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Research Paper

Prediction of Compressive Strength by Considering Practical Consideration Non-destructive Test by Artificial Neural Network

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ABSTRACT

Accurate assessment of concrete compressive strength is critical for evaluating structural performance. While nondestructive testing (NDT) methods, such as Schmidt rebound hammer tests, offer rapid and NDT gives result with reasonable accurate based on environmental factors such as temperature, humidity etc of site and condition in which test is performed. Destructive testing (DT) methods, like core cutting, provide direct and accurate results. This study aimed to bridge the gap between these approaches by developing predictive models that correlate DT and NDT results. Experimental work involved 126 laboratory-prepared samples (grades M10–M40) with curing age of 14 day and 28 day and 231 field samples from a 20-year-old structure, tested using both methods. Total 357 no. of data samples were created with different mix proportion of design, curing ages and on-site environmental exposed concrete structure without unknown grade. Most of the researches were done while preparation of samples in the laboratory. For these purposes of taking mixing both variations such as control (Laboratory) and uncontrolled(on-site) samples were to prepare as a practical condition for prediction. For generation of predict model 70% data was used with methods such as regression analysis and Cascade forward back propagation neural network (CFBPNN) were used for investigation. To validate the prediction 30% data was used which was not used in model generation. The prediction results show that the coefficients of determination (R^2) of the Regression analysis and the CFBPNN prediction models for the test set of concrete compressive strength are 95% and 99% respectively ANN model founded to be more accurate as compare to regression analysis. The validation by R^2 of the Regression analysis and the CFBPNN prediction model for the compressive strength for above dataset was 89.0% and 98%. Statistical metrics (MSE, RMSE, MAPE) further confirmed the neural network's superior accuracy.

1 Introduction

Concrete is still one of the most popular construction materials in the world due to its strength, durability, and versatility. However, the structural integrity and service life of concrete structures largely depend on their compressive strength, a key mechanical property that reflects the overall quality of the material. Concrete structures are influenced by various parameters

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such as concrete porosity, cement-aggregate ratio, grade of aggregate, type of cement, curing methods, and mixing practices during construction [1-5]. Determining compressive strength is essential for assessing safety and performance before applying additional loads or modifications to a structure [6-9]. The compressive strength of structure should be monitored on regular bases therefore there is a need for cost effective way to determine it [10, 11].

Traditionally, destructive testing (DT) methods, such as core cutting and cube compression tests, are employed to measure compressive strength [12, 13]. After collecting cube samples, than it is placed under compressive testing machine for applying a cyclic load over it then measuring the force required to break the cube. Although highly accurate, these methods are time-consuming, costly, and involve damaging the structure. Alternatively, non-destructive testing (NDT) methods, such as the rebound hammer test, provide a faster and non-invasive means of estimating concrete strength [14, 15]. The principle behind NDT is to apply a testing medium to the concrete, watch how the medium changes as a result of flaws, and then identify those changes. Rebound hammer test is based on work principle of the rebound energy is measured when a spring-loaded mass hits the concrete surface. The concrete's compressive strength and rebound energy, or R-value, are connected [16,17]. However, NDT results are approximate and often lack the precision of DT methods, with no universally established correlation between the two [18-20]. This gap in accuracy and correlation poses challenges for practical applications [20].

The development of predictive models to estimate compressive strength offers a solution to these challenges. Such models not only reduce experimental effort but also optimize costs and time associated with traditional testing methods. The first problem faced in reliable prediction model is the practical dataset because the concrete is expose to different weathers and atmospheric condition, which affects the strength of concrete. Therefore it is vital to prepare a practical dataset in order to perform a prediction. Many research used various model to predict relationship obtain from DT and NDT, This model were linear as well as nonlinear [21-25]. This is due concrete keep on gaining strength as on age, time, one don't known what was porosity, cement aggregates ratio, grade of aggregate, type of cement, curing, and mixing at the time construction involved. Regression analysis, a commonly used statistical tool, has been employed to predict the relationship between various input parameters and compressive strength [26]. While linear regression provides simplicity, the inherent nonlinearity in concrete behaviour often makes nonlinear regression more accurate [26]. Nevertheless, these models have limitations, especially when handling complex interactions between multiple variables, such as porosity, cement-aggregate ratio, curing conditions, and age of concrete [27]. The general form of the Multi-regression model can be expressed as shown in Eq. (1) [28-30]

$$y = c + \beta_1 x_1 + \beta_2 x_2 + \cdots \dots \dots \beta_n x_n + e \quad (1)$$

Where, y = dependent variable; c = intercept; $x_1, x_2, x_3 \dots x_n$ = independent variable;

$\beta_1, \beta_2, \beta_3 \dots \beta_n$ = Coefficients.

There are various raw material is used for concrete preparation there are various factors for contribution of strength therefore linear regression model is replaced by nonlinear regression model, which is found to be more accurate [26]. The least-squares fit approach is used by MRA and by using this statistical technique help in determines the relationship between one or more independent variables and a dependent variable. However, the accuracy of regression analysis is inversely proportional to the number of independent variables [28, 31]. There are various factors which contribute to strength of the concrete it is difficult or almost impossible to acquire to get this parameter of existing structure [32]. In such compound cases, other methods like Machine learning algorithm such as Artificial neural networks (ANN) are found to be impressing and accurate in terms of results [6, 25, 33-37].

