ARTIFICIAL INTELLIGENCE-BASED APPROACHES TO PREDICT CONCRETE COMPRESSIVE STRENGTH

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ABSTRACT

Accurately predicting concrete compressive strength is crucial for optimizing construction workflows and ensuring structural integrity. However, traditional methods are often costly and fail to capture the complex interplay of concrete's components. This study investigates the potential of Artificial Intelligence (AI) to overcome these limitations, paving the way for a more efficient and data-driven approach to concrete mix design. We compared five AI algorithms - Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Linear Regression (LR) - on a dataset of 1030 concrete samples from the University of California, Irvine. Following established protocols, we divided the data into training and testing sets, and then trained each AI model on the former. The models were then evaluated on the unseen testing data using four key accuracy metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2). The results were striking: Random Forests emerged as the clear victor, achieving an R^2 of 0.89, significantly higher than any other method and nearing the ideal value of 1. This indicates a remarkably strong fit between the RF model and the data, suggesting its ability to accurately predict concrete compressive strength across a diverse range of mixtures. Furthermore, RF displayed superior performance on all error metrics. Compared to its rivals, it boasts significantly lower RMSE (5.19 MPa), MAPE (12.68%), and MAE (3.57 MPa), further solidifying its claim to the title of the most accurate predictor. Visualizations confirmed these findings, with RF's predictions closely mirroring the actual compressive strength values, while other models exhibited notable deviations. These findings hold immense potential for the construction industry. This opens doors to faster and more accurate concrete mix design, leading to optimized material usage, reduced construction costs, and enhanced structural safety.

This study lays the groundwork for further research in utilizing AI for construction materials optimization. Future avenues include exploring larger datasets, incorporating additional concrete mix parameters, and investigating the potential of hybrid AI models for even greater accuracy. Ultimately, embracing AI in concrete strength prediction promises a transformative shift in the construction industry, promoting sustainability, efficiency, and enhanced structural performance.

Keywords**:** *Artificial Intelligence, Prediction, Concrete Compressive Strength, Random Forest, Artificial Neural Networks.*

1. INTRODUCTION

In recent years, concrete has emerged as the predominant construction material due to its demonstrated stability and high strength. Beyond the conventional ingredients of cement, coarse aggregate, fine aggregate, and water, various additional cement composition materials, such as fly ash, blast furnace slag, and chemical additives like superplasticizers, have gained prominence (Muliauwan et al.,2020). The incorporation of these materials not only enhances the performance of concrete but also yields economic benefits by mitigating the cost associated with Portland cement, the most expensive component of concrete mixtures.

The use of additives in concrete has become popular for improving workability, durability, and strength, introducing new complexities in modelling concrete compressive strength. Traditional modelling methods, commonly employed for predicting concrete behaviour, often struggle to provide accurate results in the presence of these additional materials. Typically, strength tests are conducted 7–28 days after the concrete casting process, leading to potential delays in subsequent construction phases (Ramezanianpour et al., 2013). Immediate adjustment of the mixture proportions in response to strength variations can lead to time and cost savings.

The nonlinear relationship between concrete components and its strength complicates mathematical modelling. The empirical equation found in current standard codes for estimating compressive strength is based on testing concrete without additional cement composition materials (Muliauwan et al.,2020). Understanding the intricate relationship between concrete composition and strength is crucial for optimizing concrete mixtures. While extensive research has traditionally relied on time-consuming and costly experimental tests, there is a pressing need for a modelling system independent of experimentation that can accurately predict concrete compressive strength.

Artificial intelligence (AI) methods have gained prominence for solving classification and regression problems due to their superior accuracy compared to conventional methods. This research focuses on developing AI techniques to predict concrete compressive strength using various components Experimental data from a machine learning repository at the University of California, Irvine (UCI), collected by Yeh (Yeh, 1998), were employed to predict the compressive strength of High-Performance Concrete (HPC). The AI modelling was implemented in Python, utilizing five predictive techniques: artificial neural networks (ANN), support vector machines (SVM), decision tree (DT), random forest (RF), and linear regression (LR). Each model was applied to predict concrete compressive strength, and their performances were systematically assessed.

