IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

Prediction of Concrete Compressive Strength by Machine Learning

Dr. Adanagouda[1], Naveen Kumar S[2], Poornachandra Prakash[3], Prema Kumari[4], Vaishnavi MM[5]
Associate Professor, Department of Civil Engineering [1]
Students, Department of Civil Engineering[2,3,4,5]
Rao Bahadur Y. Mahabaleswarappa Engineering College, Ballari, India

Abstract: *This Project report investigates the application of "PREDICTION OF CONCRETE COMPRESSIVE STRENGTH BY MACHINE LEARNING" . The advanced techniques and its applications on other engineering disciplines accelearated the different aspects and phase in engineering process. Nowadays there are so many computer aided methods widely used in civil engineering domains. The mathematical relationship between ratios of different concrete components and other influencing factors with its compression strength need to be analyzed for different engineering needs. This paper aims to develop a mathematical relationship after analyzing the above factors and to foresee the compressive strength of concrete by applying various regression techniques such as linear regression, support vector regression, decision tree regression and random forest regression on assumed data set., It was found that the accuracy of the random forest regression was considerable as per the result after applying the various regression techniques*

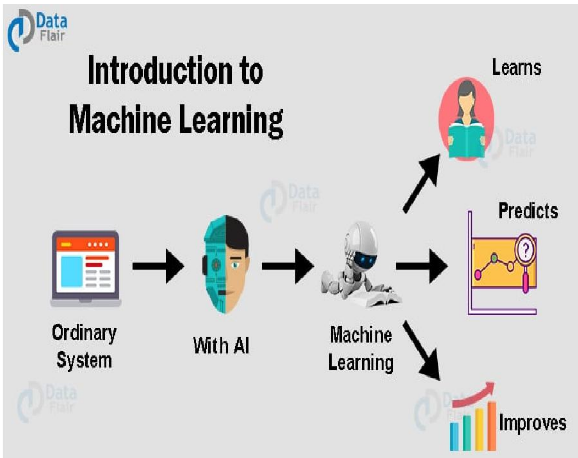
Keywords: Compressive Strength, Tree Based Method, K-Neural Network

I. INTRODUCTION

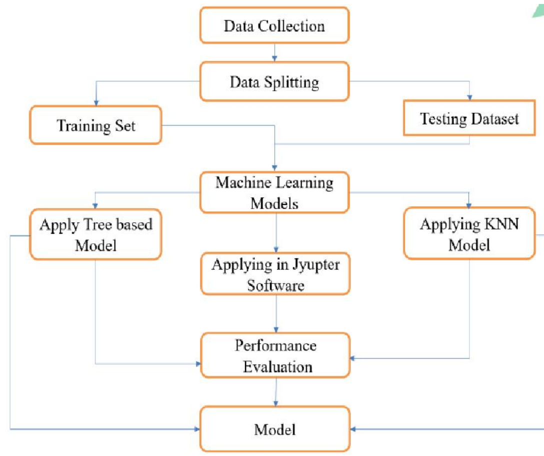
In the fields of Science, Engineering, Health sector, the information technology provides a means for access to a broad variety of methods of modeling complex systems. These methods can be applicable in the field of civil engineering especially in construction strategies. Concrete is the mixture of Cement(c), Blast Furnace Slag, Water, Super Plasticizer, Coarse and Fine Aggregate, which is widely used construction material which is used in every kind of structures mainly in buildings. The procedure of determining the proportion of appropriate ingredients for producing concrete of required strength, workability, and durability is termed as mix design. The compressive strength of concrete is one of the widely used performance measure by the engineer in designing buildings. This study primarily focuses on finding the compressive strength of concrete-One of the limitations with the current Mix Design methodology is, it provides mechanism to find out mix ratio for a given strength values but the reverse is not possible. That is for a given proportion there is no mathematical model which defines relationship between this mix components and resultant compressive strength value. So, this can be done only through physical experiments. This study primarily focused on filling this gap. This paper focuses on developing a prediction model by using machine learning techniques for predicting the compressive strength of concrete, if we are given with the mix ratio. For building this prediction model, a publically available compression strength dataset is utilized. This study also proposes a simple mathematical relationship between the coefficient (strength at infinite time) with the strength values of concrete of a particular day. The developed mathematical model is validated for commonly used concrete data. The reliable prediction of concrete strength at different days (7, 14, 28 days etc.) found excellent after the analysing the data set.

Machine Learning: Machine learning is a subfield of artificial intelligence that allows computer systems to learn from data and improve performance over time without being explicitly programmed for every task. It works by training algorithms on large datasets to identify patterns, which then enables the system to make predictions or decisions on new, unseen data. Common applications include recommendation systems, image and speech recognition, and fraud detection.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67



Machine Learning



Flow Chat

II. LITERATURE SURVEY

A brief review of literature on partial replacement of cement with fly ash, properties of partial replacement of cement with different pozzolanic materials on the concrete, strength and durability aspects are reported and discussed. Literature review on treatment methods and the mechanical properties of the concrete is also presented.

