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PREDICTING FLEXURE STRENGTH OF CERAMIC TILES MANUFACTURED BY INCORPORATING INDUSTRIAL WASTES AND COAL BOTTOM ASH USING MACHINE LEARNING MODELS

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Article Info

Abstract

The ceramic tiles industry is one of the largest industries globally and is expected to grow remarkably in the current decade. The ceramic tiles are a major source of decorations for building facades, interior design, etc. The manufacturing process of ceramic tiles is heavily dependent on the natural raw materials; hence a lot of research has been carried out to integrate various industrial wastes and coal ashes in its manufacturing. In this research project, an effort has been made to optimize the manufacturing process of ceramic tiles developed with the incorporation of industrial wastes and coal ashes, by predicting the flexure strength of ceramic tiles using different machine learning models. In this study, a comprehensive dataset was developed by combining the findings of 13 journal articles. The dataset consisted of 7 input variables, while the flexure strength of ceramic tiles was taken as an output variable. Three machine learning models were developed in this research project and their performance comparison was made. The developed machine learning models included artificial neural networks ANN, K-Nearest Neighbors and Extreme Gradient Boosting. In the later part of studies, K-Fold Cross Validation technique was applied to the best performing machine learning model to cross check the performance of the developed model. It was revealed that the ANN model performed the best among all the three machine learning models with an R2 value of 0.9795, which was authenticated by K-Fold cross Validation technique.

Keywords: *Ceramic Tiles, Machine Learning, Artificial Neural Network, K-Nearest Neighbor, Extreme Gradient Boosting, K-Fold Cross Validation*

Introduction

The ceramic industry has a huge share in global economy, and it significantly impacts our daily lives, as it provides a wide range of products. The most commonly used ceramic products in the construction industry are the ceramic tiles, which are available in various sizes and specific applications. In building construction, ceramic tiles are used for building façade, flooring, and walling for different scenarios [1-3]. As the global construction industry grows over time, so does the ceramic industry. As of 2023, the global ceramic industry is valued at 148.8B USD [4], while it is projected to grow to a size of 314.7B USD by the year 2029, with a compound annual growth rate of 8.13% [5]. The ceramic industry's rapid expansion brings about business opportunities for manufacturers, however the environmental impacts associated with the ceramic tiles production pose a great challenge for innovator, with regard to sustainability [6].

The ceramic tiles commonly composed of clays, clay minerals, and fluxing agents, which generally account for 60%, 25% and 15% of the ceramic tiles body formulation, respectively [7]. The clays utilized during the manufacturing are the locally available plastic clays, while the clay minerals are silica based material, and feldspar is the commonly used fluxing agent. The ceramic tiles manufacturing process consists of extraction of raw materials, clays preparation, mixture proportions, grinding/ball milling, spray drying, molding, glazing and drying, kiln firing, cutting and sorting, and packaging [8]. The ball milling or grinding process is also known as atomization process, and it involves grinding the ceramic formulation into very fine particles, passed through sieve #200, with the help of rigid steel balls. The firing process of ceramic tiles involves heating the green ceramic tiles at a temperature of 150-1100˚C for 35 to 40 minutes in four stages, where each phase contributes to the development of dense microstructure, e.g., mullite, responsible for the mechanical strength of the ceramic tiles [9].

The manufacturing process of ceramic tiles is highly dependent on the extraction of vital natural resource, and hence the naturally occurring ores are found to be under stress. Hence, many researchers around the globe have sought for the utilization of various waste products and ashes into the manufacturing of ceramic tiles to ease the stressed resources [10-12]. Lin et. al. explored the potential of using coal fly ash as a primary raw material for the manufacturing of ceramic tiles, and reported that the coal fly ash aided the development of mullite, during the firing process, and exhibited superior performance in comparison with the conventional ceramic tiles [13]. However, in another study, Ji et. al. reported that the coal fly ash substitution for feldspar was also favorable, due to the complex nature of firing process [14].

Mustafi et. al. studied the incorporation potential of glass waste in the ceramic tiles manufacturing, and reported the adequate performance of the resulting innovative product [15]. Montero et. al. used various dosages of urban sewage sludge and marble residues, in addition to clays, for the manufacturing of ceramic tiles and reported the optimum dosages of the aforementioned waste products which satisfy the local standard criteria for the ceramic tiles [16]. Pioro et. al. presented three different ways of processing blast furnace slag, so that the resultant processed byproduct may potentially be used as a raw material for the manufacturing of ceramic tiles [17].