2. ARTIFICIAL INTELLIGENCE METHODS

2.1 ARTIFICIAL NEURAL NETWORK (ANN)

The Artificial Neural Network (ANN) is a computational model designed to emulate the structural and functional characteristics of biological neural networks (Agatonovic-Kustrin et al.,2000). Applications of ANN can be broadly categorized as either classification models or regression models. In the context of predicting the compressive strength of concrete, extensive research has been dedicated to the use of ANN (Yeh, 1998) Researchers have explored leveraging ANN to develop concrete compressive strength models that surpass the accuracy of traditional regression models.

Among the various ANN models, the multilayer perceptron (MLP) stands out as the most widely utilized. The MLP model comprises an input layer with sensory input nodes, one or more hidden layers responsible for computation, and an output layer housing a single computational node representing the concrete compressive strength. A key learning algorithm employed for training the MLP model is the back-propagation (BP) algorithm, recognized for its effectiveness. The activation process of each neuron can be elucidated through Equations (1) and (2) (Muliauwan et al.,2020).

$$netk = \Sigma wkjoj \tag{1}$$
$$yk = f(netk) \tag{2}$$

The activation of neurons denoted as $netk$ for neuron k in the current layer is influenced by the set of neurons (j) in the preceding layer. The weight of the connection between neurons k and j is represented by wkj, while oj signifies the output of neuron j. The output yk is typically calculated using sigmoid and logistical transfer functions. A visual representation of the ANN structure is depicted in Figure 1.

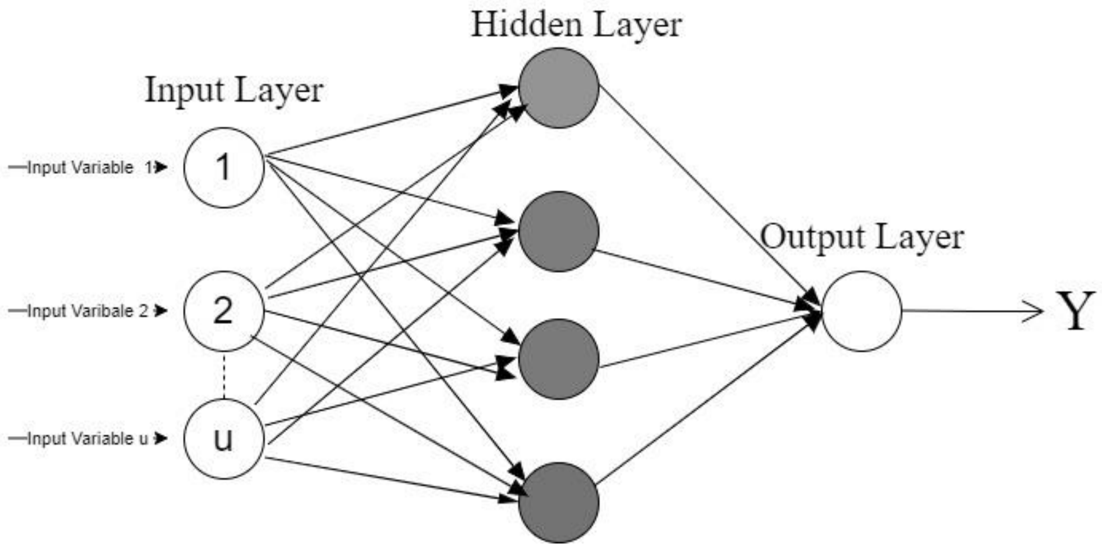

Figure 1. Illustration of ANN structure

2.2 Support Vector Machine (SVM)

Support Vector Machines (SVM), initially introduced by Vapnik in 1995 (Vapnik, 1995) have found widespread application in numerous civil engineering contexts. Particularly noteworthy is their recent prevalence in predicting concrete compressive strength. This study adopts support vector regression (ε-SVR), a specialized form of SVM, to construct an input-output model for concrete.

