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# MACHINE LEARNING MODELS FOR PREDICTING THE COMPRESSIVE STRENGTH OF CONCRETE WITH SHREDDED PET BOTTLES AND M-SAND AS FINE AGGREGATE

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***ABSTRACT:*** Machine Learning (ML) and Artificial Intelligence (AI) are closely intertwined and represent the latest cutting-edge technologies that facilitate the development of intelligent prototypes. Machine learning is a critical subset of AI that deliberates the development of self-trained algorithms that use previous databases and analysis for result predictions. By leveraging past data, machine learning empowers computers to make predictions and decisions. This study investigates the use of ML algorithms to predict the compressive strength of grade 30 concrete, incorporating shredded PET bottles and M-sand as fine aggregates. The experimental setup involved preparing concrete specimens with shredded PET bottle aggregates, varying the volume from 0% to 2% in increments of 0.5%. Different percentages of M-sand were incorporated at 25%, 50%, 75%, and 100%. The mixing proportions adhered to the standards defined by the Department of Environment (DOE). Cubic specimens were cast and cured for 7, 28, and 90 days. The study employs Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Decision Tree (DT) models, using the experimental data for predictive analysis. The evaluation of the three models for predicting compressive strength yielded interesting results: The Decision Tree (DT) model demonstrated the best performance, with a relatively low Mean Squared Error (MSE) of 5.125 and Mean Absolute Error (MAE) of 1.642 and a high $R^2$ value of 0.918, indicating that the model explains approximately 91.8% of the variance in the target variable. The DT model's ability to handle complex, non-linear data relationships made it particularly effective in evaluating concrete strength. The Multiple Linear Regression (MLR) model provided reasonable predictions but showed higher errors compared to the DT model, with MSE and MAE values of 26.663 and 4.298, respectively, and an $R^2$ score of 0.571, demonstrating a moderate ability to explain the variance in the data. Conversely, the Artificial Neural Network (ANN) model exhibited the least accuracy, with the highest errors (MSE of 112.33 and MAE of 8.52) and a negative $R^2$ score (-0.64), indicating poor model training and an inability to capture the relationships between parameters effectively, partly due to the relatively small dataset. The study highlights the potential of DT models in sustainable construction practices, emphasizing the importance of comprehensive datasets and further exploration of alternative algorithms. The findings advocate for using ML in concrete strength prediction, contributing to advancements in sustainable engineering and material science.

***ABSTRAK:*** Pembelajaran Mesin (ML) dan Kecerdasan Buatan (AI) saling berkait rapat dan mewakili teknologi canggih terkini yang membantu pembangunan prototaip pintar.

Pembelajaran mesin adalah subset kritikal AI yang menumpukan pada pembangunan algoritma dilatih sendiri menggunakan pangkalan data dan analisis terdahulu bagi meramal hasil. Dengan memanfaatkan data masa lalu, pembelajaran mesin memberi kuasa kepada komputer bagi membuat ramalan dan keputusan. Kajian ini menyelidik penggunaan algoritma ML bagi meramalkan kekuatan mampatan konkrit gred 30, menggabungkan botol PET yang dicincang dan pasir-M sebagai agregat halus. Susunan eksperimen melibatkan penyediaan spesimen konkrit dengan agregat botol PET yang dicincang, memvariasikan isipadu dari 0% hingga 2% dalam kenaikan 0.5%. Peratusan berbeza bagi pasir-M telah digabungkan pada 25%, 50%, 75%, dan 100%. Nisbah campuran mematuhi piawaian yang ditetapkan oleh Jabatan Alam Sekitar (DOE). Spesimen kubik dipadatkan dan diawetkan selama 7, 28, dan 90 hari. Kajian ini menggunakan model Regresi Linear Berganda (MLR), Rangkaian Neural Buatan (ANN), dan Pokok Keputusan (DT), manakala data eksperimen digunakan bagi analisis ramalan. Penilaian terhadap tiga model bagi meramal kekuatan mampatan menghasilkan keputusan yang menarik: Model Pokok Keputusan (DT) menunjukkan prestasi terbaik, dengan Ralat Kuasa Dua Min (MSE) yang agak rendah iaitu 5.125 dan Ralat Mutlak Min (MAE) 1.642, serta nilai $R^2$ yang tinggi iaitu 0.918, menunjukkan bahawa kira-kira 91.8% daripada model varian ini dalam pemboleh ubah sasaran. Keupayaan model DT bagi mengurus data kompleks dan tidak linear menjadikannya sangat berkesan dalam menilai kekuatan konkrit. Model Regresi Linear Berganda (MLR) memberi ramalan munasabah tetapi menunjukkan ralat lebih tinggi berbanding model DT, dengan nilai MSE dan MAE masing-masing 26.663 dan 4.298, dan skor $R^2$ 0.571, menunjukkan keupayaan sederhana bagi menjelaskan varians data. Sebaliknya, model Rangkaian Neural Buatan (ANN) menunjukkan ketepatan paling rendah, dengan ralat tertinggi (MSE 112.33 dan MAE 8.52) dan skor $R^2$ negatif (-0.64), yang menunjukkan latihan model yang lemah dan ketidakmampuan menangkap hubungan antara parameter dengan berkesan, sebahagiannya disebabkan oleh dataset yang kecil. Kajian ini menekankan potensi model DT dalam amalan pembinaan lestari, menekankan kepentingan dataset yang komprehensif dan penerokaan lanjut mengenai algoritma alternatif. Dapatan kajian menyokong penggunaan ML dalam ramalan kekuatan konkrit, menyumbang kepada kemajuan dalam kejuruteraan lestari dan sains bahan.

