Prediction of Compressive Strength of Concrete By Various Methods: A Comparative Synthesis of Conventional , Statistical, Machine Learning and Intelligent Prediction Techniques

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***Abstract*—The concrete compressive strength test acts as the basic metric for assessing the strength and quality of a structure. Laboratory testing is time-consuming and requires large amounts of resources; thus, there is a need for quick and efficient estimation methods. In this study, three estimation models were examined: Multiple Linear Regression (MLR), Quadratic Response Surface Methodology (RSM),and Artificial Neural Networks (ANN). The mixture proportions were taken according to IS 10262:2019 and IS 456:2000 standards in grades M30 to M50. Accuracy of each model was assessed using coefficient of determination (R2), Root Mean Square Error (RMSE),and Mean Absolute Error (MAE). It was proven that ANN provides better prediction performance and can be used as an efficient method**

***Index Terms*—concrete compressive strength; machine learning; artificial neural network; support vector regression; random forest; gradient boosting; Cat Boost; prediction model; explainable machine learning.**

I. INTRODUCTION

The Compressive strength is the most used mechanical parameter to determine the characteristics of the concrete by the structural engineer. Traditionally this parameter can be determined by preparing standard concrete cubes or cylinders and subjecting them to destructive compression test in laboratory compression testing machine after certain curing period of 7 and 28 days . while lab tests are considered authentic, there are some economic and practical constraints to them, which include high material wastage, high costs related to raw materials, and long duration. therefore, there is an urgent need for computerized simulations that can predict strength parameters from mix design. over the past decades, empirical relationships linking water binder ratios and constituent proportions to strength have evolved significantly. modern data-driven intelligence, such as artificial neural networks (ann), provides robust alternatives capable of modeling complex nonlinear interactions between cement, supplementary cementitious materials (scms) like slag and fly ash, aggregates, and curing age.



Fig No.1. Traditional Concrete Testing And Material Sample Examination.

II. PROBLEM STATEMENT

Traditional Concrete Strength Estimating Techniques Have Several Drawbacks Such as: High Resource Usage; Long Test Duration Times; Labour Intensive; and more. In cases where batches do not meet required structural classes, whole production cycles have to be repeated. This study aims to resolve these inefficiencies through the development and comparison of regression models versus ANN modeling.

III. LITERATURE REVIEW

The fundamental concepts of concrete mixture proportions arose based on experimental theories

concerning the inverse relation between water-to-cement ratio and final compressive strength.
Early twentieth-century formulations set the foundation for the conventional method of concrete mixture designs. With the development of computing tools, scientists started using machine learning models. In the late twentieth century, it was proved that Artificial Neural Networks can precisely evaluate high-performance concrete properties. Later experiments in the 2010s showed how useful it is to compare multivariable linear and non-linear regressions to neural approaches. In the Indian regulatory framework, IS 456:2000 gives standards that must be adhered to for plain and reinforced concrete construction. In this regard, IS 10262:2019 offers a systematic approach to design and calculate the amounts of cementitious materials, fine aggregate, coarse aggregate, and water in the concrete mixes.

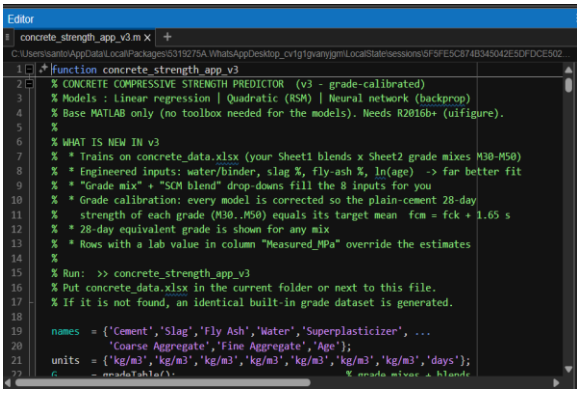


Fig No.2 . Mathematical Model Script

IV. OBJECTIVES

To predict concrete compressive strength using Artificial Neural Network (ANN), linear regression, and quadratic regression methods.
To design concrete mix proportions according to IS 10262:2019 and relevant requirements of IS 456:2000.
To compare the accuracy of the three prediction methods using R^2, MAE, and RMSE.
To identify the most accurate and cost-effective method for predicting concrete compressive strength.
To reduce the time and cost involved in estimating concrete compressive strength.

V. METHODOLOGY

Methodology in research includes a structured process involving conventional mix design principles, data gathering, algorithm training, and performance evaluation.
A. Mix Proportions and Standardization Conventional mix designs for the grades M30, M35, M40, M45, and M50 were derived from the provisions of IS 10262:2019 and IS 456:2000. The target mean compressive strength (fcm) was set based on characteristic compressive strength (fck) and standard deviation (S): fcm = fck + 1.65 × S

B. Data Gathering and Processing: A large database containing 1,080 unique mix designs was gathered using variables like cement, slag, fly ash, mixing water, superplasticizer, coarse aggregate, fine aggregate, and curing age ranging from 1 to 365 days.