SVM operates on the basis of an objective function that facilitates the estimation process of the underlying function, as elucidated in Figure 2. Notably, when confronted with nonlinear spaces, SVM employs the radial-based function (RBF) kernel as a preferred choice. This kernel is selected due to its demonstrated ability to yield superior results compared to alternative kernels. The decision to utilize ε-SVR in this study underscores the significance of SVM techniques in accurately modeling and predicting concrete compressive strength.

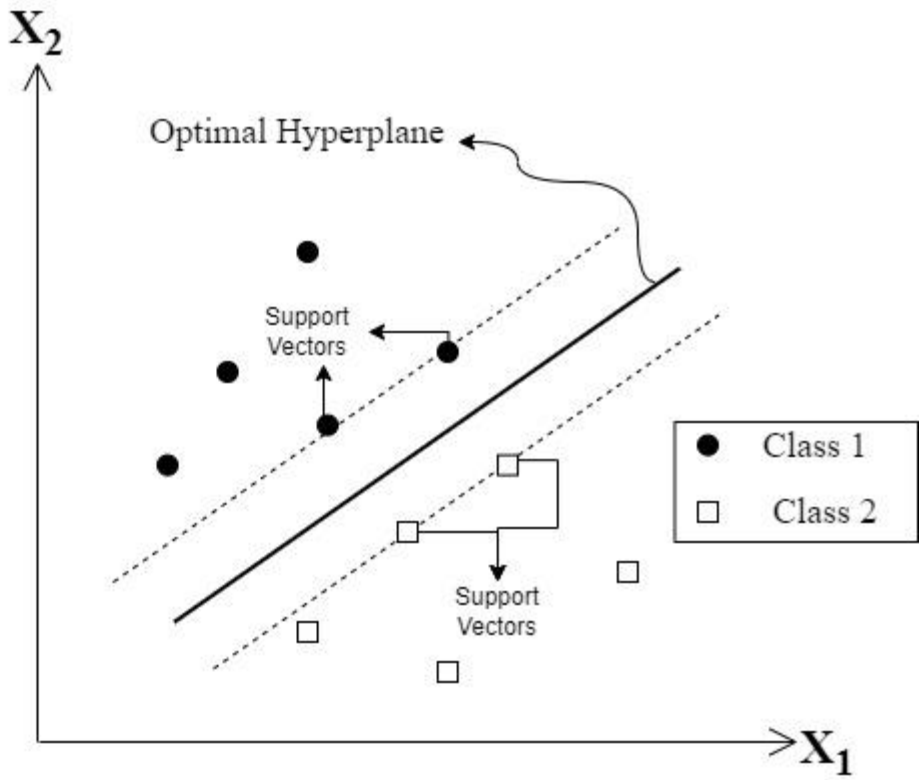

Figure 2. Illustration of hyperplane separation and determination of support vector by SVM.

The following model underlies the functional relationship between one or more independent variables with the response variable (Muliauwan et al.,2020):

$$y(x) = w^T \phi(x)+b \tag{3}$$

where $x \in R$, $y \in R$, and $\phi(x)$: R^n is the process of mapping to higher dimensional feature space.

In SVM for regression analysis, a data set of $\{X_k, Y_k\}_{K=1}^{N}$, objective functions can be formulated as follows (Muliauwan et al.,2020):

$$\text{Min. } J_p\,(w,e) = \frac{1}{2}\, w^T w\phi + c\sum_{k=1}^{N} e_k^2$$
(4)

$$\text{s.t } y_k = w^T \phi(x)+b+e_k, \quad k = 1,\ldots,N \tag{5}$$

where $e_k \in R$ is the error variable; c indicates the regularization constant.

2.3 Decision Tree (DT)

Decision trees (DTs) represent a non-parametric, rule-based methodology employed for tackling classification and regression tasks. This approach involves dividing the feature space into a sequence of elementary regions, constructing a predictive model by extracting clear decision rules from the provided training data. The appeal of decision trees in machine learning stems from their transparency and simplicity, making them a popular choice.

