Machine Learning Models for Concrete Strength Predictions Based on Rebound Hammer Measurements

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ABSTRACT

This paper presents an improved machine learning approach to predict the compressive strength of concrete from nondestructive Rebound Hammer (RH) measurements and water-to-cement (W/C) ratio. Several regression models, including Linear Regression (LR), Decision Tree (DT), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting (GB) were initially applied and experimented on a comprehensive experimental dataset. GB achieved good baseline accuracy with R^2 = 0.86 and MAE = 6.34 MPa. To improve performance, hyperparameter tuning using grid search was adopted, and the optimized GB model improved accuracy with R^2 = 0.8704 and MAE = 5.90 MPa. Other models such as XGBoost, deep neural networks, and an ensemble averaging model were then explored. Among these, XGBoost had the best overall performance of R^2 = 0.8735 and MAE = 5.85 MPa, with the tuned GB coming close. A second-order polynomial regression model was further derived from the XGBoost predictions to provide a reference equation. This polynomial equation presents a simple and comprehensible method for field engineers to estimate compressive strength from RH and W/C values alone, without the need for computers. To support practical deployment, a user-friendly application was developed using Streamlit, which enabled users to estimate concrete strength in a real-time interface. This app uses the XGBoost model and allows for fast, portable, and accurate predictions in the field. Overall, this work demonstrates the value of combining domain knowledge with modern data-driven techniques to improve the accuracy, interpretability, and usability of nondestructive testing in concrete evaluation. The proposed models and tools offer practical benefits for real-time, reliable estimation that bridge the gap between conventional field tests and intelligent predictive analytics.

Keywords-machine learning; concrete; rebound hammer; compressive strength; nondestructive testing; regression models; artificial intelligence

I. INTRODUCTION

Concrete is the most widely used building material in the world due to its strength, reliability, and cost-effectiveness [1]. Measuring its compressive strength is vital for structural integrity and long-term performance assessment. Traditionally, this is carried out using destructive tests comprising casting, curing, and crushing laboratory specimens. While these tests are accurate, they are time-consuming, labor-intensive, and impractical for in-place investigation of structures that are already built. As a practical substitute in the field, Non-Destructive Testing (NDT) methods, specifically the Rebound Hammer (RH) test, have been popular for field estimation of concrete strength [2]. The RH tests concrete surface hardness, which is related to its compressive strength. The equipment is relatively expensive but easily available, simple to operate, and needs minimal training, hence being suitable for field use [3].

Although practical, traditional RH devices rely on empirical charts for the strength estimation from rebound numbers. Standard calibration curves can be formulated in laboratory environments, but do not take into account the differences in concrete mixes, curing procedures, and exposure conditions encountered in the field. As such, they are only partly correct, particularly for hardened or non-representative mixes of concrete [4]. Some of the most significant variables, such as water-to-cement (W/C) ratio, aggregate type, aggregate condition, and surface condition, are usually neglected but exert considerable influence on the rebound number as well as the actual compressive strength [6-8]. In order to overcome these deficiencies, this paper proposes a data-driven approach using a Machine Learning (ML) approach, which can efficiently capture complex nonlinear relationships between input variables and target properties. By incorporating easily quantifiable factors like the rebound number and the W/C ratio, ML models are able to provide accurate strength predictions tailored to specific concrete conditions. Recent studies [3-12] have demonstrated the growing use of ML techniques in concrete technology. Methods such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Decision Trees (DT), and Support Vector Machines (SVM) have been successfully applied to predict the compressive strength based on the input features of various non-destructive tests, mix proportions, and curing conditions [4-11]. Ensemble techniques like Random Forest (RF) and Gradient Boosting (GB) have been found highly accurate as they can combine multiple learners and capture intricate patterns of data [5]. These techniques yield greater predictive power than the traditional statistical models and are being used in increasing measures to enhance nondestructive testing methods in civil engineering [10, 11].

