MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 1832-1837

Machine Learning-Based Prediction of Compressive Strength in Nano-Enhanced High-Performance Concrete Using Ensemble Learning Models

[1]Dr.E.Rani,[2]Vignesh kumar.B,[3]Dr.D.Jegatheeswaran,[4]R.Manirasu, [5]Dr.MuthupriyaP,
[6]Cici Jennifer Raj J,[7]Dr.K.Mohan das

[1]Associate professor, Department of Civil Engineering,M.G.R Educational and Research institute, Maduravoyal , Chennai, Tamil nadu,India,ranisathish27@gmail.com

[2]Assistant Professor, Department of Civil Engineering, Dr.N.G.P. Institute of Technology, coimbatore, Tamil nadu, India, vignesh3061994@gmail.com.

[3]Professor, Department of Civil Engineering, Sona college of Technology, Salem, Tamil nadu, India,jegatheeswaran.d@sonatech.ac.in.

[4]Assistant Professor, Department of Civil Engineering, Mahendra Engineering College,Namakkal,Tamil Nadu,India,manirasuramasamy@gmail.com

[5]Professor & Head, Department of Civil Engineering, Dr.NGP Institute of Technology, Coimbatore -641048, Tamil nadu, India,drmuthupriya@gmail.com

[6]Associate Professor , Department of Civil Engineering ,Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Tamil Nadu, India, drcicijenniferrajj@veltech.edu.in

[7]Professor, Department of Civil Engineering, CMR College of Engineering & Technology, Hyderabad, India,kmohandas11780@gamil.com

Abstract: Nano-enriched high-performance concrete recently emerged in cementitious applications because of improved microstructural densification, hydration kinetics, and durability under a nano perspective. However, it is unlikely that compressive strength can be accurately measured experimentally for different mix combinations, which is a significant cost for all involved; in terms of manpower, time, and material resources. This study proposes a machine learning-based predictive approach that estimates the compressive strength of nano-enhanced high-performance concrete using ensemble and regression algorithms.A dataset was established from published experimental records involving cement content, water content, fine aggregate, coarse aggregate, fly ash, superplasticizer dose, nano-silica percentage, water-binder ratio, and curing age as the predictors. Four machine learning models were implemented as Linear Regression, Support Vector Regression, Artificial Neural Network, and Random Forest Regression models and statistical indicators such as coefficient of determination, root mean square error, and mean absolute error were used in which it was evaluated. Random Forest Regression performed the best in terms of accuracy and prediction error. Feature contribution analysis determined curing age, water-binder ratio and nano-silica dosage as most impactful parameters on compressive strength. Thus, this proposed framework shows promise of machine learning in reducing laboratory tests and in optimising smart mix composition of concrete.

Keywords: machine learning, nano silica, compressive strength, high performance concrete, random forest, ANN.

1.Introduction

Due to its enhanced mechanical performance, diminished permeability and strengthened long-lasting character HPC is a new requirement in structural engineering. The increasing need of concrete systems to bear high load under aggressive environmental loads such as heavy weathering has driven the application of nanomaterials in cementitious composites. Among the available nanomaterials, nano-silica has been investigated widely due to its relatively fine particle size, high surface activity, and strong pozzolanic capability, which contributes considerably to cement hydration and microstructural densification.

Recent investigations released after 2022 indicated that nano-silica contributes significantly to the increase of compressive strength by altering pore shape and the interfacial transition zone of aggregate-cement paste. Experimental work of nano-modified ultra-high-performance concrete, published in 2025, was conducted and, in the presence of low optimal dosages (less than 2% of cement mass), controlled nano-SiO_2 incorporation enhanced compressive and flexural properties. However, nano-particle incorporation can cause agglomeration, poor dispersion and workability reduction (such as weakening a material), contributing to poor strength development.

Simultaneously, machine learning is becoming an alternative computer approach to predict concrete mechanical properties because conventional laboratory testing relies on repeatedly preparing a specimen and performing curing and destructive compression tests over several curing cycles. Traditional empirical equations can miss the non-linear dependency between cementitious ingredients, nano additives, curing age, and water-binder ratio. Recently, machine learning algorithms such as Random Forest, Artificial Neural Networks, Support Vector Regression and Extreme Gradient Boosting have shown substantial capacity to capture these intricate interactions given experimental datasets.