In the context of this research, decision trees serve as a benchmark for evaluating model performance relative to other ensemble models. The utilization of decision trees is pivotal in providing a basis for comparison, allowing for a comprehensive assessment of how different models perform in predicting concrete compressive strength. **Figure 3** (Muliauwan et al.,2020) provides a visual representation of a decision tree, offering insight into the structured and hierarchical nature of the decision-making process.

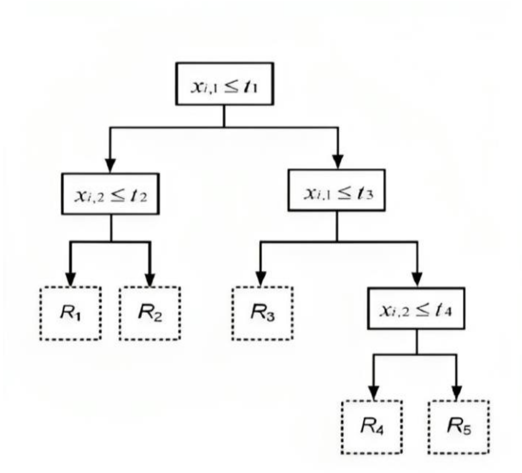

Figure 3. Illustration of Decision Tree.

2.4 Random Forest (RF)

Random Forest Regression is an effective approach for tackling regression tasks in supervised learning. This method leverages multiple decision trees, combining their outputs to derive the ultimate prediction. The result is obtained by averaging the outputs of each individual decision tree within the ensemble (Sevim, 2021). **Figure: 4** (Muliauwan et al.,2020), illustrates a representative example of a random forest regression.

The constituent decision trees, referred to as base models, actively contribute to the overall prediction process. Each decision tree in the ensemble operates independently, and their collective output is harnessed to produce a more robust and accurate regression outcome.The formulae is as follows (Torre-Tojal et al.,2022).

$$g(x) = f_0(x)+f_1(x)+f_2(x)+ \text{--------------------} \qquad (6)$$

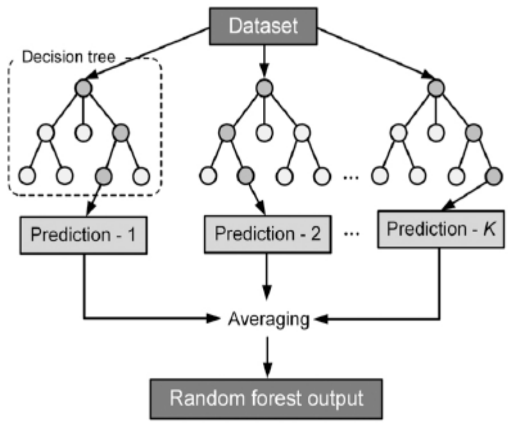

Figure 4. Illustration of Random Forest.

2.5 Linear Regression (LR)

Linear Regression (LR), an extension of the basic regression model, is employed to ascertain the relationship between a numerical response variable and two or more explanatory variables (Coppi et al.,2006) Widely used in modeling the mechanical properties of construction materials, LR was a focus of investigation in this study. The computational challenge addressed by LR involves fitting a hyperplane to an n-dimensional space, where n denotes the number of independent variables.

For a system featuring n inputs (independent variables denoted as X) and one output (dependent variable denoted as Y), the core challenge tackled by LR is the determination of unknown parameters within the linear regression model. This process is exemplified in Figure 3, where the goal is to find the optimal fit for the hyperplane that accurately represents the relationship between the input variables and the output variable.

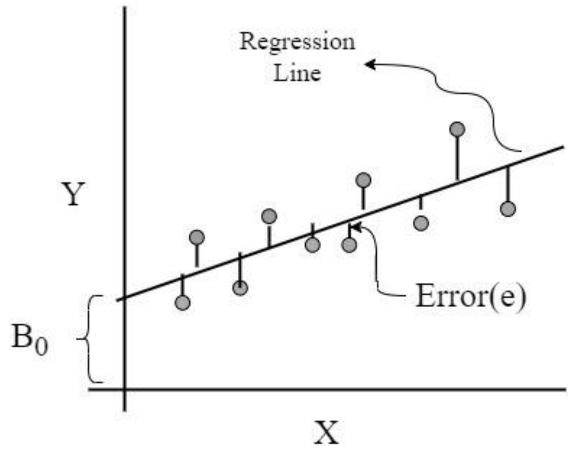

Figure 5. Illustration of linear regression.

