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Research Article

Performance evaluation of compressive strength of concrete using different machine learning algorithms

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ABSTRACT

Accurately predicting the compressive strength of concrete is crucial for ensuring structural integrity, optimizing material usage, and reducing construction costs. Conventional experimental methods, though reliable, are often labour-intensive and time-consuming. To address these limitations, this study investigates the effectiveness of machine learning (ML) algorithms as efficient alternatives for predicting concrete compressive strength. Four ML algorithms—Linear Regression (LR), Multilayer Perceptron (MLP), M5 Rule-Based Model, and Support Vector Machines (SVM)—were evaluated based on their predictive performance. A comprehensive dataset comprising 350 concrete samples was prepared, with compressive strength tests conducted in accordance with Indian standard 516. The models were trained on experimental data and were tested using varying data splits of 50%, 40%, 30%, 20%, and 10% to assess their prediction accuracy. Among the evaluated models, the MLP demonstrated superior performance, achieving a correlation coefficient (CC) of 0.98 with a 20% testing split, outperforming the other algorithms. To further validate the predictive capability of the MLP model, multiple linear regression analysis was employed, confirming its robustness and generalization ability. The findings underscore the potential of machine learning techniques, particularly the MLP model, in providing accurate, reliable, and time-efficient predictions of concrete compressive strength. This study contributes to the growing body of research focused on leveraging machine learning for enhanced decision-making in construction material design, ultimately promoting more sustainable and cost-effective construction practices.

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1. Introduction

The field of construction materials research has undergone a significant transformation with the advent of machine learning (ML) techniques, offering novel approaches for analyzing and predicting the properties of materials. Machine learning enables the development of computational models capable of learning from data and identifying complex patterns, thereby offering potentially more efficient and effective solutions to structural engineering challenges (Gürbüz and Kazaz 2024). Among these properties, compressive strength is a critical parameter that defines the quality, safety, and durability of concrete structures (Nalina 2023). The application of advanced ML algorithms to predict the compressive strength of concrete can significantly accelerate labor-intensive experimental processes and reduce associated costs (Harirchian 2024). Traditional methods for determining compressive strength often involve time-consuming laboratory tests and physical experiments. As construction demands grow and evolve, there is a pressing need for efficient, accurate, and cost-effective methods to predict compressive strength during the design phase. While these methods ensure precision, they

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are limited by high costs, delays, and constraints in real-time adaptability. In the modern era of construction and infrastructure demands, where rapid urbanization and sustainable design practices are paramount, the need for efficient and accurate methods for predicting compressive strength has become increasingly apparent. Machine learning algorithms present an innovative solution to this challenge by leveraging computational models to establish complex relationships between input features and target variables (Yeh 1998). These techniques can effectively model nonlinear relationships and process large datasets, thereby enhancing prediction accuracy and decision-making in concrete mix design. This study focuses on evaluating the performance of various machine learning algorithms for predicting the compressive strength of concrete.

2. Literature Review

The use of machine learning (ML) algorithms to predict the compressive strength of concrete has gained significant attention in recent years due to their capability to process large datasets and capture nonlinear relationships between multiple input variables. Yeh (1998) was one of the first researchers to model the strength of high-performance concrete using Artificial Neural Networks (ANNs). The study demonstrated that ANNs outperform traditional regression techniques in capturing nonlinear relationships between variables such as water-cement ratio, cement content, and curing time. Chou and Tsai (2012) investigated a combined classifier approach using support vector machines (SVM) and decision trees for concrete compressive strength prediction. The hybrid model was shown to provide enhanced accuracy compared to standalone ML algorithms. Huang et al. (2025) applied deep learning techniques such as convolutional neural networks (CNN) to predict the strength of concrete containing waste materials like glass. Their findings emphasized the importance of dataset size and preprocessing in deep learning applications. Tiep et al. (2024) introduced a novel hyperparameter tuning framework for regression tasks. Their study combined sampling algorithms with neural networks to optimize model performance, achieving higher prediction accuracy for concrete strength. Khan et al. (2025) used Optuna for automated hyperparameter tuning in predicting high-performance concrete strength. By leveraging tools like SHAP for interpretability, they provided insights into influential variables such as cement content and water-cement ratio. Ullah et al. (2025) demonstrated the effectiveness of hybrid ML models combining traditional methods with advanced optimization algorithms to estimate the tensile and compressive strength of basalt fiber-reinforced concrete.