Ilker Bekir Topcu and M.Saridmir : In this paper, a method to predict 28-day compressive strength of concrete by using multi - layer feed - forward neural networks (MFNNs) was proposed based on the inadequacy of present methods dealing with multiple variable and nonlinear problems. A MFNN model was built to implement the complex nonlinear relationship between the inputs (many factors that influence concrete strength) and the output (concrete strength). The neural network (NN) models give high prediction accuracy, and the research results conform to some rules of mix proportion of concrete. These demonstrate that using NNs to predict concrete strength is practical and beneficial. D 2000 Elsevier Science Ltd. All rights reserved**.**

Faezehossadat Khademi, Mahmoud Akbari, Sayed mohammadmehdi Jamal: The aim of this study is prediction of 28-day compressive strength of concrete by data-driven models. Hence, by considering concrete constituents as input variables, two data-driven models namely Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models are constructed for the purpose of predicting the 28-days compressive strength of different concrete mix designs. Comparing the two models illustrates that MLR model is not a suitable model of predicting the compressive strength; however, ANN can be used to efficiently predict the compressive strength of concrete**.**

M. Timur Cihan : Machine learning methods have been successfully applied to many engineering disciplines. Prediction of the concrete compressive strength (fc) and slump (S) is important in terms of the desirability of concrete and its sustainability. The goals of this study were

(i) to determine the most successful normalization technique for the datasets,

(ii) to select the prime regression method to predict the fc and S outputs,

(iii) to obtain the best subset with the Relief feature selection method, and

(iv) to compare the regression results for the original and selected subsets.

Experimental results demonstrate that the decimal scaling and min-max normalization techniques are the most successful methods for predicting the compressive strength and slump outputs, respectively. According to the evaluation metrics, such as the correlation coe8cient, root mean squared error, and mean absolute error, the fuzzy logic method makes better predictions than any other regression method. Moreover, when the input variable was reduced from seven to four by the Relief feature selection method, the predicted accuracy was within the acceptable error rate.

ISSN: 2581-9429 Volume 6, Issue 4, January 2026 Impact Factor: 7.67

P. Muthupriya , K. Subramanian and B.G. Vishnuram : Neural networks have recently been widely used to model some of the human activities in many areas of civil engineering applications. In the present paper, artificial neural networks (ANN) for predicting compressive strength of cubes and durability of concrete containing metakaolin with fly ash and silica fume with fly ash are developed at the age of 3, 7, 28, 56 and 90 days.

Ni Hong-Guang, Wang Ji-Zong: In this paper, a method to predict 28-day compressive strength of concrete by using multi - layer feed - forward neural networks (MFNNs) was proposed based on the inadequacy of present methods dealing with multiple variable and nonlinear problems. A MFNN model was built to implement the complex nonlinear relationship between the inputs (many factors that influence concrete strength) and the output (concrete strength). The neural network (NN) models give high prediction accuracy, and the research results conform to some rules of mix proportion of concrete. These demonstrate that using NNs to predict concrete strength is practical and beneficial. D 2000

Elsevier Science Ltd. All rights reserved.

Objectives

To compare the performance of different regression algorithms.

- To reduce reliance on time-consuming laboratory testing.
- To identify key mix parameters influencing compressive strength.
- To improve prediction accuracy using advanced machine learning techniques.

Optimize mix design: Identify the most cost-effective and sustainable combination of materials (cement, Water, Sand, Aggregates, Fly ash, etc.) by predicting the strength from different mix proportions, leading to optimized material usage and reduced waste.

Improve model reliability and robustness: Utilize cross-validation techniques like k-fold to ensure the models are reliable and generalize well to new, unseen data. The goal is to avoid overfitting and ensure consistent performance.

Enhance understanding through explainability: Use explainable machine learning methods to determine which input variables (e.g., water-to-binder ratio, curing age, type of binder) have the most significant impact on compressive strength.

Maintain consistency and reproducibility: Ensure the results are consistent and can be reproduced by others. This is achieved by using a fixed random state when splitting data into training and testing sets.

Predict long-term performance: Apply Tree Based models and K-Neural Netwok to predict not just immediate strength, but also long-term durability, which is crucial for evaluating the overall performance of concrete structures.

Maximize prediction accuracy: Use advanced models like K-NN Model to accurately predict compressive strength, aiming for high coefficients of determination (R^2) and low error rates (e.g., Mean Absolute Error (MAE), Root Mean Square Error (RMSE)).

III. METHODOLOGY

The purpose of this work is to create a mathematical relationship between the raw materials used to make a concert and its compression strength with the quantity, for describing the concept we introduced a machine learning pipeline.

Regression Pipeline: The machine learning used in this work is shown in figure 5 The pipeline includes the dataset, preprocessing steps and model building.

Dataset: We applied machine learning regression models to predict the concrete compression strength. The different techniques of regression considered in this study are linear regression models, random forest, support vector regression and decision tree regression model. The data set is collected from kaggle for the analysis. In this study the input variables are cement, fly ash, blast furnace slag, water, coarse Aggregate, super plasticizer. age and fine aggregate. The output variable is the concrete compressive strength which is measured in mega pascals.