With an increase in the popularity of artificial intelligence applications for the past few years, many researchers have been working on the utilization of the machine learning techniques for the mathematical modelling of experimentation phase of the research. W. Abbas et. al. developed an efficient surface neural network for the prediction of mechanical strength, i.e. compressive, tensile, and shear strength, of cementitious tile bond adhesives for replacing the source of fine aggregates for different formulation [18], while in another study, the presence of heavy metals, like zinc, arsenic, lead, etc., in the waste ashes was modelled to cater the potential health risks associated with their use [19]. S. Saif et. al. presented various machine learning models for the incorporation of ceramic production waste, e.g. glaze waste and body waste, back into the manufacturing of ceramic tiles to produce innovative and environmentally friendly ceramic tiles, which conform to the relevant ISO standards [20].

Hence, the current research work was planned to develop various machine learning models for the prediction of mechanical strength of ceramic tiles, manufactured with the addition of various industrial waste and coal ashes for better sustainability aspects. The performance validation of the machine learning models was done by performing the K-Fold Cross Validation Technique, and predictive equations were also derived in the manuscript. The derivation of predictive equations is very significant step, as it eliminates the need for model's source file, hence making this research usable for broad audience.

Methodology:

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

Fig 1.

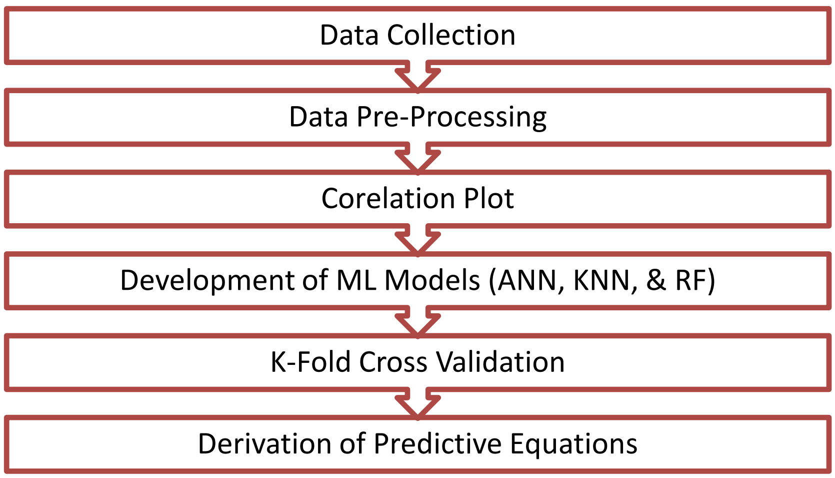


Figure 1: Methodology for the research work

Data Collection

To collect data for this research project, different research papers were accessed which focused on the development of ceramic tiles from industrial wastes and coal ashes. The mix design details and mechanical strength parameters were noted and a comprehensive dataset was developed.

Data Pre-Processing

Data Pre-Processing is a very important step for developing machine learning models. The dataset is prepared in this step which is deemed ready for the training and testing of ML models. In this steps, various tasks are performed, such as interpolating the missing data, removing null rows, and selecting appropriate number of variables. However, among all the data pre-processing tasks, the most important is Data Normalization. The entire dataset is converted into a same range, which is a pre-requisite for the convergence of ML models to an ideal output value [21]. The normalization formula used for the dataset is given by eq. (1):

$$\boldsymbol{Normalization\ Formula}: \qquad Mi = \frac{(M_{max} - M_{min})(N_i - N_{min})}{(N_{max} - N_{\min})} + M_{min} \qquad \textbf{(1)}$$

In this relation, Mi refers to the scaled parameter, while Nmax and Nmin indicate the maximum and minimum values found within the actual dataset. Mmax and Mmin denote the maximum and minimum values within the scaled range, respectively, and Ni represents the parameter to be scaled.

Correlation Plot

Correlation plot refers to the depiction of correlation coefficients of the variables in form of a heat map, which clearly illustrates the relationship between various variables. This plot demonstrates the existence of direct or inverse relationship among the variables in the dataset. The positive coefficients account for direct relation, while the negative values account for inverse relation between the variables [20].