This research develops, tunes, and compares ML algorithms, including Linear Regression (LD), DT, Support Vector Regression (SVR), Random Forest (RF), GB, and XGBoost, and a Feedforward Neural Network (FNN), on a experimental dataset. The goal is to identify the most accurate, reliable, and applicable model for optimizing the non-destructive estimation of concrete strength and to apply this model in an easy-to-use application for real-life use.

II. RESEARCH SIGNIFICANCE

The use of ML in NDT of concrete is a breakthrough in civil engineering. The RH method is widely used due to its simplicity, portability, and minimal training requirements. However, the traditional reliance on empirical charts limits its predictive precision. This study adds to the usability of RH testing by combining it with sophisticated ML models to provide more precise data-driven compressive strength predictions. The incorporation of W/C ratio as an additional input greatly improves prediction precision to tackle the mix variability, often unaddressed by standard RH charts. Furthermore, the derivation of the polynomial regression equation from the top-performing ML model enhances field usability by allowing practitioners to estimate on-site strength without executing ML codes. This bridges the gap between theoretical modeling and reality in construction practices. The process allows for real-time, low-cost, and accurate strength assessment deployable in quality control, structural evaluation, and rehabilitation design under diverse conditions and geographies.

III. EXPERIMENTAL DATA

This study employed a large experimental database compiled from published reports and in-house experiments [12]. The initial dataset consisted of 10,428 tests from 87 studies covering a wide range of concrete mix designs, compressive strength values, curing conditions, and field test measurements. An initial survey regarding completeness and consistency revealed that many studies lacked recorded W/C values. Since the W/C ratio is a vital parameter, records for analysis were collected from data only where this variable was available, which restricted the data to approximately 2500 records. The primary objective of this work is to evaluate the capability of non-destructive RH testing combined with easily obtained mix design characteristics in the prediction of compressive strength. The input features used for this study are:

- Median Rebound Number (RN): Obtained by the RH, reflects the surface hardness of the concrete.
- Water/Cement Ratio (W/C): A basic mix design parameter, which significantly affects strength development.

The target variable was fc,cyl (MPa), i.e., the 28-day compressive strength of plain concrete cylinders.

IV. MACHINE LEARNING METHODOLOGIES

The ML workflow is summarized in Figure 1, which shows the full pipeline for concrete strength prediction from data acquisition to deployment, whereas Figure 2 shows the ML models used in this study.

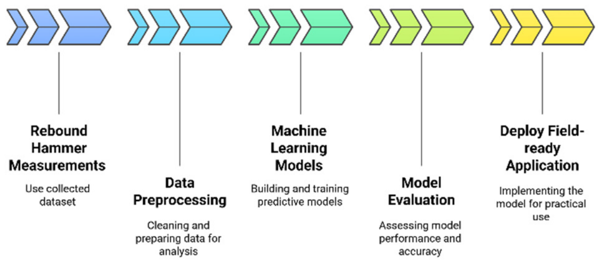

Fig. 1. Flowchart of the pipeline for concrete strength prediction.

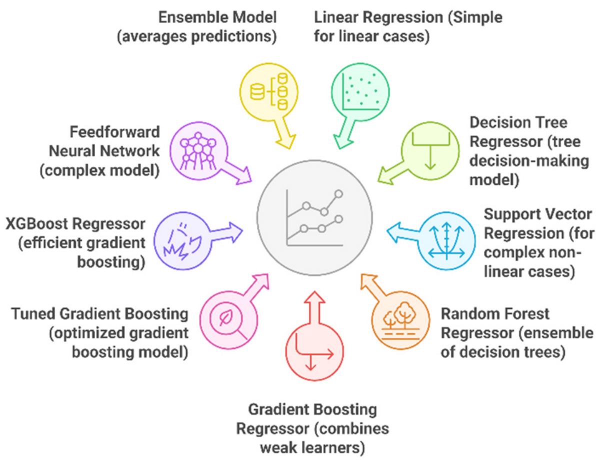

Fig. 2. ML models used in this study.