ANN have emerged as powerful tools for modeling and prediction in various engineering applications such as hydrology, meteorology, and various engineering applications [38], including the prediction of concrete compressive strength. ANN's ability to handle nonlinearity, adapt to complex patterns, and remain independent of raw material quality makes it an attractive option [39-41]. Unlike traditional regression methods, ANN mimics the human neural network structure, allowing it to process interconnected variables effectively [39]. Researchers have extensively employed ANN for both quantitative and qualitative predictions of variables in these diverse fields [38]. In the recent scenario, ANN is widely employed to predict compressive strength of concrete by various researchers [40]. In the current study, Cascade forward back propagation algorithm is used to predict compressive strength of the concrete. Prediction analysis is commonly conducted on concrete that has been prepared by substituting materials, while there is limited research on prediction analysis for RCC [22].

Despite these advancements, research on predicting compressive strength often focuses on hypothetical or controlled conditions, such as specific water-cement (W/C) ratios, curing times, and aggregate grades [24]. Limited attention has been

given to in-situ data from older reinforced concrete (RCC) structures. Additionally, while ANN has been widely used, studies focusing on the comparison between ANN and regression models for both laboratory-prepared and field-obtained data remain scarce.

This study aims to bridge these gaps by employing both regression analysis and ANN to predict the compressive strength of concrete. The following objectives of these research work are given below

1. To create different grade of concrete in the lab and taking different age of curing time. Apart from this data is also taken from site data of structure of 20 years. After collecting both the sources than studies were performed.
2. To find the best prediction models such as regression and ANN model were used for estimation of compressive strength and its effect on the ages and accuracy of methods applied on it. Validation of models are done by evaluated using statistical measures like Mean square error (MSE), root-mean-square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2)

By comparing the performance of regression and ANN models, this research seeks to identify the most accurate and efficient method for predicting compressive strength, thereby contributing to improved quality assessment and decision-making in concrete construction and maintenance. The findings will provide practical insights into the applicability of these models for both laboratory and field conditions, addressing key limitations of existing methods and offering a pathway for enhanced predictive capabilities.