***KEYWORDS:*** *M-sand, PET Bottles, Multiple Linear Regression (MLR), Decision Tree (DT) and Artificial Neural Network (ANN)*

# 1. INTRODUCTION

Plastic waste, particularly polyethylene terephthalate (PET) bottles, poses serious environmental challenges related to accumulating in landfills and pollution when incinerated. Recently, interest has grown in incorporating recycled PET particles as aggregates within concrete mixtures, giving rise to a sustainable construction material. In the construction industry, PET bottle aggregates serve as an efficient substitute for sand and conversely develop comparable compressive strength of concrete. By reducing plastic waste and conserving natural sand resources, this approach offers substantial environmental benefits [1, 2]. Moreover, PET aggregates can result in lighter concrete with improved insulation properties, enhancing sustainability. If PET-based concrete demonstrates adequate compressive strength, it unlocks potential applications in non-structural elements, low-rise construction, and sustainable building projects. Additionally, repurposing PET waste could offer economic benefits in terms of material costs [3, 4]. This research direction contributes to developing innovative construction materials that promote a circular economy, address environmental challenges, and offer potential advantages in both cost and material properties.

The exploration of alternative materials for construction purposes has been a significant area of research in the civil engineering domain, aiming to address the environmental concerns

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and resource scarcity associated with traditional materials. The use of M-sand as an alternative to river sand has been employed for a considerable period in concrete production [5].

M-Sand is produced by crushing specific types of rocks, and its physical and chemical properties can significantly differ from those of natural sand. Research studies indicate that concrete made with M-Sand exhibits a comparable or even superior compressive strength to that of concrete made with natural river sand. This can be attributed to the angular shape and rougher texture of M-Sand particles, which enhance the interlocking and bonding with cement paste in the concrete mix [5, 6].

Researchers have conducted a thorough study showing that substituting M-sand for natural sand can increase the strength of concrete. This is due to the particle size distribution of M-sand, which is often well-graded and falls within the specified limits for fine aggregate. This contributes to a denser packing of the concrete matrix, reducing the voids in the concrete and increasing its strength. The improved strength is a result of increased friction among the concrete ingredients attributed to the texture of M-sand [6, 7, 8].

The increasing popularity of M-sand is also attributed to its environmental benefits. Excessive sand mining has led to the depletion of riverbeds, raising environmental concerns and driving the search for sustainable alternatives. M-sand, made from abundant rock sources, provides a more sustainable option, reducing reliance on natural sand and lessening environmental impact. This sustainability, along with the potential for improved compressive strength, makes M-sand an appealing alternative for concrete production. [5].

A correlation exists between ML and AI, and they are the most recent trending technologies that are used in building smart systems. People are still confused with these two terms, but the fact is that both function differently. Artificial intelligence concerning building programs can think similarly to human beings, where the techniques developed are to enable computers to mimic human behaviors and thinking. Machine learning is a subset of artificial intelligence, and the primary concern is establishing algorithms that allow computers to learn without being explicitly programmed by using past data and experiences. The scenario is similar to constantly teaching a group of amateurs by providing complete training tools. As the training process increases, the experience gained also increases. Machine learning allows computers to predict and make decisions based on historical data [1, 2]. ML algorithms are usually used for forecasting and estimation purposes. The segregation of parameters under categories is termed classification. Conversely, the estimation of variables based on relationships between the dependent and independent parameters is referred to as regression [9].

Chopra et al. (2016) conducted research to predict concrete compressive strength using a machine-learning model [10]. The study included predictions for duration of 28, 56, and 91 days. The ML algorithm was developed using R software. A comparative study of the estimated values using various models was performed by using Root Mean Square Error (RMSE) and coefficient of determination (R2). The ML techniques used in the study included Artificial Neural Networks (ANN), random forests, Genetic Programming (GP), and decision trees [11]. The results indicated that the Neural Network (NN) machine learning model provided more accurate predictions for concrete compressive strength.