Development of Machine Learning Models

In this step, the pre-processed dataset was utilized to develop three ML models, i.e. Artificial Neural Network, K-Nearest Neighbors and Extreme Gradient Boosting to predict the flexure strength of the ceramic tiles, developing using industrial wastes and coal bottom ash. The general explanation about the working principles for each of the ML model is given below.

a) Artificial Neural Network (ANN)

Artificial Neural Network is an efficient ML modelling technique to predict the output for complex dataset, i.e. consisting of complex patterns. ANN model is inspired by the working of neurons in the human brain, which are interconnected and work simultaneously [22]. During the training process of the ANN model, a certain weight is assigned to each neuron, and bias from the desired output is determined. The values of weights and biases reiterated till the error reaches a very minimum value below the threshold limit [23]. Hence the training process plays an important role in determining the accuracy of the developed ANN model.

b) K-Nearest Neighbor (KNN)

K-Nearest Neighbor is a supervised machine learning technique which can be used for various tasks, like classification and regression. This ML model is non-parametric in nature, i.e. it only considers the patterns between the dataset variables and predicts the output parameter. During training of KNN model, the distance is calculated between the data points and the closest k neighbors, using the Euclidean Distance Function [24]. The value of k is deemed to be critical in the entire training process, as it involves a trade-off between variance and bias [25]. KNN model is one of the widely used ML model, due to its simplistic approach.

c) Extreme Gradient Boosting (XGB)

Extreme Gradient Boosting is an ensembled machine learning technique which can be applied to both regression and classification problems. The training process of this model involves the boosting of gradient, i.e. the weak leaners are sequentially improved by reducing errors during the reiterations [26]. XGB model is well-known for handling large datasets efficiently and prevents overfitting by using various regularization techniques.

K-Fold Cross Validation

K-Fold Cross Validation is a comprehensive statistical technique which is used to cross-check the generalizability of the developed machine learning model. During this method, the entire dataset is divided into k equally sized subsets, each known as a Fold. Generally, the value of k is taken as 5 or 10. To perform the analysis, the specified model is trained on k-1 subsets, and one subset is used as test data. Hence, the value of coefficient of determination R2 is noted as a measure of performance [27]. The k number of iterations are performed following the same procedure, and the average value of R2 is reported at the completion of the analysis. For this research project, the K-Fold Cross Validation technique was applied only to the best performing machine learning model. The schematic diagram for this technique is presented in Fig 2.

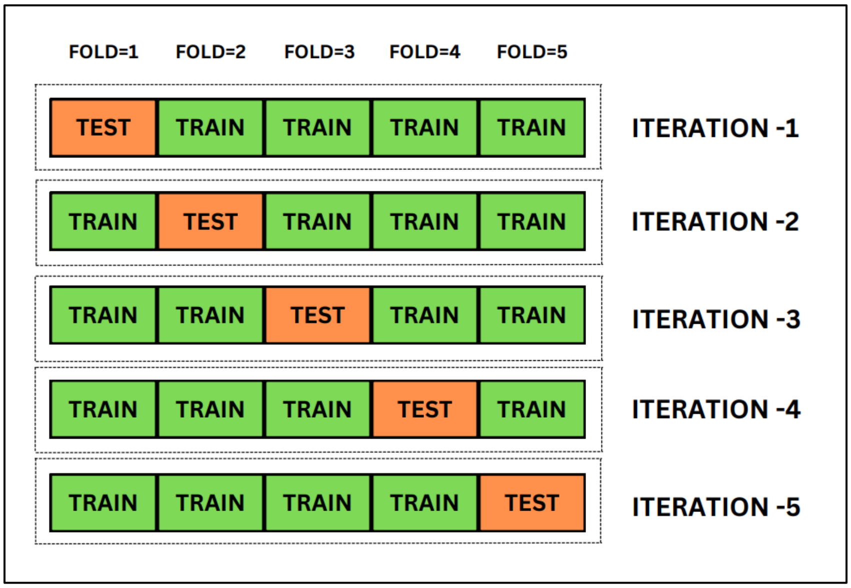


Figure 2: Systematic Diagram of K-Fold Cross Validation Technique

Results and Discussion:

