

## **PREDICTION OF COMPRESSIVE STRENGTH OF INCINERATED SEWAGE SLUDGE ASH INCORPORATED CONCRETE THROUGH MACHINE LEARNING MODELS**

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### **ABSTRACT**

The recently inaugurated Dasherbandi Sewage Treatment Plant, the largest wastewater treatment facility in South Asia, produces approximately 45 metric tons of incinerated sewage sludge ash (ISSA) daily through rotary kiln incineration, offering a sustainable pathway for reducing the carbon footprint of concrete production. However, the highly variable chemical composition of ISSA presents significant challenges for its reliable implementation in concrete. Since the experimental work required for assessing the effects of incorporating ISSA in concrete is both time-consuming and resource-intensive, machine learning (ML) models can be used to successfully predict its mechanical properties. This study compiles a dataset of 285 concrete samples sourced from both peer-reviewed literature and controlled experiments to evaluate the predictive performance of five distinct ML models: Multiple Linear Regression, Polynomial Regression, k-Nearest Neighbors (kNN), Decision Tree (DT), and Random Forest (RF). The input parameters include, but are not limited to, sample age, replacement ratio, quantities of cement and aggregate, oxide composition, superplasticizer and water to cement (w/c) ratio. After preprocessing, the performance of the developed models was estimated using statistical metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination ( $R^2$ ). The findings revealed that the RF model achieves superior accuracy with  $R^2$  value of 0.9013 with minimal RMSE of 4.22 MPa and MAE of 2.46 MPa, outperforming DT ( $R^2 = 0.8424$ ) and Multiple Non Linear Regression ( $R^2 = 0.8312$ ). Sensitivity analysis of the input features also reveal that ISSA and its oxide composition have minor influence over the compressive strength of concrete due to low rates of replacement in practice. The results of this study demonstrates the feasibility of low cost, nondestructive tests combined with ML algorithms for accurate strength prediction of ISSA concrete, supporting its effective integration into eco-friendly construction practices in Bangladesh.

**Keywords:** *Incinerated Sewage Sludge Ash; Sustainability; Machine Learning; k-Nearest Neighbors; Random Forests*

## **1. INTRODUCTION**

Concrete ranks among one of the most extensively used construction materials worldwide due to the widespread availability of its raw components, ease of handling and processing, and its unique capability to transform from a fluid mixture that fills moulds into a solid material capable of bearing structural loads. Conventional concrete production accounts for more than 8% of the total carbon emissions worldwide primarily due to the energy intensive cement sector (Kajaste & Hurme, 2016). To align with the growing emphasis on global decarbonization goals, primary constituents of concrete, cement can be partially replaced with Supplementary Cementitious Materials (SCMs) that minimize cement consumption by incorporating recycled or waste materials into concrete. These are waste or byproducts of different industries that often causes various types of pollution if not discarded or recycled properly.

Among these SCMs, Incinerated Sewage Sludge Ash (ISSA) has recently emerged as a promising eco-friendly material. It is the mineral-rich byproduct generated from the incineration of residual biosolids produced during the municipal wastewater or sewage treatment plant. The physiochemical characteristics, composition, and production technology of ISSA facilitate its use as both partial replacement of cement (Tantawy et al., 2012), cement admixtures (Donatello & Cheeseman, 2013; Ing et al., 2016) and as aggregate replacement (Lynn et al., 2015). Experimental studies conducted on the effect of ISSA on the properties of concrete report higher or similar compressive strength at low replacement levels (5-10%) both as cement and sand alternative (Cyr et al., 2007; Fontes et al., 2004; Ozturk et al., 2020). Moreover, the early strength development and porous nature of ISSA incorporated concrete (IIC) provide unique opportunities for sustainable construction practices (Yusuf et al., 2012).

In the context of Bangladesh, the Dasherbandi Sewage Treatment Plant presents a promising avenue for sustainability by producing more than 45 tons of ISSA every day (Noshin, 2025). However, significant spatial and temporal variability of the properties of ISSA poses considerable difficulties for its large-scale utilization in the construction sector. Moreover, determination of the optimal rate of replacement requires lab experiments, which are not only labor intensive and time consuming but also destructive.

