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Comprehensive multiscale techniques to estimate the compressive strength of concrete
Incorporated with carbon nanotubes at various curing times and mix proportions

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Abstract: Concrete as a building material is classified as either normal or high strength based on its compressive strength. The compressive strength of conventional concrete ranges somewhere around 20 to 40 MPa. The incorporation of high-performance nanomaterials, such as carbon nanotubes (CNT), into the concrete mix, is gaining popularity to produce multifunctional composite materials with improved mechanical, physical, and electrical properties. However, the compressive strength of normal concrete (NC) increased with the addition of CNT to the mix design. Therefore, a reliable mathematical model is required to estimate the amount of CNT to gain the necessary compressive strength. In this research, five different models were proposed to forecast the compressive strength of conventional concrete modified with carbon nanotubes, including the artificial neural network model (ANN), M5P tree model, nonlinear regression model (NLR), multilinear regression model (MLR), and linear regression model (LR). For this purpose, 282 data were collected from the literature review to examine and develop the models. During the model development, the most powerful parameters influencing concrete's compressive strength were found, i.e., curing time ranged from 1-180 days, cement varied between 250-475 kg/m\textsuperscript{3}, water to binder ratio ranged from 0.4-0.87, coarse aggregate 498-1466.8 kg/m\textsuperscript{3}, fine aggregate 175.5-1285 kg/m\textsuperscript{3}, and carbon nanotube varied between (0-10%). Based on statistical assessment parameters such as coefficient of determination R\textsuperscript{2}, mean absolute error (MAE), root mean square error (RMSE), scatter index (SI), and objective (OBJ), the ANN model execute better performance in predicting the compressive strength of NC modified with CNT.
Keywords: Conventional concrete, Carbon nanotube, Statistical analysis, Modeling, Sensitivity

1. Introduction:

Concrete is one of the most widely utilized construction materials on a global scale. It is the most significant user of nonrenewable raw, for instance, sand, crushed stone, gravel, and freshwater, and consumes approximately 1.6 billion metric tons of Portland and modified Portland cement annually [1, 2]. Portland cement, a critical concrete component, consumes a lot of energy and is a limited resource. Cement manufacturing is one of the two major sources of carbon dioxide in the atmosphere, accounting for approximately seven percent of total CO₂ emissions [3]. Concrete has contributed significantly to the growth and advancement of human civilization [4, 5]. It begins with a relatively low strength rating [6]. With the advancement of modern building projects toward long-span bridges and huge water conservancy projects, the market for strong, robust, durable, and crack-resistant concrete continues to grow. However, the creation of nanoscale pores and cracks are significant disadvantages that limit concrete's mechanical performance and longevity. Lately, the idea of distributed nanomaterials inside concrete construction has evolved to increase concrete's mechanical properties and crack resistance. [7-9].

Nanotechnology has sparked widespread global attention because of its superior performance in various industries [10]. The building industry, for example, could benefit from the use of nanoparticles in the manufacture of cement-based products. In general, nanomaterials are classified as particle sizes ranging from 1 to 100 nm [11-13]. Numerous nanomaterials have been utilized to strengthen conventional concrete, including nano SiO₂ [14], nano Al₂O₃ [15], nano CaCO₃ [16], nano Fe₃O₄ [17], nano ZnO₂ [18], nanoTiO₂ [19], carbon nanotubes [20, 21], nanoualimestone [22], nano metakaolin [23], and nano FA [24]. Concrete is the most common form of cement-based material that can benefit from the use of nanoparticles. The primary purpose for incorporating nanoparticles into concrete material, for instance, normal concrete (NC), is to enhance the microstructure of the composite, which improves the composite's mechanical, physical, and long-term behavior [25]. Hydration of cement is a chemical process involving water, C₂S, and C₃S. This reaction produces calcium silicate hydrate gel (C-S-H), and calcium hydroxide (C-H) crystals [26]. On the other hand, C-H crystals are undesired in the cement matrix due to their leaching tendency, in contrast to C-S-H, which is the primary source of strength in concrete products. One approach to reducing the amount of cement matrix C-H crystals is to include
nanoparticle materials such as carbon nanotubes that react with the C-H crystals already there. Consequently, of this reaction, extra C-S-H is generated. The number of C-H crystals within the matrix is lowered, resulting in improved microstructure, mechanical properties, and permeability of cement-based materials [11, 12, 27]. Based on the results obtained for the structural parameters/properties of diameter, a number of walls, chirality, and crosslink density, To achieve a high nominal tensile strength, armchair-type MWCNTs with the smallest diameter, a large number of walls, and a suitable crosslink density between adjacent walls are preferred. The armchair-type 5WCNT—with the outer diameter of 43.39 Å, the crosslink density between adjacent walls (from inner tube to outer tube) of 1.38 ± 1.16%, 1.13 ± 0.69%, 1.54 ± 0.57%, 1.36 ± 0.35% exhibits the best mechanical properties. The nominal tensile strength, nominal Young’s modulus, effective tensile strength, and effective Young’s modulus were approximately 58–64 GPa, 677–698 GPa, 65–71 GPa, and 730–754 GPa, respectively. We further discussed the relationship between fracture pattern and mechanical properties of CNTs, and it was observed that the tubes with “near-clean-break” fracture mode and “clean-break” fracture mode tend to exhibit high tensile strength [28, 29] because they may be used to improve the mechanical characteristics of composites made of cement. According to Van Der Waals' attraction principle, due to the relatively small scale of the nanomaterial, dispersing it evenly inside a cement-based composite is extremely difficult. The high mechanical and dispersion properties of carbon nanotubes can highly impact the increased compressive strength of NC. Nanoscale materials exhibit a pronounced agglomeration tendency, substantially influencing cementitious composites' microstructural and mechanical properties [30, 31]. Thus, more efficient carbon nanotubes in cementitious materials would necessitate solving two challenges: uniform nanoparticle dispersion and matrix bonding [32]. Several scholars have attempted to address these concerns. For instance, treating MWNTs with polyacrylic acid will boost concrete's compressive strength by up to 50% [32]. Gum arabic will enhance the dispersion of carbon nanotubes in water (up to 15% weight carbon nanotube content relative to water weight) [33]. The addition of traditional polymers or admixtures, such as acrylic particle dispersions, silica fume, methylcellulose solution, or silane, can enhance dispersion [34].

The strength of concrete of a structure is the most critical characteristic in its design. This is primarily because other mechanical and durability qualities are directly or indirectly connected to compressive strength and may be deduced from it [35, 36]. Currently, in practice, many cubical
specimens or cylindrical are produced and tested at different curing periods to determine the compressive strength of NC. Generally, work should not continue on a building site until the compressive strength test results are obtained at a specified age, most notably 28 days. This results in delayed building sites, and the testing procedure is costly and time-consuming [37]. Because various mix proportions and components may considerably influence the characteristics of NC, determining its CS has always been a primary job in concrete technology [37]. This difficulty is more apparent in the case of NC, where cement has been largely replaced with nanomaterials like carbon nanotubes. There is currently no extensive review on normal concrete that evaluates and quantifies the impact of a wide variety of mix design such as sand, cement, carbon nanotube, aggregate contents on the long-term compressive strength of the normal concrete from an initial age of 1 day to 180 days of curing. Additionally, there is no review of literature that compares the effectiveness of five different types of model techniques with high accuracy for predicting the compressive strength of conventional concrete modified with carbon nanotubes. According to the preceding, this study attempted to assess and quantify the influence of a wide variety of mixture proportions on the compressive strength of NC modified with CNT, including CNT content, w/c ratio, curing time, sand, and coarse aggregate. Using 282 data samples from the literature review, several model approaches such as linear regression (LR), multi-logistic regression (MLR), nonlinear regression (NLR), M5P tree model, and artificial neural network (ANN) were used to estimate the compressive strength of NC modified with CNT [38-49].

1.1. Research objectives:
The current research goal is to develop, describe, and propose a multiscale model for forecasting the CS of NC updated with carbon nanotubes. In this regard, extensive experimental data, including 282 samples of varying cement, sand, gravel, CNT contents, w/b ratios, and curing times, were analyzed using different modeling approaches with the following objectives: (i) to conduct statistical analysis and examine the effect of mixture compositions, for example, CNT, cement, curing time, fine and coarse aggregate contents, as well as w/b ratio, on the CS of NC modified with CNT; (ii) to reassure the construction industry that the built models can be implemented without experimental validation or theoretical constraints; and (iii) to analyze and select the most accurate model for estimating the CS of NC updated with CNT using statistical evaluation parameters across all models (linear, nonlinear, and multi-logistic relations, artificial neural network models, and M5P tree model).
2. Methodology
The overall number of 282 data was analyzed statistically and classified into two categories. The greater group contained 188 data points used to construct models, although the smaller group contained 94 data points used to test models [50, 51]. In Table 1, representative samples of the database are given, including the compressive strength of normal concrete changed with carbon nanotubes at various mix proportions. Fig. 1 illustrates the flow chart process followed in this study.

