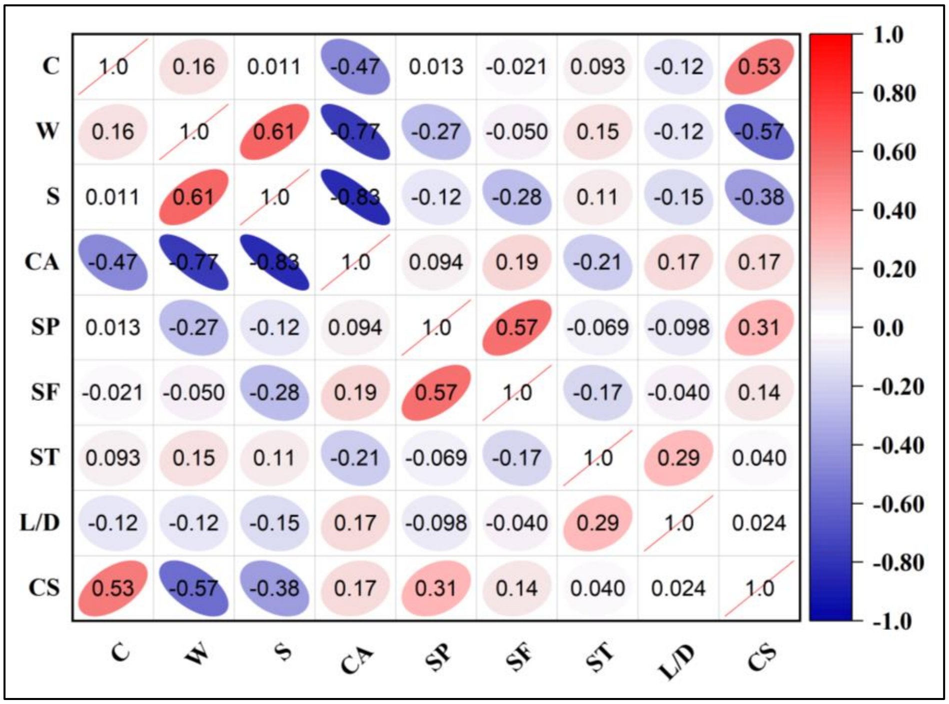



**Figure 3: Correlation Plot of the Dataset**

### Development of Machine Learning Models

In this step, three machine learning models were developed, and trained on the aforementioned dataset. The three models include ANN, KNN, and RF. The details about each of the ML models is given as follow.

### Artificial Neural Network (ANN)

To develop ANN model, MATLAB R2021a software was used, and NNTOOL command was executed. The feed forward-backward propagation technique was utilized for the development of ANN model, which consists of three computational layers, i.e., Input, Hidden and Output Layer. For this model, 5 hidden neurons were used in the hidden layer. The transfer functions for the hidden, and output layers were chosen to be PURELIN and TAN-SIGMOID, respectively [29]. These transfer function come handy for the development of predictive equations. The dataset was divided into three subsets, i.e., 70% for training, 15% for validation, and 15% for testing. The Levenberg-Marquardt (LM) algorithm was employed for the training process, as it provides convergence in lesser time and hence, is the most commonly used training algorithm for training of neural networks [23].

The schematic diagram of the developed ANN model is shown in Figure 4, while the performance of the ANN model is given in Figure 5. It was observed that the best performance of the ANN model was achieved at epoch 23, with MSE value of 0.0085214. Further, the regression plots, given in Figure 6, show that the $R^2$ value for all the three subsets, as well as for the overall dataset, comes out to be greater than 0.95, hence validating its performance and rendering it usable for research purpose.