In a study by Dantaset. et. al. (2013), the researchers analyzed the debris from construction and demolition mixed in concrete to determine its strength. They utilized a machine learning algorithm using artificial neural networks (ANN) and conducted a phase study over 3, 7, 28, and 91 days. The results of the ML model were compared with experimental results obtained from the existing literature. The training set comprised of 1178 samples, with 77.76% used for training and 22.24% for testing. The ANN model was employed to predict the concrete strength based on the testing and training results [12].

The concrete strength evaluation has been reported [13]. The researchers utilized ANN and Multiple Regression analysis as prediction tools. The additives used in concrete cement were nanosilica and copper slag. The curing times considered were 1, 3, 7, 28, 56 and 90 days. The research demonstrated that the ANN machine-learning model achieved high accuracy [13]**.** Meanwhile, Silva et al. (2020) employed ANN, RF, and SVM machine-learning algorithms to forecast concrete strength. Experimental data from previous studies from the literature was incorporated for prediction analysis, whereas Random Forest (RF) indicated more accurate predictions [14]. In addition, the prediction models of RF, LR, DT, and SVR were also used by Cherickal et al. (2021) to calculate the strength of concrete for a set of assumed data. The application regression techniques revealed accurate prediction for the random forest ML algorithm [15].

The properties of concrete were studied by Bhanu P. Koyaa (2001). The mechanical properties such as Poisson's ratio, Elasticity Modulus, Compressive strength, coefficient of expansion, and splitting strength were investigated. Machine Learning models were used, including DT, linear regression, SVM, gradient boosting, and RF. The study utilized a sample set obtained from the Wisconsin concrete mix data. The error correction methods of $R^2$ and RMSE indicated that the results produced by the SVM were more accurate than other models [16].

The technique of partial replacement of cement was incorporated by Mohammed Majeed Hameed et al. (2022) to evaluate hybrid models in order to estimate the concrete strength. The study proposed two predictive models: Support Vector Regression - Particle Swarm Optimization (SVR-PSO) and Support Vector Regression - Genetic Algorithm (SVR-GA). These models combined support vector regression (SVR) with improved particle swarm optimization (PSO) and genetic algorithm (GA), respectively. Additionally, an extreme learning machine (ELM) model was compared for evaluation using various statistical parameters. The SVR-PSO model displayed a high rate of accuracy, surpassing the SVR-GA and ELM models. The study also included sensitivity analysis to identify influential parameters affecting CS. The models considered for the study revealed improvised results of concrete compressive strength for partial cement substitution, thereby overriding the earlier studies undertaken for such models [17].

El-Mir et al. (2023) conducted a study focusing on the use of data-driven forecasting models for determining concrete strength. The main aim was to reduce the time and costs associated with laboratory tests. The study involved examining changes in the rebound hammer repeatability index for various concrete mixtures. Additionally, the study proposed new models for simplified strength prediction. To achieve this, the researchers built an experimental database and utilized machine learning models, including MMR, GPR, SVM, and DT. The findings showed that incorporating the water-to-powder ratio and concrete age improved prediction accuracy. Notably, models such as SVM/ GPR and RT outperformed others in predicting compressive strength. The study also suggested potential areas for future research, such as integrating rebound hammer tests with self-improving AI and exploring AI-based models for precise and rapid strength assessment [18].

Concrete strength estimation studies have been conducted by many researchers employing ML techniques. The research studies include usage of regression techniques such as Decision Trees (DT), k-Nearest Neighbors (kNN), Linear Regression (LR), Random Forests (RF) and

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Support Vector Machines (SVM). However, it was observed that these models have not been applied specifically to predict the strength of M-sand and fine aggregates of SPB (PET bottles).

The present study is focused on the prediction of strength when concrete is mixed with PET bottle shreds and M-sand. The estimation of compressive strength is done using ML models. This is a novel and sustainable technique to reuse waste resources and lower the environmental impact of concrete production. Concrete compressive strength is an important attribute that influences structural design, performance, and durability. As a result, it is essential to create precise and trustworthy models that can estimate the concrete strength depending on various proportion combinations and other criteria. The relevant study incorporates ML models of DT, LR, and ANN. The ML algorithm that was developed provides a cost- and time-effective solution for predicting the mechanical performance of concrete. This technique holds promise for large construction sites where traditional testing and evaluation methods can be time-consuming. The ML model facilitates precise prediction of the concrete properties relevant to experimental data.

The following are three machine learning techniques utilized in this research.

### 1.1. Multiple Linear Regression

This model uses a set of independent variables to predict the dependent variable statistically, assuming linear variation among the dependent and independent parameters. The model equation is $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{\mathrm{n}} X_{\mathrm{n}} + \varepsilon$, where $Y$ is the dependent variable, $X^1, X^2, \ldots, X_{\mathrm{n}}$ are the independent variables, $\beta_0$ is the intercept term, $\beta^1, \beta^2, \ldots, \beta_{\mathrm{n}}$ are the coefficients and $\varepsilon$ is the error term.