To address this challenge, this study employs a number of machine learning (ML) models to predict the compressive strength of IIC. Over the past decade, ML based predictive models such as decision tree (DT), random forest (RF), and artificial neural network (ANN) have been used to forecast the compressive strength of concretes with high accuracy (Han et al., 2022). But IIC remains underrepresented in current datasets and ML studies despite having high potential. This study aims to address this knowledge gap by predicting different properties of IIC using ML algorithms and to identify the most suitable ML algorithm for reliable prediction. Using a dataset compiled from extensive literature review, five parametric and non-parametric ML models were selected for this study. The performance of the ML models is evaluated based on statistical parameters to determine the best algorithm to accurately predict the compressive strength of IIC based on its constituents.

## **2. DATA COLLECTION**

The dataset used for this research was collected through a vast literature review on established studies available on ISSA incorporated concrete. In all 285 concrete samples were used to train and evaluate the ML models. (Chang et al., 2010; David & Krishnamoorthy, 2022; Fontes et al., 2016; Halliday et al., 2012; A. Jamshidi et al., 2013; M. Jamshidi et al., 2012; Khanbilvardi & Afshari, 1995; Kosior-Kazberuk, 2011; Lima et al., 2015; Rutkowska et al., 2018, 2020; Sasaoka et al., 2006; Shanti et al., 2021; Sukanya et al., 2019).

Each record in the compiled dataset consists of eight variables [sample age (days), cement (kg.m<sup>-3</sup>), ISSA (kg.m<sup>-3</sup>), water (kg.m<sup>-3</sup>), super-plasticizer (kg.m<sup>-3</sup>), fine aggregate (kg.m<sup>-3</sup>), coarse aggregate (kg.m<sup>-3</sup>) and SiO<sub>2</sub> (%)] which have been taken as input features for the prediction of compressive strength,  $f_c$  (MPa). Table 1 illustrates the statistical description of the data set extracted using Excel software. As depicted, a wide variety of compositional mixtures and replacement methods were tested in this study. Table 2 summarizes the correlation between different variables of the collected data.

Table 1: Statistical Description of Data Set

Parameters	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
Input Parameters						
Sample Age (days)	43.59	55.26	18.33	3.75	2	365
Cement (kg.m <sup>-3</sup> )	312.21	62.03	1	0.41	175	537.87
ISSA (kg.m <sup>-3</sup> )	68.01	83.68	41.18	5.83	0	730
Water (kg.m <sup>-3</sup> )	165	23.35	0.66	0.17	109	234.6
Super Plasticizer (kg.m <sup>-3</sup> )	1.29	1.89	2.44	1.51	0	10
Fine Aggregate (kg.m <sup>-3</sup> )	727.31	161.14	2.76	-0.67	0	1034
Coarse Aggregate (kg.m <sup>-3</sup> )	1070.42	185.09	-1.54	-0.16	699	1320
SiO <sub>2</sub> (%)	34.63	12.27	-1.22	0.56	17.8	54.55
Output Parameters						
Compressive Strength (MPa)	33.15	12.62	-0.54	0.11	7.9	70

Table 2: Correlation Matrix

Variable	Age	Cement	ISSA	Water	Plasticizer	FA	CA	SiO <sub>2</sub>	$f_c$
Age	1								
Cement	-0.0769	1							
ISSA	0.1329	-0.1399	1						
Water	-0.052	0.6406	-0.0082	1					
Plasticizer	-0.1304	0.5705	-0.1767	0.328	1				
FA	-0.1756	0.1919	-0.568	0.1025	0.5592	1			
CA	0.1296	-0.4237	-0.1436	-0.3338	-0.7136	-0.6481	1		
SiO <sub>2</sub>	-0.1032	0.3836	-0.0374	0.3621	0.6936	0.4443	-0.6723	1	
$f_c$	0.4037	0.2212	-0.1995	-0.1181	0.1123	-0.0077	0.1544	-0.0327	1

The correlation matrix confirms the general relationships between concrete compressive strength and its different constituents. Parameters such as age, cement and coarse aggregates tend to enhance  $f_c$ , whereas water and ISSA exhibits an adverse impact on the final  $f_c$  with negative correlation coefficients, echoing literature findings.