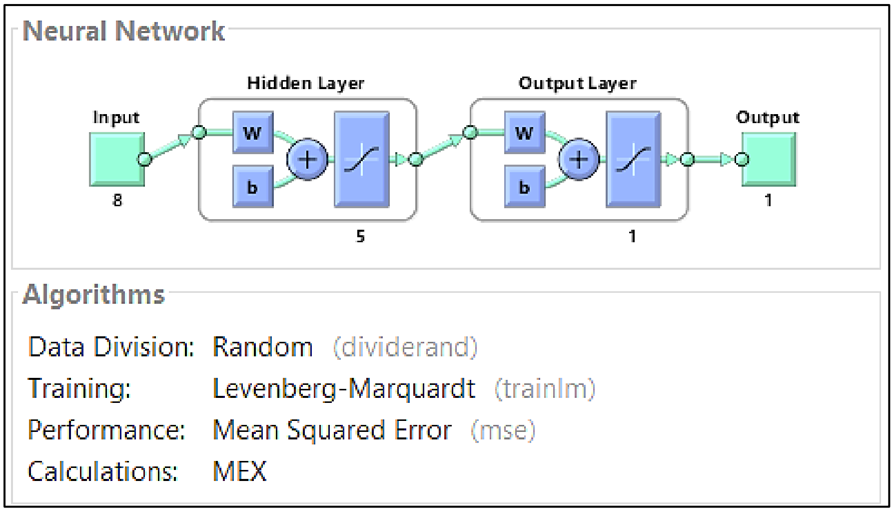



**Figure 4: Schematic Diagram of the Developed ANN Model**

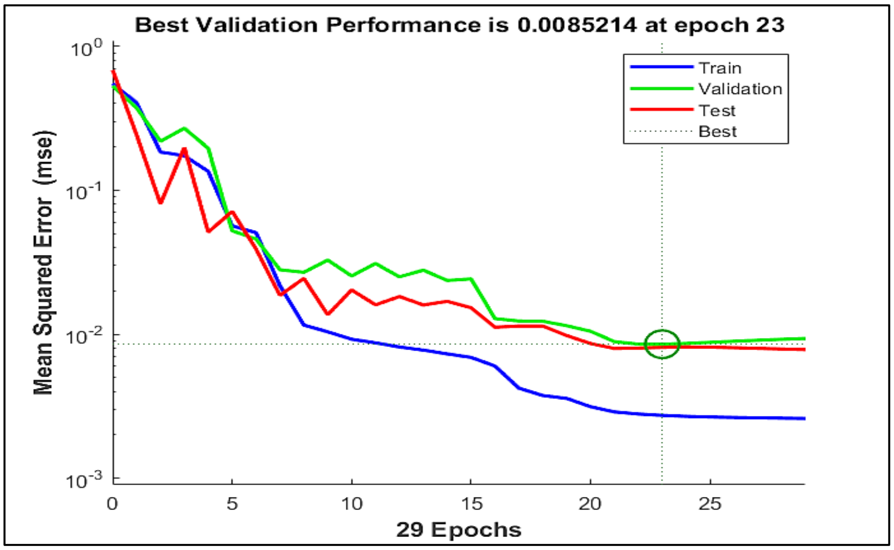



**Figure 5: Performance Plot of the Developed ANN Model**

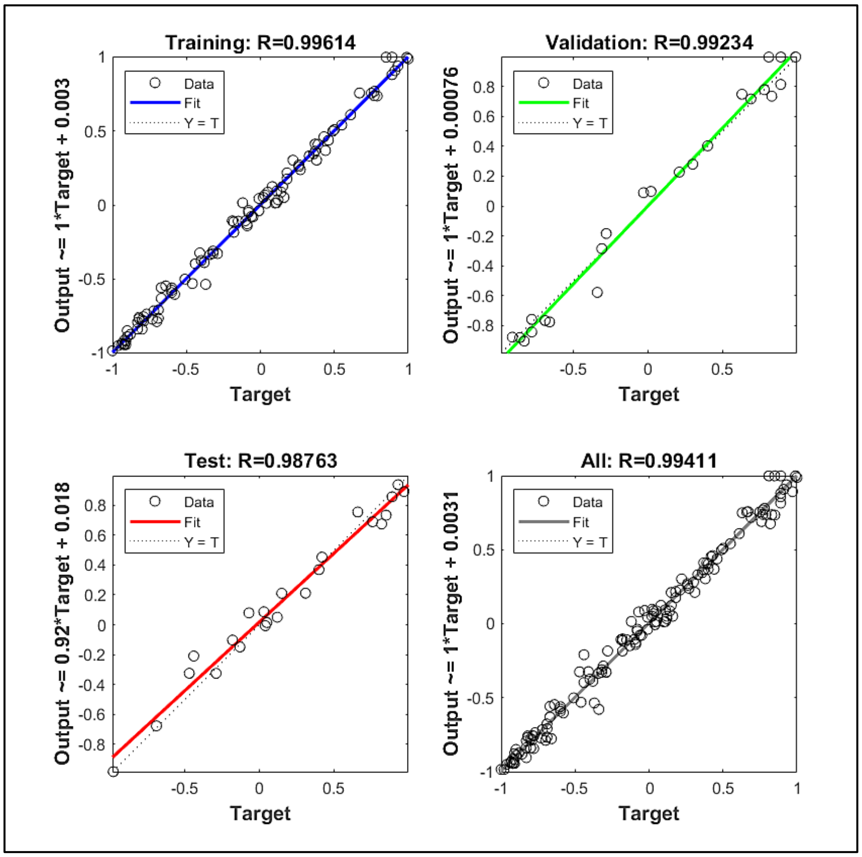



**Figure 6: Regression curves for the trained ANN Model**

## K-Nearest Neighbors (KNN) and Random Forest (RF)

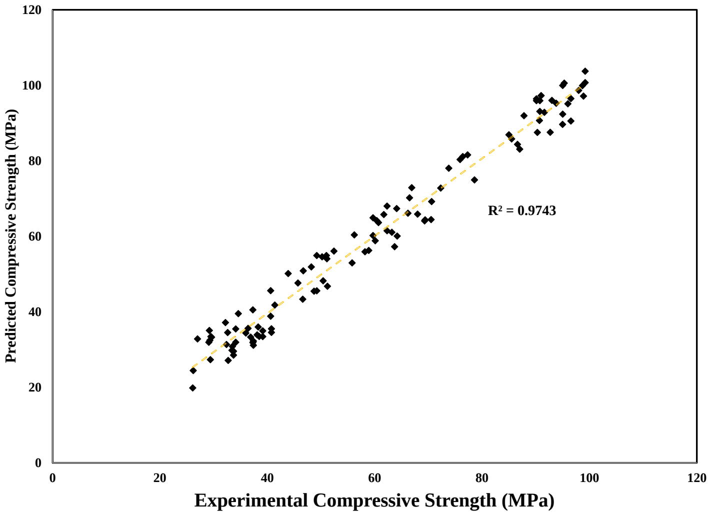
To develop KNN and RF models, Python scripting and the Anaconda Navigator Environment was used, however the modeling was done in Jupiter Lab Notebook. 70% of the dataset was used for training, while the remaining 30% was used for testing. The training parameters used