### 1.2. Decision Tree

A decision tree serves as a non-parametric algorithm in supervised learning, employed for tasks involving classification and regression. This algorithm functions by recursively dividing the feature space according to the values of input features. When making predictions, it follows a path from the root to a leaf node in the tree. Each internal node in the tree represents a decision rule, while each leaf node indicates the expected outcome. For regression tasks, the predicted values are the average or median of the target variable values within the training samples of a leaf node. This approach, using a tree-like structure instead of a single equation, is what sets decision trees apart in making predictions. $Y = \alpha_1 w_1 + \alpha_2 w_2 + \cdots + \alpha_n w_n$. In this equation, $\alpha_1, \alpha_2, \ldots, \alpha n$ represent the weights assigned to each feature and $w_1, w_2, \ldots, w_n$ represent the corresponding feature values.

### 1.3. Neural Network

The NN model draws similarities to the human neural system of the brain. The ML algorithm configures layered interconnected junctions (nodes) called neurons. The preceding layers provide each neuron with an input, which was evaluated based on the weighted sum through a governing function resulting in an output. This prediction model has diverse fields of application namely image recognition, natural language processing, and predictive modeling.

The regression equation for a neural network involves forward propagation. In a simple neural network with one hidden layer, the equation can be written as:

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$$\begin{gathered} Z_h = W_{ih}X + b_h \\ A_h = f(Z_h) \\ Z_o = W_{oh}A_h + b_o \\ A_o = Z_o \end{gathered} \tag{1}$$

Here, $X$ is the input, $W_{ih}$ and $W_{oh}$ are weight matrices, $b_h$ and $b_o$ are biased terms, and $f(\ \ )$ is an activation function applied to the hidden layer activations. Note that actual equations and network architectures vary. Different activation functions and network structures can be used to model complex relationships and improve performance.

### 1.4. Contribution to the Research

The research makes significant contributions to the field, as outlined below:

- *Comparative Analysis*: The study presents a comprehensive comparison among three distinct predictive models: Decision Tree, MLR, and NN. The forecasting model assessment deliberates its effectiveness for strength prediction and shortcomings. This analysis provides a basic reference for academicians and researchers in the selection of appropriate models for relevant applications.
- *Performance Evaluation*: The research presents a comprehensive evaluation of the predictive models using various evaluation metrics, including MSE, MAE, and $R^2$. By reporting these metrics for each model, the research provides a quantitative assessment of their accuracy, precision, and ability to explain the variance in the target variable. The assessment develops the model characteristic for effective and accurate prediction of concrete strength.
- *Model Comparison*: The comparative analysis reveals DT model to provide better estimation relative to other models. The MSE and MAE for DT are low signifying precise output. Additionally, it obtains a higher $R^2$ score, indicating a greater ability to explain the variance in the target variable. Thus, the study shows the DT strength characteristic required for relevant parametric predictions.
- *Practical Implications*: The research has practical implications for industries and organizations involved in predicting compressive strength. The determination of DT as the effective prediction model contributes to achieving a practical solution in the estimation of concrete compressive strength. This finding can assist construction companies, civil engineers, and material scientists in optimizing their processes, improving quality control, and ensuring structural integrity.
- *Future Research Directions*: The research opens avenues for future investigations. It suggests further exploration of alternative machine learning algorithms or advanced neural network architectures that could potentially improve the predictive performance for compressive strength. Additionally, the research encourages the examination of additional input features or data sources that might enhance the accuracy of predictions. These future research directions can contribute to advancing the field of predictive modeling for material properties.

Overall, the research contribution lies in its comparative analysis, performance evaluation, model comparison, practical implications, and suggestions for future research. By shedding light on the predictive models' performance for compressive strength prediction, the research provides valuable insights and guidance for researchers, practitioners, and industry professionals working in the field of material science and construction engineering.

## 2. OBJECTIVES

This study aimed to predict the concrete strength for varying proportions of M-sand and PET aggregates. The value estimation is done using ML models such as DT, ANN, and MLR. The models were tested using available data, and their accuracy was evaluated using experimental results. The model accuracy determined the precise estimation of the strength and thereby facilitated the researchers' decision of which model to incorporate for their study. The current work is a consolidated study of prediction model applications for concrete strength determination and their effectiveness in estimating the compressive strength for different proportions of M-sand and PET shreds.