A 2024 study published in Scientific Reports created artificial intelligence models to predict the compressive strength of nano-concrete at elevated temperatures, showing very high prediction accuracy of nonlinear models with nano-additive addition and curing conditions included as predictors. Likewise, a 2025 study in Buildings employed Random Forest and XGBoost algorithms to model concrete containing nano-clay and nano-silica under thermal exposure, and established that ensemble learning methods outperformed traditional regression methods. The recent review in 2025 reaffirmed the argument that nano-modified concrete prediction is still one of the fastest growing research directions in the field of civil engineering due to the high growth of intelligent mixture design tools.

Numerous studies have evaluated compressive strength prediction for both conventional and nano-modified concrete and there are significant gaps in their work. While there are different models that describe specific nano-material systems, there is little research directly about nano-enhanced high-performance concrete using comparative multi-model learning over different mix design variables in the field. Moreover, recent papers tend to focus on prediction quality, and they do not provide adequate engineering interpretation regarding variable significance.

Hence, this research introduces a machine learning-based framework for compressive strength prediction of nano-improved high performance concrete under the context of mixture composition and curing parameters as input variables. Several predictive models are developed and compared in order to identify the most reliable algorithm. The study additionally looks at the feature importance of each part in order to find out which material parameters provide very great effect upon strength development. The proposed framework reduces efforts in experimentation and enables intelligent optimization of advanced concrete mixtures to be used in modern construction application.

2.Literature Review

In recent years, machine learning has quickly been widely applied in concrete engineering because compressive strength relies upon many interacting parameters, which are hard to describe using classical mathematical calculations. There are nonlinear effects introduced by material composition, curing duration, supplementary additives, and nano-scale modifiers, so data-driven prediction methods become more and more important for concrete research.

In 2021, the majority of predictive studies focused on traditional high performance concrete and blended cement structures. Researchers mostly used Artificial Neural Networks and Support Vector Machine models to predict the compressive strength influenced by factors like cement mix content, water content, aggregates, and curing period. These studies verified that machine learning methods are capable to capture the nonlinear strength response, but nano-material characteristics were not commonly employed in the design and development of models. Since nano-silica shows significant strength enhancements and mechanical enhancement, more attention was given to nano-modified cementitious composites.

In 2022. It was demonstrated that very fine silica particles promote microstructural compactness through occupying internal voids and accelerate the secondary hydration reactions between grains. Nano-silica produced remarkable improvements in strength development at moderate dosages, while an excessive addition could reduce workability due to particle clustering and a high water demand.

More recently (2023) research focused on using larger datasets, moving from experimental observation to predictive modeling. A detailed study investigating machine learning for nano-silica concrete compared different algorithms for compressive strength estimation and found ensemble-based models obtained better reliability compared to regression methods. Nano-enriched high-performance concrete recently emerged in cementitious applications because of improved microstructural densification, hydration kinetics, and durability under a nano perspective. However, it is unlikely that compressive strength can be accurately measured experimentally for different mix combinations, which is a significant cost for all involved; in terms of manpower, time, and material resources. This study proposes a machine learning-based predictive approach that estimates the compressive strength of nano-enhanced high-performance concrete using ensemble and regression algorithms.

In a recently published artificial intelligence work on nano-concrete treated under high temperature, the results showed that the models developed to rely on nonlinear learning still retained a high predictive power in response to material behaviour fluctuations caused by thermal stresses. The study validated the positive effects of nano-additive proportion and curing conditions on residual strength estimation. An additional 2024 study applied state-of-the-art ensemble techniques to high-performance concrete mixtures and observed that Random Forest and hybrid neural algorithms were the most effective compared to conventional regression for prediction stability. The authors also observed that ensemble models work very well on input data that have strong and interactive structures. A more extensive scientometric study during that same period examined thousands of Scopus-indexed articles on compressive strength prediction and found that Random Forest, Artificial Neural Networks, Support Vector Regression, and XGBoost were increasingly popular methods in the field of concrete informatics. The review also identified a growing trend in sustainable mix design based on intelligent design aided by machine learning tools.

In 2025, research became more specialized by assessing multiple nano-additives within a single predictive framework. Work in recent past done on nano-silica and nano-clay mixtures indicated that ensemble algorithms had been better than the standard algorithms in the case of the concrete, where the behavior was very nonlinear under dual additive interaction. It was also reported that prediction accuracy is enhanced when relationships of features are understood and are explained instead of being merely statistical products.