for model development are presented in Table 2. Table 3 lists the values of three evaluation metrics: the R-squared ($R^2$) statistics, mean absolute error (MAE), and root mean square error (RMSE) for both the RF and KNN models. Figures 7 and 8 depict the experimental versus estimated results for the RF and KNN models, respectively.

**Table 2: Training Configurations for RF and KNN Model**

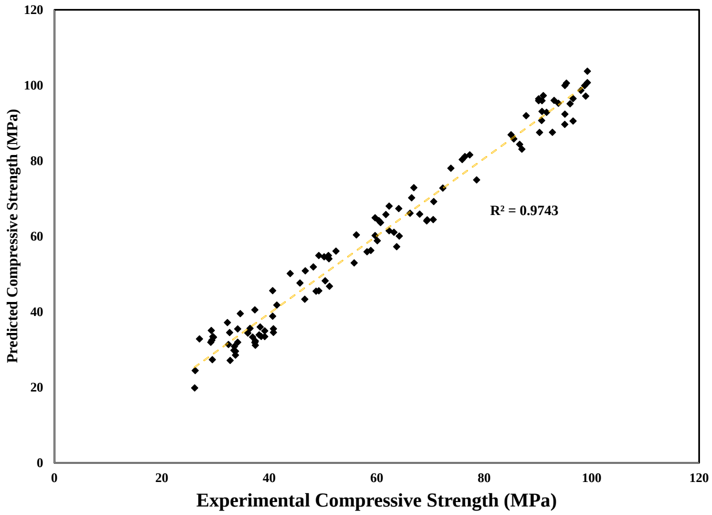
| **Model** | **Training Parameter** | **Value** |
|---|---|---|
| **RF** | Tree Count | 40 |
| | Minimum samples split | 2 |
| | Minimum sample leaf | 1 |
| | Bootstrapping | True |
| **KNN** | K neighbors | 4 |
| | Weights | Uniform |