Preprocessing: The machine learning preprocessing steps were applied to the raw datasets before they could be utilized for the regression method. In preprocessing, the following steps need to be applied. They are feature selection, scaling and data selection. In feature selection, as per the expert opinion from the domain we need to consider only the six components from the dataset by omitting Super plasticizer and fly ash. The ML regression method estimates the output value using only the selected features from the dataset. Next step is scaling in which the component values are scaled to between zero and one by using minmax scaling procedure. Next step is data selection in which age of the cement in days is calculated. Here we consider three days which is 7, 14, and 28. After feature selection curated data is ready for futher processing

Regression Algorithms: The next phase in the pipeline was building the regression model. From the curated dataset 80% is selected as training set and the rest is kept testing set. On the training data the following regressions namely liner regression, support vector regression, decision tree regression and random forest regression are explained in the preliminary section. The model is build based on the type of regressions we applied.

IV. EXPERIMENTAL INVESTIGATION

Experimental investigations in concrete materials involve a variety of tests to evaluate properties like workability, strength, and durability, using different mix designs and materials. Common tests include the slump test for workability, compressive and tensile strength tests, and water absorption tests. These studies often explore the effects of using alternative or waste materials, such as fly ash, silica fume, or recycled aggregates, on the concrete's performance

Common Tests Conducted on Concrete:

- **Slump Test**: Measures the workability of fresh concrete to determine its consistency.
- **Water Absorption Test**: Measures how much water concrete absorbs over a specific period, which can indicate its porosity.
- **Setting Time Test**: Checks the time it takes for concrete to harden, which is crucial for scheduling and project timelines.
- **Compressive Strength Test**: Evaluates the concrete's ability to withstand crushing loads by testing cylindrical or cubic specimens.

Materials Properties

- **Cement:** Initial and Final Setting Time of Cement, Specific Gravity.
- **Fly Ash**: Specific Gravity.
- **Fine Aggregate:** Specific Gravity, Sieve Analysis, Bulk Density, Water Observation.
- **Coarse Aggregate:** Specific Gravity, Sieve Analysis, Bulk Density, Water Observation.

Mix Design

Concrete mix design is the process of selecting and proportioning ingredients like cement, water, aggregates, and admixtures to produce concrete with specific properties, such as desired strength, durability, and workability. The goal is to create an economical mix that meets the performance criteria for a particular project, which involves a series of calculations, laboratory testing, and quality control steps.

V. MIX PROPORTIONING FOR A CONCRETE OF M25 GRADE

STIPULATIONS FOR PROPORTIONING

A) Grade of cement: : M25
B) Type of cement : OPC 43 grade
C) Maximum nominal size of aggregate : 20mm
D) Workability :50 mm (slump)

TEST DATA FOR MATERIALS

Cement used : OPC 43 grade
Specific gravity of cement : 03
Specific gravity of

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 4, January 2026 Impact Factor: 7.67

Coarse aggregate [at saturated surface dry] : 2.73
Fine aggregate [at saturated surface dry] : 2.62
Water absorption
Coarse aggregate : 0.5 percent
Fine aggregate :1.0 percent
Sieve Analysis
1) Coarse aggregate

Aggregate Sieve	Passing in Percentage
20mm to 12.5mm	60 %
10mm to 4.5mm	40 %

2) Fine aggregate : Conforming to grade Zone 2 of Table 9 of IS 383

STEP-1 TARGET STRENGTH FOR MIX PROPORTIONING
Where,
f'ck = target average compressive strength at 28 days,
fck= characteristic compressive strength at 28 days,
S = standard deviation, and
X = factor based on grade of concrete.
From Table 2, standard deviation, S = 4 N/mm^2. From Table 1, X = 5.5. Therefore, target strength using both equations, that is,
F'ck = fck + 1.65 S
= 25+1.65 × 4
= 31.60 N/mm^2
f'ck = fck + 5.5
= 25 + 5.5
= 30.50 N/mm^2
The higher value is to be adopted. Therefore, target strength will be as 31.60 N/mm^2 > 30.50 N/mm^2.

STEP-2 APPROXIMATE AIR CONTENT
From Table 3, the approximate amount of entrapped air to be expected in normal (non-air- entrained) concrete is 1.0 percent for 20 mm nominal maximum size of aggregate.
STEP-3 SELECTION OF WATER-CEMENT RATIO
From Fig. 1, the free water-cement ratio required for the target strength of 32 N/mm^2 is 0.36 for OPC 43 grade curve. (For PPC, the strength corresponding to OPC 43 grade curve is assumed for the trial). This is lower than the maximum value of 0.45 prescribed for 'severe' exposure for reinforced concrete as per Table 5 of IS 456. 0.44< 0.45, hence O.K.
STEP-4 SELECTION OF WATER CONTENT
From Table 4, water content = 160 kg (for 50 mm slump) for 20 mm aggregate. Estimated water content for 50 mm slump
=186+9/100 X 186
=197.16 Kg/m^3

STEP-5 CALCULATION OF CEMENT CONTENT
Water ration= 0.44
Cement = 161/0.44
= 365.90 ≈ 366 Kg/m^3
From Table 5 of IS 456, minimum cement content for 'severe' exposure condition = 320 kg/m^3
=366 Kg/m^3> 320 Kg/m^3, hence, OK.