The pipeline includes the following steps:

1. Data Preprocessing: Missing values were removed, and numerical features were scaled using StandardScaler.
2. Train-Test Split: The dataset was randomly divided into 70% train and 30% test subsets.
3. Model Training: Nine ML models were trained: LR, DT, SVR, RF, GB, Tuned GB (using GridSearchCV), XGBoost (using regularization), a Feedforward Neural Network, and an Ensemble Model (averaging predictions from GB, RF, and XGBoost).
4. Model Evaluation: All the models were assessed with the Coefficient of Determination (R^2) and the Mean Absolute Error (MAE).
5. Polynomial Development: A second-order polynomial was modeled using the best ML model to give a simple equation for field engineers.
6. Deployment of the application: An application is to be constructed to provide the best model's predictions in real-time so that it can be deployed for field evaluation.

V. RESULTS

A. *Performance Comparison of Baseline Models*

To highlight the contribution of the W/C ratio to the precision of the overall model, baseline ML models were trained using only the RN as the only input variable, and then the models were remodeled using both RN and W/C. Table I summarizes the results of this comparison along with the configuration of each model. It can be clearly seen that the performance was definitely improved by including the additional mix design information.

TABLE I. W/C CONTRIBUTION TO THE BASELINE ML MODEL ACCURACY

Model	**R^2 (RN only)**	**R^2 (RN + W/C)**	**Configuration details**
LR	0.5263	0.6907	Ordinary least squares, no regularization
DT	0.6532	0.7826	Max depth = 5, min sample split = 4
SVR	0.6438	0.7783	RBF kernel, C = 1.0, gamma = 'scale'
RF	0.7521	0.8450	100 trees, max depth = 10, bootstrapped, min samples leaf = 2
GB	0.7687	0.8618	100 estimators, learning rate = 0.1, max depth = 3

This comparison confirms that while RN alone offers a good approximation of the strength of concrete, the inclusion of W/C ratio always enhances performance, especially of the ensemble methods, making them more precise. A comparison of the ML model accuracies, ordered from most to least accurate, is provided in Table II. It can be seen that GB was the most accurate ML method. It is important to mention here that while the GB model generated the highest R^2 value of 0.86, its MAE value of 6.34 MPa seems rather high in absolute value. This may be caused by a number of reasons. The size of the dataset used in this research is large, having initially about 10,000 records. This extensive and heterogeneous dataset introduces variability in mix designs, curing environments, testing conditions, and measurement instruments. However, despite the careful selection of the dataset, discrepancies and missing parameters in some records may have affected the generalizability of the models. The RH test may be very handy and non-destructive, however, it has limitations in sensitivity and accuracy. It only tests surface hardness, which can be affected by carbonation, water, and surface finish, and provides no information on the internal structure of concrete. Therefore, a prediction error in concrete compressive strength exists. Although there is an error, the used ML models have shown significant prediction improvement over the conventional strength estimation charts obtained from RH devices, which rely on generalized empirical curves and lack consideration of the W/C ratio. In contrast, the ML models provide data-driven and customized estimates that better capture the complexity of real concrete, and for which the obtained MAE values are reasonable and informative from a practical perspective.

TABLE II. BASELINE ML MODELS ACCURACY COMPARISON

Model	**R^2**	**MAE (MPa)**
GB	0.8618	6.34
RF	0.8450	6.24
DT Tree	0.7826	7.07
SVR	0.7783	7.73
LR	0.6907	9.86

Figures 3 and 4 illustrate the relationship of the predicted and the actual compressive strength values for the GB and RF models, respectively. The points are closely clustered around the ideal 45° reference line, indicating good predictive capability. The GB model has a tighter spread with fewer extreme deviations from the actual values, so it has a superior generalization ability and nonlinear pattern identification capability. By comparison, although also performing well, the RF model tends to exhibit more scattered points at high-strength areas, which could be due to overfitting or a lack of representation for some mix configurations in the training data.