2 Methodology

The following Method is adopted as shown in Fig.1

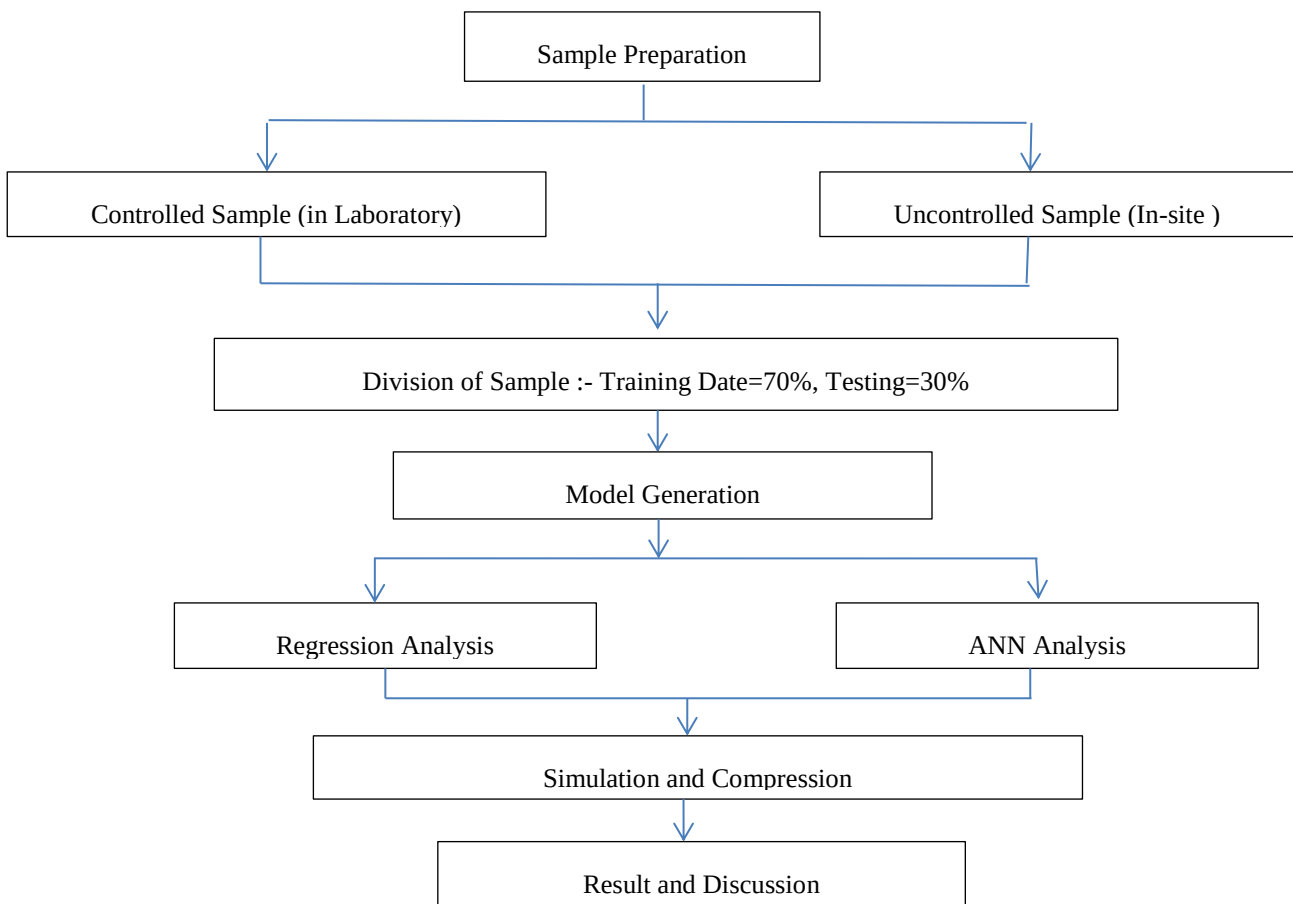


Fig. 1- Shows Chart of the methodology adopted

2.1 Sample Preparation:

The sample preparation is further divided into two ways; one is control mix design prepared into Laboratory and uncontrolled mix collected from the in-site. For control mix design is created in laboratory by various concrete grades are prepared. Concrete of grades M-10, M-15, M-20, M-25, M-30, M-35, and M-40 was used for the study and the properties of material used given Table 1. The mix design was done in accordance with IS: 10262 and IS: 456-2000 specifications [42, 43] were performed by mixed proposition is given in Table 2. Concrete cubes measuring 150 mm × 150 mm × 150 mm were cast. The specimens were demoulded after 24 hours and immersed in a curing tank filled with water, where they were cured for 14 and 28 days. For uncontrolled mix design is simulate real-world conditions, 231 field samples were collected from 20-year-old structures. Core cutting methods were employed to extract samples for destructive testing. Care was taken to ensure data integrity by minimizing uncontrolled variables, such as variations in environmental exposure and structural loads, during sample collection. This ensured consistency between laboratory and field data.

Table 1 - Properties of Material used

S. NO	Material	Property	Value
1	Cement conforming to IS: 8112-1989 [44]	Ordinary Portland Cement (OPC).	43 grade
2		Specific Gravity	3.15
3		Fineness of Cement by sieving	10%
4		Normal Consistency	25-30%
5		Initial Setting time	30 minutes
6		Final Setting time	600 minutes
7		3 days compressive strength	22 N/mm ²
8		7 days compressive strength	33 N/mm ²
9		28 days compressive strength	43N/mm ²
10	Natural River Sand as a Fine Aggregate (These values are below the maximum permissible values specified by IS-383 [45])	Grading of Sand	Zone I
11		Specific Gravity	2.57
12		Density (compacted)	1791 kg/m ³
13		Water Absorption	2.26 %
14		Fineness Modulus	2.75
15		Fines	6 %
16	Locally available crushed siliceous stone as a Coarse Aggregate (These values are below the maximum permissible values specified by IS-383 [45])	Specific Gravity	2.85
17		Density	1691 kg/m ³
18		Water Absorption	0.90 %
19		Flakiness Index	20%
20		Elongation Index	20%
21		Crushing Value	21.33 %
22		Impact Value	15.40 %
23		Fineness Modulus	6.65
24	Super plasticizer as per IS 9103- 1999 [46]	Appearance	Light brown colour
25		Specific gravity	1.12 ± 0.01
26		pH	Minimum 6
27		Chloride ion content	0.2%
28	Water	miming and curing of concrete	Potable water

Table 2 - Design mix proportion for one Cum for various grade of concrete

S.no	Materials	M10	M15	M20	M25	M30	M35	M40
1	Cement in Kq/m ³	135	195	240	265	290	320	390
2	Fly ash in Kq/m ³	130	130	130	130	110	90	90
3	Fine aggregate in Kq/m ³	913	905	875	862	786	751	845
4	Coarse aggregate in Kq/m ³	590	565	615	612	648	665	650
5	Water in Kq/m ³	170	170	166	172	175	170	170
6	Super Plasticizer	1.2	1.95	1.8	2.0	2.9	2.7	2.5

2.2 Compressive Strength Testing Methods

Mostly there are two methods of determination of compressive strength are as follows

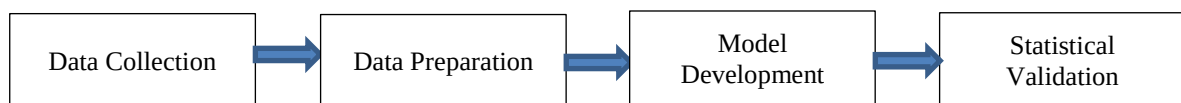
- (i) Destructive Testing (DT):- DT was carried out using a Compression Testing Machine (CTM) in accordance with IS: 516 (1959) specifications [47]. The test procedure involved placing the cured concrete cubes in the CTM and applying load until failure. The maximum load sustained by the specimen was recorded, and compressive strength was calculated.
- (ii) Non-Destructive Testing (NDT):- NDT was performed using a rebound hammer (Schmidt hammer). The rebound number was recorded, and the compressive strength was estimated using standard calibration curves. NDT is advantageous for in-situ assessments as it avoids damaging the structure while providing quick preliminary estimates of strength.

2.3 Sample Distribution

For generation for these model dataset is divided into set first is training and other is validation. There were 70% data were used for training and 30% testing dataset for validation.

2.4 Model Preparation by Regression Model

Regression analysis was employed to establish relationships between destructive and non-destructive testing results. Regression models provide a quantitative approach to decision-making by relying on empirical data rather than subjective judgment. The entire process is represented in flowchart given below.in fig.2 The analysis is performed in Microsoft Excel.