The general formula for LR models is shown in Equation 6 (Muliauwan et al.,2020).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + . . . + \beta_n X_n + \varepsilon \quad (6)$$

In the proposed model, βi is a regression coefficient (i= 1,2,3,…,n), X's values represent concrete attributes, ε is an error term, and Y is concrete compressive strength. Regression analysis estimates the unbiased values of the regression coefficients βi against the training data set.

3. METHODOLOGY

The dataset employed in this study was procured from a machine learning repository housed at the University of California, Irvine (UCI), meticulously curated by Yeh (Yeh, 1998). This dataset comprises a comprehensive collection of experimental data derived from the evaluation of 1030 concrete samples. These samples underwent rigorous testing across various university research laboratories, collectively forming the basis for assessing the predictive capabilities of each artificial intelligence (AI) method employed in this research. These five methods (ANN, LR, SVM, Decision Tree, Random Forest) were chosen for their widespread use and effectiveness in regression tasks. Benefits include ANN's ability to capture non-linear relationships, LR's simplicity, SVM's effectiveness in high-dimensional spaces, Decision Tree's interpretability, and Random Forest's ensemble robustness. However, challenges include the computational demands of ANN, LR's linearity assumption, SVM's sensitivity to parameters, Decision Tree's proneness to overfitting, and Random Forest's potential interpretability issues and computational expense.

All experimental tests adhered to standardized procedures and were conducted on a cylindrical concrete specimen with a diameter of 15 cm. This careful standardization ensured consistency and reliability in the testing process. The dataset, outlined in Table 1, encompasses nine specific variables related to High-Performance Concrete (HPC). These variables, serving as critical components of the analytical framework, provided essential insights for evaluating the effectiveness of AI methods in predicting concrete compressive strength.

Table 1. Variables that affect the compressive strength of concrete and its descriptive

Variables	Unit	Min	Mean	Max	Standard Deviation
X_1: Cement	kg/m^3	102.0	281.17	540.0	104.51
X_2: Blast-furnace slag	kg/m^3	11.0	107.28	359.4	61.88
X_3: Fly ash	kg/m^3	24.5	83.86	200.1	39.99
X_4: Water	kg/m^3	121.8	181.57	247.0	24.35
X_5: Superplasticizer	kg/m^3	1.7	8.49	32.2	4.04
X_6: Coarse aggregate	kg/m^3	801.0	972.92	1,145.0	77.75
X_7: Fine aggregate	kg/m^3	594.0	773.58	992.6	80.18
X_8: Age of testing	Day	1.0	45.66	365.0	63.17
Y: HPC compressive strength	MPa	2.3	35.82	82.6	16.71

Table 2 outlines the performance measurement model utilized to gauge the accuracy of each predictive method employed in this study. This accuracy model is derived by assessing the alignment between actual data and the predicted outcomes of the output variable. The evaluation incorporates four distinct performance measurement metrics: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R2) (Chou, 2014).

The root mean square error (RMSE) provides a measure of the average deviation between each actual data point and its corresponding predicted result. Mean absolute error (MAE) calculates the average error by considering the absolute differences between the actual data and the predicted outcomes. R-squared (R^2), a statistical metric, quantifies the proportion of variance in the dependent variable explained by the independent variables in a regression model. It ranges from 0 to 1, with higher values indicating a more robust fit.

While MAE and RMSE use absolute differences in accuracy calculations, mean absolute percentage error (MAPE) has the advantage of being unaffected by the units and sizes of the predicted and actual values. This characteristic makes MAPE more efficient in discerning relative differences between models.

The assessment of model performance in this context prioritizes the highest R2 values, indicating a stronger fit, and the lowest RMSE, MAE, and MAPE values signifying superior accuracy and predictive capability.