Preparation of Dataset

For this research project, different research papers were consulted which focused on the development of ceramic tiles with the incorporation of industrial wastes and coal ashes and those articles were shortlisted which contained the data about the mix design ratios and the flexure strength. Hence the data was gathered from 13 most relevant journal articles, and the dataset was constituted. The dataset consisted of seven input variables and the flexure strength FS was regarded as the output variable. The input variables included the percentage content of Feldspar (F), Silica (S), Plastic Clay (C), Clay Minerals (CM), Ceramic production Waste (CW), Industrial Waste (IW), and coal Bottom Ash (BA) in the mix design of the ceramic tiles formulation. The descriptive statistics of the dataset is presented in Table 1.

Table 1: Descriptive Statistics of the Dataset

Variable	Mean	Median	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range
F	19.42	14.00	14.54	211.40	-0.91	0.56	50.00
S	14.24	9.03	14.08	198.20	2.06	1.73	55.00
C	48.87	55.80	20.43	417.33	1.81	-1.34	100.00
CM	9.31	7.33	11.33	128.44	0.74	1.25	41.00
CW	2.36	0.00	4.94	24.43	3.88	2.15	20.00
IW	3.92	0.00	6.05	36.57	1.17	1.48	20.00
BA	0.78	0.00	1.86	3.46	8.06	2.72	10.00
FS	31.51	28.20	20.27	410.87	3.35	1.74	92.00

Data Pre-Processing

As outlined in the methodology section, this step focused on preparing the dataset for machine learning. The process involved tasks such as filling blank columns, deleting empty rows, and removing duplicate data points. Additionally, the dataset was normalized to a range of **-1** to **+1** for data modelling using the normalization function described in Eq. (1).

Correlation Plot

In this step, the correlation coefficients for the entire dataset were calculated and plotted in the form of a heat map, using Origin Pro 2024b software. This visualization is an important tool to present the relationship between different variables present in the dataset. It is to be noted that the presence of positive correlations depict direct relationship between two variables and the negative coefficients depict inverse relationship. The correlation coefficient value of 1 represents that the variables are statistically independent of each other. For developing ML models, it is recommended that the dataset should contain correlation coefficients values lesser than 0.5, so that no issue of multi-collinearity arises. However, for the undertaken research, this phenomenon is unlikely to occur as the variables are independent to each other in the mixture design of ceramic tiles formulation [28].

