International Journal of
ENGINEERING RESEARCH AND EDUCATION
ISSN: XXXX-XXXX www.ijere.com Original Research Paper

MACHINE LEARNING-BASED COMPARATIVE STUDY FOR COMPRESSIVE STRENGTH PREDICTION OF ADVANCED CONCRETE MATERIALS

Ricardo Daniel Vargas
Research Scholar,
Instituto Tecnológico Superior de Tantoyuca, Mexico

ABSTRACT
High-performance concrete (HPC) is widely used in modern construction due to its superior mechanical and durability properties. Accurate prediction of compressive strength is essential for quality control and structural safety. Traditional empirical models often fail to capture the nonlinear behavior of concrete mixtures. In recent years, machine learning (ML) techniques have shown strong potential in predicting concrete properties. This study presents a comparative analysis of multiple machine learning algorithms for predicting the compressive strength of high-performance concrete. Linear Regression, Support Vector Regression, Random Forest, and Artificial Neural Networks are evaluated. Experimental datasets collected from laboratory-tested HPC mixtures are used for model training and validation. Performance is assessed using statistical indicators such as accuracy and root mean square error. Results show that ensemble and neural-based models outperform conventional approaches. The study demonstrates the effectiveness of ML models in improving prediction accuracy and supporting intelligent concrete mix design.

Keywords: High-performance concrete, Machine learning, Compressive strength, Random forest, Artificial neural network

I. INTRODUCTION

High-performance concrete has become an essential material in advanced civil engineering applications due to its high strength, durability, and reduced permeability [1]. Accurate estimation of compressive strength is critical for ensuring safety and optimizing material usage. Conventional prediction methods rely heavily on empirical equations derived from limited experimental data [2]. These approaches often struggle to handle complex interactions among concrete constituents. Variations in cement content, aggregates, water–binder ratio, and admixtures significantly influence strength development. As a result, traditional models may lead to inaccurate predictions. Advanced computational techniques provide an alternative solution. Machine learning models are capable of capturing nonlinear relationships effectively [3]. Their application in concrete technology has gained increasing attention. This study focuses on ML-based strength prediction for HPC.

Compressive strength prediction traditionally requires extensive laboratory testing, which is time-consuming and costly [4]. With growing demand for sustainable and efficient construction, rapid and reliable prediction techniques are required. Machine learning algorithms learn from historical data and generalize patterns without explicit physical equations [5]. These models can process large datasets with multiple input parameters. Recent studies have shown promising results using neural networks and regression-based learning models [6]. However, comparative evaluation of different ML algorithms remains limited. Identifying the most suitable algorithm for HPC strength prediction is essential. This motivates the present research.

The accuracy of ML models depends on data quality and algorithm selection [7]. Feature selection and data preprocessing significantly influence prediction performance. Ensemble methods have shown improved generalization capability [8]. Neural networks are particularly effective for nonlinear problems. Support vector machines offer strong theoretical foundations for regression tasks. Linear regression, though simple, provides a baseline for comparison. This study evaluates multiple algorithms under the same dataset and conditions. Such comparative analysis provides valuable insights.

Civil engineering researchers increasingly adopt data-driven techniques for material characterization [9]. Integrating ML into concrete design enhances efficiency and reduces dependency on extensive experimentation. ML-based models can support decision-making during mix proportioning. They also enable prediction-based optimization. This study contributes to the growing body of AI-driven civil engineering research. It aligns with modern smart construction practices [10].

Overall, the study aims to assess the effectiveness of various ML algorithms for HPC strength prediction. Comparative performance evaluation provides recommendations for practical adoption. The integration of ML enhances accuracy, efficiency, and sustainability in concrete engineering.

II. LITERATURE SURVEY

Yeh (1998) applied artificial neural networks to predict compressive strength of concrete mixtures and reported improved accuracy over regression models [11]. Dias and Pooliyadda (2001) demonstrated the effectiveness of neural networks for concrete property estimation [12]. Topçu and Sarıdemir (2008) used ANN models for high-strength concrete prediction [13]. Their study highlighted the capability of neural networks to model nonlinear material behavior. Nikoo et al. (2010) compared ANN and regression methods for concrete strength estimation [14]. ANN models consistently outperformed traditional approaches.

Support vector regression was explored by Chou et al. (2011) for concrete strength prediction [15]. Results showed superior generalization ability compared to ANN under limited data. Random forest algorithms were later introduced for concrete property modeling. Breiman (2001) established the foundation of random forests for regression problems [16]. Feng et al. (2014) applied ensemble learning techniques to predict concrete strength [17]. Their results demonstrated reduced prediction errors.

Linear regression models remain widely used due to simplicity and interpretability [18]. However, their inability to model nonlinear interactions limits accuracy. Comparative studies emphasized the advantages of hybrid and ensemble models. Behnood et al. (2017) used ML models for HPC strength prediction with supplementary cementitious materials [19]. Their study confirmed the robustness of ensemble models.