**Table 3: Evaluation metrics for RF and KNN model**

| Model | $R^2$ | | MAE | | RMSE | |
|---|---|---|---|---|---|---|
| | Training Data | Test Data | Training Data | Test Data | Training Data | Test Data |
| **RF** | 0.9743 | 0.9710 | -0.1078 | 0.0791 | 1.1253 | 0.5422 |
| **kNN** | 0.9765 | 0.9669 | 0.1483 | -0.0824 | 1.5486 | 0.5651 |

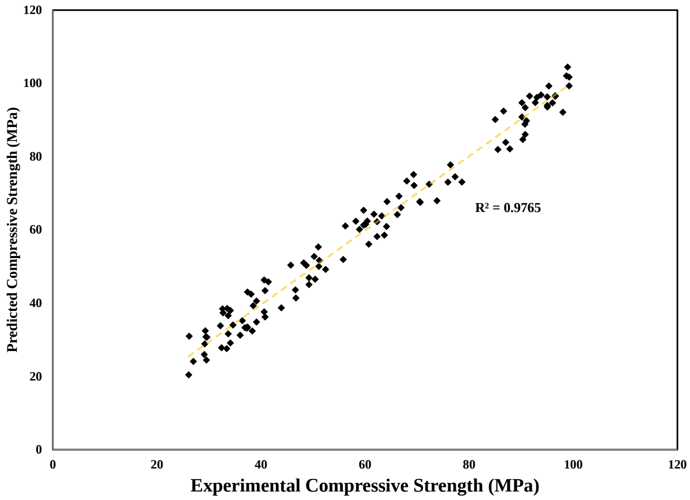



(a) Training Data

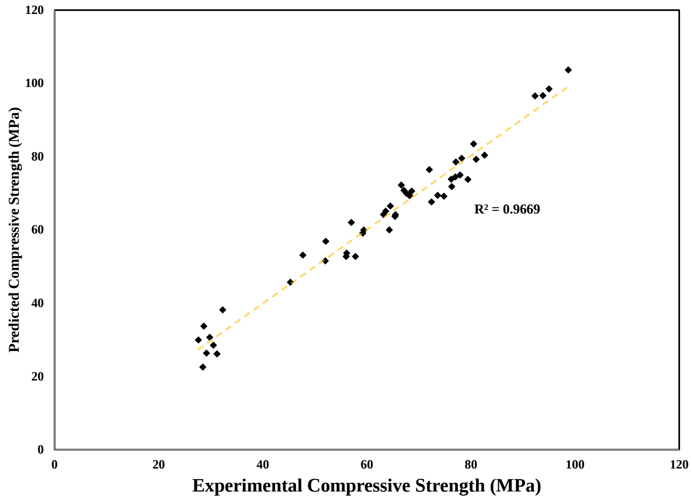



(b) Test Data

**Figure 7: Plot of Predicted vs Experimental values for RF Model**




(a) Training Data




(b) Test Data

**Figure 8: Plot of Predicted vs Experimental values for KNN Model**

## K-Fold Cross Validation

To perform K-Fold Cross Validation technique, ANN model was chosen for the analysis, as the overall coefficient of determination value was found to be higher in the case ANN model, as compared to KNN and RF model. Hence the dataset was divided into five subsets, and five iterations were performed by consecutively interchanging training and test data, as illustrated in Figure 2. It was observed that upon performing the K-Fold Cross Validation Analysis, the average value of $R^2$ came out to be 0.9665, which is higher than the local industrial standard of 0.95, hence validating the performance of the machine learning model. The values of $R^2$ for all the iterations are given in Table 4.