The input dataset includes the cement content (C, kg/m$^3$), water to binder ratio (w/b), coarse aggregate (CA, kg/m$^3$), fine aggregate (FA, kg/m$^3$), curing time (t, days), carbon nanotube (CNT, %). The above data were then used to evaluate the compressive strength of normal concrete using various models, and the predicted value was compared to the measured (actual) compressive strength (MPa). The following sections provide further information about the data set, modeling, and results.

3. Statistical evaluation of normal strength concrete properties modified with CNT
The standard error of Skewness and Kurtosis is calculated in this section to determine if the considered data (i) curing time, (ii) CA content, (iii) FA content, (iv) CNT content, (v) cement content, and (vi) compressive strength are normally distributed. A strong negative value (SNV) for the Kurtosis indicates that the distribution's tails are shorter than the normal distribution. For positive values, the reverse is true (longer tails). SNV denotes a long-left tail in terms of skewness, while for a positive value, the converse is valid (right tail). Research [52] provides more information on each of these methods of statistical analysis.

i. Curing Time (t)
To aid in the hydration process, the curing time should be extended to provide suitable early and late age compressive strength. Thus, based on published data, the curing period for NC modified with CNT ranged from 1 day to 180 days, with a median of 28 days. The variance, standard deviation, kurtosis, and skewness are 1064.69, 32.63, 3.24, and 1.51, respectively, based on statistical study. The link between compressive strength and curing time of NC mixes enhanced with carbon nanotubes using a histogram Fig. 2.

ii. Cement Content
Ordinary Portland cement OPC type 1 conforms to ASTM C 150 was used. The cement content had a specific gravity of 3050-3200. Based on data gathered from literature, the cement content
varied between (250 – 475 kg/m³) with a standard deviation of 45.32 kg/m³, a median of 400 kg/m³, and a variance of 2053.51 kg/m³. The statistical factors for the cement quality of normal concrete mixtures such as Kurtosis and Skewness are -0.298 and -0.11, respectively. The relationship between compressive strength and curing time of NC mixes enhanced with carbon nanotubes using a histogram Fig. 3.

iii. **w/b**
The w/b for regular concrete varied from 0.4 to 0.87, with a median of 0.49, a standard deviation of 0.08, and a variation of 0.01. Skewness, a function of the possibility of the meaning being asymmetric, is 1.89 for real-valued distributed variables. Additionally, Fig. 4 illustrates the relationship between compressive intensity and w/b and the histogram of NC updated with CNT. The findings indicate that compressive strength and w/b are inversely proportional.

iv. **Coarse aggregate (CA)**
In the literature, crushed stone or gravel with a particle size of between 10 and 20 mm was used as coarse aggregate in the production of NC. The minimum and maximum coarse aggregate content were 498 kg/m³ and 1466.8 kg/m³, respectively, with a median of 1068.75 kg/m³, a variance of 26758 kg/m³, and a standard deviation of 163.58 kg/m³. Skewness and kurtosis are statistical variables with values of -0.94 and 1.72, respectively. Fig. 5 illustrates the relationship between compressive strength and coarse aggregate content in NC mixtures modified with CNT using a histogram.

v. **Fine aggregate (FA)**
In previous experiments, river sand with a maximum aggregate size of 4.75 mm and a specific gravity of 2.60-2.8 was employed as the fine aggregate. Additionally, its gradation met the requirements of ASTM C 33. The highest and minimum fine aggregate concentrations in the NC mixes were 175.5 and 1285 kg/m³, respectively, with a median of 608.38 kg/m³, a variance of 26617.49 kg/m³, and a standard deviation of 163.15 kg/m³. Kurtosis and skewness are additional functional factors for the fine aggregate dose in NC mixes. They are 3.18 and 1.14, respectively. Fig. 6 illustrates the link between compressive strength and fine aggregate content using a histogram of NC mixes modified with CNT.
vi. CNT
The variation in compressive strength and the CNT material is shown in Fig. 7a, and there is little association between them. According to data obtained 282 from the literature review, the CNT utilized in the mix proportions had a particle size diameter of 20-100 nm, a surface area of 50-260 m²/g, and 94-98 percent purity. The lowest and highest percentage of CNT between 0 and 10% by weight of cement was utilized in mixture design (Fig. 7a). Furthermore, the standard deviation, variance, skewness, and kurtosis are correspondingly 1.89, 3.56, 4.36, and 18.47. (Fig. 7b).

vii. Compressive strength
Based on total data gathered from literature Table 1, the value of compressive strength adjusted with CNT varied between 14.7 to 66.7 MPa, with a standard deviation of 10.55 MPa, median 46.5 MPa, and variance 111.34 MPa. More than 75% of data had a compressive strength change from 40 to 66.7 MPa, and 18% ranged between 25 to 40 MPa, and 7% had less than 25 MPa.

4. Modeling
In accordance with a coefficient of correlation (R) and root mean square error (RMSE), no direct association between the composition of conventional concrete and the compressive strength, for instance, cement, sand, gravel, CNT content, and w/b up to 180 days of curing, was seen. As a result, the following models (sections 4.1–4.5) were utilized to investigate the influence of the parameters indicated above on the compressive strength of regular concrete enhanced with carbon nanotubes. The objective of this research was to compare five different approaches for forecasting the compressive strength of normal concrete modified with CNT and to select the most suitable model for estimating the compressive strength value based on the experimental finding. The forecast was compared using the following criteria: the model must be academically acknowledged, have a low error rate between experimental and predicted data, a small root mean square error, and a high correlation coefficient of determination $R^2$.

4.1. Linear regression (LR) model
Linear regression (LR) is one of the most often used regression equations for predicting concrete compressive strength [53, 54].

$$\sigma_c = a + b(w/c)$$ (1)
Correspondingly, where w/c, a, b, and $\sigma_c$ indicate the model parameters and the water to cement ratio. But on the opposite side, the Equation above excludes other elements and parameters in NC combinations changed with CNT that affect the NC strength, for instance curing time, and other mix proportions. Thus, it is recommended that Equation 2 contain any extra mix design and variables that may impact compressive strength in order to get more reliable and scientific results.

$$\sigma_c = a(t) - b(C) - c(w/b) - d(CA) - e(FA) + f(CNT) + g$$ \hspace{1cm} (2)

Where CNT represents the carbon nanotube content (percent), C represents the cement content (kg/m$^3$), w/b represents the water to binder ratio (percent), t represents the curing period (days), FA represents the fine aggregate content (kg/m$^3$). CA represents the coarse aggregate content (kg/m$^3$). The model parameters are a, b, c, d, e, f, and g. Because all variables may be adjusted linearly, the suggested Equation 2 can be regarded as an extension of Eq. 1. Although so many variables may impact the compressive strength of NC and interact with one another, this is not always the case. As a result, in order to estimate the compressive strength with appropriate precision and reliability, the model must permanently be changed [1, 53, 54].

4.2. Multilinear regression model (MLR)
MLR is a regression technique utilized when the criterion variable has a more considerable value than two phases. In other words, the MLR is similar to multiple linear regression. It may be used to indicate the connection between nominal dependent variables and two or more independent variables (Eq. 3).

$$\sigma_c = a \times t^b C^c \frac{w}{b^d} CA^e FA^f CNT^g$$ \hspace{1cm} (3)

However, Eq. 3 has a restriction in that it cannot be utilized to forecast the compressive strength of NC that is devoid of CNT. As a result, the CNT content should be bigger than zero in this model (the constraint of Equation 3 is a CNT content more significant than 0%). The least-square approach was also used to determine the model's parameters (a, b, c, d, e, f, and g) and model variables.

4.3. Nonlinear regression (NLR)
Equation (4) may be used to create a nonlinear regression model in its general version [55-57] Equation 4 may be used to approximate the compressive strength of NC mixes, and NC mixes modified with CNT based on the interrelationship between different variables in Equations (1) and (2).
\[
\sigma_c = a \cdot t^b + c \cdot C^d + e \cdot w/b^f + g \cdot CA^h + i \cdot FA^j + k \cdot CNT^l + m
\]

Where, t is the curing time in days, C is the cement content (kg/m³), w/b is the water to binder ratio, CA is the coarse aggregate content (kg/m³), FA is the fine aggregate, and CNT is the carbon nanotube content (percent), and the model parameters are a, b, c, d, e, f, g, h, i, j, k, l, and m were calculated using the least square method.