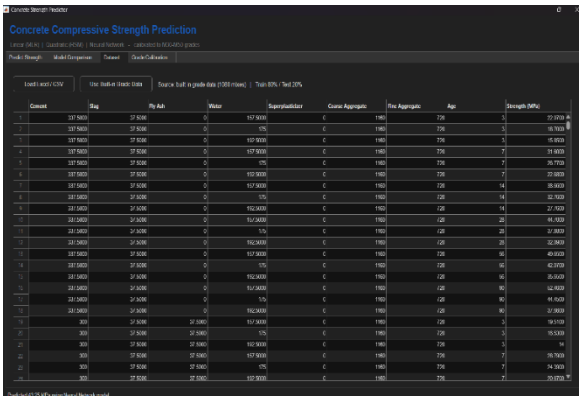


Fig No.3. DATASET Table

C. Models and Methods:
Three different models were used:
1) Linear Regression (MLR): Examines the linear relationship between mix parameters and compressive strength output.

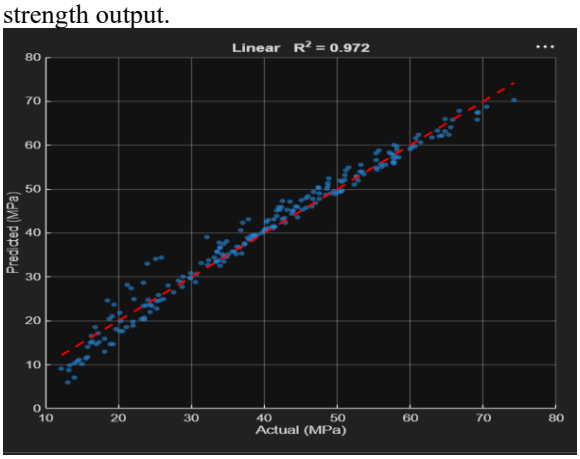


Fig No.4. Graph Of linear Regression

1). Linear Regression
Performance indicators

R2	MAE	RMSE
0.972	1.82MPa	2.52MPa

2) Quadratic Response Surface (RSM): Takes into account the curvature and interactions between constituent ratios and strength gain.

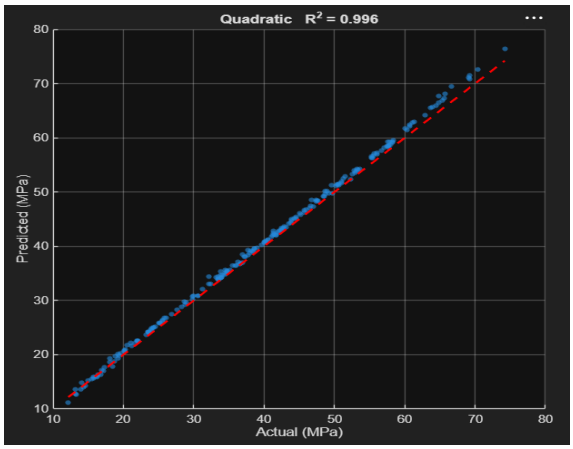


Fig No.5. Graph Of Quadratic Regression .

Quadratic Regression
Performance indicators

R2	MAE	RMSE
0.996	0.84MPa	0.97MPa

3) Artificial Neural Network (ANN): Back propagation neural network architecture trained with optimal hidden layers to map

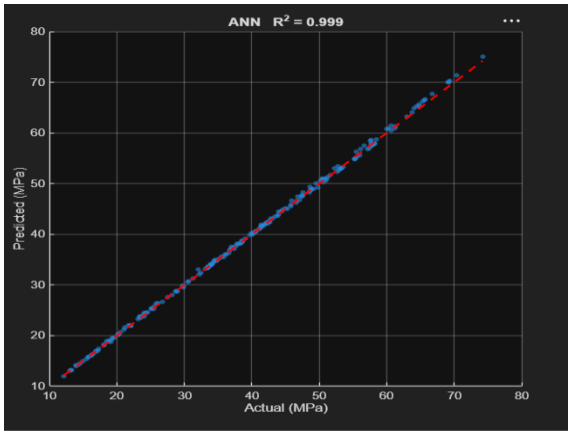


Fig No.6. Graph Of Artificial Neural Network Regression

ANN Regression:
Performance indicators

R2	MAE	RMSE
0.996	0.84MPa	0.97MPa

VI. EXPERIMENTAL SETUP AND SAMPLE TESTING.

Physical tests were conducted on physical specimen cubes which had the size of 150 mm x 150 mm x 150 mm and were prepared as per the laboratory water submersion conditions. The cubes were prepared as per IS specifications before conducting the test in CTM.