Table 2. Indicators of prediction model accuracy.

Performance measurement	Mathematical formula
Coefficient of determination (R^2).	$R=1-\frac{RSS}{TSS}=1-\frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2}$
Root Mean Squared Error (RMSE)	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y-y')2}$
Mean Absolute Percentage Error (*MAPE*)	$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y-y'}{y}\right\rvert$
Mean Absolute Error (*MAE*)	$MAE=\frac{1}{n}\sum_{i=1}^{n}\lvert y-y'\rvert$

The Python SKlearn Library's AI model is leveraged to construct a precise prediction model, although the platform is known for its user-friendly interface in AI methods, a detailed flow chart is essential to ensure the development of an accurate prediction model. The process involves five key steps, each contributing to the robustness and reliability of the model:

a. Data Input: This initial step involves the collection of data, serving as the foundation for subsequent model development.

b. Training and Testing: The input data undergoes division into two distinct groups—training and testing. The training set, constituting 70% of the data, is utilized to create prediction models tailored to fit the dataset. Simultaneously, the testing set, comprising 30% of the data, is employed to assess the performance of the constructed prediction models.

c. AI Prediction Model Learning: This step involves the training of the AI prediction model using the designated training data, enabling it to learn and adapt to the underlying patterns in the dataset.

d. Testing AI Prediction Models: Subsequently, the AI prediction models undergo testing using the designated testing data to evaluate their performance and accuracy.

e. Prediction Results Evaluation: The final step involves assessing the prediction results obtained for each model using four accuracy indicators—root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R^2).

The entire process is visually represented in Figure 6, providing a comprehensive flow diagram elucidating the step-by-step procedure for building the AI prediction model using a single model. This meticulous approach ensures a thorough understanding of the model development process and facilitates the evaluation of its predictive capabilities.

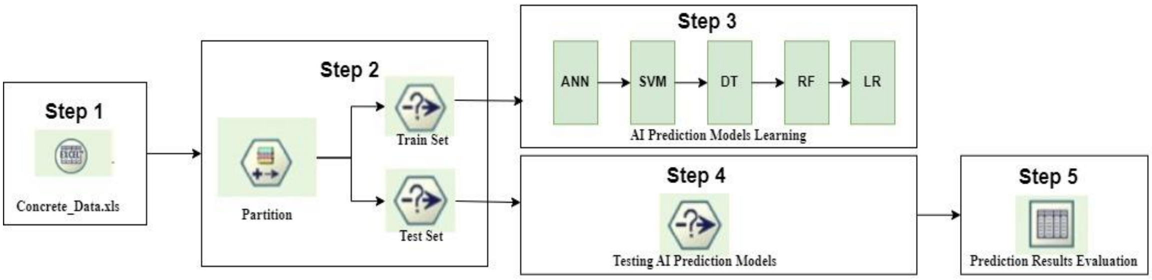

Figure 6. Flow diagram of the formation of AI prediction using a single model.

4. Results and Discussions:

This research undertaking involves a comprehensive examination aimed at assessing the predictive performance of various artificial intelligence (AI) models concerning the concrete compressive strength of a dataset comprising 1030 concrete samples. Within this dataset, a stratified division is implemented, with 723 samples earmarked for training purposes, and the remaining 307 reserved for testing.

The AI models scrutinized in this study, namely Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Linear Regression (LR), are configured with default parameters sourced from the sklearn library, ensuring a standardized baseline for comparison.

As outlined earlier, the assessment of each prediction method encompasses a suite of metrics, including R-squared (R2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). These metrics collectively offer a nuanced understanding of the accuracy and precision exhibited by each AI model in predicting concrete compressive strength.

In summarizing the outcomes of this thorough analysis, the results are succinctly presented in Table 3, shedding light on the performance of each method specifically when applied to the testing dataset. This tabulated representation serves as a valuable reference, enabling a detailed exploration of the nuanced strengths and limitations inherent in each AI model's ability to predict concrete compressive strength.