In order to prevent the possibility of bias due to substantial variance in different variables depicted in Table 1, the input features used in the dataset are normalized against their maximum values. The initial dataset was a randomly separated into a training set (80%), used for parameter tuning and a testing set (20%) were used to evaluate the predictive capability of the models.

### 3. METHODOLOGY

#### 3.1 Machine Learning Models

Five ensemble and nonensemble ML approaches were employed with Python scripting using Spyder (Version 6.0.7) for the prediction of compressive strength of IIC. The methods include: multiple linear regression (MLR), multiple nonlinear regression (MNLr), k-nearest neighbor (kNN), decision tree (DT) and random forest (RF). The following subsections describe the key characteristics of each.

##### 3.1.1 Multiple Linear Regression Model

A multiple linear regression model illustrates the relationship between dependent variable (response), denoted as  $y$ , and two or more independent variables (input parameters) by fitting a plane to an  $n$  – dimensional space using least square residuals method, where  $n$  is the number of independent variables.

$$Y = \beta_0 + \sum_{i=1}^n \beta_i X_i + \varepsilon \quad (1)$$

where  $Y$  is the actual concrete compressive strength,  $\beta_0$  is a constant,  $\beta_i$  is a regression coefficient where  $i=1, 2, \dots, n$ , and  $\varepsilon$  is an error term. The  $X_i$  terms refer to the input parameters.

##### 3.1.2 Multiple Nonlinear Regression Model

According to previous research, the relation between input features and the compressive strength of concrete is complex and nonlinear (Cook et al., 2019). Hence, in order to increase the prediction accuracy, polynomial features can be adopted with different polynomial degrees. In this study polynomial of degree 2 is implemented, the equation for which is expressed below.

$$Y = \beta_0 + \sum_{i=1}^n \beta_{i1} X_i + \sum_{j=1}^n \beta_{j2} X_i^2 + \varepsilon \quad (2)$$

where  $Y$  is the actual concrete compressive strength,  $\beta_0$  is a constant,  $\beta_i$  and  $\beta_j$  are regression coefficients for linear and quadratic terms where  $i, j=1, 2, \dots, n$ , and  $\varepsilon$  is an error term. The  $X_i$  terms refer to the input parameters.

##### 3.1.3 k-Nearest Neighbors

The k-nearest neighbors model, also known as ‘lazy algorithm’ (Asteris et al., 2021), is a non-parametric ML model that attempts to determine the value of other observations on the basis of distance functions, namely: Euclidean, Minkowski and Manhattan distances. Firstly, the algorithm calculates  $k$  neighbors’ Euclidean distances. Then, among  $k$  neighbors, each category’s data points are counted, and new data points are assigned with the most neighbors (Altman, 1992).

$$\text{Euclidean Distance, } d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (3)$$

where  $x_i$  and  $y_i$  are values of  $i$ th feature for points  $x$  and  $y$  and  $n$  is the data dimension.

##### 3.1.4 Decision Tree

The Decision Tree model splits the data into smaller subsets in the form of a tree structure where internal nodes represent decision rules. There are three types of nodes: (i) root node (RN) (ii) decision node (DN) and (iii) leaf node (LN). Using the Iterative Dichotomiser 3 (ID3) algorithm, the dataset is split into several branches based on feature conditions by measuring entropy, which is a measure of data impurity. Entropy is defined as:

$$\text{Entropy}(S) = - \sum_{i=1}^n P_i \log_2(P_i) \quad (4)$$

Where  $P_i$  is the probability of samples belonging to class  $i$ , and  $n$  is the number of possibilities.

At each DN, further branches are formed by selecting features that maximize information gain, defined as the reduction of entropy between successive nodes. This recursive partitioning process continues until all data are classified, forming LNs, that is the regression value which in this case is compressive strength.