Oyebisi et al. (2024) incorporated optimization techniques in ML models to enhance the prediction accuracy for slurry infiltrated fiber concrete. The study highlighted the need for domain-specific customization in ML applications. Salami et al. (2024) focused on the influence of feature selection in ML models for predicting the compressive strength of concrete. The study demonstrated that proper feature engineering could significantly enhance prediction accuracy. Feature engineering refers to the process of selecting, modifying, or creating relevant input variables (features) that help machine learning (ML) models make accurate predictions. Pan et al. (2025) applied ensemble learning to predict recycled concrete's compressive strength, emphasizing the importance of cleaning datasets and identifying key predictors. Ghoniem and Nour (2025) applied ML models to predict the mechanical properties of sandstone concrete with varying compaction levels and silica fume ratios. Their results demonstrated the adaptability of ML for diverse concrete compositions. Li et al. (2025) investigated the performance of circular concrete-filled steel tubular columns using ML-based strength prediction models, combining traditional mechanics and advanced ML techniques. In this study, Linear Regression serves as a fundamental baseline model for regression tasks. It establishes a linear relationship between input variable and the target variable, which, in this case, is the compressive strength of concrete. Despite its simplicity, LR offers interpretability and provides insights into how individual variable affect strength predictions. Its inclusion ensures a comparative understanding of how more complex models improve upon this baseline. MLP, a type of artificial neural network, is capable of capturing complex, nonlinear relationships within data. Since concrete compressive strength is influenced by multiple interacting factors (e.g., material composition, curing time), MLP can model these nonlinearities effectively. Its robust learning ability allows it to generalize well across different datasets, making it ideal for predicting material properties with inherent variability. The M5 Rule-based model combines decision trees with linear regression, providing both interpretability and predictive power. It creates piecewise linear models that adapt to local patterns in the data, offering a balance between accuracy and explainability. This makes it suitable for complex engineering datasets where relationships between variables may vary across different ranges. SVM is known for its ability to handle high-dimensional data and model nonlinear relationships using kernel functions. For predicting concrete compressive strength, SVM can manage complex interactions between variables with high precision. It is also less prone to overfitting, especially in scenarios where the dataset is not large, ensuring robust predictions.

This study contributes to the existing body of work on concrete strength prediction by providing a comprehensive comparison of different machine learning models, including MLP, SVR, M5 Rule, and Linear Regression. Unlike previous studies that focused on single-model applications, this research highlights the strengths and limitations of each model under varying training-to-testing data splits. The findings emphasize the importance of selecting an appropriate ML model and training percentage to achieve reliable predictions, reducing the reliance on extensive laboratory testing. Furthermore, this study demonstrates that MLP outperforms traditional and rule-based models, reinforcing the need for advanced ML techniques in concrete durability assessment and predictive analytics.

2.1. Linear regression model

Linear regression is a fundamental statistical and machine learning algorithm used to model the relationship between one dependent variable (y) and one or more independent variables ($x_1, x_2, .., x_n$) (Aydın et al. 2024; Öztaş et al. 2005). The model assumes a linear relationship between the variables and predicts the value of (y) based on the given inputs. In simple linear regression, there is only one independent variable (x). The relationship is modeled in Eq. (1) as:

$$y = \beta_0 + \beta_{1x} + \epsilon \tag{1}$$

where:
y is the dependent variable (target);
x is the independent variable (predictor);
β_0 is the intercept (value of y when x=0);
β_1 is the slope coefficient (rate of change of y with respect to x);
ϵ is the error term (accounts for deviations of actual y from predicted y).

While in multiple linear regression, there are n independent variables ($x_1, x_2, .., x_n$). The relationship is modeled as in Eq. (2).

$$y = \beta_0 + \beta_{1x_1} + \beta_{2x_2} + \cdots + \beta_{nx_n} + \epsilon \tag{2}$$

2.2. Multi-layer perceptron model

A Multilayer Perceptron (MLP) is a class of artificial neural networks (ANN) designed for supervised learning tasks such as classification and regression. MLPs are capable of learning complex nonlinear relationships between inputs and outputs, making them highly versatile in a variety of applications, including image recognition, language processing, and predictive modeling. It consists of three main layers: the input layer, hidden layers, and the output layer. The input layer received the input feature while the hidden layer apply transformation using weighted sums and activation functions and the output layer produces the predictions. Forward propagation and backpropagation are two key processes in training artificial neural networks like the Multilayer Perceptron (MLP). They work together to ensure that the network learns from data, minimizes errors, and adjusts its weights and biases effectively. Forward propagation computes the output of the network given the inputs, by passing data through each layer (Topçu and Sarıdemir 2008). The input feature ($x_1, x_2, .., x_n$) are fed into the network. Each neuron computes a weighted sum of its inputs, adds a bias, and applies an activation function as mentioned in Eq. (3).

$$z_j = \sum_{i=1}^{n} w_{ij}\, x_i\, b_j \qquad a_j = f(z_j) \tag{3}$$

where:
w_{ij} is the weight connecting input i to neuron j;
b_j is the bias for neuron j;
$f(z_j)$ is the activation function (e.g., ReLU, Sigmoid, Tanh).