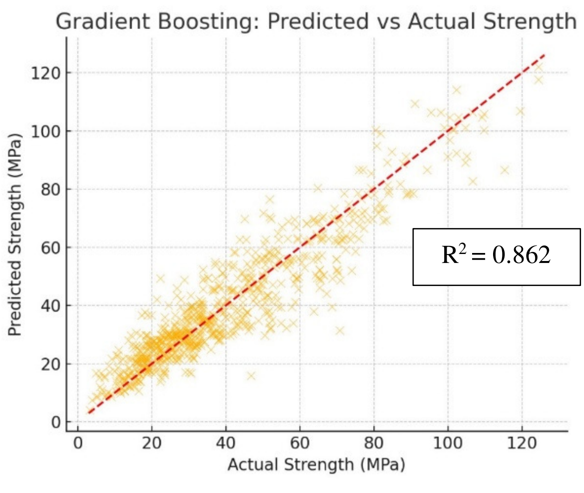

Fig. 3. GB: Predicted vs actual compressive strength.

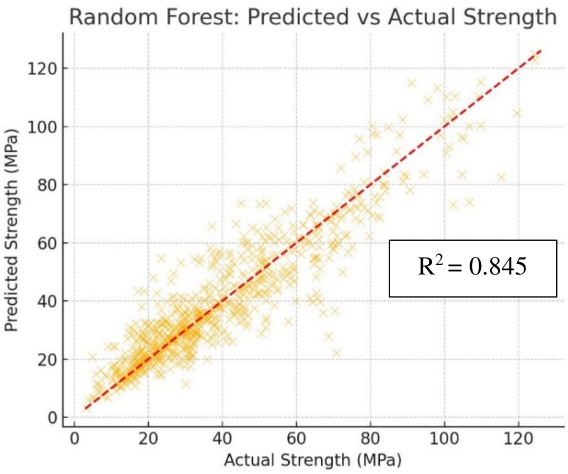

Fig. 4. RF: Predicted vs actual compressive strength.

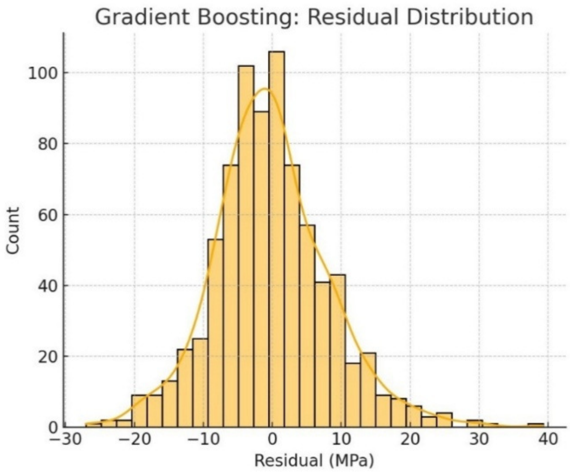

Fig. 5. GB residual distribution.

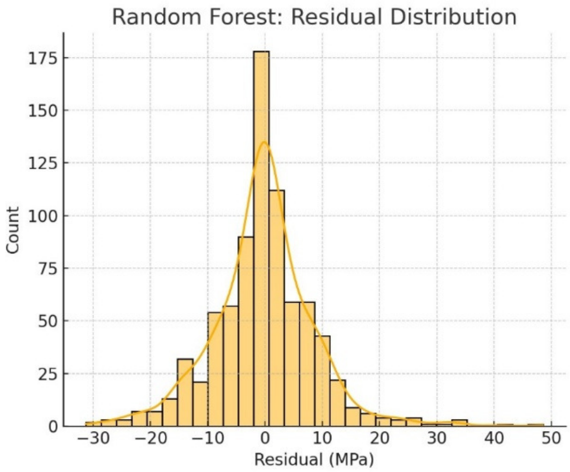

Fig. 6. RF residual distribution.