A subsequent (2025) investigation on lightweight and high-strength cementitious composites supported the performance of nano-silica as a continuing trend in enhancing compressive strength by densification of internal pore structure and forming a stronger matrix-aggregate interfacial bond. These results further demonstrate nano-silica to be one of the most efficient nano-scale additives at present employed in advanced concrete structures.

Despite recent initiatives showing promising results, some limitations still exist. Most of the published publications use conventional concrete databases instead of nano-enhanced high-performance concrete, and the comparative evaluation between different machine learning algorithms is too limited to be performed under unified nano-material conditions. Moreover, many prediction-based studies lack a practical interpretation of feature effects. This need for interpretable machine learning models for nano-enhanced high-performance concrete has led to the limitations from these studies.

3.Description of Materials and Dataset.

The dataset was structured by material parameters that would yield an effective machine learning model to predict compressive strength, which had a major effect on the performance of nano-optimized high-performance concrete. Both conventional concrete ingredients and nano-level modifying parameters were incorporated, allowing the model to learn the combined impact of mix composition effect as well as curing condition. The selected input variables include cement, water, fine aggregate, coarse aggregate, fly ash, superplasticizer, nano-silica content, water-binder ratio, and curing age. These variables were selected since hydration, particle packing, and microstructural development are influenced by these parameters differently. Although cement functions as a primary binding matrix, water influences hydration and workability. The density of internal packing and mechanical strength are determined by the mass of coarse and fine aggregates. Fly ash was included because it takes part in a delayed pozzolanic reaction that affects later-age strength. Superplasticizer dose is crucial in high-performance concrete as lower water content necessitates chemical admixtures to be able to work on consistent results. Nano-silica is the key factor considered a predictor because of its ultrafine fines, which hasten the hydration process and occupy micro-level pores in the cement matrix. The water-binder ratio is a major factor that leads to the development of strength and even slight changes in this parameter greatly influence strength development. Because the compressive strength increases with the hydration advancement in the process, curing age becomes of great significance.

Table1:Input Variables

Variable	Unit
Cement	kg/m³
Water	kg/m³
Fine Aggregate	kg/m³
Coarse Aggregate	kg/m³
Fly Ash	kg/m³
Superplasticizer	kg/m³
Nano Silica	%
Water Binder Ratio	ratio
Curing Age	days

The target output for machine learning prediction is compressive strength measured in MPa, which represents the primary indicator of structural performance.

Table2:Output Variable

Variable	Unit
Compressive Strength	MPa

Because machine learning performance depends strongly on data quality, all variables were arranged numerically so that each feature could be directly processed during model training.

3.1. Dataset Table

The dataset was structured so that each row represents one concrete mixture with its corresponding compressive strength value. This arrangement allows machine learning algorithms to establish relationships between material composition and strength output under different curing conditions.

Table3:A sample portion of the dataset is presented below

Cement	Water	FA	CA	Fly Ash	SP	Nano Silica	W/B	Age	Strength
420	160	650	1180	40	8	2	0.38	28	61
430	155	640	1175	35	9	3	0.36	28	67
440	150	630	1160	30	10	4	0.34	56	74