The output layer applies the same process and generates predictions ($\hat{y}$) based on the activations of the previous layer. Backpropagation updates the weights and biases of the network to minimize the error between predicted ($\hat{y}$) and actual (y) values. Use a loss function (e.g., Mean Squared Error or Cross-Entropy Loss) to calculate the error as mentioned in Eq. (4).

$$\text{Loss} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{4}$$

Backpropagation calculates the gradient of the loss function with respect to each weight and bias using the chain rule of calculus as mentioned in Eq. (5).

$$\frac{\partial \text{Loss}}{\partial w_{ij}} \tag{5}$$

Gradients represent how much the weights/biases need to change to reduce the loss. Using gradient descent, update the parameters to minimize the loss as mentioned in Eq. (6).

$$w_{ij} \leftarrow w_{ij} - \eta \frac{\partial \text{Loss}}{\partial w_{ij}} \tag{6}$$

where:
η is the learning rate (step size for updates).

Gradients are propagated backward through the network, layer by layer, starting from the output layer and moving toward the input layer.

2.3. M5 rule model

The M5 Rule Model is a decision-tree-based algorithm used for regression tasks (Quinlan 1992). It combines aspects of decision trees with linear regression models to create a hybrid approach. Developed by Quinlan in 1992, the M5 algorithm is particularly effective for modeling nonlinear relationships and handling large datasets with continuous target variables. M5 constructs a decision tree by recursively splitting the data based on feature values to minimize error. Unlike traditional decision trees that predict constant values at the leaves, M5 associates each leaf node with a linear regression model, allowing for better predictions. The algorithm selects the feature and split point that minimizes the variance of the target variable within each subset. Variance reduction is calculated as mentioned in Eq. (7).

$$\Delta T = \text{var}(T) - \left(\frac{|T_1|}{|T|}\text{var}(T_1) + \frac{|T_2|}{|T|}\text{var}(T_2)\right) \tag{7}$$

where:
T is the original dataset;
T_1, T_2 are the subsets after split;
$|T|$ is the number of samples in T.

At each leaf node, M5 fits a linear regression model as mentioned in Eq. (8).

$$y = \beta_0 + \beta_{1x_1} + \beta_{2x_2} + \cdots + \beta_{nx_n} + \epsilon \tag{8}$$

This allows the model to generalize better and capture trends in the data (Witten and Frank 2005).

2.4. Support vector machine model

Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification, regression, and outlier detection tasks. It works by finding the optimal hyperplane that separates data points into distinct classes or predicts continuous values in the case of regression (Vapnik 1995).

The hyperplane is expressed as mentioned in Eq. (9).

$$w^T x + b = 0 \quad (9)$$

where:
w is the weight vector;
x is the input feature vector;
b is the bias term.

SVM maximizes the margin (M) between support vectors while ensuring correct classification as mentioned in Eq. (10).

$$M = \frac{2}{\|w\|} \quad (10)$$

The optimization problem is to maximize this margin, which is equivalent to minimizing $\|w\|$ subject to the condition that all data points are correctly classified as mentioned in Eq. (11).

Constraints:

$$y_i(w^T x_i + b) \geq 1, \forall i \quad (11)$$

where:
y_i is the class label of the i-th data point (+1 or −1);
x_i is the feature vector of the i-th data point.

To solve the optimization problem, SVM uses Lagrange multipliers (Smola and Schölkopf 2004).

The Lagrangian formulation for the primal problem as mentioned in Eq. (12).

$$L(w, b, \alpha) = 21\|w\|2 - i = 1\sum n\alpha_i \quad [y_i(w^T x_i + b) - 1] \quad (12)$$

3. Methodology

In this study, concrete mix was prepared using IS 10262 (2019) code. Total 350 number of cubes of dimension 150mm×150mm×150 mm were casted with different mix design and were cured at 27±2 °C for 28 days. The specimens were tested at 7 and 28 days for compressive strength of concrete. The mix ingredients consist of cement, flyash, Alco-fine, ground granulated blast furnace slag, water, fine aggregates and coarse aggregates and admixture as mentioned in Table 1.

Table 1. Mix design proportions.