**Fig. 2 - Flowchart of the Regression Process**

2.4.1 Procedure

- (i) Data Collection: Both laboratory and field data were compiled, including compressive strength values from DT and rebound numbers from NDT.
- (ii) Data Preparation: The dataset was divided into training (70%) for generation of model and validation (30%) subsets of model.
- (iii) Model Development: A mathematical equation was formulated to predict compressive strength (Y) as compressive strength obtain by DT, based on independent variables ($X_1, X_2, \dots, X_k$), such as rebound numbers.

2.5 Model Preparation Artificial Neural Network (ANN) Model

Due to the flexibility to handle and transform complex structural problem in simple structure ANN has attracted many research towards it [28, 48-50]. It's popular for handling the complex and non-linear function, estimate for unseen inputs and use observed data [49]. It has found large range of application especially in computer and environmental science, Structural dynamic, medicine, image processing and genetic biology [49, 51]. It also provides fast and practical solution for any non-linear problem in construction and structure related problem.

The CFBPNN was chosen for this study. CF models resemble standard feedforward neural networks, but with the key distinction of including weighted connections from the input to each layer, as well as between successive layers. Though two-layer feedforward networks can theoretically learn any input-output mapping, deeper feedforward architectures may be able to acquire more complex relationships more efficiently. The general structure of a CF model is illustrated in Fig. 3. For this model net flow inflow net_j to the j^{th} node for the i^{th} layer is define as flow (Eq.2)

$$net_j = \sum_{l=1}^m x_l W_{lj} + b_j \quad (2)$$

Where, W_{kj} is a vector of synaptic weights and x_j is a vector of inputs for the j^{th} nodes (i-1)the layer, b_j are the baisses

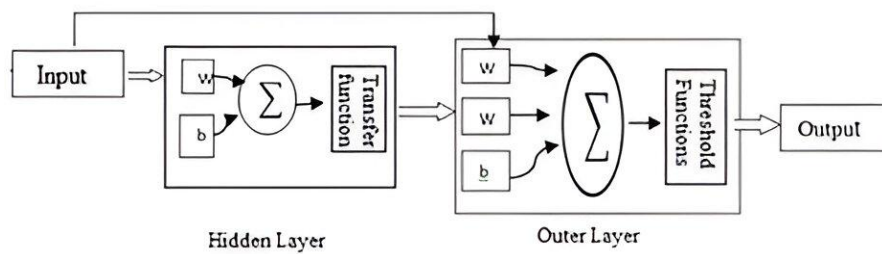


Fig. 3 - Cascade Forward Network General Structure

2.5.1 Procedure

- (i) Normalization Data :- Basic inputs for ANN modeling are compressive strength obtain NDT and DT method from field and Lab data. First step in ANN is to prepare data set by Normalization (Or Min-Max scaling) of data in Excel as Equ.10. It is the process of scaling data in such a way that all data points lie in a range of 0 to 1. Thus, this technique, makes it possible to bring all data points to a common scale. The mathematical formula for normalization is given as:Equ.3.

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \quad (3)$$

Where

x' = Normalized value of NDT/DT Compressive strength data set between 0 and 1

x = NDT/DT Compressive strength

x_{max} = Maximum value of NDT/DT Compressive strength

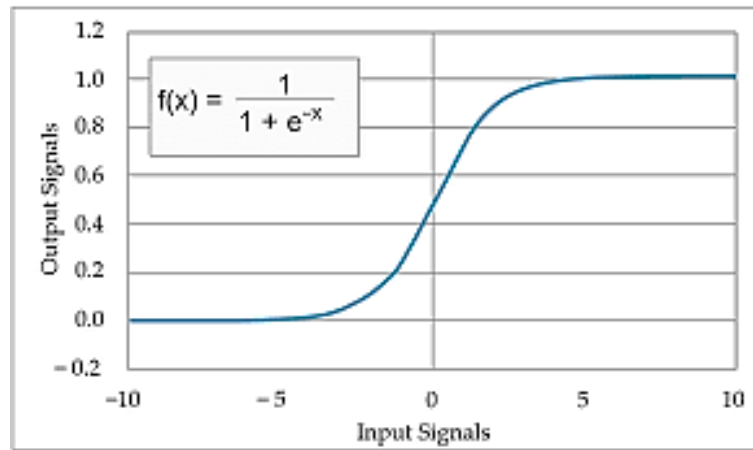
x_{min} = Minimum value of NDT/DT Compressive strength

- (ii) Selection of Model Architecture: The CF model included weighted and neurons connections between inputs layers, hidden layers, and outputs layers, allowing efficient learning of complex relationships. The input layer and output layer are fixed based on the parameter that are available but hidden layers determine based on trial error based on best results. The weight was assigned randomly and number of neurons to each layer of nodes were also determine by least MSE.
- (iii) Training: The model was trained using the Levenberg-Marquardt (LM) algorithm, which provides fast convergence and high accuracy based training the CF with lowest MSE as compare other algorithm, LM algorithm were used the equation is as given in Eq(4) . The CFBPNN was employed for updating the weights. However, the main characteristic of this network is that each layer of neurons is connected to all previous layers [52, 53].

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T \varepsilon_k \quad (4)$$

Where, X_k is a vector of current weights and biases. ε and J are respectively, the vector and Jacobean matrix of the network errors; μ is a scalar which indicates how to use the memory and calculation speed of the Jacobean matrix; k is iteration number; I is the unit matrix, and Superscript T indicates transposition.