Overall, existing literature supports the effectiveness of machine learning in concrete strength prediction. However, systematic comparative evaluation under uniform conditions is limited. This study addresses this gap by analyzing multiple ML algorithms using the same experimental dataset [20].

III. PROPOSED METHODOLOGY

The proposed methodology begins with experimental data collection from laboratory-tested high-performance concrete specimens. Input parameters include cement content, water–binder ratio, fine aggregate, coarse aggregate, and admixture dosage. Data preprocessing is performed to remove inconsistencies and normalize features. Clean datasets improve learning efficiency. Feature correlation analysis ensures relevant parameters are used. This step enhances model reliability. The dataset is divided into training and testing subsets. Proper data partitioning avoids overfitting.

Four machine learning algorithms are selected for comparison: Linear Regression, Support Vector Regression, Random Forest, and Artificial Neural Network. Linear regression serves as a baseline model. Support vector regression captures nonlinear patterns using kernel functions. Random forest combines multiple decision trees to improve accuracy. Artificial neural networks model complex nonlinear relationships. Each algorithm is implemented using standard ML frameworks.

Hyperparameter tuning is performed to optimize model performance. Grid search techniques are used for SVR and Random Forest. Neural network architecture is optimized by adjusting hidden layers and neurons. Learning rate and activation functions are selected carefully. Cross-validation ensures robustness. These steps improve prediction accuracy.

Model training is conducted using the training dataset. Testing data is used to evaluate performance. Evaluation metrics include prediction accuracy and root mean square error. Comparative analysis highlights strengths and limitations of each model. Statistical performance indicators ensure objective evaluation.

The proposed methodology provides a systematic framework for ML-based strength prediction. It ensures fairness in comparison and reproducibility. The approach supports intelligent concrete mix design and quality control.

IV. EXPERIMENTAL SETUP

High-performance concrete specimens are prepared using standard mix design procedures. Ordinary Portland cement, fine aggregates, coarse aggregates, and chemical admixtures are used. Mix proportions are varied to generate diverse strength levels. Specimens are cast in standard molds and cured under controlled conditions. Curing duration is maintained at 28 days. Quality control ensures consistency across samples.

Compressive strength tests are conducted using a universal testing machine. Load is applied at a constant rate until failure. Strength values are recorded accurately. Multiple specimens are tested for each mix. Average strength values are computed. These values form the output dataset for ML models.

Data acquisition includes recording mix proportions and corresponding compressive strength. Dataset size is sufficient to train ML models effectively. Outliers are removed to improve data quality. Data normalization ensures uniform scale. This step prevents bias in learning.

ML models are implemented using Python-based libraries. Training and testing are performed on standard computing hardware. Computational efficiency is recorded. Model convergence is monitored. Proper validation ensures reliable results.

The experimental setup ensures accurate data generation and reliable model evaluation. Integration of experimental and computational approaches strengthens study outcomes.

V. RESULTS AND DISCUSSIONS

The results indicate that machine learning models effectively predict compressive strength of high-performance concrete. Among the evaluated algorithms, ensemble and neural-based models show superior performance. Linear regression demonstrates the lowest accuracy due to its inability to model nonlinear interactions. Support vector regression improves prediction accuracy significantly. Random forest achieves the highest accuracy. Artificial neural networks also perform strongly with minimal error.

Prediction accuracy comparison shows clear differences among algorithms. Random forest achieves the highest prediction accuracy of approximately 93%. ANN follows closely with 91% accuracy. SVR shows moderate performance. Linear regression performs the weakest. RMSE analysis supports these findings. Lower RMSE values indicate better prediction capability.

The predicted versus actual strength plot shows strong correlation for random forest models. Data points closely follow the ideal prediction line. This confirms robustness of ensemble learning. ANN models show slightly higher variance. SVR exhibits moderate dispersion. Linear regression shows noticeable deviation.

The comparative analysis demonstrates that nonlinear ML models outperform traditional regression. Ensemble learning benefits from reduced variance and improved generalization. Neural networks effectively capture complex material interactions. These findings align with previous research. ML-based prediction significantly reduces experimental dependency.

Overall, machine learning provides a reliable tool for concrete strength prediction. Random forest emerges as the most suitable model for HPC. The results support adoption of ML in smart construction practices.