## 3. METHODOLOGY

The methodology followed in this research involved the following steps in the estimation of compressive and flexural strength of concrete composite mixture using ML models:

- *Experimental Setup*: Concrete specimens were prepared using shredded PET bottle aggregates as an alternative to conventional aggregates. The PET bottle aggregate volume varied from 0% to 2% in increments of 0.5%. Different percentages of M-sand were incorporated for 25%, 50%, 75% and 100%. The mixing proportions adhered to the standards defined by the Department of Environment (DOE). Cubic specimens were cast and cured for 7, 28, and 90 days.
- *Data Collection*: The necessary data for model development was collected from the experimental data, including the proportions of river sand, PET bottle aggregates, M-sand, and the curing duration. The output parameter measured was the concrete compressive strength.
- *Python Programming*: Python, specifically the Anaconda Navigator platform, was utilized for model development. The ML algorithms of DT, ANN, and MLR were implemented using appropriate libraries and frameworks.
- *Data Preparation*: The data cluster was segregated into 80% training dataset and 20% test dataset. This process helped in evaluating the model performance and reliability of implementing new datasets.
- *Model Training*: The training set was used to train the decision tree, MLR, and ANN models. These models were trained to establish the relationship between the input parameters (river sand, PET bottle aggregates, M-sand, and curing duration) and the output variables (compressive and flexural strengths).
- *Error Definition and Model Evaluation*: The assessment of model accuracy and predictive performance involved the utilization of error definition techniques, including MAE, MSE, and RMSE. These metrics quantified the disparities between predicted values and actual values. The model exhibiting the smallest error values was deemed the most proficient for forecasting purposes.

The model estimation accuracy was tested using a set of unseen test data. The obtained values of the compressive and flexural strength were compared with the experimental values to evaluate the model's ability to predict strength for different proportional mixtures of concrete.

The research aims to develop an accurate predictive model using machine learning techniques to estimate the compressive strengths of various concrete composites. The methodology involved data collection, model training, error analysis, and validation to identify

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the most effective forecasting model. This study contributes to the field of concrete strength predictions.

In this research, Anaconda, an open-source software distribution, was used to create the required software environment. Jupyter Notebook, an interactive computing platform, facilitated code development, data exploration, and documentation. The model was trained on 80% of the dataset, and its performance was evaluated using 20% of the test dataset. The model was trained for the relationship approximation among different parameters. The appropriateness of the relations trained was tested using a 20% test dataset.

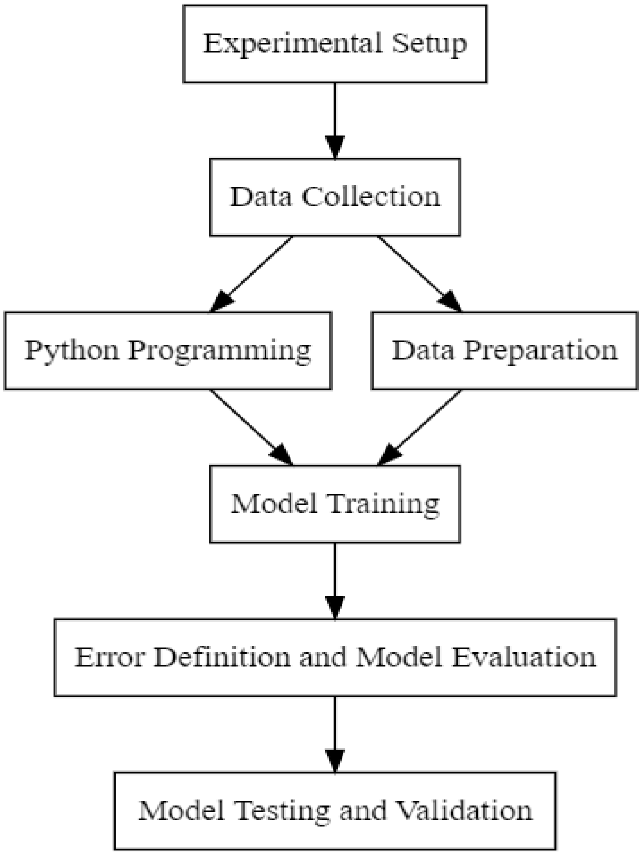


Figure 1. Flow Chart of Machine Learning Model Methodology

## 4. ERRORS

Machine learning (ML) algorithms are designed to make predictions based on a training dataset where the desired outcomes are already known. After being trained on this dataset, the model is then tested using a separate dataset to predict results, which are subsequently compared to the actual outcomes. Any discrepancies between the desired and predicted results are referred to as errors, and they serve as a measure of the accuracy of the ML algorithm.

It is important to note that ML models may encounter unknown variables or factors that can affect their accuracy, resulting in irreducible errors. These errors are inherent and cannot be eliminated or reduced. This variation between desired and predicted output can be minimized to enhance the model's performance effectiveness.

In summary, ML algorithms are trained to predict outcomes using known data, and their accuracy is assessed by comparing their predictions to actual outcomes. Irreducible errors can arise from unknown variables. Nevertheless, model optimization techniques can be applied to minimize the differences between desired and predicted results.