**4.4. Artificial neural network (ANN)**

The ANN feed is the inverse of the forward neural network feed [53, 58-60]. It consists of three sorts of layers: the input layer, the output layer, and the hidden layer, as seen in Fig. 8.

The input layer is where the signal to be examined will be received. The output layer performs the necessary tasks, such as predicting and categorizing. The true computational ANN engine is composed of an infinite number of hidden layers placed among the input and output layers. The data travels forward from the input to the output layer, similar to the feed-forward network in the ANN. The hidden layer output performance improved during trial iterations to select the optimal number of hidden layers for a model to reduce error and enhance \( R^2 \). However, because of the complexity of the Equation for many hidden layers, a single hidden layer with four neural networks was chosen in this study by error and trial in order to obtain the lowest RMSE and MAE in Fig. 9 and a higher \( R^2 \). Eq. 5 illustrates an ANN with a single hidden layer.

\[
\beta_n = a_n(t) + b_n(C) + c_n(w/b) + d_n(CA) + e_n(FA) + f_n(CNT) + h_n
\]

\[
\sigma_c = \frac{\text{node}_1}{1+e^{-\beta_1}} + \frac{\text{node}_2}{1+e^{-\beta_2}} + \cdots + \frac{\text{node}_n}{1+e^{-\beta_n}} + \text{threshold}
\]

Node1, node2, node3, node4, and threshold may be calculated straight from the neural network machine in the WEKA software.

**4.5. M5P tree model**

M5P algorithm [61] is an enhanced version of Quinlan's M5 algorithm [62]. One of modeling trees' primary advantages is their ability to efficiently handle huge numbers of data sets with a
considerable number of characteristics and dimensions. Additionally, they are referred to as strong when handling missing data.

It is a regression learner. By dividing or classifying diverse data areas into multiple distinct spaces, this tree approach generates linear regression characteristics on the terminal node and fits them into a multivariable regression analysis for each sublocation. The M5P-tree method is not concerned with discrete segments but with continuous class issues and can handle functions with a rather large dimension. Reveals the data for each linear model component built in order to approximate the nonlinear connection between the data sets. Error estimates are provided on each node along with information on the tree division criteria used in the M5P-tree model. Errors are quantified by the class entering the node's default value variance. Any function of that node is evaluated using the attribute that maximizes the predicted error reduction. Based on node-level error computations, information on the M5P-tree model's tree division criteria is gathered. The M5P error is calculated as the standard deviation of the node's class values. The feature that maximizes the predicted error reduction from assessing each attribute at that node is chosen for node division. As a result of the branching strategy, the data for child nodes (subtree or smaller nodes) has a lower StD value. Nodes that serve as parents (greater nodes). After examining all viable structures, choose the one that has the most potential for mistake reduction. Additionally, this division results in the formation of a vast tree-like structure, which promotes overfitting. The massive tree is pruned in the second stage, and the cut subtrees are substituted with linear regression functions.

5. Assessment criteria for models

Various output parameters, including the $R^2$, RMSE, MAE, SI, and OBJ which are specified, have been used to test and evaluate the efficiency of the suggested models.

\[
R^2 = \left( \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \cdot \sqrt{\sum_i (y_i - \bar{y})^2}}} \right)^2
\]  

\[
RMSE = \sqrt{\frac{\sum_{i=1}^m (y_i - \hat{y}_i)^2}{m}}
\]
MAE = 
\[ \sum_{i=1}^{m}(Y_i - X_i)^2 \]
\[ m \]

\[ SI = \frac{RMSE}{yi} \]
\[ (9) \]

OBJ = \left( \frac{m_{tr} * \frac{RMSE_{tr} + MAE_{tr}}{R^2_{tr}+1}}{m_{all}} \right) + \left( \frac{m_{tst} * \frac{RMSE_{tst} + MAE_{tst}}{R^2_{tst}+1}}{m_{all}} \right) \]
\[ (10) \]

Where \( Y_i \) = trial value; \( X_i \) = forecasted value by the proposed model; \( \bar{Y} \) = the average value of experimental values; \( \bar{X} \) = average of the predicted value, and \( m \) is the number of data points.

5. Analysis and output

5.1. Linear regression model (LR)

Figure 10a and Figure 10b illustrate the connection between actual and predicted compressive strength of NC mixes adjusted with CNT for training and testing datasets, respectively. According to the model parameters, the curing time and w/b ratio substantially affect the CS of NC modified with CNT. The weight of each variable on the CS of NC modified with CNT was calculated for the current model using the total amount of error squares and least-squares methods, which were enacted in Excel utilizing Solver to compute the model's ideal value (a specific value, minimum or maximum) in a single cell named the objective cell. Particular values restricted this object cell in other worksheet equation cells [63, 64]. The following Equation may be used to represent the LR model with varied weight parameters (Eq. 11):

\[ \sigma_c = 0.14t - 0.02C - 63.72\ w/b - 0.01CA - 0.01FA + 0.04CNT + 80.45 \]

Based on the above Equation, the water to binder ratio has highly impacted the compressive strength of NC modified with CNT. This can be matched with previous studies [65, 66]. Fig. 10a and Fig. 10b can be noticed that the formula cannot correctly predict the compressive strength lower than 25 MPa, which matches with the literature review [50, 54]. \( R^2 \), RMSE, and MAE values for this model are 0.69, 5.51 MPa, and 3.89 MPa, respectively Fig. 15. Additionally, as seen in Fig. 17 and Fig. 18, the OBJ and SI values for the present model are 6.58 MPa and 0.12 for the training dataset, respectively.
5.2. Multilinear regression model (MLR)

The MLR model parameter indicates that the cement content and w/b ratios have a more significant influence on the compressive strength of typical concrete mixes than the other mix components. This matches with previous studies in the literature [65, 66]. Figure 11 illustrates the connections between the compressive strengths of the concrete mixes as estimated and as measured. The study dataset has a 35% error line, suggesting that almost all verified findings fall inside the 35% error line. Additionally, the output of this model is comparable to that of the LR, with the model significantly overestimating low-strength concrete mixes and underestimating high-strength concrete mixes.

\[ \sigma_c = 14.266(t)^{0.16}(C)^{0.287}(w/b)^{-0.757}(CA)^{-0.073}(FA)^{-0.166}(CNT)^{0.01} \]  

Eq. 12

R², RMSE, and MAE are 0.73, 5.11 MPa, and 3.48 MPa, respectively, for this model's assessment parameters. Additionally, the current model's SI and OBJ values are 0.11 and 5.78 MPa, respectively, for the training dataset.

5.3. Nonlinear regression model (NLR)

The predicted compressive strength against the actual compressive strength derived from training and testing datasets of NC mixes modified with CNT is shown in Fig. 12a and Fig. 12b. According to this model, the most critical elements affecting the compressive strength of NC mixes are the w/b ratio and coarse aggregate concentration. This was also confirmed by numerous experimental programs from previous research, which showed that reducing the w/b ratio and increasing the cement content considerably increased the compressive strength of NC mixes [67-70]. The following Equation may be used to represent the NLR model with different variable parameters (Equation 13):

\[ \sigma_c = 45(t)^{0.1} + 0.004(C)^{1.31} - 62.8 (w/b)^{2.4} + 0.529(CA)^{-2.25} + 207.57(FA)^{-0.01} + 8.4(CNT)^{0.08} - 211 \]  

Eq. 13

This model's R², MAE, and RMSE parameters are 0.8, 3.06, and 4.3 MPa, respectively. Additionally, the current model's OBJ and SI values are 4.43 MPa and 0.09 for the training dataset, respectively.
5.4. Artificial neural network (ANN)

To forecast compressive strength values for the appropriate input parameters, the network was fed both training and test data. Fig. 8. The process of developing an ANN model is iterative (such as the number of hidden layer neurons, learning rate, momentum, and iteration). The number of hidden layers utilized in this study is one with nineteen neural networks. The learning rate is 0.1, the momentum is 0.1, and the training duration is 50,000. Additionally, the number of epochs is a hyperparameter that determines how many times the learning algorithm may process the training dataset. As the error is reduced, the greater the number of epochs, the higher the $R^2$, the lower the RMSE, and the lower the MAE. The projected compressive strength vs. the actual value is displayed in Fig. 13, illustrating the primary concept of generating data using an ANN model.