STEP-6 PROPORTION OF VOLUME OF COARSE AGGREGATE AND FINE AGGREGETE CONTENT

From Table 5, the proportionate volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.44 = 0.7. the present case water-cement ratio is 0.44. Therefore, volume of coarse aggregate is required to be increased to decrease the fine aggregate content. As the water-cement ratio is lower by 0.14, the proportion of volume of coarse, aggregate is increased by 0.028 (at the rate of ∓ 0.01 for every ± 0.05 change in water- cement ratio). Therefore, corrected proportion of volume of coarse aggregate for the water-cement ratio of 0.44 = 0.7 + 0.028 = 0.728.

Volume of fine aggregate content = 1 – 0.72 = 0.28

STEP-7 MIX CALCULATIONS:

The mix calculations per unit volume of concrete shall be as follows:

Total volume = 1 m^3

Volume of entrapped air in wet concrete =0.01 m

$$\text{Volume of cement} = \frac{\text{Mass of cement}}{\text{Specific gravity of cement}} + \frac{1}{1000}$$

= (366/3) + (1/1000)

= 0.122 m^3

$$\text{Volume of water} = \frac{\text{Mass of water}}{\text{Specific gravity of water}} + \frac{1}{1000}$$

= (161/1000) + (1/1000)

= 0.161 m^3

e) Mass of coarse aggregate = Volume of coarse aggregate×Sp gravity CAx1000

= 0.44 x 2.73 x 1000

= 1201.2 ≈ 1202 Kg/m^3

f) Mass of fine aggregate = Volume of course agg × Specific gravity of fine agg x1000

= 0.28 x 2.62 x 1000

= 733.60 ≈ 734 Kg/m^3

STEP-8 MIX PROPORTIONS OF TRAILS

Cement	= 366 Kg/m^3
Water	= 161 Kg/m^3
Fine aggregate	= 734 Kg/m^3
Coarse aggregate	= 1202 Kg/m^3
Free water-cement ratio	= 0.44%

REQUIRED QUANTITY OF CONCRETE

1. Volume of cube	: 0.15 x 0.15 x 0.15	= 0.003375 m^3
2. No of Cubes 6	: 0.003375 x 6	= 0.02025 m^3
3. Required Cement	: 0.02025 x 366	= 7.42 Kg
4. Required Water	: 0.02025 x 161	= 3.26 liters
5. Required Fine aggregate	: 0.02025 x 734	= 14.86 Kg
6. Required coarse aggregate	: 0.02025 x 1202	= 24.34 Kg

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

Specimen Casting and Curing

Mixing of Concrete

Hand mixing is the process of mixing the various materials of concrete manually. Mixing concrete without a mixer is used only for small works. Mixing of materials shall be done on masonry platform or at iron sheet plates.

The hand mixing concrete may be done as detailed below:

Mixing of Concrete

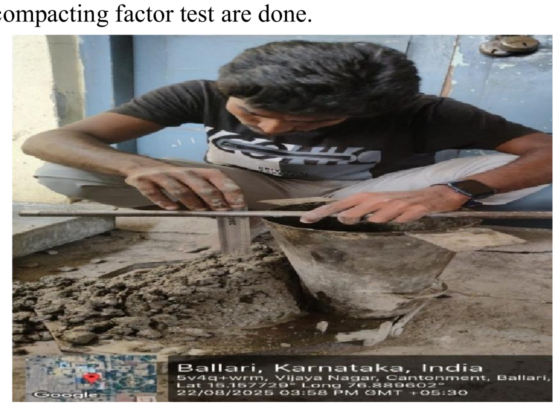
Spread the measured quantity of sand on the platform, and then cement shall be dumped on the sand. The sand and cement shall be mixed thoroughly with the help of shovels in the dry state. The measured amount of coarse aggregate shall be spread out, and the mixture of sand cement spread on it and mixed properly. Depression is made at the centre of the mixed materials. Add 75% of the required quantity of water in the depression and mix with the help of shovels. Add the remaining amount of water and continue the mixing process till a uniform colour and consistency of concrete is obtained. Time of mixing concrete should not exceed 3 minutes. The mixing platform should be washed at the end of the day's work.

Workability: A quantity of methods is available for measure the workability on fresh concrete.

Slump test:

Measure the workability of fresh concrete is difficult one. Number of trails has done the researchers to calculate the importance and vital property of concrete. The above methods are satisfactory for measuring this property.

In this project slump test and compacting factor test are done.



Slump Testing

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

Size of Test Specimens: Test specimens should be cubes, cylinders and beams. The size of cube is 150 X 150 X 150 mm the size of aggregates does not exceed 20 mm.