**Table 4: Values of K-Fold Cross Validation Analysis**

| | K-Folds | | | | |
|---|---|---|---|---|---|
| | **K=1** | **K=2** | **K=3** | **K=4** | **K=5** |
| **$R^2$** | 0.9491 | 0.9410 | 0.9779 | 0.9851 | 0.9797 |

## Derivation of Predictive Equations

In this step, ANN model constants were utilized to derive estimation relationship for the calculation of compressive strength of the steel fibers reinforced concrete incorporating silica fume. The neuron parameters assigned during the training process are used to develop predictive equations for compressive strength. These equations are formed by multiplying the weights with the corresponding input variables for each neuron, considering the transfer function. The outputs are then obtained by summing these products and applying the bias [30]. Table 5 provides the weights and biases obtained during the ANN model training, which are subsequently used to formulate the predictive equations.

**Table 5: Parameters and offsets (Weights and Biases) for the ANN Model**

| Hidden Neuron | WEIGHTS | | | | | | | | | BIAS | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Input-Hidden layer | | | | | | | | Output – Hidden Layer | Hidden layer | Output layer |
| | C | W | S | CA | SP | SF | ST | L/D | | | |
| **A** | 0.84 | -0.72 | -1.47 | -0.32 | 1.08 | 0.88 | 0.58 | 0.74 | 1.57 | -1.47 | -0.07 |
| **B** | 0.82 | -1.38 | 3.77 | 0.83 | -7.16 | 1.75 | -0.18 | 0.16 | -3.31 | -2.43 | |
| **C** | -2.36 | 2.55 | -1.37 | 3.08 | 2.37 | -0.63 | 0.88 | 0.45 | 0.23 | -5.61 | |
| **D** | 1.53 | -4.18 | 1.70 | 0.32 | -1.10 | -0.22 | -0.04 | -0.08 | 1.81 | -0.69 | |
| **E** | -0.25 | 2.99 | -1.42 | 2.47 | 4.03 | -2.73 | 0.17 | -0.17 | -3.20 | 0.48 | |

The general equation for the estimation of compressive strength CS of steel fibers reinforced concrete incorporating silica fume is given by eq. (2).

$$\begin{aligned} CS = -0.07 + \left(1.57 * \tanh(A)\right) - \left(3.31 * \tanh(B)\right) + \left(0.23 * \tanh(C)\right) \\ + (1.81 * \tanh(D)) - (3.20 * \tanh(E)) \end{aligned} \quad (2)$$

The values of model contents are given by the following equations.

$$A = -1.47 + 0.84 * C - 0.72 * W - 1.47 * S - 0.32 * CA + 1.08 * SP + 0.88 * SF + 0.58 * ST + 0.74 * \frac{L}{D} \tag{2.1}$$

$$B = -2.43 + 0.82 * C - 1.38 * W + 3.37 * S + 0.83 * CA - 7.16 * SP + 1.75 * SF - 0.18 * ST + 0.16 * \frac{L}{D} \tag{2.2}$$

$$C = -5.61 - 2.36 * C + 2.55 * W - 1.37 * S + 3.08 * CA + 2.37 * SP - 0.63 * SF + 0.88 * ST + 0.45 * \frac{L}{D} \tag{2.3}$$

$$D = -0.69 + 1.53 * C - 4.18 * W + 1.70 * S + 0.32 * CA - 1.10 * SP - 0.22 * SF - 0.04 * ST - 0.08 * \frac{L}{D} \tag{2.4}$$

$$E = 0.48 - 0.25 * C + 2.99 * W - 1.42 * S + 2.47 * CA + 4.03 * SP - 2.73 * SF + 0.17 * ST - 0.17 * \frac{L}{D} \tag{2.5}$$

## Conclusions:

In this research project, 156 data points were collected from 17 different research papers to develop three machine learning models for the prediction of compressive strength for the steel fibers reinforced concrete. The performance of the models was compared, and later predictive equations were also derived for the same purpose. Following conclusion were drawn from this study.

a) The ANN exhibited higher value of $R^2$ than KNN and RF Model. For instance, the value of $R^2$ for the overall dataset in ANN model came out to be 0.9941, which was greater than the both models.
b) K-Fold Cross Validation Technique results were found in line with the 1st finding. The average values of $R^2$ for all of the five folds came out to be 0.9665 which was greater than the local standard of 0.95, thus validating the efficiency of the developed machine learning model.
c) The predictive equations were derived from the ANN model's training parameters. These equations were found to be easily modelled on excel spreadsheets, hence increasing the significance of the current research.

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