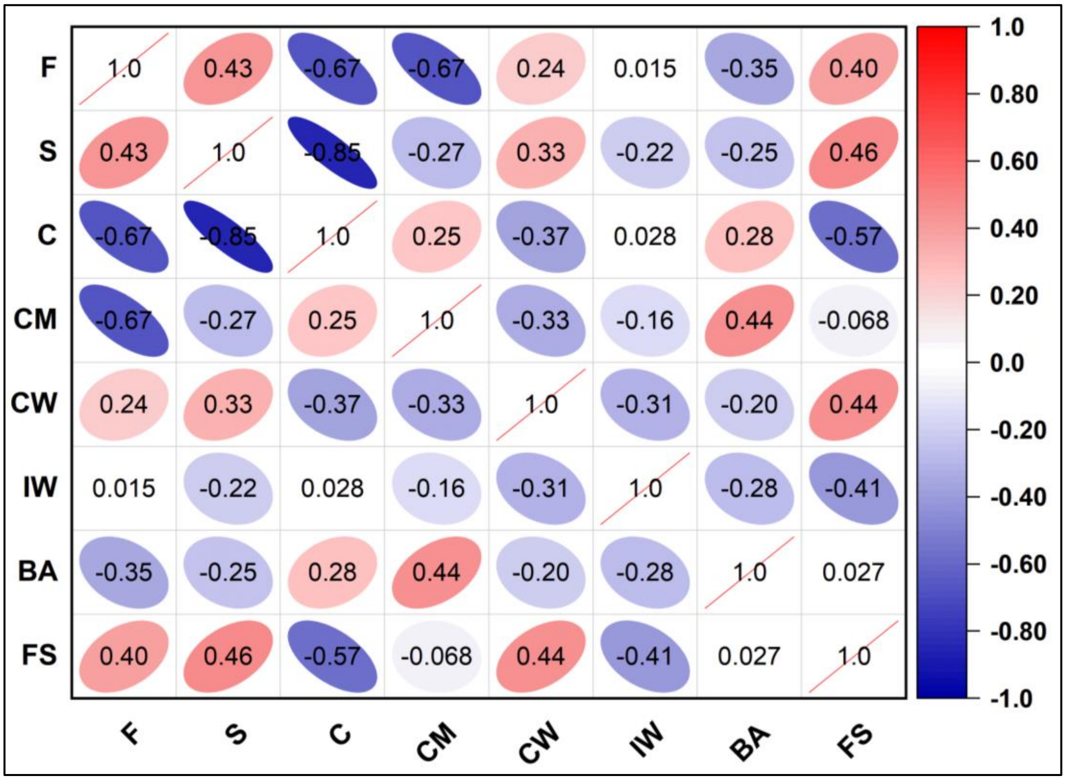


Figure 3: Correlation Plot of the Dataset

Development of Machine Learning Models

In this step, three machine learning models were developed and trained using the previously prepared dataset. These models include Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and Extreme Gradient Boosting (XGB). The specific details of each model are given below.

(a) Artificial Neural Network (ANN)

The ANN model was developed using MATLAB R2021a software, with the NNTOOL command executed for implementation. The model utilized a feedforward-backward propagation technique and consisted of three computational layers: Input, Hidden, and Output. The hidden layer included 8 neurons, with the transfer functions PURELIN and TAN-SIGMOID selected for the output and hidden layers, respectively [29]. These functions are particularly useful for deriving predictive equations. The dataset was split into three subsets: 70% for training, 15% for validation, and 15% for testing. The Levenberg-Marquardt (LM) algorithm was used for training due to its ability to converge quickly, making it one of the most commonly used algorithms for neural network training [21].

The schematic presentation of the developed neural network regression model is given in Fig 4, and the best performance plot of the neural network is shown in Fig 5. During the computation process consisted of 6 epochs, while the best performance was achieved at epoch 0 with normalized mean square error value of 0.0079414. The regression plots developed by the neural network model are presented in Fig 6, which depict that the determination coefficients for all the three subsets, and the overall dataset is found to be above 0.95, hence fulfilling the criteria of local industry and validating the performance of the developed model.