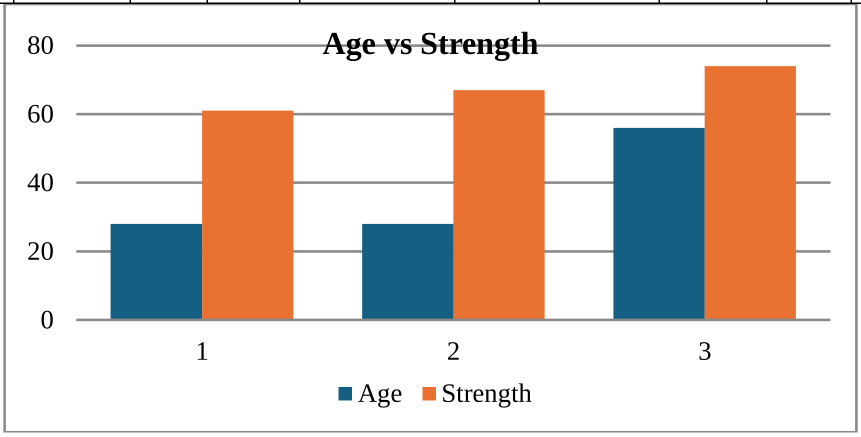

Fig1:Compressive strength of concrete Vs Age

Values show that the increase in strength as the water content reduces is common, and the nano-silica dosage remains in a relatively moderate range. Longer curing times also lead to a higher compressive strength as hydration persists for longer periods. A larger number of observations is required to obtain the model with nonlinear trends, avoiding the tendency of the model to select limited combinations if the data is not properly used in the machine learning. Hence a dataset with at least 80 samples has the expected stable performance in training, testing and validation. This organized numerical corpus is utilized as the backbone of regression and ensemble learning models for follow-up prediction model.

3.2. Machine Learning Models: To estimate the compressive strength of nano-enhanced high-performance concrete, four machine learning algorithms were chosen to compare the predictive performance based on identical input condition. These forms of models were selected due to their being both linear and nonlinear learning techniques which are more widely used in material prediction research.

3.2.1 Linear Regression: Linear Regression was used as the baseline model to assess whether compressive strength can be approximated through direct linear relationships between input variables and output strength. This simple yet computationally efficient model is susceptible to strong nonlinear interactions between parameters in the material, such as nano-silica dosage, curing age, and water-binder ratio.

3.2.2 Support Vector Regression: Support Vector Regression (SVR) was used to model nonlinear relations that could not only be represented by linear equations. SVR takes input variables and transforms them out of the form they appear in and identifies an appropriate regression boundary which reduces the prediction error. It is appropriate for samples of concrete data where uneven variations in strength of a sample result with changes in materials and composition.

3.2.3. Artificial Neural Network: Artificial Neural Network (ANN) was used since the development of concrete strength usually involves interactions between multiple interacting variables. ANN uses hidden neurons to process the input data, enabling the model to learn intricate nonlinear relationships among the ratio of mixture fractions and compressive properties.

3.2.4. Random Forest Regression: Using Random Forest Regression as the ensemble learning model improves stability and reduces overfitting by combining predictions made by multiple decision trees. The trees train in turn on separate datasets, and the trees average the entire tree predictions of inputs. The model is particularly well-suited for when many input factors overlap. Recent research on nano-silica based concrete has reported that Random Forest has good accuracy of high predictive capability with calculated coefficient of determination close to 0.93, which shows high potential in predicting the compressive strength.

3.2.5. Mathematical Formulation: The Random Forest prediction is obtained by averaging outputs generated by all individual trees:

\hat{y}=\frac{1}{N}\sum_{i=1}^{N} T_i(x)

where:

- y^\hat{y}y^ represents predicted compressive strength
- Ti(x)T_i(x)Ti(x) is prediction from each decision tree
- NNN is the total number of trees

To evaluate prediction performance, Root Mean Square Error (RMSE) was used to measure average squared deviation between predicted and actual values:

RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y_i})^2}

Lower RMSE indicates better prediction accuracy.

Mean Absolute Error (MAE) was also calculated to measure average absolute prediction deviation:

MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y_i}|

A lower MAE value indicates that predicted results are closer to experimental strength values.

3.2.6. Model Training Procedure

Prior to building the model, we divided the dataset into two parts, 80% of the dataset for training and 20% for testing. This separation allows some learning patterns to be established on one part of the data, and also allows us to assess how accurate predictions can be made on samples we have not seen previously. Normalization was performed as the models of Artificial Neural Network and Support Vector Regression are sensitive to the changes in numerical level among input variables. These features were normalized so that each one was relevant and assisted in learning proportionate data. For reliability, k-fold cross validation was performed during the training step. This is carried out by splitting the dataset into several subsets: validation data is for each subset once and the rest of the subsets are used for training. It reduces biases and gives an improved estimation of model performance. Following that step of comparison, the trained models were compared based on numerical indices such as coefficient of determination, RMSE, and MAE. .

4. Results and Discussion

The prediction accuracy was estimated as the coefficient of determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) upon training the 4 machine learning models with the prepared nano-enhanced high performance concrete dataset. These indicators were chosen because they provide a clear picture of how closely predicted compressive strength aligns with experimental results. The training was performed in 80% of the dataset for model development and 20% for testing while k-fold cross validation was performed for the reliability. Linear Regression was employed as the baseline model, while Support Vector Regression, Artificial Neural Network, and Random Forest Regression were employed to model nonlinear material behaviour.