### 4.1. Mean Absolute Error (MAE)

The accuracy of estimating data can be evaluated using MAE. It provides absolute mean value, indicating an appropriate scale of deviation between model prediction and actual value. The absolute values obtained are unaffected by outliers [19-21]. MAE is calculated by Eq. (2).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|f\left(\hat{\phi}\right)_i - f(\phi)_i\right| \tag{2}$$

### 4.2. Mean Squared Error (MSE)

Mean Squared Error (MSE) serves as a metric utilized to gauge the average of the squared discrepancies between predicted values and actual values. This metric offers an assessment of the extent to which the model's predictions correspond with the genuine values. By calculating the average of these squared differences, MSE accentuates larger errors, thereby assisting in quantifying the comprehensive accuracy of the model's predictions [20-22].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(f\left(\hat{\phi}\right)_i - f(\phi)_i\right)^2 \tag{3}$$

### 4.3. R-squared Score R²

R-squared ($R^2$) functions as a statistical indicator that signifies the portion of the variability in the dependent variable explained by the independent variables within a regression model. This metric is determined using the equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(f(\phi)_i - f\left(\hat{\phi}\right)_i\right)^2}{\sum_{i=1}^{N}\left(f(\phi)_i - \bar{f}(\phi)_i\right)^2} \tag{4}$$

Here, $\sum$ represents summation, $f(\phi)$ is the actual value of the dependent variable, $\bar{f}(\phi)$ is the mean of the dependent variable, and $f\left(\hat{\phi}\right)$ is the predicted value based on the regression model. The numerator represents the sum of squared differences between the actual values and the mean, while the denominator represents the sum of squared differences between the actual values and the predicted values.

R-squared ranges from 0 to 1, where 1 indicates a perfect prediction, and 0 indicates that the model doesn't explain any variability in the dependent variable. However, R-squared alone doesn't provide information about prediction accuracy or precision, so it should be used alongside other evaluation metrics for a comprehensive assessment of the regression model [21, 22].

## 5. RESULTS AND DISCUSSION

Table 1 depicts the MSE, MAE, and $R^2$ scores for each model. The prediction accuracy is good for low values of MSE and MAE. Conversely, the variance for the value target is dependent on the $R^2$ value. These parameters determine that the DT model has better performance than the ANN and MLR, with ANN being the least accurate. The evaluation of the three models for predicting compressive strength yielded interesting results.

The Decision Tree model demonstrated the best performance, with a relatively low MSE of 5.125 and MAE of 1.642. Additionally, it achieved a high $R^2$ of 0.918, indicating that the model explains around 91.8% of the variance in the target variable. It is evident that the DT model predicts the concrete strength more accurately.

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The Multiple Linear Regression model also provided reasonable predictions, although it showed higher errors compared to the Decision Tree model. The MSE and MAE values were 26.663 and 4.298, respectively, while the $R^2$ score was 0.571. Although this model performs less accurately than the Decision Tree model, it still demonstrates a moderate ability to explain the variance in the data, as presented in Fig.2.