Component	Dataset of concrete mix		
	min (kg/m³)	max (kg/m³)	average (kg/m³)
Cement	130	650	330
GGBS	0	325	74
Flyash	0	360	59
Alco- fine	0	65	5
20mm	438	745	663
10mm	220	510	349
CRF	530	1100	836
Water	140	180	155
Admixture	1.017	8.45	5.24
Compressive strength (MPa)	12.99	96.73	48.34

For machine learning, WEKA software version 3.8.6 was used. A total of 350 datasets were taken as input. The input dataset consists of cement, GGBS, flyash, Alco-fine, 20mm, 10mm Crush sand, admixture. While the output dataset consists of compressive strength .The input and output dataset was normalized and then the dataset was trained and tested with different percentages as 50%, 40%, 30% 20% and 10% with different machine learning algorithms using WEKA software version 3.8.6. The denormalization of output dataset was done to revert back the predictions to their original scale. Statistical parameters such as coefficients of correlation (CC), coefficients of determinations (R^2), mean square error (MSE), mean absolute error (MAE) and root mean square error (RMSE) are evaluated for each machine learning model. Later Multi-linear regression equation for parameters compressive strength was developed from origin software. The statistical parameters developed were compared with multi linear regression and machine learning model statistics.

For MLP model, Sigmoid function was used with epoch 500, learning rate 0.25 and hidden layer 8. The training algorithm used is backward propagation. In Support Vector Regression (SVR), the key hyperparameters include epsilon range 0.001 while alpha ranges from 0.25 and kernel parameters.

4. Results and Discussion

This section presents the performance of the different machine learning model for predicting compressive strength, evaluated across varying training-to-testing data splits. Metrics such as Correlation Coefficient (CC), Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were analyzed to assess the model's accuracy and reliability. The compressive strength of concrete is influenced by various factors, such as water-cement ratio, cement content, aggregate properties, and curing conditions. These factors introduce inherent variability in the dataset, which the model attempts to capture.

4.1. Linear regression model

The CC values ranged from 0.95 to 0.97, indicating a strong linear relationship between predicted and actual compressive strengths as mentioned in Table 2. The predicted values of compressive strength and actual values of compressive strength using linear regression model are mentioned in Fig. 1.

Table 2. Linear regression model performance.

Strength	Testing				
	50%	40%	30%	20%	10%
CC	0.95	0.95	0.95	0.96	0.97
R^2	0.91	0.90	0.90	0.92	0.93
MAE (MPa)	4.98	5.08	4.96	4.26	3.86
MSE (MPa)	39.04	41.94	42.53	29.05	24.63
RMSE (MPa)	6.25	6.48	6.52	5.39	4.96

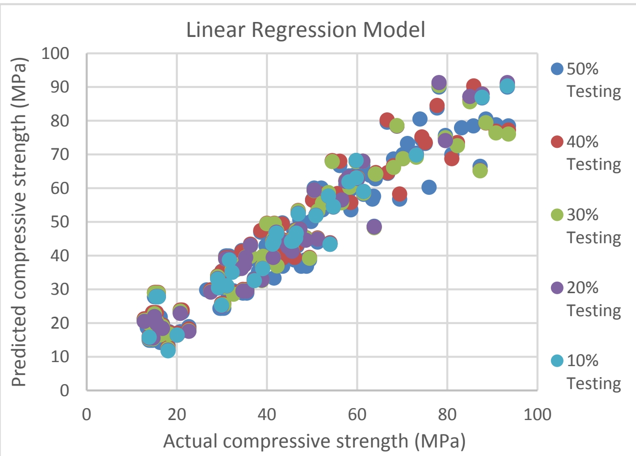

Fig. 1. Linear model prediction efficiency.

Higher training percentages led to slight improvements in CC, with the highest value (0.97), observed at 90% training data. This suggests that linear regression effectively captures the dominant linear trends in the dataset. The reduction in MAE and RMSE as training data increases reflects the model's improved ability to minimize absolute and squared errors in predicting compressive strength. At 50% training data, RMSE is 6.25 MPa, indicating larger deviations from actual compressive strength. At 90% training data, RMSE drops to 4.96 MPa, showing improved precision in predictions. The R^2 values ranged from 0.90 to 0.93, showing the proportion of variance in the compressive strength explained by the model. Then improved as training data increased, with the best value (0.93) achieved at 90% training data. The higher errors RMSE of 6.25 MPa at 50% training may be linked to insufficient training data capturing the variability of compressive strength. Higher RMSE values at lower training percentages (e.g., 6.25 MPa at 50% training) may be attributed to insufficient training data, limiting the model's ability to capture the full variability of compressive strength. This variability stems from differences in concrete composition, such as water-cement ratios and aggregate quality, as well as experimental inconsistencies in compressive strength measurement.