Curing

The test specimens are placed free from vibrations for 24 hours. The heat should be 22 to 32°C. After completion of 24 hours they should distinct for identification , removed from moulds and placed in clean water tank with Normal water curing and Chemical curing at temperature 24 to 30°C until they are used for testing. In this project the cube were tested at 7 and 28 days. Chloride attack is considered as one of the most severe durability problems for structures constructed in marine environment. To simulate the effect of marine environment 1% sodium chloride was used in this study for curing the concrete specimens to study their behaviour in aggressive marine environment.

Curing

Testing Specimens: Completion of curing period the specimens are used for testing purpose through two different manners. They are

A) Destructive test

1. Compressive strength test: The specimens be casted for testing at the ages of 7, 28 and 56 days. The cubes were tested by using compression testing machine. The procedure explained detailed manner.

Compressive strength =P/A

Where,

P= Failure load.

A =Area of cube.

Compressive Strength Test

SOFTWARES TOOLS USED

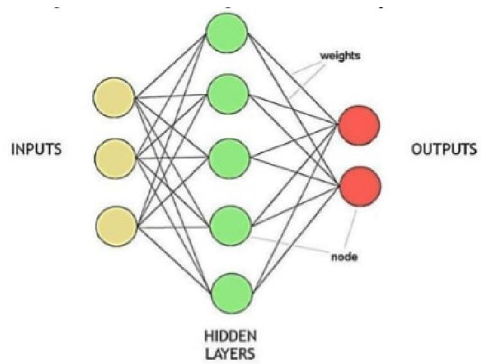
Introduction about Machine Learning and Other Software used

List of Software Used

Juypter Software

Artificial Neural Network Model
Tree Regression Model

Artificial Neural Network Model: ANN a paradigm for computation and knowledge representation is originally inspired by the understanding and abstraction of the biological structure of neurons and internal operation of the human brain. The biological brain consists of billions of highly interconnected neurons forming a neural network. Neural networks are a series of interconnected artificial neurons which are trained by using available data to understand the underlying pattern. They consist of series of layers with number of processing elements within each layer. The layer can be divided into input layer, hidden layer and output layer. Information is provided to the network through the input layer, the hidden layer processes the information by applying and adjusting the weights and biases and output layer gives output.



Tree Based Regression Model: Tree-based methods in machine learning are a class of supervised learning algorithms that use decision trees to model relationships between input features and target variables. These methods are widely used for both classification and regression tasks due to their interpretability and ability to handle complex, non-linear data structures.

Core Concept: Decision Tree: A hierarchical, flow-chart-like structure where each internal node represents a test on an attribute, each branch represents an outcome of the test, and each leaf node represents a class label (for classification) or a predicted value (for regression).

Feature Splitting: Tree-based algorithms begin by selecting more informative features to split a data set based on a specific criterion, such as Gini impurity or information gain etc.

Recursive splitting: The selected feature of dataset is used to split the data in two, and the process is repeated for each resulting subset, forming a hierarchical binary tree structure. This recursive splitting until stops a predefined criterion, like a maximum depth or a minimum number of samples per train data, is met as long as it lasts.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

VI. RESULTS

LABOURATORY RESULTS:

Experimental Results for Destructive Testing Method

Compression Test:

Universal Testing Machine

Plane Concrete of M25:

Age in Days	Cement (kg/m^3)	Water (kg/m^3)	Coarse (kg/m^3)	Sand (kg/m^3)	Experimental Result (N/mm^2)
7	366	161	1202	734	20.44
28	366	161	1202	734	30.67

10% Fly ash Replacement of Cement

Age in Days	Cement (kg/m^3)	Water (kg/m^3)	Fly ash (kg/m^3)	Coarse (kg/m^3)	Sand (kg/m^3)	Experimental Result (N/mm^2)
7	330	161	36	1202	734	17.34
28	330	161	36	1202	734	28.88

Age in Days	Cement (kg/m^3)	Water (kg/m^3)	Fly ash (kg/m^3)	Coarse (kg/m^3)	Sand (kg/m^3)	Experimental Result (N/mm^2)
7	257	161	108	1202	734	14.66
28	257	161	108	1202	734	25.33

30% Fly ash Replacement of Cement

Comparsion of Concrete 3 mixes

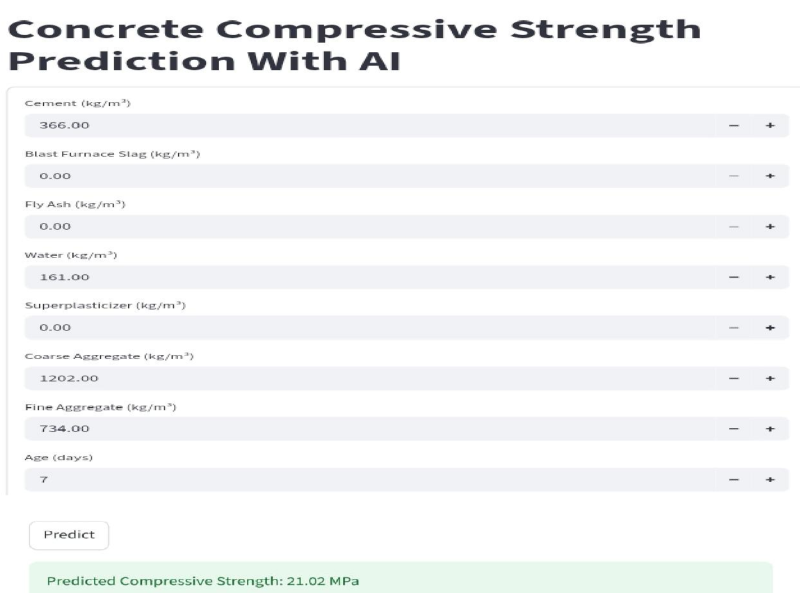
Age in Days	Plain Concrete (N/mm^2)	10% Fly ash (N/mm^2)	30% Fly ash (N/mm^2)
7	20.44	17.34	14.66
28	30.67	28.88	25.33