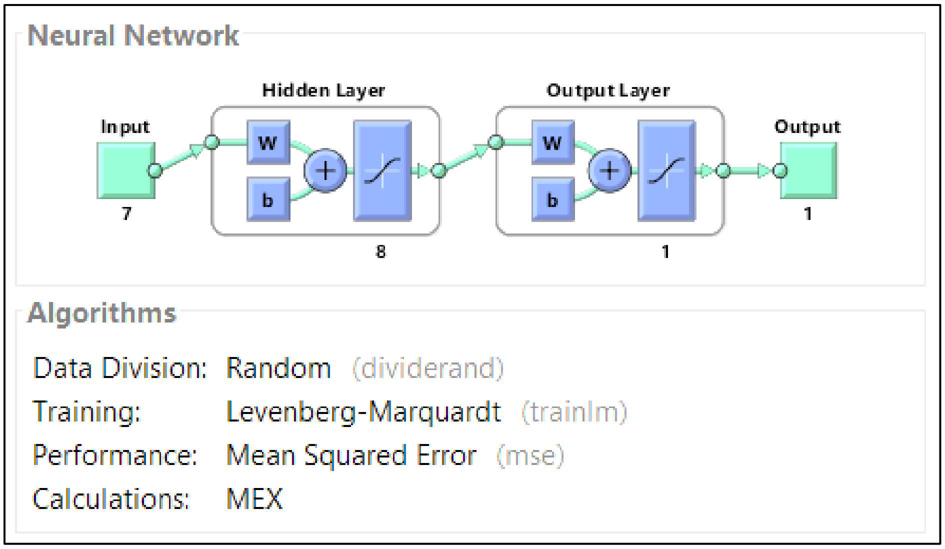


Figure 4: Schematic Diagram of the Developed ANN Model

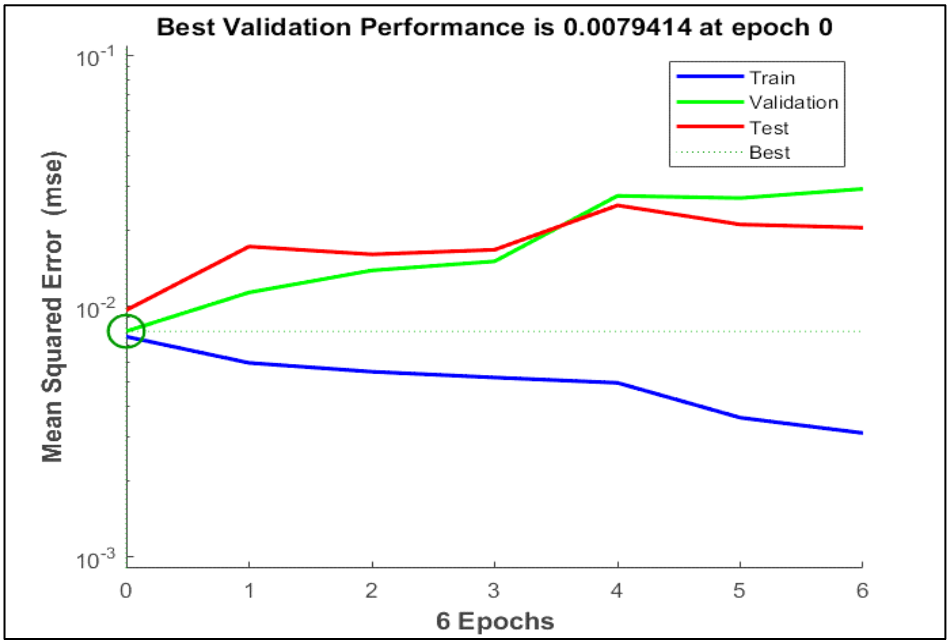


Figure 5: Performance Plot of the Developed ANN Model

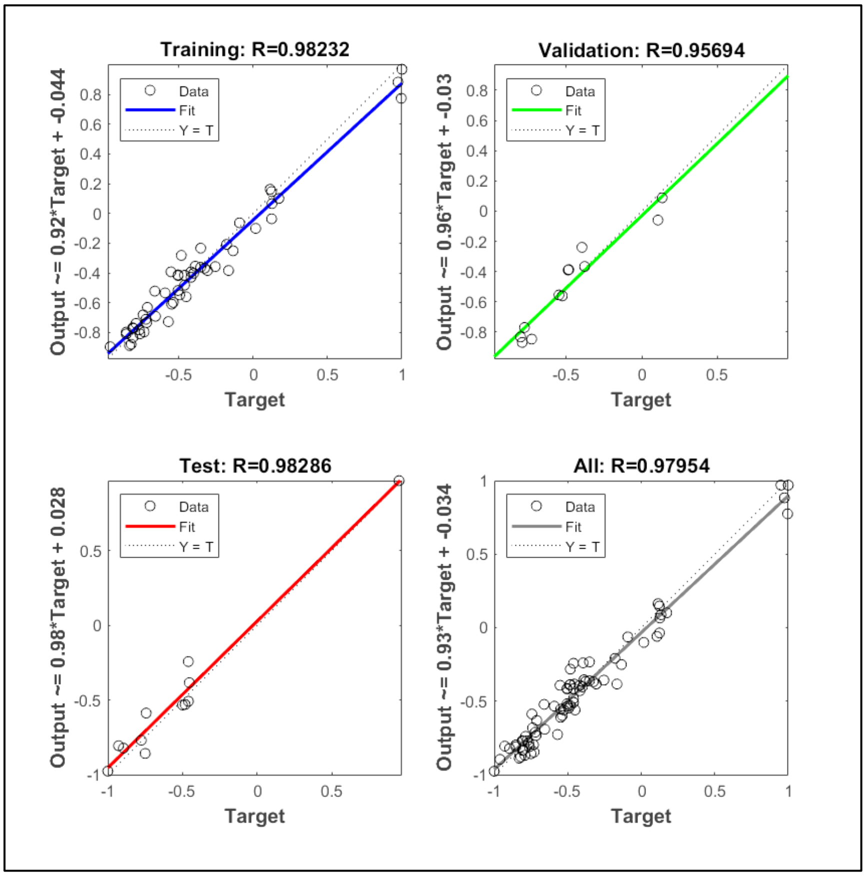


Figure 6: Regression Plots for the Developed ANN Model

(b) Extreme Gradient Boosting (XGB) and K-Nearest Neighbors (KNN)