4.2. Multi-layer perceptron model

The CC values range from 0.96 to 0.98, indicating a very strong relationship between the predicted and actual compressive strength values as mentioned in Table 3. The highest CC 0.98 was observed with 80% training data, demonstrating the model's ability to learn complex relationships with sufficient training data. The predicted values of compressive strength and actual values of compressive strength using MLP model are mentioned in Fig. 2. The R^2 values are consistently around 0.91–0.92, indicating that approximately 91–92% of the variance in compressive strength is explained by the model. While R^2 values are stable, the slight dip to 0.90 at 70% training suggests some variability in performance. MAE values range from 4.17 MPa to 5.20 MPa, reflecting the average prediction error in compressive strength. The best MAE 4.17 MPa was observed at 90% training, indicating the model's improved accuracy with more training data indicating better alignment with actual compressive strength.

Both MSE and RMSE metrics decrease as training data increases, except for a slight rise at 70% training, indicating variability in the model's learning process. MSE dropped from 35.60 MPa 50% training to 31.46 MPa 90% training. RMSE improved from 5.97 MPa 50% training to 5.61 MPa at 90% training. The small deviations in performance at 70% training with R^2 0.90 and RMSE 6.66 MPa suggest that MLP may be sensitive to data distribution and hyperparameter settings. MLP relies heavily on hyperparameter tuning (e.g., number of layers, neurons, learning rate, batch size).The observed variability at 70% training suggests that the model is somewhat sensitive to the specific data distribution in that training split. If the data distribution changes, the model may struggle to generalize, leading to fluctuations in R^2 and RMSE. MLP performance is influenced by learning rate, activation functions, and weight initialization. The training process might have settled into a suboptimal local minimum, leading to slightly worse predictions.

Table 3. Multi-layer perceptron model performance.

Strength	Testing				
	50%	40%	30%	20%	10%
CC	0.96	0.96	0.97	0.98	0.96
R^2	0.91	0.92	0.90	0.91	0.91
MAE (MPa)	4.71	4.59	5.20	4.60	4.17
MSE (MPa)	35.6	33.78	44.37	33.14	31.46
RMSE (MPa)	5.97	5.81	6.66	5.76	5.61

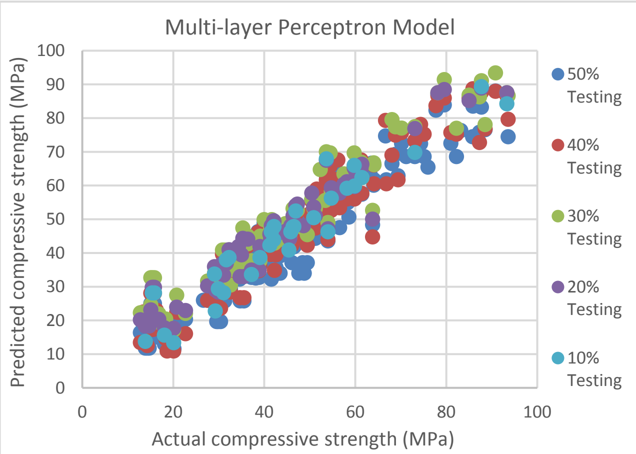

Fig. 2. Multi-layer perceptron model prediction efficiency.

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4.3. M5 rule model

The M5 Rule-Based Model was evaluated for predicting the compressive strength of concrete using different training-to-testing splits as mentioned in Table 4. The CC values range from 0.86 to 0.92, indicating a moderate to strong relationship between predicted and actual compressive strength values. The highest CC 0.92 is observed at both 50% and 90% training data splits, suggesting better predictions with these configurations. The M5 Rule Model leverages these relationships by combining decision trees and linear regression at leaf nodes. The predicted values of compressive strength and actual values are mentioned in Fig. 3. The moderate CC 0.86 –0.92 suggests the model captures the dominant trends but struggles with complex nonlinear dependencies compared to models like MLP. The MAE and RMSE values indicate that the model can provide quick and moderately accurate estimates of compressive strength, reducing the need for extensive laboratory testing. The R^2 values range from 0.74 to 0.87, indicating that the model explains up to 87% of the variability in compressive strength. The R^2 values drop significantly at 70% training 0.74, suggesting potential overfitting or underfitting issues. The MAE values range from 3.00 MPa to 5.28 MPa, reflecting the average prediction error. The best MAE 3.00MPa is achieved at 90% training, while the largest error occurs at 60% training 5.28MPa. MSE values drop significantly from 39.04 MPa for 50% training to 15.34 MPa for 90% training, demonstrating improved predictions with more training data. RMSE follows a similar trend, reducing from 6.25 MPa to 3.92 MPa at 90% training. Higher training data (90%) leads to better generalization, with the best performance in terms of CC, R^2, and MAE. Lower training splits (50–70%) show inconsistent performance, possibly due to overfitting or underfitting. The M5 Rule-Based Model works well for capturing dominant trends but struggles with complex nonlinear relationships, where neural networks like MLP might perform better. Errors decrease as training data increases, indicating the model benefits from more training examples.