Prediction Result of Tree Regression Method

```
# Collect input into dictionary
user_input = {
    'Cement': cement,
    'Blast Furnace Slag': slag,
```

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 4, January 2026 Impact Factor: 7.67

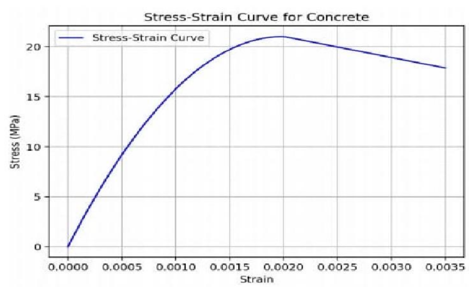
```
    'Fly Ash': fly_ash,
    'Water': water,
    'Superplasticizer': superplasticizer,
    'Coarse Aggregate': coarse_agg,
    'Fine Aggregate': fine_agg,
    'Age': age
  }
    # --- Stress-Strain Curve ---
    st.subheader("Stress–Strain Curve")

    def plot_stress_strain(fc, eps0=0.002, epsu=0.0035, model="hognestad"):
      strain = np.linspace(0, epsu, 200)

      if model == "hognestad":
        stress = fc * (2*(strain/eps0) - (strain/eps0)**2)
        stress[strain > eps0*2] = 0
      elif model == "linear":
        stress = np.where(strain <= eps0, fc*(strain/eps0),
                np.where(strain <= epsu, fc*(1 - (strain-eps0)/(epsu-eps0)), 0))
      else:
        raise ValueError("Unknown model type. Choose 'hognestad' or 'linear'.")
```



IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

Stress-Strain Curve

The stress-strain curve is generated using Hognestad's parabolic relationship.

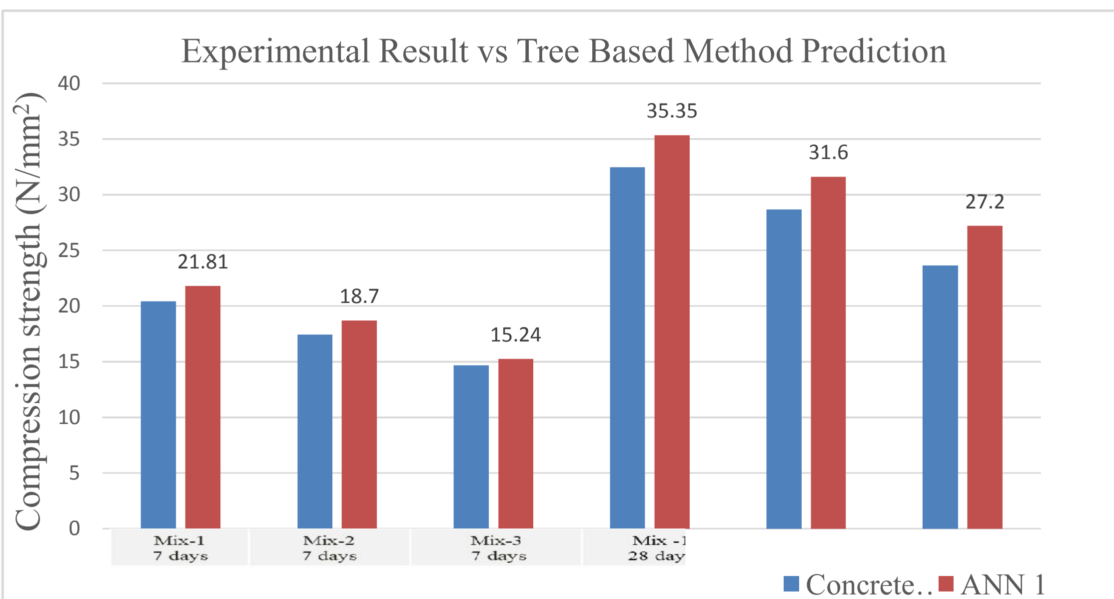


Comparison of distractive test and prediction of concrete strength

Days	Various Mixes	Concrete Compressive Strength	ANN 1
7	Plain Concrete	20.44	21.81
7	10% Fly ash	17.44	18.7
7	30% Fly ash	14.66	15.24
28	Plain Concrete	32.48	35.35
28	10% Fly ash	28.66	31.6
28	30% Fly ash	23.65	27.2