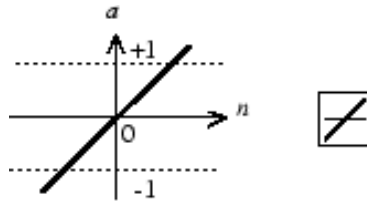
(iv) Activation Functions: Log-sigmoid transfer functions were used in the hidden layer, and pure linear functions were used in the output layer to optimize performance. Log-sigmoid transfer function as hidden layer and pure linear threshold functions as output layer were used to reach the optimized status [54]. A log-sigmoid function, also known as a logistic function, is given by the relationship (Eq. 5) and Linear Transfer Function is Eq. 6:



$$\sigma(t) = \frac{1}{1+e^{-\beta t}} \quad (5)$$

Where β is a slope parameter

$A = \text{purelin}(N)$ takes an S -by- Q matrix of net input (column) vectors, N , and returns an S -by- Q matrix equal to N , A .



$$A = \text{purelin}(n) \quad (6)$$

(D) Validation of Models: A separate validation dataset (30% of the data) was used to evaluate model performance. Statistical metrics such as MSE Eq.(7), RMSE Eq.(8), R^2 Eq.(9), and MAPE Eq.(10) were calculated to assess accuracy.

$$MSE = \frac{\sum_{i=1}^n (Q_{exp} - Q_{cal})^2}{n} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Q_{exp} - Q_{cal})^2}{n}} \quad (8)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^n (Q_{exp} - Q_{cal})}{\sum_{i=1}^n Q_{exp}} \right]^2 \quad (9)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{Q_{exp} - Q_{cal}}{Q_{exp}} \right| \quad (10)$$

Where, Q_{exp} = Observed value; Q_{cal} = Predicted value; n = Number of observations

3 Result and Discussions

3.1 General

In order to create a practical condition, various grade of concrete in the lab and taking different age of curing time. Apart from this data is also taken from site data of structure of 20 years. After collecting both the sources of data than studies were performed for prediction models such as regression and ANN model were used for estimation of compressive strength and its effect on the ages and accuracy of methods applied on it. Validation of these done by above mention statistical parameters.

3.2 Regression Analysis:

The correlation regression relation between DT and NDT on different concrete grade mixes of M10, M15, M20, M25 M30, M35, and M40 with different age 14 and 28 days as given in Table 5. Comparative statically regression parameters of various concrete as shown in Table 6.

Table 5 - Regression Equation for various grades for different Days of strength

S.No	Type	Equation for 14 Days	Equation for 28 Days
1	M10	$DT = 7.69 + 0.169 NDT$	$DT = 8.78 + 0.211 NDT$
2	M15	$DT = 11.15 + 0.169 NDT$	$DT = 12.97 + 0.211 NDT$
3	M20	$DT = 15.19 + 0.169 NDT$	$DT = 16.84 + 0.211 NDT$
4	M25	$DT = 18.74 + 0.169 NDT$	$DT = 20.56 + 0.211 NDT$
5	M30	$DT = 22.47 + 0.169 NDT$	$DT = 24.40 + 0.211 NDT$
6	M35	$DT = 26.34 + 0.169 NDT$	$DT = 28.45 + 0.211 NDT$
7	M40	$DT = 30.36 + 0.1688 NDT$	$DT = 32.28 + 0.211 NDT$

Table 6 - Regression Statistics and ANOVA Test

S.No	Parameters	14 Days	28 Days	2 year
1.	Multiple R	0.98	0.97	0.77
2.	R Square	0.97	0.95	0.52
3.	Adjusted R Square	0.97	0.95	0.57
4.	Standard Error	1.43	2.22	1.00
5.	Observations	126	126	119
6.	Significance F	2.7E-101	5.09E-83	0.027

From Table 5. that the correlation between DT and NDT methods, specifically the strength characteristics for all grade concrete within 14-day days and 28 days. The regression correlation as from Table 6 such as Multiple R, R Square and Adjusted R Square between DT and NDT methods is higher in 14 days test as compare to 28 days. Similarly Standard error and NOVA Test confirm this result which shows less value in 14 days as compares to 28 days. This confirms use of NDT method into higher grade of concrete differs as compare to DT. After testing data set of 20 years from field situ data of, taking data set of 119 no samples, the regression correlation result given in table 6 such as Multiple R, R Square and Adjusted R Square between DT and NDT methods decreases as compare 14 days and 28 days. Similarly Standard error and NOVA Test confirm this result which shows increases value from 14 days and 28 days. The prediction error NDT increases as compare to DT as the age of the concrete increases. As for Non-destructive test are concern rebound hammer test is used due its simplicity and cost effective that why it is primarily used. The rebound number depends upon the rebound value obtain by hammer which can be contaminated by several factors such as the surface condition of the concrete, age of the concrete, impact angle while taking reading and type of hammer used. From experiment one can predict as this test is not suitable for

concrete that is very hard or very soft. As far strength of concrete depends upon various factors such as age, concrete porosity, cement aggregates ratio, grade of aggregate, type of cement, curing, and mixing. To guarantee precise outcomes, the concrete floor must be spotless and devoid of any scattered particles or trash. The hammer ought to be positioned straight against the floor, and it's important to record several measurements at various spots to verify uniformity. Moreover, the hammer's selection must match the concrete being examined.