Table 4. M5 rule model performance.

Strength	Testing				
	50%	40%	30%	20%	10%
CC	0.92	0.89	0.86	0.89	0.92
R^2	0.87	0.79	0.74	0.79	0.87
MAE (MPa)	4.19	5.28	4.99	4.21	3.00
MSE (MPa)	39.04	41.94	42.53	39.05	15.34
RMSE (MPa)	6.25	6.55	6.79	6.23	3.92

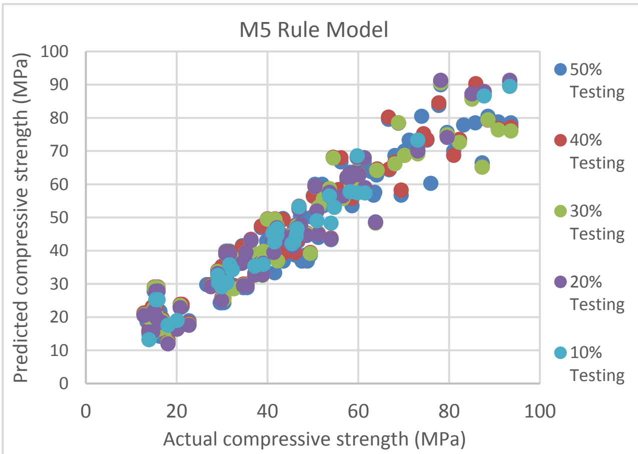

Fig. 3. M5 rule model prediction efficiency.

4.4. Support vector machine model

The analysis uses metrics such as Correlation Coefficient (CC), Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to assess the model's performance and reliability as mentioned in Table 5. The CC values range from 0.95 to 0.97, indicating a very strong relationship between predicted and actual compressive strength values. As the testing percentage decreases, CC improves slightly, reaching its peak 0.97 at 10% testing, demonstrating the model's ability to generalize well with sufficient training data. The R^2 values range from 0.90 to 0.94, indicating that up to 94% of the variance in compressive strength is explained by the model. R^2 improves as the testing percentage decreases, reflecting better predictions with more training data. The compressive strength of concrete is influenced by a complex interplay of factors such as water-cement ratio, curing conditions, and aggregate properties. The SVM model, with its capacity to handle nonlinear relationships via kernel functions, effectively captures these interactions as mentioned in Fig. 4. The high CC and R^2 values suggest that SVM models are well-suited for predicting compressive strength, especially in datasets with complex dependencies.

Table 5. Support vector machine model performance.

Strength	Testing				
	50%	40%	30%	20%	10%
CC	0.95	0.95	0.95	0.96	0.97
R^2	0.91	0.91	0.90	0.92	0.94
MAE (MPa)	4.80	4.80	4.80	4.00	3.70
MSE (MPa)	39.68	40.20	41.69	26.91	22.65
RMSE (MPa)	6.30	6.34	6.46	5.19	4.76

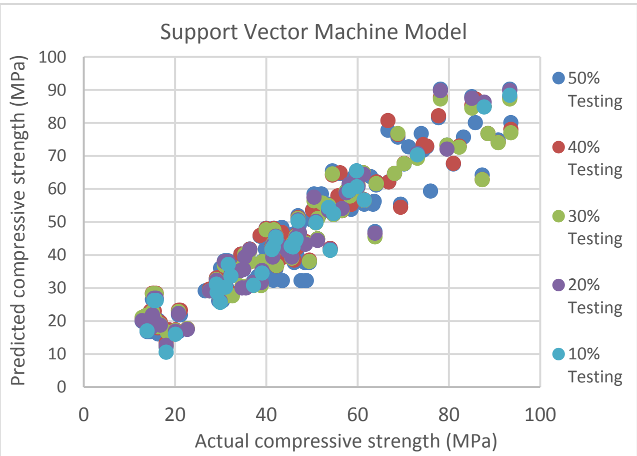

Fig. 4. Support vector machine model prediction efficiency.