Table 3. The results of the performance evaluation model of the prediction on testing data

Methods	**Testing Result**			
	R^2	**RMSE (MPa)**	**MAPE (%)**	**MAE (MPa)**
ANN	0.76	7.67	20.82	5.86
SVM	0.66	9.13	32.11	7.44
DT	0.77	7.49	15.76	4.67
RF	**0.89**	**5.19**	**12.68**	**3.57**
LR	0.57	10.28	32.20	8.23

Upon a careful examination of Table 3, it becomes evident that Random Forests (RF) outperforms all other existing methods across the board in terms of all four accuracy indicators. RF achieves an R-squared (R2) value of 0.89, surpassing the values obtained by other methods and coming notably close to the maximum value of 1. This high R2 value indicates a robust fit of the RF model to the data.

Additionally, RF demonstrates a lower error rate when compared to all other methods. Specifically, RF exhibits values of 5.19 MPa, 12.68%, and 3.57 MPa for Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), respectively. These metrics collectively signify the accuracy and precision of the RF model in predicting concrete compressive strength.

In contrast, the alternative methods produce RMSE, MAPE, and MAE values that substantially deviate from those achieved by RF, further highlighting the superiority of Random Forests in this particular predictive task. To provide a visual representation of the predicted results, Figures 6 and 7 illustrate the outcomes of Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and Linear Regression (LR). These visualizations offer additional insights into the performance of each method and underscore the notable success of Random Forests in this predictive modelling endeavour.