Figures 5 and 6 are plots of the residual distributions, or the deviation between the actual and the predicted compressive strength, from the GB and RF models, respectively. The GB model is displaying a near-normal distribution centered at zero with very limited spread, so it has a small bias and symmetric under- and over-predictions. The RF model is also quite centered but has longer tails, which suggests larger prediction errors. These findings confirm the superiority of the GB model in generating accurate and reliable predictions when presented with a diverse dataset.

B. Model Optimization and Evaluation

To obtain more accurate predictions than those obtained from the baseline models, tuning and advanced models were implemented as follows:

- GB with Hyperparameter Tuning: GridSearchCV was used to fine tune the main parameters of the GB model, specifically n_estimators, learning_rate, max_depth, and subsample. This resulted in a performance boost, where R^2 increased to 0.8704 and MAE dropped to 5.90 MPa. This proves the impact of parameter optimization on the generalization ability of the model.
- XGBoost Implementation: The XGBoost model, which is known for its efficiency and regularization capabilities, was utilized. It slightly outperformed the above tuned GB model with $R^2 = 0.8735$ and MAE = 5.85 MPa, which indicates its robustness and suitability for regression tasks.
- Neural Network Modeling: An FNN was developed using Keras in TensorFlow. Although the FNN has a deeper architecture and can handle non-linearity, it was underperformed by the two models above with $R^2 = 0.8289$ and MAE = 6.99 MPa, which is mostly due to the relatively small dataset and limited number of features.
- Ensemble Averaging: An ensemble model was created to average the predictions of the tuned GB, RF, and XGBoost. The ensemble model showed competitive performance with $R^2 = 0.8685$ and MAE = 6.05 MPa, while individual models like XGBoost still slightly outperformed it.

The additional models above demonstrate the benefit of model tuning and diversity. While GB and XGBoost remained the best models in terms of performance, neural networks and ensemble techniques provided a useful understanding of model behavior and potential trade-offs. A comparison of the optimized and advanced ML model accuracies is provided in Table III.

TABLE III. OPTIMIZED AND ADVANCED MODEL ACCURACY COMPARISON

Model	R^2	MAE (MPa)
Tuned GB	0.8704	5.90
XGBoost	0.8735	5.85
Ensemble (avg)	0.8685	6.05
FNN	0.8289	6.99

Figure 7 shows the residual distribution for the XGBoost model. The Figure gives a clear view of the way residuals are being centered around zero and normally distributed, indicating good model performance.

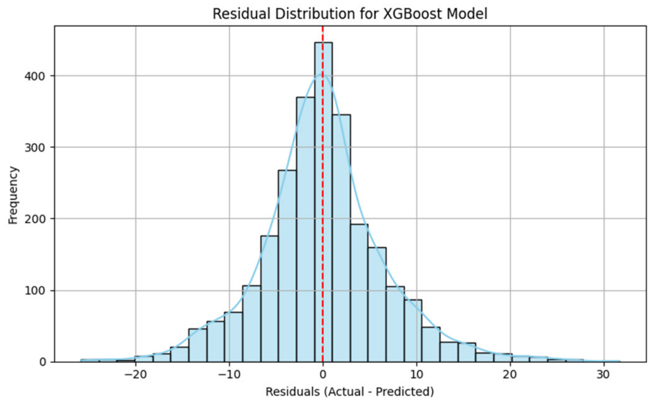

Fig. 7. XGBoost residual distribution.