Combine regression of dataset 14 days, 28 days and 2 years there were total 357 no (70 % model generation + 30% Testing) model was generated with random data of 238 no and remaining 119 no were used for validation of model The overall equation (11) using all grade of concrete.

$$DT = 0.442 + 0.982 \text{ NDT} \quad (11)$$

Statistical data such as Multiple R, R Square, Adjusted R Square and Standard Error are 0.985, 0.970, 0.97 and 1.61 Statistical parameters such MSE, RMSE and MAPE were found out 119 no data sample for validation as shown in table 7. Therefore, there is need to find accurate tool and technic to find best solution for non-linear problem.

3.3 ANN Modeling:

Choosing the right configuration of hidden neurons for a given situation is frequently difficult. A lot of research based on prior work, as well as trial and error based on the performance of the given task. The two important steps involved in model preparation are model inputs and determination of model architecture and parameters. Basic inputs for ANN modeling are compressive strength obtain NDT and DT method from field and Lab data.

First step in ANN is to prepare data set by Normalization (Or Min-Max scaling) of data in Excel using above formula. It is the process of scaling data in such a way that all data points lie in a range of 0 to 1. Thus, this technique, makes it possible to bring all data points to a common scale.

Second step is selection of ANN has a multilayered structure which consists of input layer, hidden layer and an output layer. In this study, Cascade forward (CF) backpropagation artificial intelligence model has been trained with the dataset of compressive strength obtain by NDT and DT Methods. All the programming of ANN modelling is done in MATLAB R2024a. The architecture of CF is discussed in theoretical background as it is similar feed-forward back propagation networks. Using Single hidden layer because its power to solve complex nonlinear problem [49, 55]. Model parameters as shown in Table 4 are obtained from the above experiment as a result of training and testing process. Total 357 data is divided into training data (70%) and testing dataset (30%) for model reparation and testing. For the ANN model formation, 238 samples is further divided into Training, Testing and Validation our data set is randomly assign from training, testing and validation set containing 70% of training, 15% of Validation and 15% for testing.

Table 4 - Parameters find for given used in neural network

Number of hidden layers	1
Number of hidden neuron	5
Number of epochs	100
Transfer function of layer in hidden layer	Tan-sigmoid
Transfer function of layer in output layer	pure linear
Weight/bias learning function.	Levenberg-Marquardt (LM) algorithm
Best linking weights and biases	Random

Best validation performance is calculated mean square error (MSE) is obtain at 78 epochs obtains error is 0.002 as shown Fig. 4 correlation coefficient of training, validation, testing and overall is 0.987, 0.982, 0.985 and 0.986 as shown in fig.5