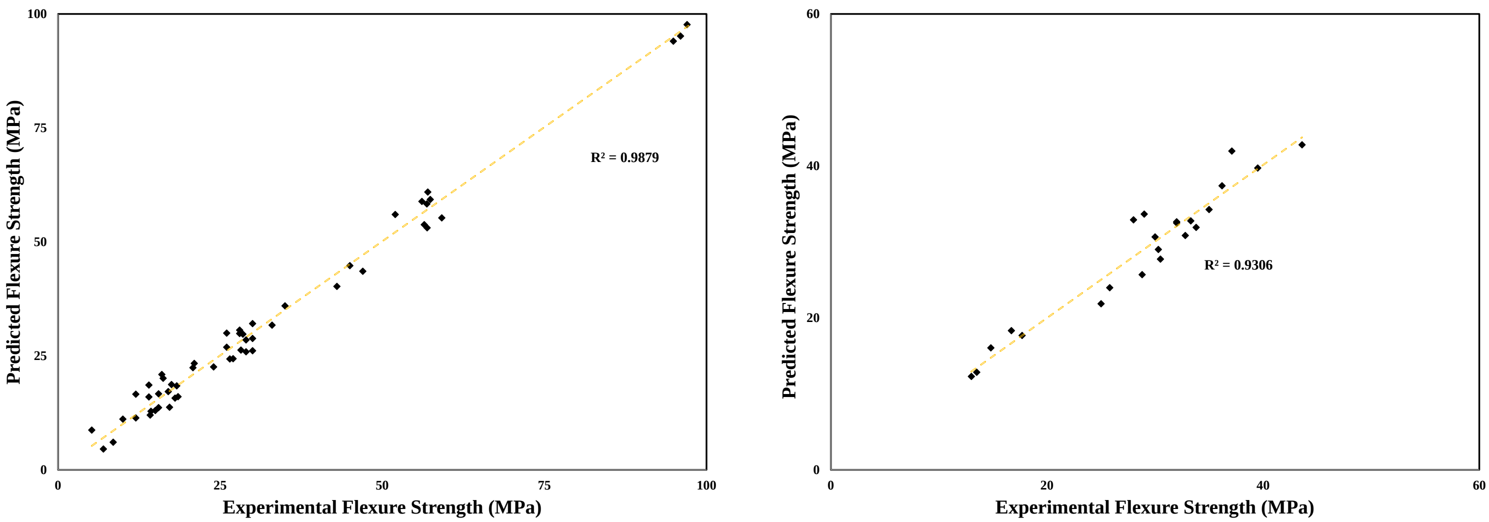
For developing the XGB and KNN models, Python coding was done in Google Colab virtual environment and the necessary libraries of Python were used for machine learning. The dataset was divided into two sub-sets, i.e. 80% for training of models and 20% for testing. Table 2 lists the training parameters of XGB and KNN model, respectively, while the performance matrix, i.e., R^2, MAE and RMSE, values of the machine learning models are given in Table 3. The experimental values versus the predicted values plots for the developed machine earning models are presented in Fig 7 and 8.

Table 2: Training Parameters for XGB and KNN Model

Model	Training Parameter	Value
XGB	Booster	gbtree
	Eta (learning rate)	0.4
	Number of boosting	450
	Lambda	1.0
KNN	K neighbors	5
	Weights	Uniform