C. Polynomial Approximation and Model Deployment

The polynomial approximation serves as a lightweight alternative for the XGBoost model, enabling field engineers to estimate concrete compressive strength without the need for real-time ML infrastructure. The obtained polynomial approximation closely tracks XGBoost predictions with R^2 of 0.998, so it is highly reliable. This makes it suitable for use in spreadsheet calculators, mobile apps, or field estimation tools where deploying a full ML model may not be practical. The final second-order polynomial equation fitted to the XGBoost predictions was found to be:

$$f_c = 1.9865\,\mathrm{RN} + 173.9580\,\mathrm{W/C} + 0.0202\,.\,\mathrm{RN}^2 - 4.3081\,(\mathrm{RN}\,.\,\mathrm{W/C}) - 65.9262\,.\,(\mathrm{W/C})^2 - 58.7151 \quad (1)$$

Equation (1) offers a fast, interpretable, and accurate estimation of concrete strength using only two inputs. Accordingly, it provides a practical alternative in engineering situations with limited computational resources.

Figure 8 shows the polynomial vs XGBoost prediction, and Figure 9 shows the polynomial regression surface fit to the XGBoost model. As may be observed in Figure 8, the second-degree polynomial surface fit is quite successful at capturing the nonlinear interaction between RN and W/C. The prediction strength is expected to rise with increasing RN and fall with increasing W/C, according to engineering justification and from the learned model behavior.

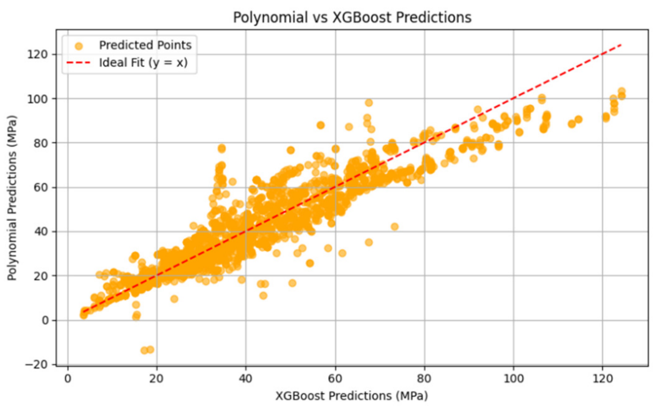

Fig. 8. Polynomial vs XGBoost prediction.

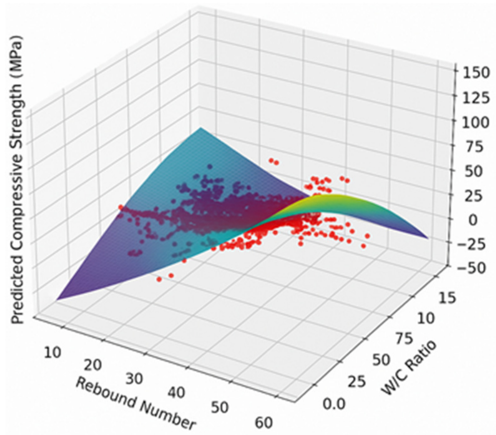

Fig. 9. Polynomial regression surface fit to the XGBoost model.

To enhance usability and real-world applicability, the best performing model, which is the XGBoost, has been deployed in a lightweight user-friendly application using Streamlit (open-source Python library). The application allows users, such as field engineers and construction professionals, to input the RN and W/C values and receive an instant estimated compressive strength. The application was made to be:

- User-friendly, with minimal interface, and no technical background needed.
- Portable, so it can be deployable on laptops, tablets, or mobile phones.
- Fast, with no backend server latency.
- With offline capability, and with the possibility of being converted to a stand-alone desktop or mobile app if needed.

This deployment demonstrates how ML research can be translated into a practical decision support tool for engineering applications and to bridge the gap between model development and field requirements. The interface of the app is shown in Figure 10.