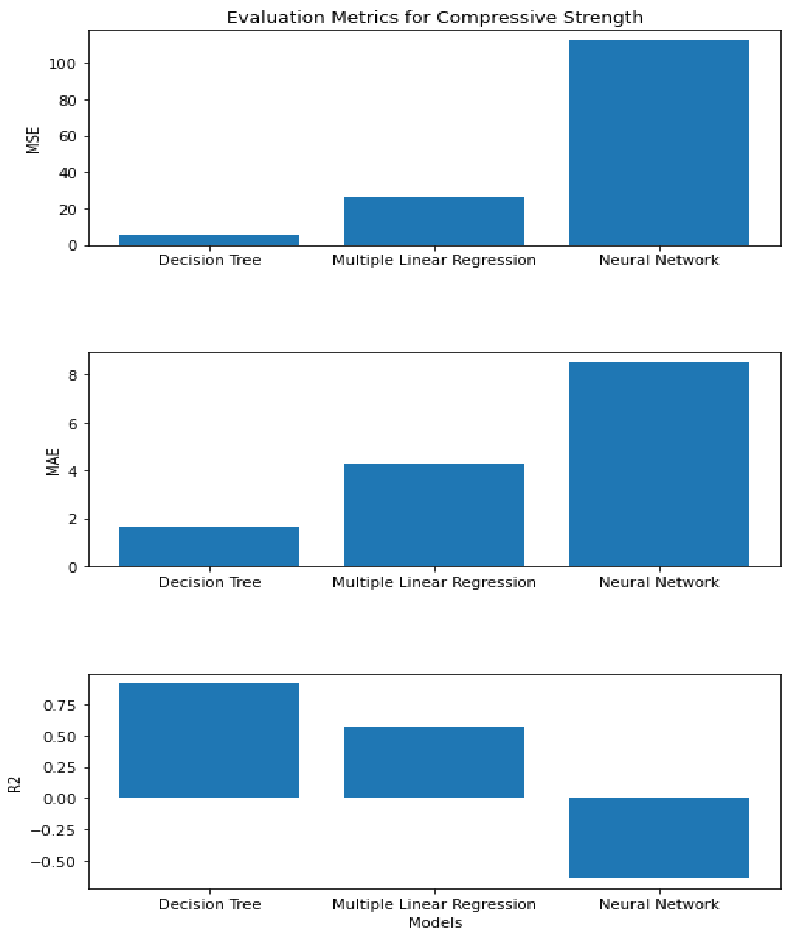


Figure 2. Regression Evaluation Metrics for Compressive Strength

The NN model exhibited the least accuracy among the three models. It exhibited the highest errors, with an MSE of 112.33 and an MAE of 8.52. Furthermore, the $R^2$ score was negative (-0.64), specifying that the model training for capitalizing on the relations between parameters did not yield, which is also evident in Fig.5. The obtained outputs infer that the DT model is highly suited for concrete strength prediction, which can also be deduced from Fig.4., followed by the Multiple Linear Regression model. However, further analysis and experimentation might be necessary to improve the performance of the Neural Network model. Nadimalla et al. (2022) developed machine learning models to predict the workability of concrete mixes containing manufactured sand (M-sand), shredded PET bottles, and river sand. Workability was measured by the slump, VeBe time (using a vibration densitometer), and compaction factor. The authors created MLR and DTR models using experimental data on these concrete properties. The DTR model, which handles nonlinear relationships better, proved superior at predicting all three workability measures with lower errors compared to MLR [23].

Table 1. Error Evaluation Metrics

| Machine Learning Models | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | R-squared Score ($R^2$) |
|---|---|---|---|
| Decision Tree | 5.13 | 1.64 | 0.92 |
| Multiple Linear Regression | 26.66 | 4.30 | 0.57 |
| Neural Network | 112.33 | 8.52 | -0.64 |

The multiple linear regression equation for calculating the compressive strength can be expressed as:

$$CompressiveStrength = \beta_0 + \beta_1 \times sand + \beta_2 \times PET + \beta_3 \times Msand + \beta_4 \times curing\ days \quad (5)$$

Where:

$\beta_0$ = 34.45 (intercept or constant term)

$\beta_1$ = -0.00 (coefficient associated with the "sand" input feature)

$\beta_2$ = 0.01 (coefficient associated with the "PET" input feature)

$\beta_3$ = -0.00 (coefficient associated with the "M sand" input feature)

$\beta_4$ = 0.11 (coefficient associated with the "curing days" input feature)

This equation calculates the compressive strength based on the weighted sum of the input features: sand, PET, M sand, and curing days, along with the intercept term $\beta_0$. The multiple linear regression algorithm determines the optimal values of the coefficients through the learning process, considering the relationships between the input features and the target variable (compressive strength) in the training data.

The proposed equation by the decision tree for calculating the compressive strength can be expressed as:

$$CompressiveStrength = \alpha_1 \times sand + \alpha_2 \times PET + \alpha_3 \times Msand + \alpha_4 \times curing\ days \quad (6)$$

Where:

$\alpha_1$ = 0.15 (weight or coefficient associated with the "sand" input feature)

$\alpha_2$ = 0.13 (weight or coefficient associated with the "PET" input feature)

$\alpha_3$ = 0.28 (weight or coefficient associated with the "M sand" input feature)

$\alpha_4$ = 0.44 (weight or coefficient associated with the "curing days" input feature).

In this analysis, we compare the performance of three prediction methods—Multiple Linear Regression (MLR), Decision Tree (DT), and Artificial Neural Network (ANN)—using the provided data and graph. The DT method demonstrates the highest correlation with actual values, showing an $R^2$ of 0.9318. This suggests that the DT method captures the relationship between variables effectively, making it the most reliable method for this dataset. The MLR method shows a moderate correlation ($R^2$ = 0.705), indicating reasonably good predictive accuracy, but it remained less effective than DT. This method struggles with non-linear relationships and extreme values, leading to more significant prediction errors. In contrast, the ANN method demonstrates poor predictive performance with an $R^2$ of 0.0435. The predictions are widely scattered and do not align well with the actual values.

The DT model outperforming the MLR and ANN models in concrete strength estimation is attributed to the following.

- Decision Trees are non-linear models that can capture complex relationships in the data. In the case of predicting compressive strength, there might be non-linear interactions among input features that are better captured by a Decision Tree than a linear model like MLR [13] [24].
- The Artificial Neural Network model did not perform well as compared to the DT model and MLR Model because it is a more complex model that requires more data to train. The dataset used in the experiment was small, which may not have been enough to train the ANN model effectively [24].