Fig No.7. CTM Testing.

Specimens were loaded uniaxially until ultimate structural failure occurred, observing crack patterns, diagonal shear planes, and core integrity.



Fig No.8. Tested Sample Crack Patterns.

VII. RESULTS AND DISCUSSION

Predictive capabilities of the linear regression, quadratic regression, and ANN models were tested on the experimental test samples. Grade calibration coefficients (κ) were used for matching the output results with the desired mean strengths(fcm).
The user interface of the Mathematical Model (fig .9) is simple for user to simply understanding and predict compressive strength of concrete easily and in a matter of seconds. It has three performance indicators which compare results with these indicators and give nearly accurate compressive strength as a result it saves material, time and any hidden cost which are included in testing. It also has mineral admixtures composition like fly ash, Slag etc.

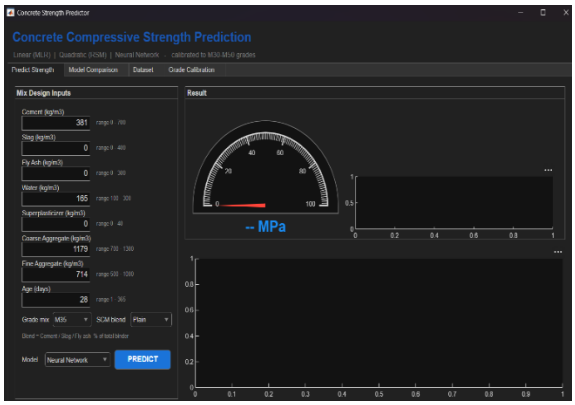


Fig No.9. User Interface of the Model

Grade Calibration: On the window of grade calibration all grades are separated according to their requirements and it gives the values of strength and N test, the graph represents compressive strength of each grade according to their curing period.

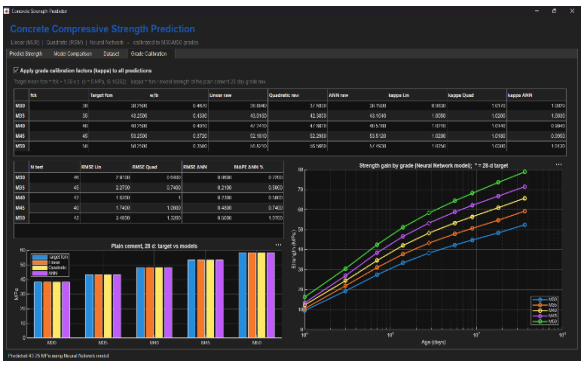


Fig No.9. Grade Calibration

Comparison of All Models: the graphs of all models give the clear understanding of compressive strength of concrete and their curing period a according to grade of concrete.

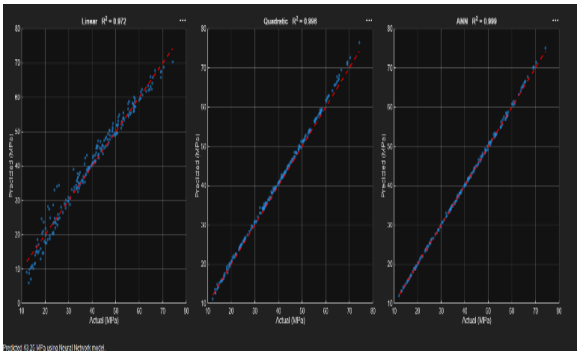


Fig No.10. Comparison of all models.

Prediction of Compressive strength
Input all the data
Cement-387 kg/m3
Slag – 43 kg/m3
Fly Ash – 0 kg/m3
Water – 160 kg/m3
Superplasticizer – 0 kg/m3
Coarse Aggregate – 1170 kg/m3
Fine Aggregate – 690 kg/m3
Age – 28 days
Grade Mix – M45
SCM Blend – 90/10/0

Click on Predict
User interface shows the result
= 52.6 MPa



Fig No.10. Actual Result of Compressive Strength of concrete

VIII. CONCLUSION

Predictive capability of Linear Regression, Quadratic Regression, and ANN models was compared using experimental test samples. Grade correction factor (κ) was used for matching outputs with mean target strength (fcm). This work has been able to prove the practicality of prediction models by computation. The key findings from this experiment have been presented as follows:

1) Predictions done through Artificial Neural Network models are far superior than those made by linear and quadratic regression models, which yielded outstanding R2 value of 0.9990 and RMSE of 0.3540 MPa.
2) Mix proportions that follow IS 10262:2019 and IS 456:2000 standards offer sound empirical limits for training machine learning algorithms.
3) Predictive modeling helps save material wastage, labor costs, and time of testing, leading to sustainable quality control of construction.

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