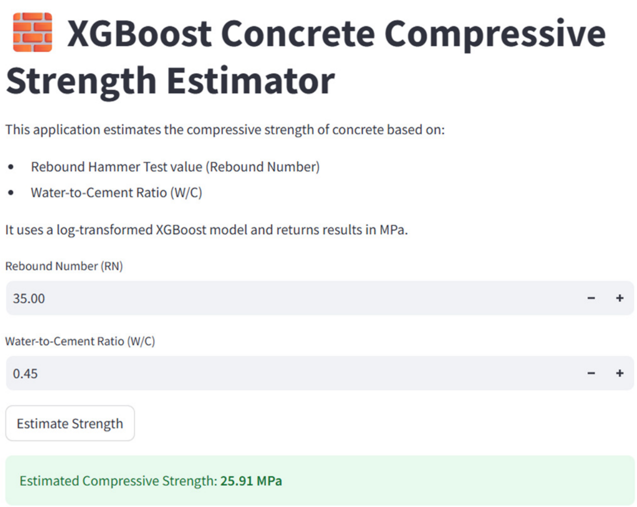

Fig. 10. The deployed application for concrete strength estimation.

D. Sensitivity Analysis

Sensitivity analysis results are provided in Table IV. The Table illustrates the individual effect of each of the input features on the prediction strength. A ±10% variation in RN significantly changes the strength of the prediction, which confirms its position as a top predictor. A 10% rise in RN raises the strength by approximately 11.5 MPa, and a decrease of 10% reduces the strength by a similar amount. It can also be seen that an increase in the W/C ratio leads to a reduction in strength, as would be expected from the well-established concrete mixture practices. These results are aligned with the engineering theory, verifying model interpretability and use.

TABLE IV. SENSITIVITY ANALYSIS

Variable	–10% Prediction (MPa)	+10% Prediction (MPa)	Change direction
RN	33.66	45.14	Increase
W/C Ratio	42.05	38.63	Decrease

VI. DISCUSSION, LIMITATIONS, AND FUTURE WORK

Table V summarizes the performance of the ML models developed and tested in this research for predicting concrete compressive strength using RN and W/C as inputs. Models were evaluated based on the coefficient of determination (R^2) and Mean Absolute Error (MAE), with additional observations based on behavior and suitability. Among all models, XGBoost gave the overall best performance, followed by the tuned GB model. Simpler models like LR and SVR performed poorly because they have limited ability to capture the nonlinear relationships within the data. The ensemble approach which combines predictions of a large number of robust learners, gave competitive results with improved stability. These findings justify the choice of tree-based models, in this case GB and XGBoost, as optimal for strong and real-time estimation under field conditions.

TABLE V. COMPARATIVE PERFORMANCE OF ALL THE TESTED ML MODELS

Model	R^2	MAE (MPa)	Notes
GB	0.8618	6.34	Best balance of accuracy and generalization
RF	0.8450	6.24	Slightly lower MAE, but prone to overfitting
DT	0.7826	7.07	Overfits easily but good for interpretability
SVR (RBF Kernel)	0.7783	7.73	Not ideal for this dataset without normalization/tuning
LR	0.6907	9.86	Assumes linearity so it is insufficient for complex behavior
Tuned GB	0.8704	5.90	Improved performance through hyperparameter tuning
XGBoost	0.8735	5.85	Best overall performance, fast and robust
Ensemble (avg)	0.8685	6.05	Simple average ensemble of GB + RF + XGBoost
FNN	0.8289	6.99	Struggles with generalization and needs more tuning and data

Although the obtained results were promising, several limitations of the current study need to be mentioned. Firstly, the dataset used, although it was extensive, can never cover all the possible variability of concrete types, environmental conditions, and material properties in various construction environments. Also, major influencing parameters such as curing time, temperature, humidity, aggregate properties, and admixtures, were not considered or included in the dataset, which may affect the generalizability of the models. Secondly, while XGBoost, GB, and RF models were highly accurate, they are generally "black-box" models with poor interpretability compared to traditional statistical techniques. Thirdly, although a polynomial of concrete strength was obtained for improved usability, it remains an approximation of the ML behavior.