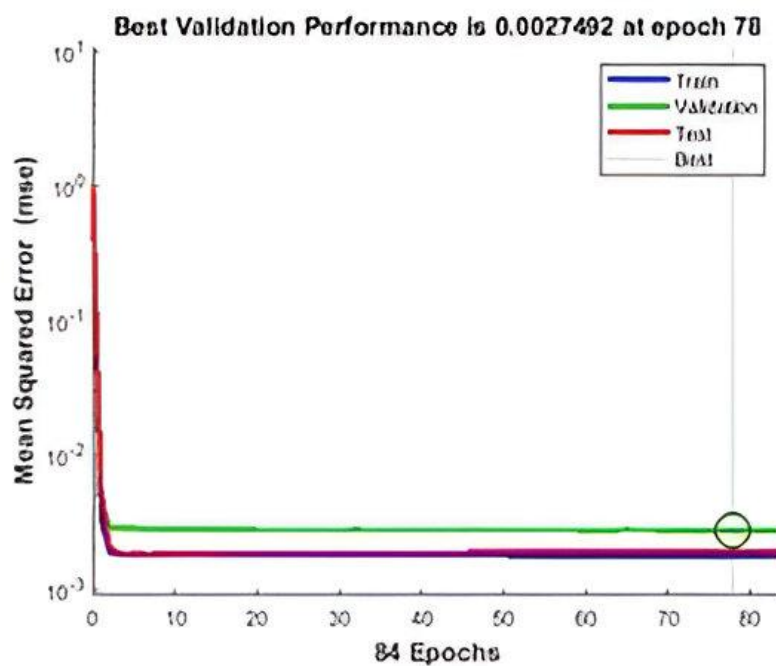


Fig.4 - Best validation performance in terms mean square error

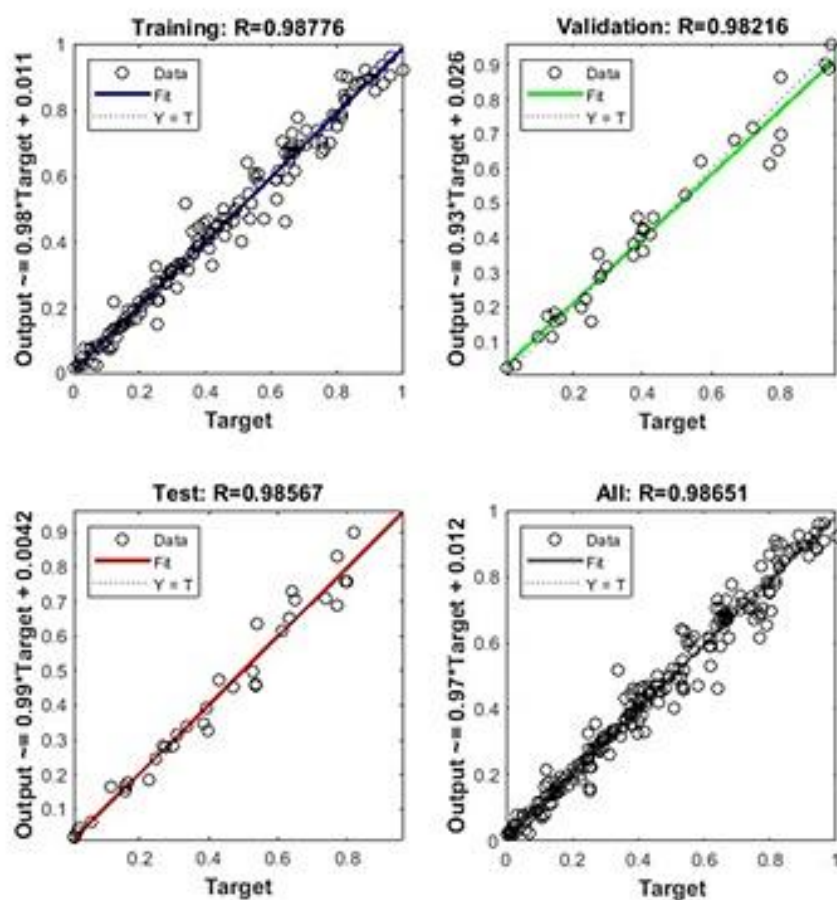


Fig. 5 - correlation coefficient of training, validation, testing and overall of ANN Model

3.4 Validation of the Models:

The predictions of models regression analysis and ANN models are done by testing data which is not used in model generations. 30 % (119 samples) from total data set were used for validation of model. Statistical parameters such as MSE, RMSE and MAPE (%) were used for validation parameters as given Table.7. From Table it is very clear ANN models ability to handle complex of concrete by comparing the prediction performance evaluation indexes of the regression model and ANN model. ANN model was found that for the prediction of compressive strength of concrete with different curing ages and different grades of concrete. The error between the predicted and measured values of the ANN model was smaller, indicating that the ANN model has better performance and higher accuracy in predicting concrete compressive strength.

Table 7- Statistical parameters of test samples

S.No	Statistical parameters	Regression	ANN Model
1	MSE	2.90	0.022
2	RMSE	1.70	0.469
3	MAPE (%)	4.70	0.206

Correlation of relation between the prediction and Actual values R^2 value of regression values 0.89 and 0.98 for regression and ANN models is given in the Fig. 6 (a & b)

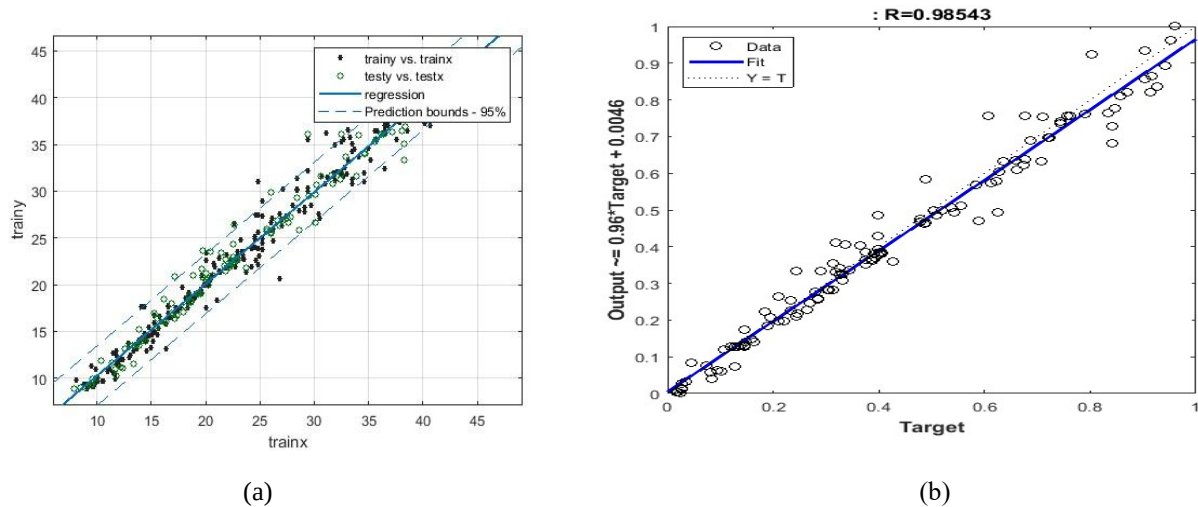


Fig.6 - (a, b) Correlations Values by regression analysis and ANN Model

3.5 Discussion

Now a day the construction of high-rise building is going common in growing urbanization and requirement of infrastructure a stage of maintenance and rehabilitation of existing structure. The retrofitting and repair of the existing structure have become a prominent research area in today's engineering construction. The considerable financial impact resulting from the degradation of concrete structures has surpassed initial projections, leading to increased scrutiny of the durability of concrete structures as a key measure of structural integrity. Primarily, two approaches were used to evaluate the compressive strength through DT and NDT [12]. In the process of DT, the structure is damaged, but it is acknowledged that DT provides the highest level of accuracy. However, this method requires a considerable amount of time and is expensive. NDT methods are extensively utilized to assess the integrity of concrete structures especially regarding their compressive strength due to its simplicity and cost-effective to use. Research has indicated that factors the concrete compressive strength depends upon mix design and age which determine by NDT can be utilization for prediction by various Models such as regression and artificial neural network techniques. Both methods (DT and NDT) have its own influences on compressive strength due to its advantage and disadvantage on strength outcomes. Consequently, this study seeks to propose a robust

methodology for forecasting concrete compressive strength by creating a practical condition by preparing various grades of concrete in lab and collecting data from field, Therefore this research work aim to utilize the effective way of predicting concrete compressive strength by DT and NDT test results.