### 3.1.5 Random Forest

Random forest (RF) is an ensemble learning algorithm that integrates multiple classification and decision tree (CART) models and aggregates their outputs to produce accurate predictions, mitigating the high variance inherent in individual trees. Each tree is built using a randomly selected subset of training set, splits at each node are determined from a randomly chosen subset of input variables and designates the prediction with most votes as the final output (Chopra et al., 2018).

## 3.2 Performance Metrics

In this study, the prediction performance for the ML models was evaluated based on three widely used statistical parameters: coefficient of determination ( $R^2$ ), root mean squared error (RMSE) and mean absolute error (MAE). The mathematical formulations to estimate these parameters are shown in Eqn. (5) to (7)

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_{exp,i} - Y_{pre,i})^2}{\sum_{i=1}^n (Y_{exp,i} - \bar{Y}_{eav})^2} \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_{exp,i} - Y_{pre,i})^2} \quad (6)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_{exp,i} - Y_{pre,i}| \quad (7)$$

In each equation mentioned above,  $Y_{exp}$  and  $Y_{pre}$  represent the experimental and predicted values respectively.  $\bar{Y}_{eav}$  is the averaged experiment value. The value of  $n$  is the total number of observations.

## 4. RESULTS AND DISCUSSION

### 4.1 Result Analysis

After hyperparameter tuning of the specified ML models to predict the compressive strength of IIC, the obtained results were compared based on the performance metrics. Table 3 summarizes the performance matrices of the results from the training and validation dataset.

Table 3: Performance evaluation parameters of applied models using training and testing data sets

Model	Results of Training Set			Results of Testing Set		
	R <sup>2</sup>	RMSE	MAE	R <sup>2</sup>	RMSE	MAE
Multiple Linear Regression	0.4185	8.9767	7.3568	0.4444	10.0141	8.0683
Multiple Nonlinear Regression	0.9081	3.568	2.7358	0.8312	5.5191	4.0282
k-Nearest Neighbor	0.8661	4.6826	3.5074	0.7759	5.5773	4.3269
Decision Tree	1	0	0	0.8424	5.3336	2.8705
Random Forest	0.9861	1.3862	0.9182	0.9013	4.2201	2.4556

The results of the performance evaluation concludes that RF model has superior capability to accurately predict the compressive strength of IIC compared to the other applied models. It achieved the best correlation between the predicted and actual values, achieving an  $R^2$  of 0.9013 followed by DT ( $R^2 =$

0.8424), MNLR ( $R^2 = 0.8312$ ), kNN ( $R^2 = 0.7759$ ). MLR is the least performing model in the study, with the lowest  $R^2$  (0.4444) and highest errors (MAE = 8.0683, RMSE = 10.0141). These findings confirm the nonlinear and complex relationship between compressive strength and concrete constituents, which is verified by the considerably lower RMSE and MAE value obtained from models incorporating nonlinearity such as MNLR (MAE = 4.0282, RMSE = 5.5191) and kNN (MAE = 4.3269, RMSE = 5.5773).

Among all the algorithms, tree-based algorithms show the most promising results. DT model attains perfect fit (RMSE = 0) in the training phase, signifying an extreme case of overfitting. It has failed to generalize the inherent relationships. This problem is effectively mitigated in the RF approach by combining multiple trees. Figure 1 depicts the graphical representation of the obtained results from each model.