Future studies should explore the addition of other NDT parameters such as the Ultrasonic Pulse Velocity (UPV), surface moisture, temperature, and time-dependent behavior. The use of explainable AI (XAI) techniques may also help in bridging the gap of interpretability. Moreover, using the models on mobile or web platforms with real-time prediction capabilities can enhance their usability in the field.

VII. CONCLUSIONS

This study demonstrates that Machine Learning (ML) approaches offer a powerful, data-driven alternative for predicting concrete compressive strength from non-destructive Rebound Hammer (RH) measurements and water-to-cement (W/C) ratios. By developing and comparing a variety of models, including Linear Regression (LR), Decision Tree (DT), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GB), XGBoost, and neural networks, tree-based methods emerged as the most effective. XGBoost was the best overall ($R^2 = 0.8735$, MAE = 5.85 MPa), closely followed by the optimized GB model ($R^2 = 0.8704$, MAE = 5.90 MPa), both surpassing traditional regression techniques in accuracy, stability, and reliability. Sensitivity analysis of features reinforced the fact that Rebound Number (RN) is positively correlated with compressive strength and that higher W/C ratios unfavor it, in accordance with intuitive understanding from the field of civil engineering. Including W/C as a second input variable was found essential for characterizing mix variability. For practical application, a second-order polynomial approximation model was derived from XGBoost predictions. The polynomial is very accurate ($R^2 = 0.998$ vs. XGBoost), with an interpretable approximation that can be applied in spreadsheets, mobile apps, and other field applications without access to ML infrastructure. Finally, the deployment of an application using Streamlit enables engineers to perform real-time strength estimation using only RH and W/C inputs. This demonstrates a successful translation of advanced ML into a practical, accessible decision-support tool, and bridges the gap between computational modeling and field engineering practice.

The novelty of this study lies in three aspects:

First, it introduces the combined use of RH and W/C ratio as joint predictors within the ML approach. Most of the previous research [9-11] relied on surface rebound values or UPV-based features, but this work shows that integrating mix design parameters such as W/C has enhanced prediction accuracy by improving the R^2 score from 0.69 (for RH alone) to 0.87 (for RH+W/C). This result shows the important role of mix characteristics in non-destructive testing strength prediction, which wasn't addressed in previous works.

Second, the study applies advanced ensemble learning models (GB and XGBoost) and performs hyperparameter tuning to achieve higher performance than previously published works, which used ANN or SVR models [3-6]. The used models in this study demonstrate improved accuracy, stability, and generalization over a large dataset compiled from over 80 published sources. This validates the adaptability and scalability of ensemble tree methods for real-world mixed data in concrete evaluation.

Third, this work translates the predictive model into a field-usable engineering tool by deriving a second-order polynomial regression equation from the XGBoost predictions. Unlike previous studies that stop at model validation, this research provides a mathematically interpretable and easy formula to enable strength estimation without much computational resources. Furthermore, by deploying a user-friendly Streamlit application, the work bridges the gap between research and practice, and helps engineers to perform real-time and offline compressive strength estimation. This integration of ML interpretability, field usage, and deployment readiness are among the important contributions of this study.

This work also contributes to the interpretability of ML-based concrete evaluation. The sensitivity analysis confirms that the model aligns with engineering theory where the strength increases with rebound number and decreases with higher W/C ratios. This provides empirical validation of the ML models used in this work.

In summary, this research establishes a novel hybrid approach that combines non-destructive testing data, mix design parameters, and advanced ensemble learning techniques to deliver interpretable and field-deployable models. The developed polynomial equation and real-time app extend the findings of prior ML studies [4-11], and also transform them into a practical, portable, and explainable solution. Accordingly, this study makes scientific and practical contributions to the literature on intelligent concrete diagnostics and opens the way for data-driven, reliable, and accessible quality assessment tools in civil engineering practices.

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