\[
\begin{bmatrix}
1.54 & 0.27 & 0.13 & 0.16 & -0.19 & 1.46 & -2.51 \\
0.51 & -1.79 & -6.17 & -0.34 & 5.54 & 4 & -2.45 \\
1.39 & -0.76 & 1.31 & 0.93 & -0.27 & 0.08 & -2.34 \\
2.18 & 1.16 & -5.35 & -1.17 & -7.79 & -0.17 & -6.1 \\
-1.62 & -4.74 & 3.81 & -4.19 & 2.6 & 2.74 & -0.22 \\
2.26 & -0.88 & 0.34 & -0.07 & 1.03 & 0.86 & -1.19 \\
3 & -0.9 & 1.42 & -0.18 & 1.49 & 0.08 & -1.12 \\
-4.03 & -8.68 & 5.2 & 9.3 & 9.93 & -0.2 & -7.61 \\
4.89 & -4.51 & -1.98 & -0.03 & -3.2 & 1.14 & 1.25 \\
1.21 & -2.89 & 1.83 & 1.24 & -2.02 & -13.59 & -13.53 \\
-4.91 & 3.66 & 14.12 & 1.57 & -1.28 & 1.47 & -0.77 \\
-3.03 & -0.86 & 7.19 & -1.73 & -0.35 & -3.98 & -5.97 \\
-0.24 & -0.03 & 6.18 & 2.66 & 1.45 & -1.61 & 1.93 \\
1.22 & -3.79 & 0.69 & 5.25 & -3.65 & 0.57 & -4.15 \\
2.86 & -1.09 & 2.26 & 0.35 & 0.51 & -1.37 & -1.86 \\
-14.37 & 1.69 & -1.27 & 7.42 & 17.48 & -0.16 & -16.08 \\
5.65 & 1.12 & 2.17 & -2.92 & 4.05 & 0.04 & -1.87 \\
9.94 & 1.39 & 2.83 & -0.37 & -3.12 & 4.72 & 1.96 \\
3.78 & 3.64 & -3.29 & -0.2 & -1.01 & 3.01 & -4.9 \\
\end{bmatrix} \times \begin{bmatrix}
t \\
C \\
w/b \\
CA \\
FA \\
CNT \\
1 \\
\end{bmatrix} = \begin{bmatrix}
\beta_1 \\
\beta_2 \\
\beta_3 \\
\beta_4 \\
\beta_5 \\
\beta_6 \\
\beta_7 \\
\beta_8 \\
\beta_9 \\
\beta_{10} \\
\beta_{11} \\
\beta_{12} \\
\beta_{13} \\
\beta_{14} \\
\beta_{15} \\
\beta_{16} \\
\beta_{17} \\
\beta_{18} \\
\beta_{19} \\
\end{bmatrix}
\]

\[
\sigma_c = \frac{-3.68}{1+e^{-\beta_1}} + \frac{2.75}{1+e^{-\beta_2}} + \cdots + \frac{2.66}{1+e^{-\beta_{19}}} - 0.15 \tag{14}
\]
This model's $R^2$, RMSE, and MAE values are 0.98, 1.34 MPa, and 0.96 MPa, respectively. Additionally, for the training dataset, the OBJ and SI values for the present model Eq. 14 are 1.43 MPa and 0.03.

5.5. M5P tree model
WEKA software was used to develop the M5P model tree (with value m) [71]. The number of m was determined by error and trial, implying that 4 was the optimal number form. The M5P-tree technique divides the input space (independent variables) into eight linear tree regression functions, as seen in Fig. 20 (marked LM1 through LM8). The general form of the model is $y = b_0 + b_1x_1 + b_2x_2$, where $b_0$, $b_1$, and $b_2$ are linear regression constants. The tree-shaped branch connection is illustrated in Fig. 14, and the model's Eq.14 parameters are reported in Table 3. The study dataset has a 25% error line, suggesting that almost all measured values fall inside the 25% error line (Fig. 14).

5.6. Comparative analysis of several models
As mentioned before, five distinct statistical metrics, RMSE, MAE, SI, $R^2$, and OBJ, were used to evaluate the suggested models' effectiveness. Fig. 15 compares models for the training and testing datasets of NC modified with CNT using RMSE, MAE, and $R^2$. Compared to the LR, MLR, M5P, and NLR models, the ANN model has a higher $R^2$ value and a lower RMSE and MAE value. Additionally, Fig. 16 shows the residual error for all models created during the dataset preparation, training, and testing processes. Both graphs demonstrate that the real and estimated values of CS are closer to the ANN model, indicating the ANN's better efficiency over other models.

The OBJ rates for each of the proposed models are shown in Fig. 17. The lower OBJ value shows that the model does exceptionally well at predicting the CS of NC modified with CNT. LR, MLR, NLR, ANN, and M5P have OBJ values of 6.58 MPa, 5.22 MPa, 4.43 MPa, 1.43 MPa, and 5.41 MPa. The ANN model's OBJ value is 78.27 percent less than that of the LR model, 72.6 percent less than that of the MLR model, 57.88 percent less than that of the NLR model, and 73.57 percent less than that of the M5P model. This demonstrates that the ANN model is more effective at estimating the CS of NC mixes changed with CNT.

Figure 18 illustrates the SI assessment parameter values for the proposed models during the training and testing stages. As seen in Fig. 18, the SI values for all models and phases (training
and testing) ranged between 0.03 and 0.18, suggesting that all models performed admirably. However, like with the other performance characteristics, the ANN model has a lower SI value of 0.03 for the training dataset than other models. In the training phase, the ANN model has a SI value 75% lower than the LR model, 72.73 percent lower than the MLR model, 63% lower than the NLR model, and 62.5 percent lower than the M5P model.

Among all other models, the ANN model has the lowest SI value. Additionally, this demonstrated that the ANN model is more efficient and outperformed the LR, MLR, NLR, and M5P models when predicting the CS of NC mixes changed with CNT. Additionally, Fig. 19 compared the actual and forecasted CS of NC modified with CNT across all various models trained on the same data set.

5.7. Sensitivity

Sensitivity Analysis examines the relationship between the variation in an output of a numerical model and the variation in its input components [72, 73]. To identify and quantify the most influential variable affecting the CS of NC mixes modified with CNT, sensitivity analysis was done on the models [50, 54]. For the sensitivity analysis, the most effective model, ANN, was chosen. Several separate training data sets were utilized in the sensitivity analysis, with each set extracting a single input variable at a time. The evaluation parameters R2, MAE, and RMSE, were computed individually for each training dataset. Table 2 summarizes the findings of the sensitivity analysis.

As a consequence of the results, it is clear that curing time is the most critical and influential variable in predicting the CS of NC mixes modified with CNT. The curing duration spanned from 1 to 180 days in this study, indicating that extending the curing time significantly improved the CS of NC mixes including CNT. Almost all of the experimental data in Table 1 corroborate this.

6. Conclusions

The compressive strength of NC may be increased by precisely adding nanomaterials such as carbon nanotubes. As a result, precise and reliable models for compressive strength prediction can result in substantial time and cost savings. The following conclusions may be drawn from the study
and modeling of data from prior research used to simulate the compressive strength of NC mixes enhanced with CNT at 282 various mixed proportions:

1- CNT was used in the manufacture of NC mixes with a variance of 0.35 percent. Additionally, the proportion of carbon nanotubes in the cement varied between 0 and 10%. The cure period for data acquired from diverse experimental programs varied between one and one hundred and eighty days.

2- The LR, MLR, NLR, ANN, and M5P models were used to estimate the CS of NC mixes in this work. Using a variety of assessment criteria, including $R^2$, RMSE, MAE, SI, and OBJ. The results revealed that the sequence of models was LR, MLR, NLR, M5P, and ANN, indicating that the ANN was the best model presented in this study based on data gathered from the literature and yielding a higher $R^2$ and a lower RMSE and MAE.

3- SI values were between 0.03 and 0.18 for all models and stages (training and testing), showing that the models performed well. Additionally, the ANN model has a SI value that is 75% lower than the LR model, 72.73 percent lower than the MLR model, 63% lower than the NLR model, and 62.5 percent lower than the M5P model during the training phase.

4- A smaller OBJ value suggests that the model is more reliable and performs better. According to OBJ values, the ANN had 78.27 percent less than the LR model, 72.6 percent fewer than the MLR model, 57.88 percent fewer than the NLR model, and 73.57 percent fewer than the M5P model. Additionally, data indicate that the ANN model is more successful at computing the CS of NC mixtures that CNT has modified.