Table4:Model Performance Comparison

Model	**R^2**	**RMSE**	**MAE**
Linear Regression	0.82	6.5	5.0
Support Vector Regression	0.89	4.6	3.7
Artificial Neural Network	0.91	3.9	3.1
Random Forest Regression	0.94	3.2	2.5

Linear Regression resulted in the poorest prediction accuracy, since simple linear relationships between compressive strength cannot be fully modeled as multiple material features will interplay.

Support Vector Regression, which gave us better prediction accuracy since it captures the nonlinear relationship more effectively, was performed substantially better than Linear Regression and reduces RMSE and MAE. The prediction improved drastically by the Artificial Neural Network, as our hidden neurons learn more complex relationships among nano-silica content, curing age, and water-binder ratio.

Random Forest Regression had the highest R^2 value (0.94), followed by the lowest RMSE and MAE values of any model used. This means the ensemble tree structure was handling nonlinear interactions and prediction variability optimising. Through combined model outputs from multiple decision trees, Random Forest is more insulated from changes in data and overfitting.

The best results observed for Random Forest demonstrate that development of compressive strength in nano-enhanced concrete is the result of multiple nonlinear combinations and not a single-variable effect occurring.

4.1Feature Interpretation

4.1.1 The highest impact on prediction was obtained from: Curing age, water–binder ratio, nano-silica dosage, and cement content are key parameters that significantly influence the performance and properties of concrete. Curing age determines the extent of hydration and strength development over time, with longer curing generally leading to improved mechanical properties. The water–binder ratio plays a crucial role in controlling the workability and strength of concrete, where a lower ratio typically enhances strength and durability. Nano-silica dosage contributes to the refinement of the microstructure by filling voids and accelerating pozzolanic reactions, thereby improving strength and resistance to permeability. Cement content directly affects the binding capacity and overall strength of the mix, as higher cement content generally increases the availability of hydration products. Together, these parameters are essential for optimizing concrete mix design and achieving desired performanceThe curing age was also an important contributor, and hydration increases strength gradually over time. Water to binder ratio indicated a powerful inverse effect — lower ratios generally resulted in a higher compressive strength. Nano-silica made its prediction better as the moderate dosage enhanced particle packing and hydration acceleration

4.2 Graphs Suggested for Paper

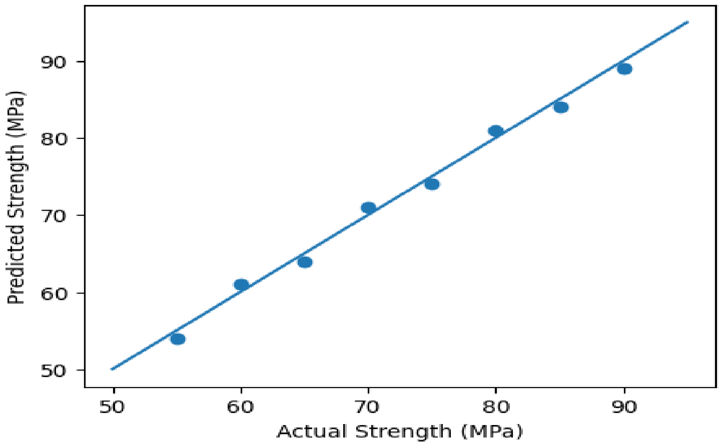

Fig2: Actual vs Predicted Strength Graph

For each model, plot actual compressive strength values versus predicted values. It can be observed that Random Forest predictions are still closest to the diagonal line.