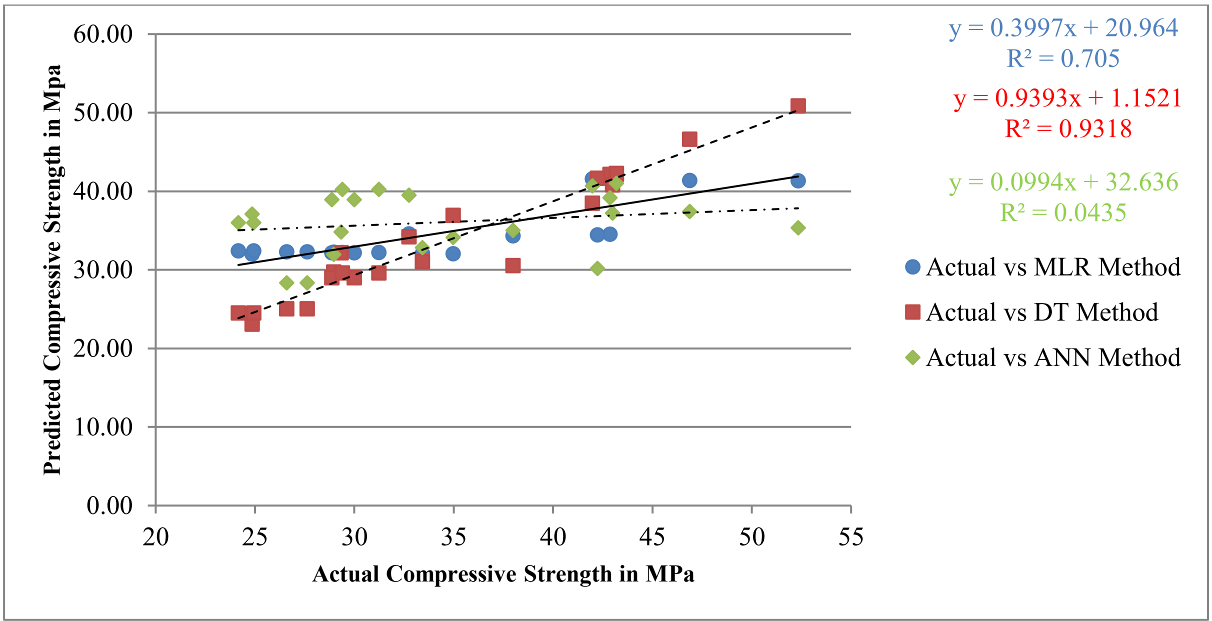


Figure 3. Actual vs Predicted Compressive Strength

## 6. CONCLUSION

The results show that the DT model provides an accurate prediction compared to MLR and ANN. The MAE and MSE values are low for the DT model, which indicates good accuracy. Additionally, the Decision Tree model has the highest R-squared score, implying that it explains a significant portion of the variance in the compressive strength.

The Decision Tree model outperforming the MLR and ANN models in predicting compressive strength can be attributed to several factors:

- Decision Trees are non-linear models that can capture complex relationships in the data. In the case of predicting compressive strength, there might be non-linear interactions among input features that are better captured by a Decision Tree than a linear model like MLR.
- The ANN model did not perform as well as the Decision Tree model because it is a more complex model that requires more data to train effectively. The dataset used in the experiment was relatively small, which may not have been enough to train the Artificial Neural Network model effectively.

In contrast, the Multiple Linear Regression model demonstrates moderate performance with higher MSE and MAE values and a lower R-squared score. Unfortunately, the Neural Network model emerges as the poorest performer, yielding the highest MSE and MAE values along with a negative R-squared score, suggesting its ineffectiveness in explaining the variance in the compressive strength. Overall, the Decision Tree model stands out as the most accurate and reliable option for predicting compressive strength based on the given evaluation metrics.

## 7. LIMITATIONS

While this research work explores the estimation of compressive strength in concrete using ML algorithms, it is important to acknowledge some potential limitations:

- *Data availability and quality*: The accuracy of ML models heavily depends on the quality and quantity of data used for training. Limited or insufficient data may result in less reliable predictions. Additionally, the data quality, such as measurement errors or inconsistencies, can impact the accuracy of the models.
- *Generalizability*: The research focuses on a specific concrete mixture composed of M-sand and PET fine aggregates. The findings may not be directly applicable to different concrete mixtures or compositions. Generalizing the results to a broader context may require further validation and experimentation.
- *Feature selection*: The choice of features or variables used in the ML models can influence their performance. It is crucial to ensure that all relevant factors affecting compressive strength are considered and appropriately included in the models. Failure to include important features or incorporating irrelevant ones can lead to inaccurate predictions.
- *Model selection and performance*: The research employs three ML algorithms: decision tree, multiple linear regression, and ANN. However, there might be other ML algorithms that could potentially yield better results. The performance comparison may not include all possible algorithms, limiting the understanding of the best-performing model for this specific task.
- *Interpretability*: While ML algorithms provide accurate predictions, they often lack interpretability. Understanding the underlying reasons or relationships behind the predictions made by the models can be challenging. In domains where interpretability is crucial, such as engineering or construction, this limitation might restrict the practical application of the models.

These limitations should be considered when interpreting the results of the research and its potential application in real-world scenarios. Further studies and validations are necessary to address these limitations and enhance the reliability and applicability of the proposed ML models.

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