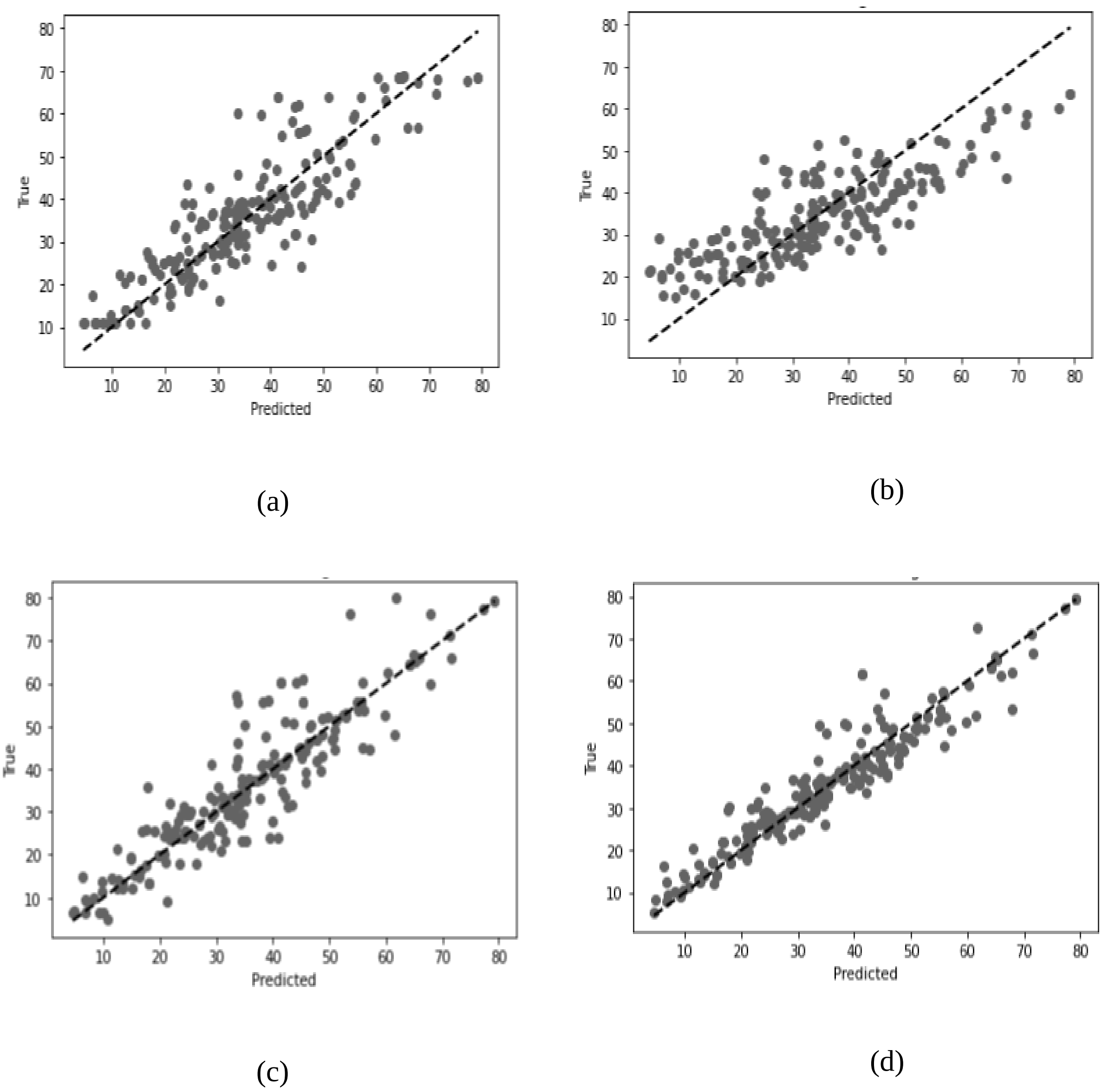

Figure 7. Comparison of prediction and actual results in testing data using (a) ANN method, (b) SVM method, (c) DT method, and (d) RF method.

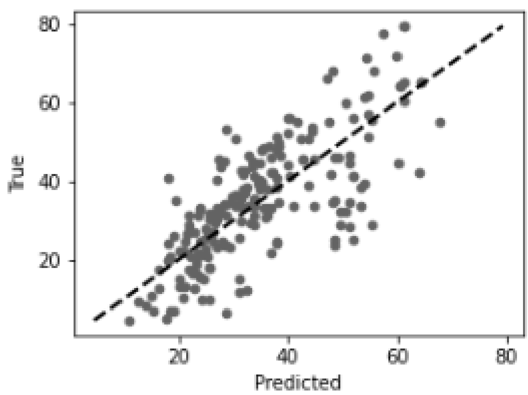

Figure 8. Comparison of prediction and actual results in testing data using LR method.

Upon inspecting the figures presented above, it becomes evident that the accuracy of prediction results is closely linked to their proximity to the diagonal line. Moving from Figure 7 to Figure 8, a discernible trend emerges: the prediction results generated by Random Forests (RF) exhibit a closer alignment with the diagonal line compared to the results obtained from other methods.

This trend leads to the conclusion that the accuracy of RF predictions surpasses that of the alternative methods. The proximity of each data point from RF to the diagonal line signifies a higher level of precision and fidelity in capturing the true patterns within the dataset. In essence, the visual progression from one figure to the next solidifies the assertion that Random Forests demonstrate superior accuracy in predicting concrete compressive strength when compared to other methodologies. The consistency in the alignment with the diagonal line serves as a compelling visual indicator of the robust predictive capabilities exhibited by the RF model.

5. CONCLUSION

This research undertakes a comprehensive comparative analysis, exploring the efficacy of various artificial intelligence (AI) models in predicting concrete compressive strength. Leveraging a dataset encompassing 1030 concrete samples, these samples serve as the foundational elements for constructing a robust database. This database, in turn, is utilized for creating a predictive model and rigorously testing its accuracy.

The performance evaluation of each method involves a nuanced examination using four key accuracy indicators: R-squared (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The experiments are meticulously executed using the Python programming language.

The noteworthy finding of this study reveals that Random Forests (RF) outshines other models in terms of accuracy across all performance measures. Random forest works better as it is an ensemble learning method with high accuracy and less risk of overfitting, as well as having more features than any other machine learning models. The RF model showcases optimal performance when evaluated through the four indicators, establishing its superiority in predicting concrete compressive strength. Importantly, the research successfully demonstrates the capability of AI methods to accurately predict concrete compressive strength without the necessity for extensive laboratory experiments. This highlights the potential of AI techniques to enhance efficiency and accuracy in the realm of concrete strength prediction.

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