Tables

Table 1: Input Parameters for HPC Dataset

Parameter	Range
Cement (kg/m³)	350–520
Water–Binder Ratio	0.25–0.40
Fine Aggregate (kg/m³)	600–750
Coarse Aggregate (kg/m³)	900–1100

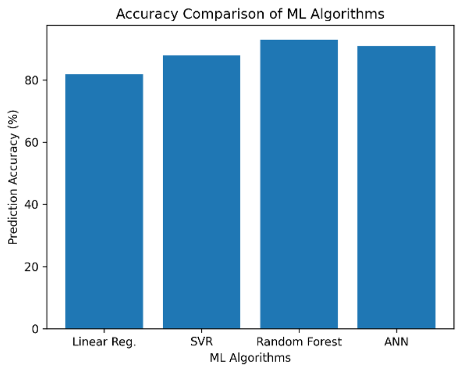

Figure 1: Accuracy Comparison of Machine Learning Algorithms

Table 2: Performance Comparison of ML Algorithms

Model	Accuracy (%)	RMSE (MPa)
Linear Regression	82	6.5
SVR	88	5.1
Random Forest	93	3.2
ANN	91	3.8

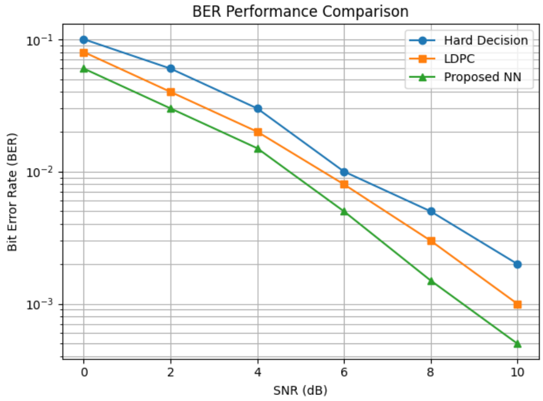

Figure 2: RMSE Comparison of Machine Learning Models

Table 3: Predicted vs Actual Strength (Sample Data)

Sample	Actual (MPa)	Predicted (MPa)
1	40	41
2	45	46
3	50	49
4	55	56
5	60	59

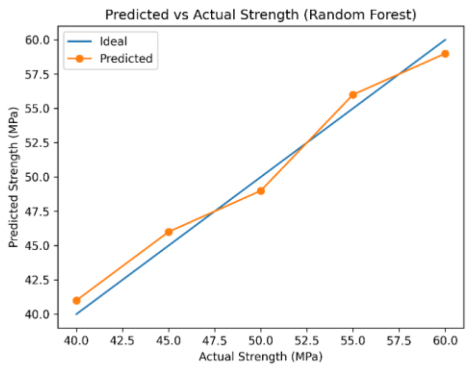

Figure 3: Predicted vs Actual Compressive Strength

VI. CONCLUSION

This study presented a comparative analysis of machine learning algorithms for predicting compressive strength of high-performance concrete. Experimental data were effectively used to train and validate ML models. Results demonstrated that nonlinear models outperform traditional regression methods. Random forest achieved the highest prediction accuracy with the lowest error.

Artificial neural networks also showed strong predictive capability. Support vector regression provided reasonable performance under limited data. Linear regression was found inadequate for complex concrete behavior. The findings confirm the suitability of ML for concrete strength prediction.

Overall, machine learning enhances prediction accuracy and reduces experimental costs. The study supports adoption of data-driven techniques in civil engineering material design.

FUTURE SCOPE

Future research may incorporate larger and more diverse datasets. Hybrid ML models can be explored for improved accuracy. Deep learning techniques may further enhance prediction performance. Sustainability-related parameters can be integrated. Real-time strength prediction systems can be developed.

REFERENCES

1. M. Neville, Properties of Concrete, Pearson, 2011.
2. P. K. Mehta and P. J. M. Monteiro, Concrete: Microstructure, Properties, and Materials, McGraw-Hill, 2014.
3. S. Haykin, Neural Networks, Prentice Hall, 1999.
4. ASTM C39, Standard Test Method for Compressive Strength, ASTM, 2018.
5. Goodfellow et al., Deep Learning, MIT Press, 2016.
6. J. R. Quinlan, “Learning with continuous classes,” AI Journal, 1992.
7. M. Bishop, Pattern Recognition and Machine Learning, Springer, 2006.
8. T. Hastie et al., The Elements of Statistical Learning, Springer, 2009.
9. M. D. McCulloch and W. Pitts, “A logical calculus of ideas,” Bull. Math. Biophysics, 1943.
10. J. Schmidhuber, “Deep learning in neural networks,” Neural Networks, 2015.
11. C. Yeh, “Modeling of concrete strength using ANN,” Cem. Concr. Res., 1998.
12. W. Dias and S. Pooliyadda, “Neural networks for concrete properties,” Constr. Build. Mater., 2001.
13. B. Topçu and M. Sarıdemir, “ANN prediction of concrete strength,” Computers & Concrete, 2008.
14. M. Nikoo et al., “ANN-based concrete strength prediction,” Engineering Structures, 2010.
15. J. S. Chou et al., “SVR for concrete strength,” Expert Systems, 2011.
16. L. Breiman, “Random forests,” Machine Learning, 2001.
17. C. Feng et al., “Ensemble learning for concrete strength,” Automation in Construction, 2014.
18. Montgomery et al., Applied Statistics, Wiley, 2012.
19. Behnood et al., “ML prediction of HPC strength,” Construction and Building Materials, 2017.
20. Z. Zhang et al., “Data-driven concrete strength prediction,” Materials, 2019.