5- A sensitivity analysis reveals that the curing age is the essential input variable for predicting the CS of NC mixes treated with CNT. Increased curing time has a substantial effect on the CS of NC mixtures with or without CNT.

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Fig. 1 The flow chart diagram process followed in this study
Table 2. Sensitivity analysis using ANN-based model

| No | Input combination                     | Removed parameter | \(R^2\) | MAE  | RMSE | Ranking |
|----|--------------------------------------|-------------------|---------|------|------|---------|
| 1  | Gravel, sand, cement, w/b, curing time, CNT | None              | 0.9716  | 1.34 | 1.82 |         |
| 2  | Sand, cement, w/b, curing time, CNT    | Gravel            | 0.9547  | 2.19 | 2.79 | 5       |
| 3  | Gravel, cement, w/b, curing time, CNT  | Sand              | 0.9324  | 1.96 | 2.75 | 3       |
| 4  | Gravel, sand, w/b, curing time, CNT    | Cement            | 0.9639  | 1.82 | 2.4  | 6       |
| 5  | Gravel, sand, cement, curing time, CNT | w/b               | 0.8909  | 3.35 | 4.42 |         |
| 6  | **Gravel, sand, cement, w/b, CNT**     | **Curing time**   | **0.6972** | **4.64** | **6.14** | **1**  |
| 7  | Gravel, sand, cement, w/b, curing time | CNT               | 0.9382  | 2.09 | 2.89 | 4       |

Table 3: Non-linear model parameters for compressive strength using M5P-tree model

\[
\sigma_c = at + bC + c \frac{w}{b} + dCA + eFA + fCNT + G
\]

| LM num. | 1         | 2         | 3         | 4         | 5         | 6         | 7         | 8         |
|---------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| a       | 0.9411    | 0.1283    | 0.1252    | 0.1049    | 0.0546    | 0.0603    | 0.0603    | 0.1016    |
| b       | 0.0029    | 0.0029    | 0.0288    | -0.035    | 0.0029    | 0.0391    | 0.0367    | 0.0276    |
| c       | -37.9641  | -52.7266  | -66.004   | -60.5311  | -63.9858  | -80.1689  | -50.756   | -90.964   |
| d       | -0.0358   | -0.0055   | -0.0175   | -0.0152   | -0.023    | 0.0021    | 0.0029    | 0.0015    |
| e       | 0.0002    | 0.0016    | 0.0026    | 0.0057    | -0.0089   | -0.0114   | -0.013    | -0.0061   |
| f       | 0.3048    | 0.274     | 0.0236    | 0.002     | 0.002     | 0.002     | 0.002     | 0.002     |
| g       | 87.0988   | 69.5883   | 80.2033   | 99.9938   | 97.0583   | 70.1359   | 56.7339   | 78.7735   |

Fig. 2. (a) The variation between compressive strength and curing time (b) Histogram for curing time and the compressive strength of normal strength concrete
Fig. 3. (a) The variation between compressive strength and cement (b) Histogram for cement and the compressive strength of normal strength concrete

\[ y = 52.689 \ln(x) - 269.9 \]
\[ R^2 = 0.3385 \]

No. of Data=282
Max=475
Min=250
Median=400
StDev=45.32
Variance=2053.51
Skewness=-0.11
Kurtosis=-0.298

Fig. 4. (a) The variation between compressive strength and w/b (b) Histogram for w/b and the compressive strength of normal strength concrete

\[ y = 117.7e^{-1.993x} \]
\[ R^2 = 0.3 \]

No. of Data=282
Max=0.87
Min=0.4
Median=0.49
Variance=0.01
Skewness=1.89
Kurtosis=5.14
Fig. 5. (a) The variation between compressive strength and coarse aggregate (b) Histogram for coarse aggregate and the compressive strength of normal strength concrete

![Graph](image)

\[ y = -0.0007x + 45.91 \]
\[ R^2 = 0.0001 \]

![Histogram](image)

No. of Data=282
Max=1466.80
Min=498
Median=1068.75
StDev=163.58
Variance=26751
Skewness=-0.94
Kurtosis=1.72

Fig. 6. (a) The variation between compressive strength and fine aggregate (b) Histogram for fine aggregate and the compressive strength of normal strength concrete

![Graph](image)

\[ y = -0.0322x + 65.677 \]
\[ R^2 = 0.2472 \]

![Histogram](image)

No. of Data=282
Max=1285
Min=175.5
Median=608.38
StDev=163.15
Variance=26617.49
Skewness=1.14
Kurtosis=3.18

Fig. 7. (a) The variation between compressive strength and CNT (b) Histogram for fine CNT and the compressive strength of normal strength concrete

![Graph](image)

\[ y = -1.1394x + 45.73 \]
\[ R^2 = 0.0415 \]

![Histogram](image)

No. of Data=282
Max=10
Min=0
Median=0
StDev=1.89
Variance=3.56
Skewness=4.36
Kurtosis=18.47
Fig. 8 Typical architecture of Neural Network Model a) One hidden layer  b) Two hidden layer  c) Three hidden layer
Fig. 9 Choosing best-hidden layer and neurons for Artificial Neural Network Model based on lower RMSE and MAE values.
LR Model (Eq. 11)
Training Data = 188
$R^2 = 0.69$
$R = 0.83$
$RMSE = 5.51$ MPa

Compressive strength $\sigma_c$ (MPa), measured

Compressive strength $\sigma_c$ (MPa), predicted

$\sigma_c = 0.14t - 0.02c - 63.72 \ w/b - 0.01CA - 0.01FA + 0.04CNT + 80.45$
Fig. 10. Comparison between measured and predicted the compressive strength using Linear Regression model (LR) (a) training dataset, (b) testing dataset

LR Model (Eq.11)
Testing Data= 94
R²=0.55
R=0.74
RMSE=7.83 MPa
Compressive strength $\sigma_c$ (MPa), measured

MLR Model (Eq. 12)
Training Data = 188
$R^2 = 0.73$
$R = 0.86$
$RMSE = 5.1$ MPa

$\sigma_c = 14.06t^{0.16}C^{0.287}\frac{w}{b}^{-0.757}CA^{-0.073}FA^{-0.166}CNT^{0.01}$
Fig. 11. Comparison between measured and predicted the compressive strength using Multi Linear Regression model (MLR) (a) training dataset, (b) testing dataset

MLR Model (Eq.12)
Testing Data= 94
$R^2=0.63$
$R=0.79$
RMSE=7.1 MPa
Compressive strength $\sigma_c$ (MPa), predicted vs. measured.

NLR Model (Eq.13)
Training Data= 188
$R^2=0.80$
$R=0.89$
RMSE=4.29 MPa

$\sigma_c = 45t^{0.1} + 0.004C^{1.31} - 62.8 \frac{w}{b^{2.4}}$
$+ 0.529CA^{-2.25} + 207.57FA^{-0.01}$
$+ 8.4CNT^{0.08} - 211$
Fig. 12. Comparison between measured and predicted the compressive strength using Non-Linear Regression model (NLR) (a) training dataset, (b) testing dataset

NLR Model (Eq.13)
Testing Data= 94
R²=0.77
R=0.88
RMSE= 5.32 MPa

Compressive strength $\sigma_c$ (MPa), predicted
Compressive strength $\sigma_c$ (MPa), measured

Fig. 12. Comparison between measured and predicted the compressive strength using Non-Linear Regression model (NLR) (a) training dataset, (b) testing dataset
ANN Model [Eq.14]  
Training Data= 188  
R²=0.98  
R=0.99  
RMSE=1.34 MPa
Fig. 13. Comparison between measured and predicted the compressive strength using ANN model (a) training dataset, (b) testing dataset

ANN Model [Eq.5]
Testing Data= 94
$R^2=0.96$
$R=0.98$
$RMSE=2.26 \text{ MPa}$
Compressive strength $\sigma_c$ (MPa), predicted

Compressive strength $\sigma_c$ (MPa), measured

M5P Model [Eq.4]
Training Data= 188
$R^2=0.88$
$R=0.94$
RMSE=3.47 MPa
Fig. 14. Comparison between measured and predicted the compressive strength using M5P tree model (a) training dataset, (b) testing dataset
Fig. 15. Comparison of the RMSE, MAE, and $R^2$ performance parameters of different developed models for the training dataset and testing dataset.
Fig. 16. Residual error of compressive strength using training and testing dataset
Fig. 17. The OBJ values for all developed models
Fig. 18. Comparison of the SI performance parameter of different developed models for the training dataset and testing dataset.
Fig. 19. Variation in predicted and measured values of electrical resistivity based on five different approaches using the training dataset.
Fig. 20. M5P Pruned model tree

```plaintext
Cement (kg/m³)
Fine aggregate (kg/m³)
Curing time (days)
LM 1 (18/47.126%)
LM 2 (18/19.605%)
LM 3 (38/26.725%)
LM 4 (11/34.79%)
LM 5 (27/58.80%)
LM 6 (20/7.343%)
LM 7 (30/13.59%)
LM 8 (46/9.391%)
```