Comparison of distractive test and prediction of concrete strength

Prediction of K- Neural Network Method

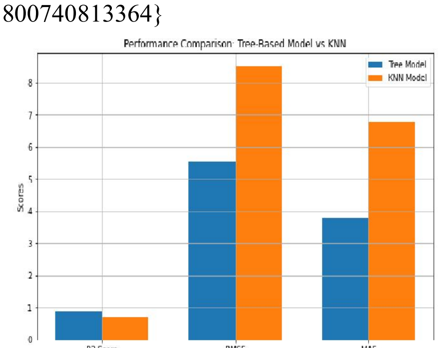


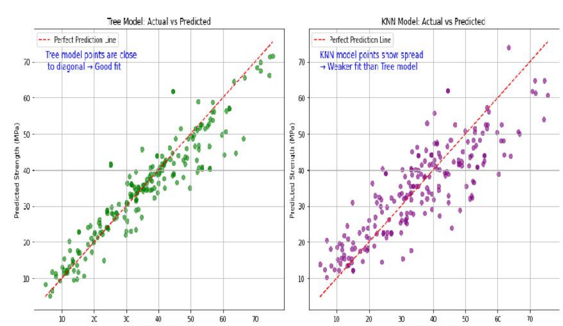
PREDICTION OF COMPRESSIVE STRENGTH USING ML
TREE-BASED MODEL vs KNN MODEL (Corrected Version)