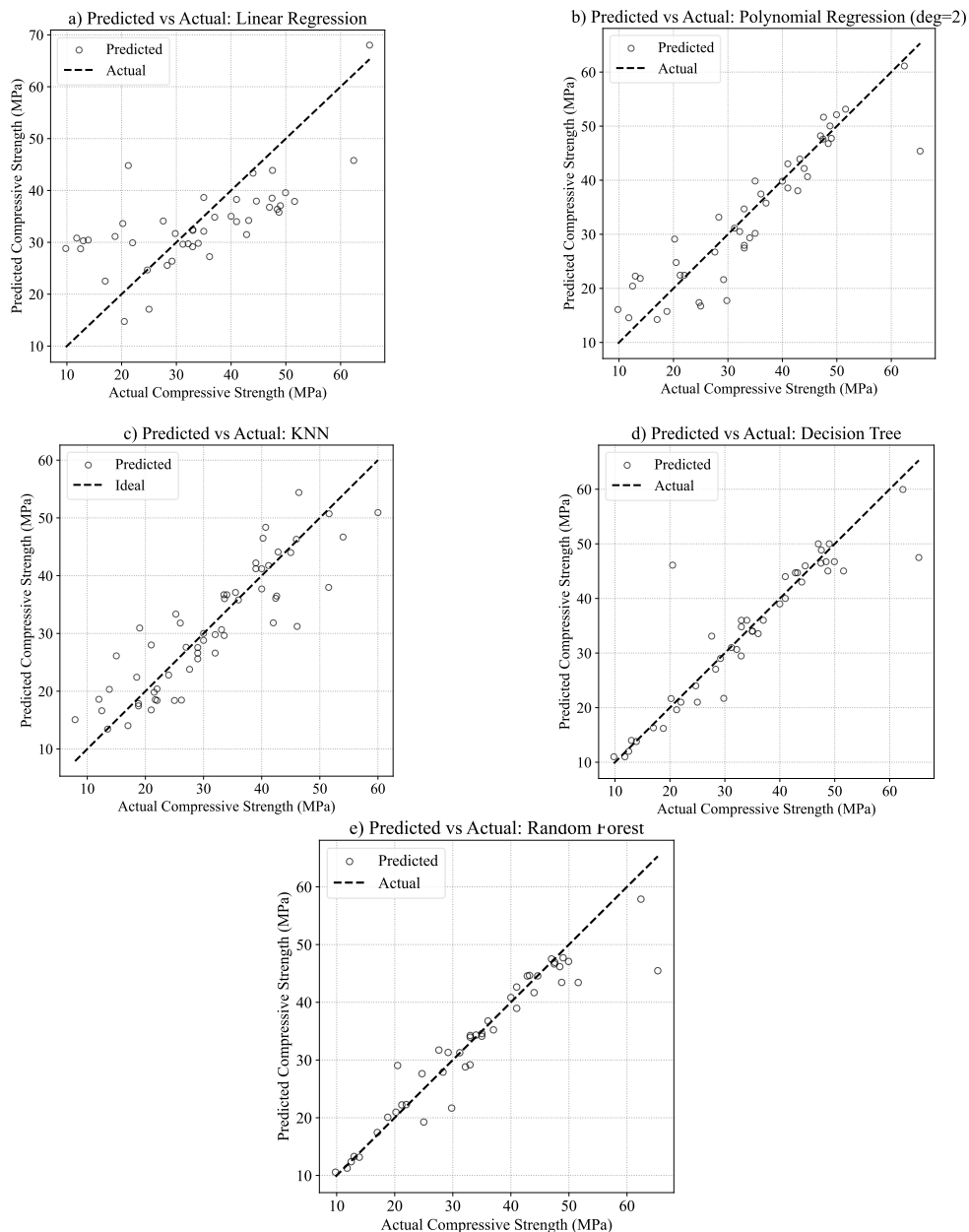


Figure 1: Relationship among predicted and actual compressive strength of (a) MLR; (b) MNLR; (c) kNN; (d) DT; (e) RF

## 4.2 Sensitivity Analysis

The relative importance of each input variables on the output results should be analyzed in order to fully understand how individual components of the concrete mix affect the compressive strength of IIC. This allows the selection of suitable factors to improve analytical accuracy and efficiency of the ML models. Sensitivity analysis (SA) is carried out mathematically by using the following equations:

$$N_i = f_{max}(x_i) - f_{min}(x_i) \quad (8)$$

$$SA = \frac{N_i}{\sum_{j=1}^n N_j} \quad (9)$$

where  $f_{max}(x_i)$  and  $f_{min}(x_i)$  is the maximum and minimum outputs of the predictive model respectively. As illustrated in Figure 2, age and cement are the most influencing parameters, whereas percentage of silica and ISSA were the least affecting the compressive strength of concrete. It reflects the delayed strength development of IIC, as well as the diverse oxide composition of ISSA found in literature. The rank of order of importance was discovered to be age (28.04%) > cement (21.05%) > water (17.83%) > coarse aggregate (17.16%) > fine aggregate (9.26%) > plasticizer (4.82%) > ISSA (3.64%) > SiO<sub>2</sub> (2.2%). Further investigation is required to validate these findings.