The MAE values range from 4.80 MPa (at 50–30% testing) to 3.70 MPa (at 10% testing). The consistent improvement in MAE at lower testing percentages highlights the model's increasing accuracy as more data is used for training. MSE decreases significantly from 39.68 MPa at 50% testing to 22.65 MPa at 10% testing, reflecting reduced prediction errors with larger training datasets. RMSE also follows a downward trend, dropping from 6.30 MPa to 4.76 MPa, further confirming improved precision in predictions. MAE improves from 4.80 MPa (at 50% testing) to 3.70 MPa (at 10% testing), demonstrating that more training data allows the SVM model to better generalize the relationships between features and compressive strength.

The low RMSE values, particularly 4.76 MPa at 10% testing, indicate that the model delivers predictions with minimal deviation from actual compressive strength values. The SVM model's ability to handle nonlinear data (via kernel functions) makes it particularly suitable for datasets where compressive strength exhibits complex dependencies on mix proportions and curing condition.

4.5. Multi-linear regression

To validate the predictive capability of the machine learning-based approach, the Multiple Linear Regression (MLR) model was evaluated using a dataset containing concrete mix properties. The model was constructed to predict compressive strength based on key mix components. The derived regression equation is:

CompressiveStrength = – 1495.02827 + 0.58745 × Cement + 0.57517 × GGBS + 0.77427 × Flyash + 0.74902 × Alcofine + 0.5704 × 20mm + 0.55811 × 10mm + 0.5276 × CRF + 1.51772 × Water + 3.95817 × Admix

The coefficients in the regression equation represent the impact of each component on the compressive strength of concrete. Cement (+0.58745) has a positive and significant impact, reflecting its role as a primary binder. Ground Granulated Blast Furnace Slag (+0.57517) indicates that (GGBS) contributes to strength by enhancing hydration and reducing voids. Flyash (+0.77427) positively influences strength through pozzolanic reactions. Alcofine (+0.74902) indicates that the high coefficient for Alcofine indicates its effectiveness in improving strength, likely due to its ultra-fineness and high reactivity.

- 20mm Aggregate (+0.5704) and 10mm Aggregate (+0.55811) indicate that the coarse aggregates enhance strength by providing a solid framework for the concrete matrix.
- CRF (Crusher Rock Fines) (+0.5276) indicates that fines contribute to improved packing density, enhancing compressive strength.
- Water (+1.51772) indicates that the positive coefficient suggests that water is a key activator for hydration, but excessive water can reduce strength.
- Admixture (+3.95817) indicates that the admixtures significantly enhance strength by improving workability and reducing water demand.
- The negative intercept (–1495.02827) reflects the combined effect of unmeasured factors and baseline mix properties, serving as a constant offset for the regression equation. The CC value obtained was 0.96, R^2 0.92 and MAE 4.18 MPa with RMSE 6.31 MPa were calculated and compared with different machine learning models.

5. Limitations of the Machine Learning Models

While the machine learning models used in this study demonstrate strong predictive capabilities, several limitations must be considered:

- Data Dependency: The performance of ML models is highly dependent on the quality and quantity of training data. Insufficient or biased data can lead to overfitting or underfitting, affecting prediction accuracy.
- Hyperparameter Sensitivity: Models like MLP and SVR require careful tuning of hyperparameters, which can significantly impact their performance. Suboptimal hyperparameters may lead to higher errors.
- Computational Complexity: Advanced models such as MLP and SVR require more computational resources compared to simpler models like linear regression or M5 rule-based models. This can limit their practical application in resource-constrained environments.
- Generalization Issues: While ML models perform well on the training dataset, their ability to generalize to new, unseen data may be limited, especially if the training data does not sufficiently represent all possible variations in concrete mix properties.
- Interpretability: Some ML models, particularly neural networks, act as black boxes, making it difficult to interpret their decision-making process. This can be a drawback for practical applications where explainability is crucial.

Future research should focus on improving model generalization by incorporating more diverse datasets, optimizing hyperparameter selection, and exploring hybrid modeling approaches that combine ML techniques with domain knowledge in concrete materials science.

6. Conclusions

This study evaluated the performance of four machine learning models—Linear Regression (LR), Multi-Layer Perceptron (MLP), M5 Rule-Based Model, and Support Vector Machine (SVM)—in predicting the compressive strength of concrete. The models were assessed based on key metrics such as Correlation Coefficient (CC), Coefficient of Determination (R^2) Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) across varying training-to-testing data splits.