This study employed both regression and ANN models to predict the compressive strength of concrete using data collected through DT and NDT methods. The results demonstrate the effectiveness of ANN models in providing higher predictive accuracy compared to regression models. However, certain observations and limitations need to be discussed in detail to better understand the performance of the models and potential avenues for improvement.

Model Performance by Regression Analysis:-The regression model effectively captured the relationship between the input variables and compressive strength, achieving R^2 values of 98%, 97%, and 87% for 14-day, 28-day, and 2-year-old concrete samples, respectively. These values indicate strong predictive capability for younger concrete, but the accuracy declined with the age of the concrete. This can be attributed to the nonlinear behavior of concrete strength over time, which may not be fully captured by a linear regression approach.

Model performance by ANN:-The ANN model, specifically the combined feedforward backpropagation neural network (CFBPNN), outperformed the regression model in terms of accuracy. The flexibility of ANN in handling complex, nonlinear relationships contributed to its superior performance. With an R^2 value consistently exceeding 95%, ANN demonstrated its ability to generalize across diverse datasets, even in the presence of varying site conditions and testing parameters. This highlights the robustness of ANN as a predictive tool for compressive strength.

Sample Size Considerations:-The current study utilized a relatively small training dataset due to limitations in available field and laboratory data. While the results are promising, the small sample size may reduce the generalizability of the models to a wider range of conditions. Expanding the dataset by including more samples, especially from field structures with varying ages, grades, and site conditions, would significantly enhance the reliability and applicability of the models. For a stable result for any ANN model large sample size is required as compare to small.

Comparison of Regression and ANN Models:-Regression models, while simpler to implement, are limited in their ability to capture nonlinear dependencies between variables. On the other hand, ANN models excel in this regard due to their ability to learn complex patterns from data. However, ANN models require larger datasets for effective training to avoid issues such as overfitting and poor generalization. The results of this study clearly demonstrate the superiority of ANN for predicting compressive strength, particularly when dealing with heterogeneous datasets and nonlinear relationships.

Key Observation:

- ANN models are more effective for scenarios where multiple interacting variables influence the outcome, as seen with NDT-based predictions.
- Regression models may still be valuable for simpler, linear relationships or when datasets are small.

Limitations and suggestion improvements for future work

- Data Availability:-**The limited dataset used for model training and validation may have introduced biases, potentially impacting the reliability of the results. Future studies should aim to collect more diverse datasets, encompassing a wide range of concrete grades, ages, and environmental conditions.
- Field Variability:-**Variations in site conditions, such as surface orientation (vertical or horizontal), moisture content, and testing instrument accuracy, may affect NDT measurements and, consequently, the prediction accuracy. These factors should be standardized or explicitly accounted for in future models.
- Model Complexity:-**ANN models, while accurate, can be computationally intensive and may require parameter tuning for optimal performance. This increases the complexity of their application in real-world scenarios compared to regression models. Incorporation of future Advanced Techniques may include such as Advanced machine learning techniques, such as support vector machines (SVM) and ensemble methods, could be explored to further improve prediction accuracy. Optimization algorithms, such as the Whale Optimization Algorithm and Gray Wolf Optimization Algorithm, could be employed to fine-tune model parameters. Integration of Hybrid Models:-Hybrid approaches combining regression, ANN, and heuristic optimization techniques could provide a balanced solution, leveraging the strengths of each method.
- Sensitivity Analysis:-**Future studies should perform sensitivity analyses to identify the most influential factors affecting compressive strength prediction and refine the models accordingly.

- (e) Real-Time Applications:-Incorporating real-time NDT data collection and model predictions into construction monitoring systems could provide on-site assessments of structural integrity.

While this study underscores the potential of ANN in accurately predicting concrete compressive strength, its success hinges on the availability of extensive and diverse datasets. Expanding the dataset, addressing field variability, and leveraging advanced computational methods will pave the way for more reliable and practical predictive models. Future work should focus on these aspects to establish a standardized methodology for compressive strength prediction in structural engineering.

4 Conclusion

Rehabilitating and retrofitting aging structures is a critical focus in engineering, with concrete compressive strength being a key indicator of performance. This study utilized regression analysis and a CFBPNN to predict compressive strength using data from laboratory-prepared concrete grades (M10–M40) and 20-year-old field structures. The following conclusions are mainly drawn:

- The established regression analysis and CFBPNN model were employed to predict the concrete compressive strength using 70 % of the sample data as the training set. It is found overall training generation of model regression analysis and CFBPNN model is given R^2 is 0.95 and 0.99 respectively both model. ANN model founded to be more accurate as compare to regression analysis
- The validation is done by 30 % as the test set which is not used in model generation. R^2 of the Regression analysis and the CFBPNN prediction model for the compressive strength for above dataset was 89.0 % and 98 %. Further result were confirm by applying statistical parameters MSE, RMSE and MAPE (%) which is low in CFBPNN model as compare to Regression analysis

While promising, the study is limited by the relatively small dataset of 357 samples. Expanding the dataset and incorporating advanced techniques in future research will further enhance the predictive accuracy and practical applicability of these models for evaluating concrete structures.

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