DOI: 10.48175/IJARSCT-31006

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor

# 1. Load Dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/concrete/compressive/Concrete_Data.xls"
df = pd.read_excel(url)
# FIXED TARGET COLUMN NAME
target_col = "Concrete compressive strength(MPa, megapascals) "
X = df.drop(target_col, axis=1)
y = df[target_col]
# -------------------------------------------------
# 2. Train-Test Split
# -------------------------------------------------
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.2, random_state=42
)
# ---- TREE PLOT ----
plt.subplot(1, 2, 1)
plt.scatter(y_test, tree_pred, color="green", alpha=0.6)
plt.plot(line, line, 'r--', label="Perfect Prediction Line")
plt.xlabel("Actual Strength (MPa)")
plt.ylabel("Predicted Strength (MPa)")
plt.title("Tree Model: Actual vs Predicted")
plt.legend()
plt.grid(True)
plt.text(min_val, max_val * 0.9,
        "Tree model points are close\n to diagonal → Good fit",
        fontsize=12, color="blue")
KNN MODEL PERFORMANCE:
{'R2 Score': 0.8804736437891982, 'RMSE': 5.549746077460416, 'MAE': 3.7793
800740813364}
```





Result of the Artificial Neural Network model

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, January 2026
Impact Factor: 7.67

Regression Score : 0.8804/100 = 88.04 %
Result : KNN Model Concrete Prediction = 88.04 %
Calculation of KNN Model Comparing with the Tree Based Model

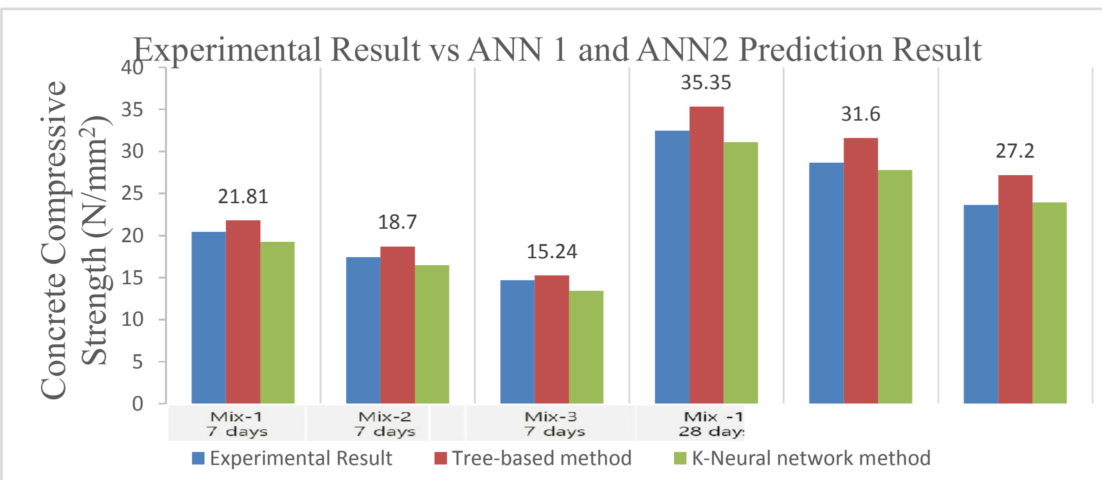
7 days
- Plain Concrete = 21.81 x 0.8840 = 19.20 N/mm^2
- 10% Fly ash = 18.70 x 0.8840 = 16.46 N/mm^2
- 30% Fly ash = 15.24 x 0.8840 = 13.41 N/mm^2

28 days
- Plain Concrete = 35.35 x 0.8840 = 31.12 N/mm^2
- 10% Fly ash = 31.60 x 0.8840 = 27.82 N/mm^2
- 30% Fly ash = 27.20 x 0.8840 = 23.94 N/mm^2

Compression Result

Results of K-NN Method

Days	Various Mixes	Concrete Compressive Strength	ANN 1	ANN 2
7	Plain Concrete	20.44	21.81	19.28
7	10% Fly ash	17.44	18.7	16.46
7	30% Fly ash	14.66	15.24	13.41
28	Plain Concrete	32.48	35.35	31.12
28	10% Fly ash	28.66	31.6	27.82
28	30% Fly ash	23.65	27.2	23.94



Final Comparison of Concrete Mix

Finding Errors in Concrete Compressive Strength Between ANN 1 , ANN 2

Final Comparison of Concrete Mix

Concrete Compressive Strength	ANN 1	ANN 2	Error
20.44	21.81	19.28	-0.21
17.44	18.7	16.46	-0.28
14.66	15.24	13.41	0.67
32.48	35.35	31.12	-1.51
28.66	31.6	27.82	-2.10
23.65	27.2	23.94	-3.84

Prediction of Concrete Compressive of all 3 Methods. ANN1 (Tree based Method) Considered as Best Regression Method.

VII. CONCLUSION

The Technological advancement in the field of machine learning pave a great way to reach interdisciplinary research applications. One such problems in civil engineering, to find a mathematical relationship for the amount of different components used for creating a concrete mix and the compression used for creating mix and compression strength was considered.

Based on the results, it has been found that a numerical technique, ANN model, can be used reliably to predict compressive strength of concrete, rather than using costly experimental investigation. The results of this study will give some helpful information to construction engineers and structural designers and this proposed ANN model can be used as an efficient tool to support the decision process in the concrete construction projects as a function of mix proportions

Artificial neural networks are capable of learning and generalizing from examples and experiences. This makes artificial neural networks a powerful tool for solving some of the complicated civil engineering problems. In this study, using these beneficial properties of artificial neural networks in order to predict the 7 and 28 days compressive strength and durability of concretes containing fly ash without attempting any experiments were developed with two different multilayer artificial neural network architectures namely ANN-I and ANN-II.

In the two models developed in ANN method, a multilayered feed forward neural network with a back propagation algorithm was used. In ANN-I model, one hidden layer was selected. In the hidden layer 10 neurons were determined. In ANN-II model, two hidden layers were selected. In the first hidden layer ten neurons and in the second hidden layer ten neurons were determined. The models were trained with input and output data. Using only the input data in trained models the 7 and 28 days compressive strength and durability of concretes containing.

Many such computationally solvable problems exist in civil engineering domain which has very high relevance in real time Application. In this paper, mix proportions were used as the input variables of the data driven models. Further research is required to investigate the effect of type of input variables on the prediction results.

In experimental designs, where the number of the simultaneously uncontrollable effect variables is high, it is crucial to reduce the number of the experiments to save costs and time. Therefore, the predicted values close to the actual values need to be obtained with the minimum number of the experiments.

In this paper we proposed a machine learning pipeline, using different regression techniques for predicting the compression strength of a particular concrete mix. Then different machine learning models were tried and Tree based Model gives less values and chosen as best regression model.

REFERENCES

[1]. B. Topçu and M. Sarıdemir, "Prediction of compressive strength of concrete containing fly ash using artificial neural networks and fuzzy logic," Computational Materials Science, vol. 41, no. 3. pp. 305-311, 2008.

[2]. F. Khademi, M. Akbari, S. M. Jamal, and M. Nikoo, "Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete," Frontiers of Structural and Civil Engineering, vol. 11, no. 1, pp. 90-99, 2017.

[3]. M. Timur Cihan, Tekirdag Namık, C, orlu "Prediction of Concrete Compressive Strength and Slump by Machine Learning Methods" Vol. 2019, Article ID 3069046,2019

[4]. P. Muthupriyaa, K. Subramanianb, and B. Vishnuramc, "Prediction of compressive strength and durability of high preformance concrete by artifical neural networks " Int. J. Optim. Civil Eng, Vol. 1, pp. 189-209, 2011.

[5]. H.-G. Ni and J.-Z. Wang, "Prediction of compressive strength of concrete by neural networks," Cement and Concrete Research, vol. 30, no. 8, pp. 1245-1250, 2000.

[6]. Oztas, M. Pala, E. Ozbay, E. Kanca, N. C™, aglar, and M.A. Bhatti, "Predicting the compressive strength and slump of high strength concrete using neural network," Construction and Building Materials, vol. 20, no. 9, pp. 769-775, 2006.

[7]. Y. J. Kim, J. Hu, S. J. Lee, and B. J. Broughton, "Prediction of Compressive Strength of Aerated Lightweight Aggregate Concrete by Artificial Neural Network," Applied Mechanics and Materials, vol. 84, pp. 177-182, 2011