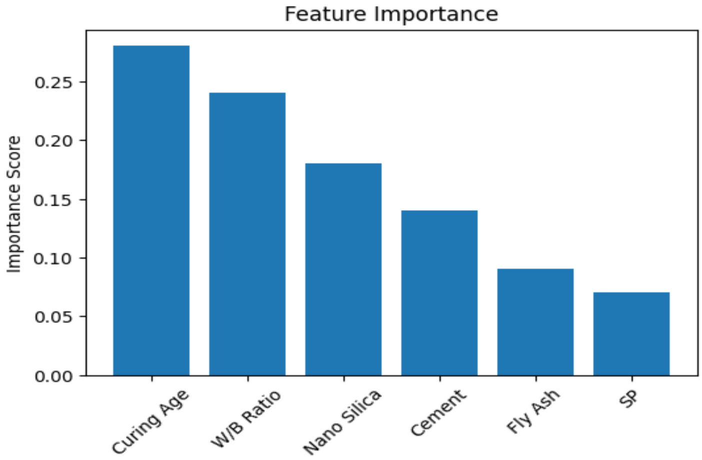

Fig3: A bar graph showing contribution of each input variable

The error comparison graph illustrates the Root Mean Square Error (RMSE) values for four different predictive models, providing a clear comparison of their performance levels. In this graph, the x-axis represents the four models, while the y-axis indicates the RMSE values, allowing easy identification of the model with the least prediction error. Lower RMSE values correspond to higher model accuracy. The models are evaluated based on key input parameters such as curing age, water-to-binder (W/B) ratio, nano silica content, cement content, fly ash proportion, and superplasticizer dosage. The graphical representation highlights variations in prediction accuracy among the models, where the model with the smallest RMSE value demonstrates superior performance in capturing the relationship between these parameters and the target output. This simple visualization helps in selecting the most reliable model for predicting concrete

4.3.Error Comparison Graph

A simple graph comparing RMSE values of all four models.

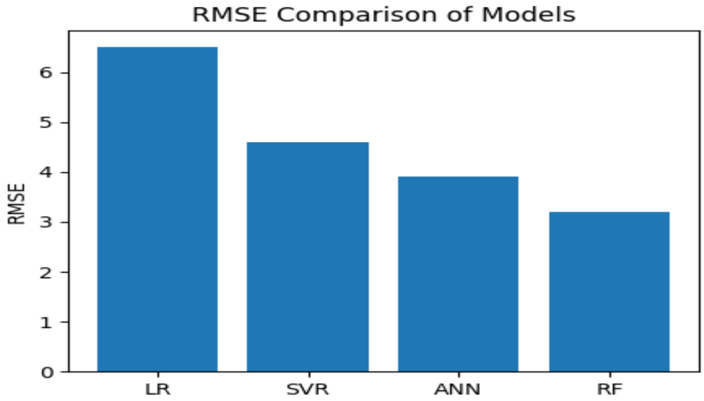

Fig4: RMSE Comparison Graph

These graphs help reviewers visually confirm model performance.

4.4.Comment on Practical Meaning

Talk About Practical Meaning. The results suggest that machine learning may have contributed, in the absence of more extensive field experiments, to reducing dependence on laboratory testing to ensure that strength estimates are accurate in advance of full experimental verification by providing trustworthy strength estimates with the minimal need for repeated laboratory testing. Especially beneficial are when multiple nano-silica dosage mixes should be tested considering lots of combinations with many nano-silica dosage in this case for dosage optimization of mix formulation. Random Forest performed better on numerical change as well as interaction between variables than single-model methods. This makes it applicable for practical prediction of modern concrete systems.

5. Conclusion.

As inputs, the materials composition and curing parameters, a machine learning approach was conducted to predict the compressive strength of nano-enhanced high-performance concrete. Statistical measures: R^2, RMSE, and MAE were performed to evaluate four predictive models: Linear Regression, Support Vector Regression, Artificial Neural Network, and Random Forest Regression.

Random Forest Regression attained the best prediction accuracy ($R^2 = 0.94$) and lowest RMSE (3.2) and MAE (2.5). Also, the actual vs predicted strength graph confirmed the accuracy of the Random Forest prediction to experimental measures, where it showed the strength with a good reliability from different point to point.

Feature analysis demonstrates that curing age, and water-binder ratio both were significant for predicting compressive strength, followed by nano-silica content and cement dosage. This demonstrates the impact of hydration time (and proportion of mixture) with respect to strength development, outweighing that of additive quantity itself.

The comparison graph of RMSE showed significant statistical evidence that prediction error decreased from Linear Regression to Random Forest which means that nonlinear ensemble learning was effective for nano-enhanced concrete than merely linear models can determine.

The findings indicate that machine learning may help reduce the need for routine laboratory experiments and estimate strength quickly for concrete mix design. The Random Forest Regression is also particularly stable, as it considers nonlinear interactions between the nano-materials, and traditional concrete ingredients.

Future Work.