The following conclusions summarize the findings:

The selection of machine learning models for this study was based on their ability to capture both linear and nonlinear relationships in the dataset, their predictive accuracy, and their computational efficiency. MLP Model was selected for its ability to model complex nonlinear dependencies in the dataset. It demonstrated superior performance, with the highest CC and R^2 values, making it the most accurate model for compressive strength prediction. Support Vector Machine was selected due to its strong performance in handling high-dimensional data and its robustness in capturing nonlinear patterns. Although slightly less accurate than MLP, it performed well in reducing prediction errors. M5 Rule-Based Model was selected which included as it combines decision trees with linear regression, offering interpretability and reasonable predictive capability. While it struggled with complex nonlinear relationships, it provided quick estimations with moderate accuracy. While Linear Regression was used as a baseline model to evaluate how well simple linear relationships explain compressive strength variations. Though computationally efficient, its performance was lower than that of advanced ML models, justifying the need for more complex algorithms

In linear regression model, achieved a high CC of 0.97 and R^2 of 0.93 at 90% training, indicating a strong ability to explain the variance in compressive strength. While the model performed well, its assumption of linear relationships limits its ability to capture complex nonlinear dependencies, leading to relatively higher error metrics MAE=3.86 MPa and RMSE=4.96 MPa. Suitable for applications where linear trends dominate and simplicity is preferred. The MLP model demonstrated excellent predictive performance, with the highest CC of 0.98 and consistent R^2 values around 0.92. Its ability to model nonlinear relationships resulted in competitive error metrics MAE=4.17 MPa and RMSE=5.61 MPa at 90% training. The MLP model is ideal for capturing complex patterns in datasets, making it a powerful tool for predictive modeling in concrete mix design. The M5 model achieved a maximum CC of 0.92 and R2 of 0.87, with the best error metrics MAE=3.00 MPa and RMSE=3.92 MPa observed at 90% training. While its hybrid approach combining decision trees and linear regression makes it interpretable, its performance was less consistent across all splits, especially for datasets with complex nonlinear dependencies. Suitable for scenarios where simplicity and interpretability are prioritized over absolute accuracy. The SVM model showed strong predictive capabilities, with a CC of 0.97 and the highest R^2 of 0.94, demonstrating its ability to explain up to 94% of the variability in compressive strength. Error metrics MAE=3.70 MPa and RMSE=4.76 MPa at 10% testing highlighted its robustness and accuracy, particularly for datasets with nonlinear relationships. SVM's flexibility through kernel functions makes it an excellent choice for modeling compressive strength with complex dependencies. All four models demonstrated high accuracy in predicting compressive strength, with SVM and MLP excelling in capturing nonlinear relationships, and M5 Rule providing the lowest errors under specific conditions. Among the four model, MLP model exhibited excellent and higher cc values as compared with other machine learning models. The MLP model demonstrated the highest CC value of 0.98 with a 20% testing split, indicating a very strong correlation between predicted and actual values. It also achieved an R^2 value of 0.92, suggesting that it explains approximately 92% of the variance in compressive strength. The MLP model showed superior performance in capturing nonlinear relationships in the dataset, reducing RMSE and MAE values across various training-testing splits. SVM also performed well, achieving CC values between 0.96 and 0.98 and R^2 values around 0.91. The model was able to capture complex patterns in the data but exhibited slightly higher errors than MLP, particularly in MAE and RMSE, suggesting sensitivity to hyperparameter tuning. The M5 model showed moderate performance, with CC values ranging from 0.86 to 0.92 and R^2 values between 0.74 and 0.87. While it effectively combined decision trees with linear regression, it struggled with capturing highly nonlinear relationships, resulting in higher MAE and RMSE values compared to MLP and SVM. While linear regression provided reasonable estimates with CC values of 0.95 to 0.97 and R^2 values of 0.90 to 0.93, it was outperformed by the more complex ML models. The relatively higher RMSE values indicate that linear regression may not fully capture the nonlinear effects influencing compressive strength. Overall, the MLP model outperformed other approaches in terms of correlation and error reduction, making it the most suitable technique for predicting compressive strength in this study. Even when compared with multi linear regression model statistics the MLP model performance showed excellent results.

The performance of all models improved significantly as the training data increased, highlighting the importance of sufficient and high-quality data for model training. Based on the comparative analysis, an 80% training and 20% testing split is recommended for developing a robust model. This split consistently demonstrated strong correlation values (CC∼0.98), high explanatory power (R^2∼0.92), and minimized errors (MAE and RMSE). While 90% training also showed strong results, it may reduce the model's generalizability due to limited testing data. On the other hand, lower training percentages (e.g., 50–60%) exhibited higher errors, likely due to insufficient training data. Therefore, an 80–20 split balances training effectiveness and model validation, ensuring reliable compressive strength predictions. The results suggest that incorporating nonlinearity and advanced learning mechanisms significantly enhances prediction accuracy.

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Author Contributions

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Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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