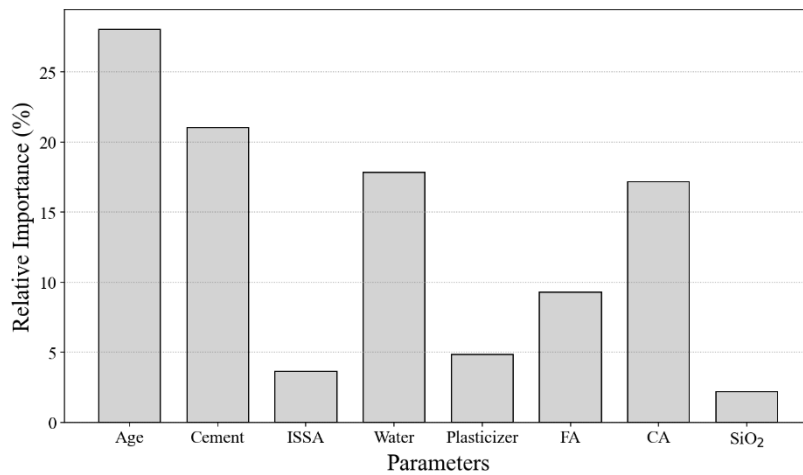


Figure 2: Contribution of input features to output

## 5. CONCLUSIONS

In this study, a comprehensive analysis of 285 data sets on the compressive strength of ISSA incorporated concrete was collected by conducting a structured literature review, which was used to train five machine learning (ML) algorithms: multiple linear regression (MLR), multiple nonlinear regression (MNLr), k-nearest neighbors (kNN), decision tree (DT) and random forest (RF). The findings suggest the following conclusions:

- The ensemble ML approaches were more accurate at prediction compared the other models, as evidence by their higher R<sup>2</sup> scores and lower errors (RMSE and MAE). The results of all models except MLR were in the acceptable range.
- RF outperforms all other models in terms of predictive capability, attaining the maximum coefficient of determination (R<sup>2</sup>) of 0.90 and the lowest RMSE value of 4.22 MPa and MAE of 2.46 MPa, while MLR is the least performing method with R<sup>2</sup> score of 0.44 and RMSE of 10.01 MPa and MAE of 8.07 MPa. Corresponding values of R<sup>2</sup> for DT, MNLr, and kNN models was noted to be 0.84, 0.83 and 0.78 respectively.
- Sensitivity analysis of the input parameter reveal that age of the concrete is the most influential feature in predicting  $f_c$ , followed by cement and water, with relative importance values of

0.2804, 0.2105 and 0.1783 respectively. On the other hand, ISSA, plasticizers and silica were observed to have comparatively lower information gain, indicating their lesser impact on  $f_c$ .

- The proposed models can form the framework for successfully implementing ISSA incorporated concrete in different structure.

It is recommended that other advanced ML techniques such as ANN and MSP trees be employed to compare their results for the prediction of outcomes. Moreover, data points and the number of outcomes should be expanded through lab work and field tests while maintaining consistency in experimental design and properties of ISSA in future studies. The input parameters could be enhanced by including factors such as: climatic features, temperature and method of incineration and gradation of ISSA along with in-depth characteristics of the raw materials (e.g., strength of cement and gradation of aggregates) to ensure better response from the models.

## DECLARATION OF USE OF AI

The authors acknowledge the use of artificial intelligence tools (e.g., ChatGPT, deepseek) to assist with grammatical correction and language polishing during the preparation of this manuscript. The study design, data collection, data analysis and interpreted conclusions were not influenced by the aforementioned AI tool. The authors retain full responsibility for the originality and integrity of the work.

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