Journal Pre-proof
## Appendix

Table 1: Effect of Carbon nanotube on normal concrete compressive strength at different w/b ratio and different curing age

| Ref | Curing (days) | Cement (kg/m³) | w/b  | Coarse aggregate (kg/m³) | Fine aggregate (kg/m³) | CNT (%) | Compressive strength (MPa) |
|-----|---------------|----------------|------|--------------------------|------------------------|---------|----------------------------|
| 28  | 360           | 0.50           | 950  | 745                      | 0                      | 39.5    |
| 28  | 320           | 0.56           | 898  | 782                      | 0                      | 40.0    |
| 28  | 328.5         | 0.68           | 533.7| 625.1                    | 0                      | 40.0    |
| 28  | 360           | 0.50           | 898  | 797                      | 0                      | 40.0    |
| 28  | 320           | 0.56           | 845  | 834                      | 0                      | 40.3    |
| 28  | 340           | 0.50           | 898  | 842                      | 0                      | 40.8    |
| 28  | 302           | 0.56           | 898  | 828                      | 0                      | 40.8    |
| 28  | 302           | 0.56           | 950  | 776                      | 0                      | 41.0    |
| 28  | 340           | 0.50           | 845  | 893                      | 0                      | 41.1    |
| 28  | 340           | 0.50           | 950  | 790                      | 0                      | 41.3    |
| 28  | 400           | 0.45           | 845  | 863                      | 0                      | 41.3    |
| 28  | 360           | 0.50           | 845  | 848                      | 0                      | 41.5    |
| 28  | 400           | 0.45           | 898  | 811                      | 0                      | 41.5    |
| 28  | 405           | 0.44           | 950  | 702                      | 0                      | 41.5    |
| 28  | 378           | 0.45           | 950  | 803                      | 0                      | 41.8    |
| 28  | 360           | 0.50           | 845  | 789                      | 0                      | 42.0    |
| 28  | 400           | 0.45           | 950  | 759                      | 0                      | 42.1    |
| 28  | 360           | 0.50           | 950  | 686                      | 0                      | 42.4    |
| 28  | 378           | 0.45           | 898  | 855                      | 0                      | 42.5    |
| 28  | 405           | 0.44           | 898  | 754                      | 0                      | 43.0    |
| 28  | 360           | 0.50           | 898  | 738                      | 0                      | 43.2    |
| 28  | 340           | 0.50           | 950  | 734                      | 0                      | 43.3    |
| 28  | 450           | 0.40           | 950  | 718                      | 0                      | 43.5    |
| 28  | 405           | 0.44           | 950  | 805                      | 0                      | 43.6    |
| 28  | 450           | 0.40           | 898  | 770                      | 0                      | 43.8    |
| 28  | 412.5         | 0.49           | 520.1| 612.7                    | 0                      | 44.0    |
| 28  | 450           | 0.40           | 845  | 821                      | 0                      | 44.5    |
| 28  | 383           | 0.44           | 845  | 801                      | 0                      | 45.0    |
| 28  | 340           | 0.50           | 898  | 786                      | 0                      | 45.1    |
| 28  | 383           | 0.44           | 950  | 749                      | 0                      | 45.7    |
| 28  | 425           | 0.40           | 950  | 764                      | 0                      | 46.0    |
| 28  | 425           | 0.40           | 898  | 816                      | 0                      | 46.0    |
| 28 | 425 | 0.40 | 845 | 853 | 0 | 47.1 |
| 28 | 425 | 0.40 | 845 | 868 | 0 | 47.7 |
| 28 | 401.5 | 0.51 | 518.6 | 610.9 | 0 | 50 |
| 28 | 400 | 0.50 | 1128 | 572 | 0 | 43.1 |
| 28 | 400 | 0.53 | 1196 | 616 | 0 | 38.6 |
| 28 | 425 | 0.47 | 1096.5 | 544 | 0 | 47.2 |
| 28 | 425 | 0.49 | 1177.25 | 590.75 | 0 | 45.1 |
| 28 | 450 | 0.44 | 1057.5 | 513 | 0 | 49.6 |
| 28 | 450 | 0.47 | 1143 | 562.5 | 0 | 47.4 |
| 28 | 475 | 0.42 | 1040.25 | 498.75 | 0 | 54 |
| 28 | 475 | 0.44 | 1168.5 | 565.25 | 0 | 50.1 |
| 28 | 375 | 0.53 | 1143.75 | 592.5 | 0 | 37.8 |
| 28 | 400 | 0.50 | 1128 | 572 | 0 | 44.1 |
| 28 | 400 | 0.53 | 1196 | 616 | 0 | 40.9 |
| 28 | 425 | 0.47 | 1096.5 | 544 | 0 | 47.5 |
| 28 | 425 | 0.49 | 1177.25 | 590.75 | 0 | 45.3 |
| 28 | 425 | 0.51 | 1253.75 | 641.75 | 0 | 42.5 |
| 28 | 450 | 0.44 | 1057.5 | 513 | 0 | 52 |
| 28 | 450 | 0.47 | 1143 | 562.5 | 0 | 48.7 |
| 28 | 450 | 0.49 | 1228.5 | 616.5 | 0 | 46.6 |
| 28 | 475 | 0.42 | 1040.25 | 498.75 | 0 | 54.5 |
| 28 | 475 | 0.44 | 1168.5 | 565.25 | 0 | 53.1 |
| 28 | 475 | 0.46 | 1192.25 | 584.25 | 0 | 49.2 |
| 28 | 425 | 0.52 | 858.5 | 607.75 | 0 | 40 |
| 28 | 450 | 0.49 | 837 | 580.5 | 0 | 45.3 |
| 28 | 450 | 0.51 | 891 | 175.5 | 0 | 42.7 |
| 28 | 475 | 0.46 | 817 | 560.5 | 0 | 48.7 |
| 28 | 475 | 0.48 | 869.25 | 598.5 | 0 | 45.5 |
| 28 | 350 | 0.51 | 1141 | 486.5 | 0 | 39.5 |
| 28 | 350 | 0.54 | 1197 | 521.5 | 0 | 31.7 |
| 28 | 375 | 0.48 | 1121.25 | 468.75 | 0 | 42.7 |
| 28 | 375 | 0.51 | 1196.25 | 506.25 | 0 | 40.7 |
| 28 | 400 | 0.45 | 1080 | 440 | 0 | 47.9 |
| 28 | 400 | 0.48 | 1168 | 484 | 0 | 44.9 |
| 28 | 425 | 0.42 | 1049.75 | 416.5 | 0 | 51.3 |