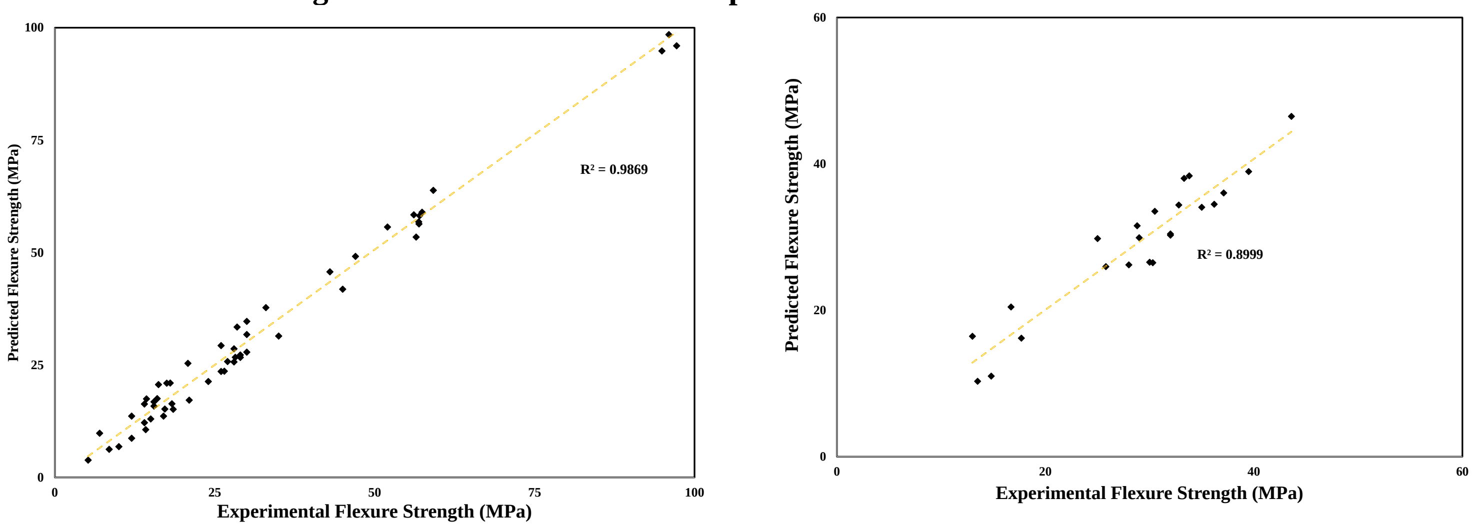
Table 3: Performance parameters for XGB and KNN model

Model	R^2		MAE		RMSE	
	Training Data	**Test Data**	**Training Data**	**Test Data**	**Training Data**	**Test Data**
XGB	0.9879	0.9306	-0.1144	-0.0418	0.8404	0.2166
KNN	0.9869	0.8999	-0.2296	-0.3251	1.6861	1.5588



(a) Training Data **(b) Test Data**

Figure 7: Plot of Predicted vs Experimental values for XGB Model



(a) Training Data **(b) Test Data**

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

K-Fold Cross Validation:

Due to the higher maximum value of coefficient of determination R^2 exhibited by the ANN among all the machine learning models, ANN model was chosen for performing the K-Fold Cross Validation analysis.

For this technique, the dataset was divided into 5 folds, as presented in the schematic diagram, Fig. 2. Further, 5 number of reiterations were performed for the dataset and the R2 value was noted for each iteration. The R^2 values for each of the iteration performed are given in Table 4. The analysis result revealed that the overall R^2 value for the overall dataset comes out to be 0.9537, hence fulfilling the criteria of the local industry and authenticates the performance of the developed ANN model for practical usage.

Table 4: Values of K-Fold Cross Validation Analysis

K-Folds	K=1	K=2	K=3	K=4	K=5
R^2	0.9345	0.9519	0.9377	0.9786	0.9657

Conclusions:

In this research project, the flexure strength of the ceramic tiles manufactured by the incorporation of industrial wastes and coal bottom ash in the mixture design was predicted by developing three machine learning models and their performance comparison was carried out. The dataset included findings from 13 journal articles. The main conclusion drawn from this study are as follows:

- **a)** The Artificial Neural Network model showed higher value of R^2 as compared to other machine learning models, i.e., K-Nearest Neighbors and Extreme Gradient Boosting. The R2 value for the overall dataset was found to be 0.9795 in case of neural network model.
- **b)** Extreme Gradient Boosting model exhibited enhanced performance as compared to K-Nearest Neighbors model, in terms of mean absolute error and root mean square error. The MAE and RMSE values for XGB models were found to be -0.1144 and 0.8404, respectively for training data, while -0.0418 and 0.2166, respectively for the test data.
- **c)** The K-Fold Cross Validation analysis results consolidated the findings reported in 1st conclusion. The average R2 value for the overall dataset obtained by performing this analysis technique was found to be 0.9537, hence authenticating the effective performance of the developed ANN model.

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