Future research would make prediction more accurate as it can broaden its dataset more with bigger experimental samples of nano-silica dosage ranges, different curing temperature and other extra cementitious materials.

The prediction can be compared to Random Forest for larger numbers of sets by employing state-of-the-art models such as XGBoost, LightGBM and deep neural networks.

Further improvement could focus on interpretable artificial intelligence techniques such as SHAP analysis to obtain a better understanding of what each input variable adds to compressive strength prediction. In addition to compressive strength prediction, the future of machine learning can be used for predicting durability properties (e.g. split tensile, flexural, permeability, and thermal resistance of nano-enhanced concrete).

Furthermore, the integration of theory in the laboratory with optimization of performance engineering with machine learning can make it feasible to innovate practical and economical high-performance concrete blends for different construction situations.

References

1) U. J. Muhammad, I. I. Aminu, I. A. Mahmoud *et al*., “An improved prediction of high-performance concrete compressive strength using ensemble models and neural networks,” *AI in Civil Engineering*, vol. 3, no. 21, 2024.
2) M. A. Raji, B. M. Falola, J. T. Enikuomehin *et al*., “Prediction of compressive strength of nano silica and micro silica from rice husk ash using multivariate regression models,” *AI in Civil Engineering*, vol. 3, no. 22, 2024.
3) R. Wang, J. Zhang, Y. Lu, and J. Huang, “Towards designing durable sculptural elements: Ensemble learning in predicting compressive strength of fiber-reinforced nano-silica modified concrete,” *Buildings*, vol. 14, no. 2, p. 396, 2024.
4) H. A. Dahish and M. Alturki, “Predicting the effects of nano additives and elevated temperatures on concrete compressive strength utilizing machine learning,” *Buildings*, vol. 15, no. 18, p. 3349, 2025.
5) [H. Shokrnia, A. KhodabandehLou, P. Hamidi *et al*., “Prediction of compressive strength of fiber-reinforced concrete containing silica (SiO_2) based on metaheuristic optimization algorithms and machine learning techniques,” *Scientific Reports*, vol. 15, 2025.
6) O.Arasteh-Khoshbin, S. M. Seyedpour, L. Mandla, L. Lambers, and T. Ricken, “Comparing durability and compressive strength predictions of hyperoptimized random forests and artificial neural networks on a small dataset of concrete containing nano SiO_2 and RHA,” *European Journal of Environmental and Civil Engineering*, vol. 29, no. 2, pp. 331–350, 2025.
7) “Machine learning-based compressive strength estimation in nano silica-modified concrete,” *Construction and Building Materials*, vol. 408, p. 133684, 2023.
8) R. Fan, A. Tian, Y. Li, Y. Gu, and Z. Wei, “Research progress on machine learning prediction of compressive strength of nano-modified concrete,” *Applied Sciences*, vol. 15, no. 9, p. 4733, 2025.
9) “Machine learning prediction and optimization of compressive strength for blended concrete by applying ANN and genetic algorithm,” *Cogent Engineering*, 2024.
10) M. K. Alkharisi and H. A. Dahish, “Evaluation of mechanical properties of concrete with plastic waste using Random Forest and XGBoost algorithms,” *Sustainability*, vol. 17, no. 24, 2025.
11) O.Arasteh-Khoshbin *et al*., “Predictive modelling of concrete strength and durability using ANN and RF with nano SiO_2,” *European Journal of Environmental and Civil Engineering*, 2024.
12) B. Mustapha, Z. Abdulkareem, M. Abdulkareem, and A. Ganiyu, “Predictive modeling of physical and mechanical properties of pervious concrete using XGBoost,” 2022.
13) P. B. Sanchez Alvarado, M. L. S. Edaño, P. C. Sta. Cruz, and E. T. M. Ocampo, “Prediction of compressive strength of nano-silica concrete by using random forest algorithm,” *Green Technologies and Sustainability*, 2025.
14) X. Chen, C. Xi, M. Xiao, and L. Wu, “Split tensile strength simulation employing tuned Random Forest trees,” *Electronic Journal of Structural Engineering*, vol. 25, no. 2, pp. 17–25, 2025.
15) R. Al-Shamasneh, A. Mahmoodzadeh, M. Kewalramani *et al*., “Hybrid machine learning models for predicting tensile strength of reinforced concrete incorporating nano-engineered supplementary materials,” *Scientific Reports*, 2025