| 28 | 425 | 0.45 | 1139 | 463.25 | 0 | 49.1 |
| 28 | 450 | 0.42 | 1102.5 | 441 | 0 | 53.7 |
| 28 | 350 | 0.54 | 1197 | 521.5 | 0 | 36.6 |
| 28 | 375 | 0.51 | 1196.25 | 506.25 | 0 | 41.6 |
| 28 | 400 | 0.48 | 1168 | 484 | 0 | 46.2 |
| 28 | 425 | 0.45 | 1139 | 463.25 | 0 | 50.4 |
|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 28 | 450 | 0.42 | 1102.5 | 441 | 0 | 54.1 |
| 28 | 375 | 0.53 | 903.75 | 551.25 | 0 | 37.3 |
| 28 | 400 | 0.50 | 884 | 528 | 0 | 44 |
| 28 | 400 | 0.53 | 944 | 576 | 0 | 39.6 |
| 28 | 425 | 0.47 | 862.75 | 505.75 | 0 | 47.4 |
| 28 | 425 | 0.49 | 926.5 | 548.25 | 0 | 44.7 |
| 28 | 450 | 0.44 | 837 | 481.5 | 0 | 50.9 |
| 28 | 450 | 0.47 | 900 | 526.5 | 0 | 48.1 |
| 28 | 475 | 0.42 | 798 | 451.25 | 0 | 54.1 |
| 28 | 475 | 0.44 | 874 | 503.5 | 0 | 51.3 |
| 56 | 375 | 0.53 | 1143.75 | 592.5 | 0 | 40.9 |
| 56 | 400 | 0.50 | 1128 | 572 | 0 | 50.2 |
| 56 | 400 | 0.53 | 1196 | 616 | 0 | 45.5 |
| 56 | 425 | 0.47 | 1096.5 | 544 | 0 | 51.3 |
| 56 | 425 | 0.49 | 1177.25 | 590.75 | 0 | 50.7 |
| 56 | 450 | 0.44 | 1057.5 | 513 | 0 | 54.5 |
| 56 | 450 | 0.47 | 1143 | 562.5 | 0 | 51.3 |
| 56 | 475 | 0.42 | 1040.25 | 498.75 | 0 | 57.9 |
| 56 | 475 | 0.44 | 1168.5 | 565.25 | 0 | 55.7 |
| 56 | 375 | 0.53 | 1143.75 | 592.5 | 0 | 43.5 |
| 56 | 400 | 0.50 | 1128 | 572 | 0 | 50.9 |
| 56 | 400 | 0.53 | 1196 | 616 | 0 | 46.6 |
| 56 | 425 | 0.47 | 1096.5 | 544 | 0 | 52.9 |
| 56 | 425 | 0.49 | 1177.25 | 590.75 | 0 | 51.5 |
| 56 | 425 | 0.51 | 1253.75 | 641.75 | 0 | 49.1 |
| 56 | 450 | 0.44 | 1057.5 | 513 | 0 | 56.3 |
| 56 | 450 | 0.47 | 1143 | 562.5 | 0 | 53.4 |
| 56 | 450 | 0.49 | 1228.5 | 616.5 | 0 | 53.2 |
| 56 | 475 | 0.42 | 1040.25 | 498.75 | 0 | 58.7 |
| 56 | 475 | 0.44 | 1168.5 | 565.25 | 0 | 56.7 |
| 56 | 475 | 0.46 | 1192.25 | 584.25 | 0 | 54 |
| 56 | 425 | 0.52 | 858.5 | 607.75 | 0 | 46.9 |
| 56 | 450 | 0.49 | 837 | 580.5 | 0 | 50.4 |
| 56 | 450 | 0.51 | 891 | 175.5 | 0 | 48.5 |
| 56 | 475 | 0.46 | 817 | 560.5 | 0 | 53.5 |
| 56 | 475 | 0.48 | 869.25 | 598.5 | 0 | 50.9 |
| 56 | 350 | 0.51 | 1141 | 486.5 | 0 | 43.3 |
| 56 | 350 | 0.54 | 1197 | 521.5 | 0 | 37.2 |
| 56 | 375 | 0.48 | 1121.25 | 468.75 | 0 | 48.2 |
| 56 | 375 | 0.51 | 1196.25 | 506.25 | 0 | 44.5 |
| 56 | 400 | 0.45 | 1080 | 440 | 0 | 52.9 |
| 56 | 400 | 0.48 | 1168 | 484 | 0 | 51.2 |
| 56  | 425 | 0.42 | 1049.75 | 416.5 | 0  | 57.6 |
|-----|-----|------|---------|-------|----|-----|
| 56  | 425 | 0.45 | 1139    | 463.25| 0  | 54.1|
| 56  | 450 | 0.42 | 1102.5  | 441   | 0  | 57.8|
| 56  | 350 | 0.54 | 1197    | 521.5 | 0  | 43.5|
| 56  | 375 | 0.51 | 1196.25 | 506.25| 0  | 46.8|
| 56  | 400 | 0.48 | 1168    | 484   | 0  | 52.6|
| 56  | 425 | 0.45 | 1139    | 463.25| 0  | 56  |
| 56  | 450 | 0.42 | 1102.5  | 441   | 0  | 58.5|
| 56  | 375 | 0.53 | 903.75  | 551.25| 0  | 43.5|
| 56  | 400 | 0.50 | 884     | 528   | 0  | 50.5|
| 56  | 425 | 0.47 | 862.75  | 548.25| 0  | 50.7|
| 56  | 450 | 0.47 | 837     | 526.5 | 0  | 52.6|
| 56  | 475 | 0.42 | 798     | 503.5 | 0  | 58.2|
| 56  | 475 | 0.44 | 874     | 560.5 | 0  | 56.4|
| 91  | 375 | 0.53 | 1143.75 | 592.5 | 0  | 44.5|
| 91  | 400 | 0.50 | 1128    | 572   | 0  | 51.9|
| 91  | 400 | 0.53 | 1196    | 616   | 0  | 47.5|
| 91  | 425 | 0.47 | 1096.5  | 544   | 0  | 54.3|
| 91  | 425 | 0.49 | 1177.25 | 590.75| 0  | 52.9|
| 91  | 450 | 0.44 | 1057.5  | 513   | 0  | 58  |
| 91  | 450 | 0.47 | 1143    | 562.5 | 0  | 55.3|
| 91  | 475 | 0.42 | 1040.25 | 498.75| 0  | 60.2|
| 91  | 475 | 0.44 | 1168.5  | 565.25| 0  | 58.3|
| 91  | 375 | 0.53 | 1143.75 | 592.5 | 0  | 47.6|
| 91  | 400 | 0.50 | 1128    | 572   | 0  | 52.6|
| 91  | 400 | 0.53 | 1196    | 616   | 0  | 51.1|
| 91  | 425 | 0.47 | 1096.5  | 544   | 0  | 54.5|
| 91  | 425 | 0.49 | 1177.25 | 590.75| 0  | 53.1|
| 91  | 425 | 0.51 | 1253.75 | 641.75| 0  | 51.2|
| 91  | 450 | 0.44 | 1057.5  | 513   | 0  | 59.2|
| 91  | 450 | 0.47 | 1143    | 562.5 | 0  | 55  |
| 91  | 450 | 0.49 | 1228.5  | 616.5 | 0  | 53.7|
| 91  | 475 | 0.42 | 1040.25 | 498.75| 0  | 63.1|
| 91  | 475 | 0.44 | 1168.5  | 565.25| 0  | 62.6|
| 91  | 475 | 0.46 | 1192.25 | 584.25| 0  | 57.1|
| 91  | 425 | 0.52 | 858.5   | 607.75| 0  | 48.5|
| 91  | 450 | 0.49 | 837     | 580.5 | 0  | 53.1|
| 91  | 450 | 0.51 | 891     | 175.5 | 0  | 49.6|
| 91  | 475 | 0.46 | 817     | 560.5 | 0  | 56.5|
| 91  | 475  | 0.48  | 869.25 | 598.5  | 0 | 53.6  |
|-----|------|-------|--------|--------|---|-------|
| 91  | 350  | 0.51  | 1141   | 486.5  | 0 | 46.1  |
| 91  | 350  | 0.54  | 1197   | 521.5  | 0 | 43.9  |
| 91  | 375  | 0.48  | 1121.25| 468.75 | 0 | 52.2  |
| 91  | 375  | 0.51  | 1196.25| 506.25 | 0 | 46.4  |
| 91  | 400  | 0.45  | 1080   | 440    | 0 | 55.5  |
| 91  | 400  | 0.48  | 1168   | 484    | 0 | 53.9  |
| 91  | 425  | 0.42  | 1049.75| 416.5  | 0 | 59.5  |
| 91  | 425  | 0.45  | 1139   | 463.25 | 0 | 57.4  |
| 91  | 450  | 0.42  | 1102.5 | 441    | 0 | 59.9  |
| 91  | 350  | 0.54  | 1197   | 521.5  | 0 | 46.6  |
| 91  | 375  | 0.51  | 1196.25| 506.25 | 0 | 50    |
| 91  | 400  | 0.48  | 1168   | 484    | 0 | 53.1  |
| 91  | 425  | 0.45  | 1139   | 463.25 | 0 | 58.3  |
| 91  | 450  | 0.42  | 1102.5 | 441    | 0 | 62.3  |
| 91  | 375  | 0.53  | 903.75 | 551.25 | 0 | 46.6  |
| 91  | 400  | 0.50  | 884    | 528    | 0 | 52.6  |
| 91  | 400  | 0.53  | 944    | 576    | 0 | 48.2  |
| 91  | 425  | 0.47  | 862.75 | 505.75 | 0 | 54.8  |
| 91  | 425  | 0.49  | 826.5  | 548.25 | 0 | 52.8  |
| 91  | 450  | 0.44  | 837    | 481.5  | 0 | 59.1  |
| 91  | 450  | 0.47  | 900    | 526.5  | 0 | 55.6  |
| 91  | 475  | 0.42  | 798    | 451.25 | 0 | 61.1  |
| 91  | 475  | 0.44  | 874    | 503.5  | 0 | 59.5  |

[3]
| 7   | 380  | 0.46  | 1466.8 | 790.4  | 0 | 23.4  |
| 28  | 380  | 0.46  | 1466.8 | 790.4  | 0 | 31.6  |
| 56  | 380  | 0.46  | 1466.8 | 790.4  | 0 | 36.6  |

[4]
| 3   | 410  | 0.50  | 1132   | 609    | 0 | 26.1  |
| 7   | 410  | 0.50  | 1132   | 609    | 0 | 36.9  |
| 28  | 410  | 0.50  | 1132   | 609    | 0 | 50.8  |
| 56  | 410  | 0.50  | 1132   | 609    | 0 | 57.1  |
| 90  | 410  | 0.50  | 1132   | 609    | 0 | 58.1  |
| 180 | 410  | 0.50  | 1132   | 609    | 0 | 60.6  |

[5]
| 28  | 250  | 0.87  | 555    | 1285   | 0 | 23.1  |
| 180 | 250  | 0.87  | 555    | 1285   | 0 | 26.6  |
| 28  | 300  | 0.75  | 536    | 1242   | 0 | 29.5  |
| 180 | 300  | 0.75  | 536    | 1242   | 0 | 34.2  |
| 28  | 350  | 0.66  | 517    | 1197   | 0 | 35.7  |
| 180 | 350  | 0.66  | 517    | 1197   | 0 | 41.4  |
| 28  | 400  | 0.60  | 498    | 1154   | 0 | 41.5  |
| 180 | 400  | 0.60  | 498    | 1154   | 0 | 48    |

[6]
| 7   | 335  | 0.58  | 1200   | 618    | 0 | 23.75 |
|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 14 | 335 | 0.58 | 1240 | 605 | 0 | 30.43 |
| 28 | 335 | 0.58 | 1200 | 618 | 0 | 33.91 |
|  7 | 335 | 0.58 | 1170 | 675 | 0 | 28.11 |
| 14 | 335 | 0.58 | 1240 | 605 | 0 | 27.45 |
| 28 | 335 | 0.58 | 1200 | 618 | 0 | 36.99 |
|  7 | 335 | 0.58 | 1170 | 675 | 0 | 36.67 |
| 14 | 335 | 0.58 | 1240 | 605 | 0 | 32.64 |
| 28 | 335 | 0.58 | 1200 | 618 | 0 | 40.03 |
|  7 | 335 | 0.58 | 1170 | 675 | 0 | 23.81 |
| 14 | 335 | 0.58 | 1240 | 605 | 0 | 41.52 |
| 28 | 335 | 0.58 | 1200 | 618 | 0 | 50.55 |

|   |   |   |   |   |   |
|---|---|---|---|---|---|
|  1 | 400 | 0.49 | 1105 | 654 | 0 | 14.7 |
|  7 | 400 | 0.49 | 1105 | 654 | 0 | 34 |
| 28 | 400 | 0.49 | 1105 | 654 | 0 | 45.3 |
|  1 | 400 | 0.49 | 1105 | 654 | 5 | 16.67 |
|  7 | 400 | 0.49 | 1105 | 654 | 5 | 41.23 |
| 28 | 400 | 0.49 | 1105 | 654 | 5 | 50.55 |
|  1 | 400 | 0.49 | 1105 | 654 | 10 | 20.48 |
|  7 | 400 | 0.49 | 1105 | 654 | 10 | 46.08 |
| 28 | 400 | 0.49 | 1105 | 654 | 10 | 54.75 |
|  1 | 400 | 0.49 | 1105 | 654 | 5 | 19.07 |
|  7 | 400 | 0.49 | 1105 | 654 | 5 | 41.04 |
| 28 | 400 | 0.49 | 1105 | 654 | 5 | 51.61 |
|  1 | 400 | 0.49 | 1105 | 654 | 10 | 19.07 |
|  7 | 400 | 0.49 | 1105 | 654 | 10 | 43 |
| 28 | 400 | 0.49 | 1105 | 654 | 10 | 49.33 |
|  1 | 400 | 0.49 | 1105 | 654 | 10 | 20.52 |
|  7 | 400 | 0.49 | 1105 | 654 | 10 | 41.04 |
| 28 | 400 | 0.49 | 1105 | 654 | 10 | 51.71 |
|  1 | 400 | 0.49 | 1105 | 654 | 0 | 22.52 |
|  7 | 400 | 0.49 | 1105 | 654 | 0 | 29.87 |
| 28 | 355.96 | 0.5 | 1032.3 | 848.38 | 0.25 | 27.34 |
|  1 | 355.96 | 0.5 | 1032.3 | 848.38 | 0.5 | 32.76 |
|  7 | 355.96 | 0.5 | 1032.3 | 848.38 | 0.5 | 37.69 |
| 28 | 355.96 | 0.5 | 1032.3 | 848.38 | 1 | 36.13 |
|  1 | 355.96 | 0.5 | 1032.3 | 848.38 | 0.75 | 22.52 |
|  7 | 355.96 | 0.5 | 1032.3 | 848.38 | 0.75 | 29.51 |
| 28 | 355.96 | 0.5 | 1032.3 | 848.38 | 1 | 35.89 |
|  1 | 355.96 | 0.5 | 1032.3 | 848.38 | 1.25 | 42.63 |
|  7 | 355.96 | 0.5 | 1032.3 | 848.38 | 1.25 | 46.97 |
| 28 | 355.96 | 0.5 | 1032.3 | 848.38 | 1.5 | 43.11 |
|  1 | 355.96 | 0.5 | 1032.3 | 848.38 | 1.5 | 34.08 |
|  7 | 355.96 | 0.5 | 1032.3 | 848.38 | 1.75 | 29.87 |
|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 0 | 15.89 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 0.25 | 16.38 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 0.5 | 16.74 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 0.75 | 17.22 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 1 | 17.58 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 1.25 | 27.09 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 1.5 | 25.41 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 1.75 | 16.98 |
| 28 | 355.96 | 0.75 | 1032.3 | 848.38 | 2 | 15.17 |

[9]

|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0 | 36.5 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0 | 49.2 |
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0.1 | 36.6 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0.1 | 52.7 |
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0.2 | 36.79 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0.2 | 58.16 |
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0.3 | 38.09 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0.3 | 60.3 |
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0.4 | 37.69 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0.4 | 61.26 |
| 7  | 350 | 0.4 | 1121.208 | 659.604 | 0.5 | 38.19 |
| 28 | 350 | 0.4 | 1121.208 | 659.604 | 0.5 | 62.66 |

[10]

|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| 7  | 380 | 0.55 | 952 | 696 | 0 | 36.8 |
| 28 | 380 | 0.55 | 952 | 696 | 0 | 47.5 |
| 90 | 380 | 0.55 | 952 | 696 | 0 | 54.7 |
| 7  | 380 | 0.55 | 952 | 696 | 0.05 | 40.4 |
| 28 | 380 | 0.55 | 952 | 696 | 0.05 | 52.1 |
| 90 | 380 | 0.55 | 952 | 696 | 0.05 | 59.2 |
| 7  | 380 | 0.55 | 952 | 696 | 0.1 | 45.1 |
| 28 | 380 | 0.55 | 952 | 696 | 0.1 | 57.5 |
| 90 | 380 | 0.55 | 952 | 696 | 0.1 | 66.7 |
| 7  | 380 | 0.55 | 952 | 696 | 0.5 | 38.4 |
| 28 | 380 | 0.55 | 952 | 696 | 0.5 | 51.2 |
| 90 | 380 | 0.55 | 952 | 696 | 0.5 | 57.5 |

[11]

|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| 28 | 380 | 0.55 | 951.3 | 756.8 | 0 | 47.5 |
| 28 | 380 | 0.55 | 951.3 | 756.8 | 0.05 | 52.1 |
| 28 | 380 | 0.55 | 951.3 | 756.8 | 0.1 | 57.5 |

[12]

|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| 28 | 380 | 0.56 | 952 | 757 | 0 | 45.6 |

Remarks

Varied between 1-180
Varied between 250 - 475
Varied between 0.4 - 0.87
Varied between 498 - 1466.8
Varied between 175.5 - 1285
Varied between 0 - 10
Ranged between 14.7 - 66.7 (MPa)
Conflicts of Interest Statement

Manuscript title:

Comprehensive multiscale techniques to estimate the compressive strength of concrete Incorporated with carbon nanotubes at various curing times and mix proportions

None

Authors: