Civil Engineering and Architecture 13(6): 4254-4265, 2025 http://www.hrpub.org
DOI: 10.13189/cea.2025.130612

Innovative AI Approaches for Concrete Strength Prediction: Towards Sustainable Buildings

Areen Arabiat[1,*], Muneera Altayeb[1], Tariq Alkhrissat[2]

[1]Department of Communications and Computer Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Jordan
[2]Department of Civil Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Jordan

Received June 16, 2025; Revised September 2, 2025; Accepted September 17, 2025

Cite This Paper in the Following Citation Styles

(a): *[1] Areen Arabiat, Muneera Altayeb, Tariq Alkhrissat , "Innovative AI Approaches for Concrete Strength Prediction: Towards Sustainable Buildings," Civil Engineering and Architecture, Vol. 13, No. 6, pp. 4254 - 4265, 2025. DOI: 10.13189/cea.2025.130612.*

(b): *Areen Arabiat, Muneera Altayeb, Tariq Alkhrissat (2025). Innovative AI Approaches for Concrete Strength Prediction: Towards Sustainable Buildings. Civil Engineering and Architecture, 13(6), 4254 - 4265. DOI: 10.13189/cea.2025.130612.*

Abstract Concrete's compressive strength is crucial for sustainability and quality. Advanced machine learning methods can minimize environmental impact and enhance mix design. Hybrid and ensemble-based approaches are being explored for accurate strength estimates, promoting sustainable construction techniques in civil engineering. ML techniques provide accurate first predictions of desired results. To predict concrete compressive strength, the study assesses several machine learning techniques, including Random Forest (RF), Decision Trees (DT), Multi-layer Perceptron (MLP), and Bagging. This study used open-source ML software called Waikato Environment for Knowledge Analysis (Weka). The dataset was obtained from the Kaggle platform, which was divided into a training dataset and a testing dataset. The features of this dataset were fed to the model. Then, the model was evaluated to examine the effectiveness of the suggested model in predicting concrete strength. This assessment used statistical indicators that include coefficient correlation (R^2), mean absolute error (MAE), relative absolute error (RAE), mean square error (MSE), and root mean square error (RMSE). According to the experimental data results, RF had the highest coefficient correlation, at 0.9604. However, the coefficient correlation for Bagging was 0.9384, the DT was 0.9238, and the coefficient correlation for MLP was 0.8722.

Keywords Random Forest, Decision Trees, Multi-Layer Perceptron, Machine Learning, Bagging, Sustainability

1. Introduction

Concrete is the most prevalent building material globally, with yearly output surpassing 30 billion tons, attributed to its flexibility, durability, and cost-effectiveness [1]. Compressive strength at 28 days is a crucial factor in structural design, influencing a structure's capacity to endure stresses and guaranteeing long-term safety [2]. Conventional laboratory testing for compressive strength is sometimes time-consuming, expensive, and susceptible to human or process mistakes [3]. The manufacturing of cement, the principal binding agent in concrete, considerably contributes to worldwide CO_2 emissions, making it a focal point in sustainability initiatives. To tackle environmental and performance issues, supplemental cementitious materials (SCMs) such as fly ash, blast furnace slag, and other industrial by-products have been progressively included into concrete mixes [4,5]. Although these elements enhance sustainability, they simultaneously complicate concrete mix design, so making the prediction of compressive strength more difficult. In recent years, artificial intelligence (AI) and machine learning (ML) have developed into potent instruments for modeling intricate, nonlinear connections, providing swifter and more precise predictions than conventional empirical methods [6,7]. The technical field of the design of concrete mixes is experiencing a transformational phase

through the use of effective techniques based on ML [8]. This work investigates the prediction of concrete compressive strengths using ML approaches, employing various extensive datasets obtained from concrete mix designs. The emphasis on improving the precision of strength forecasts for standard applications has ramifications that go beyond the limits of typical construction. By using current datasets in conjunction with data-driven models, ML may independently identify latent patterns and derive significant insights [9]. This technique accounts for concrete mixes' intrinsic complexity and related features. There has been extensive research on the use of ML in the field of concrete science [10]. Several studies have used machine learning to forecast concrete strength across various mix types spanning high-performance concrete [11] to eco-friendly mixes [12] employing methods such as artificial neural networks, support vector machines, and decision trees. Although these models provide encouraging outcomes, the majority of current research assesses individual algorithms in isolation [13,14]. Consequently, there is a lack of systematic comparison research evaluating the efficacy of single-model techniques versus ensemble learning strategies such as bagging or random forests in the realm of concrete compressive strength prediction. This disparity is significant since ensemble approaches often enhance prediction accuracy and resilience by amalgamating the strengths of many learners [15-17]. In contrast, ensemble methods that integrate several learning classifiers (or predictive models) have been suggested to enhance the efficacy of individual learning techniques [18,19]. The three techniques for integrating several prediction models into a singular model are voting, bagging, and stacking combination approaches. Nevertheless, a literature survey reveals an absence of studies that have contrasted individual models with ensemble learning strategies in predicting compressive strength. Specifically, existing studies only construct their prediction models using individual statistical or ML methods; it remains uncertain if prediction models using ensemble learning techniques may outperform singular approaches in the context of compressive strength prediction. Beskopylny et al. [20] assessed ML techniques such as Random Forest, Linear Regression, Support Vector Regression, and CatBoost for predicting compressive strength in vibro centrifuged concrete under different operating circumstances. This is accomplished by using a thorough database of experimental values acquired in lab settings, along with Sklearn 1.3.2, Optuna 3.5.0, and Python 3.10.11. Metrics like MAE, MSE, RMSE, MAPE, and R^2 were used to evaluate these models' accuracy. An average MAE of 0.89, MSE of 4.37, RMSE of 2.09, MAPE of 2%, and R^2 of 0.94 were displayed by the top model, CatBoost. However, Yang et al. [21] developed a prediction model for fly ash concrete (FAC) using ML techniques such as genetic programming, support vector regression, random forest, XGBoost, backpropagation artificial neural networks, and an adaptive network-based fuzzy inference system. We optimized each program's structure and hyperparameters using the particle swarm optimization (PSO) algorithm. With R^2 and MSE values of 0.9072 and 11.4546, respectively, the outcome demonstrated that the PSO-XGBoost model performed the best overall. To estimate the compressive strength of concrete, the authors in [22] presented an Automated Machine Learning-Shapley Additive Explanations (AutoML-SHAP) technique that uses multilayer stacking and K-fold bagging for model selection and tuning using a dataset containing 1030 sets of concrete compressive strength. This collaborative method improves concrete's performance by producing accurate, effective, and fully interpretable models. Without human assistance, the AutoML-SHAP model predicts compressive strength better than other ML models. It is automatically generated, with a prediction performance equivalent to R^2 = 0.96, RMSE = 3.63, and MAE = 2.41. Khan et al. [23] developed a novel XG Boost model to predict the compressive strength of ultra-high-performance concrete (UHPC) manufactured with recycled glass powder under typical damp curing conditions. Three hundred nine datasets were used to train the model, and its performance was evaluated using the Gini index and SHAP values. Silica fume, water-binder ratio, water-powder ratio, and virtual packing density were revealed to be essential elements of the model, which had a 95% accuracy range. The mean ratio between the model and tested mixtures was 0.956, and the majority of the data fell within a 15% error range. A user-friendly interface was developed to optimize UHPC systems. To maximize prediction accuracy in high-performance concrete compressive strength prediction, the author in [24] suggested tree ensemble techniques. By combining DT with ensemble learning techniques, single ensemble models improve prediction accuracy by 8.75–6.33%. The Bag DT and Random sub-spaces (RS) DT variants are not as effective as the Gradient boosting (GB) DT model. An ensemble method with two levels is suggested for integrating predictors across several resampling. According to the study, GB-RS DT (R^2=0.9520), GB–GB DT (R^2=0.9456), and Bag–Bag DT (R^2=0.9368) are the best models for high-performance concrete (HPC) compressive strength forecasting. The ensemble models also considerably increase prediction accuracy compared to the single DT model. The study of [25] employed ML to forecast compressive strength and examined the impact of a cement-based blend of RHA and FA on the characteristics of concrete. The effect of input factors was analyzed by statistical and parametric analyses using 138 data points. According to the findings, the mixture with the highest fly ash content and lowest rice husk ash content proved to be the strongest. Silica was found in both ashes, which gave them good pozzolanic qualities, according to X-ray fluorescence examination. The study also employed PDP (Partial Dependence Plot) and SHAP (SHapley Additive exPlanations) analyses to determine the best

parameters for enhancing strength, and the XGBoost model's R^2 value was 0.84. In addition, an interpretable shear strength prediction model for reinforced concrete beam (RCB) with stirrups was presented by Shu et al. [26], utilizing Bayesian optimization and Explainable Boosting Machine (EBM). The EBM algorithm reveals the prediction process by breaking down the expected shear strength into separate form functions. ML tasks are automatically completed via Bayesian optimization to save computing costs. The model produces the most accurate predictions with R^2, MAE, and RMSE of 0.9293, 35.42, and 50.99, respectively, using a database of 372 specimens for validation. The innovation of this article is the use of machine learning to compare results with those of earlier studies in the body of existing literature using computational intelligence approaches, namely Random Forest (RF), Decision Trees (DT), Multi-Layer Perceptron (MLP), and Bagging. In order to fill a particular absence in comparative evaluations of individual models against ensemble techniques, the paper presents a novel method by using Weka for the systematic review of these models in predicting concrete strength. By employing a large dataset for training—70% of which is used for testing—the study increases validity and reliability. Additionally, the evaluation of these well-established models' predictive capacity and generalization performance is enhanced by the separation of datasets and the application of 10-fold cross-validation. The outcomes are assessed using necessary statistical measures, such as R^2, MAE, RAE, MSE, and RMSE, which offer a thorough examination of the model's efficacy and make significant contributions to the field of concrete strength prediction utilizing cutting-edge machine learning approaches.

2. Methodology

The suggested model in this study compares the performance of several classifiers utilizing Java-based ML software to assess the effectiveness of techniques for predicting concrete strength systems. The data used in the classification was obtained from the Kaggle platform. However, the pre-processing stage is the most critical step in developing an ML classifier. Following the preparation step, the dataset is fed into an ML model. Data categorization has traditionally consisted of training and testing techniques. 30% of the investigation's data should be tested with 10-fold cross-validation, while 70% should be trained with RF, DT, MLP, and Bagging classifiers. The classifiers were utilized in this work to predict concrete strength. The findings will be assessed using confusion matrices, which include multiple numeric categories: R^2, MAE, RAE, MSE, and RMSE. Figure 1 represents the system architecture for concrete strength prediction, while Figure 2 depicts the suggested model for concrete strength prediction.

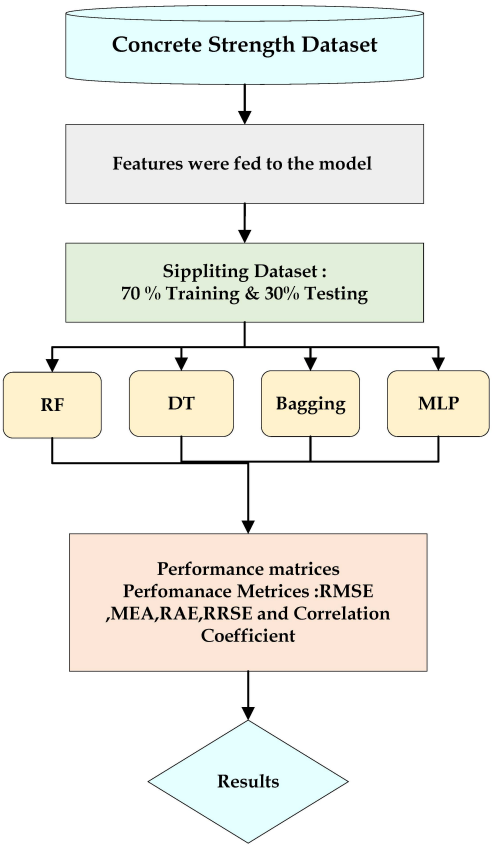

Figure 1. System architecture for concrete strength systems prediction

```
=== Run information ===

Scheme:       weka.classifiers.trees.RandomForest -P 100 -I 100 -num-slots 1 -K 0 -M 1.0 -V 0.001 -S 1
Relation:     ConcreteStrengthData
Instances:    1030
Attributes:   9
              CementComponent
              BlastFurnaceSlag
              FlyAshComponent
              WaterComponent
              SuperplasticizerComponent
              CoarseAggregateComponent
              FineAggregateComponent
              AgeInDays
              Strength
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

RandomForest

Bagging with 100 iterations and base learner

weka.classifiers.trees.RandomTree -K 0 -M 1.0 -V 0.001 -S 1 -do-not-check-capabilities

Time taken to build model: 1.29 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient                  0.9604
Mean absolute error                      3.2794
Root mean squared error                  4.7449
Relative absolute error                 24.3348 %
Root relative squared error             28.3898 %
Total Number of Instances             1030
```

Figure 2. Concrete strength prediction model

The data utilized in this study were taken from Kaggle [27]. The dataset consists of 1030 records and eight features, which include the following: (Cement Component, Blast Furnace Slag, Fly Ash Component, Water Component, Superplasticizer Component, Coarse Aggregate Component, Fine Aggregate Component, and Age in Days). The data set must be in CSV format to be compatible with the proposed model. Figure 3 depicts all attributes for the concrete strength prediction model.

2.1. Data Preprocessing

Reliability and data quality are essential for forecasting models to be successful. The ability of ML algorithms to generalize is impacted by data preprocessing, which includes feature extraction, data cleaning, outlier observation elimination, and missing data repair to create a smaller, more informative dataset [28].

2.2. Machine Learning Approaches

ML is the use of artificial intelligence (AI) that offers an environment to be used without programming as a structural enhancement of the fact.

Machine ML focuses on creating systems that can collect data and use it to learn how to make decisions in the future [29]. This section explores algorithms such as RF, DT, MLP, and bagging techniques, as shown in Figure 4, which are utilized in determining the strength of concrete. This study categorizes data into multiple readings to determine concrete strength.

2.2.1. Multi-Layer Perceptron

MLPs are linked neural networks composed of three layers: input, hidden, and output. The input layer receives raw data, which represents characteristics or variables. Hidden layers, located between the input and output layers, perform an activation function on the weighted sum of inputs. The output layer generates the model's output based on the issue it is supposed to answer, such as binary or multiclass classification [30,31]. The model is composed of layers with individual neurons, each providing input weights. An activation function processes these weights to account for nonlinearity. Data is entered consecutively, accuracy is evaluated, and weight adjustments are made. However, the model undergoes an iterative process to enhance its accuracy and learning capabilities [32,33]. Figure 5 depicts an MLP diagram.

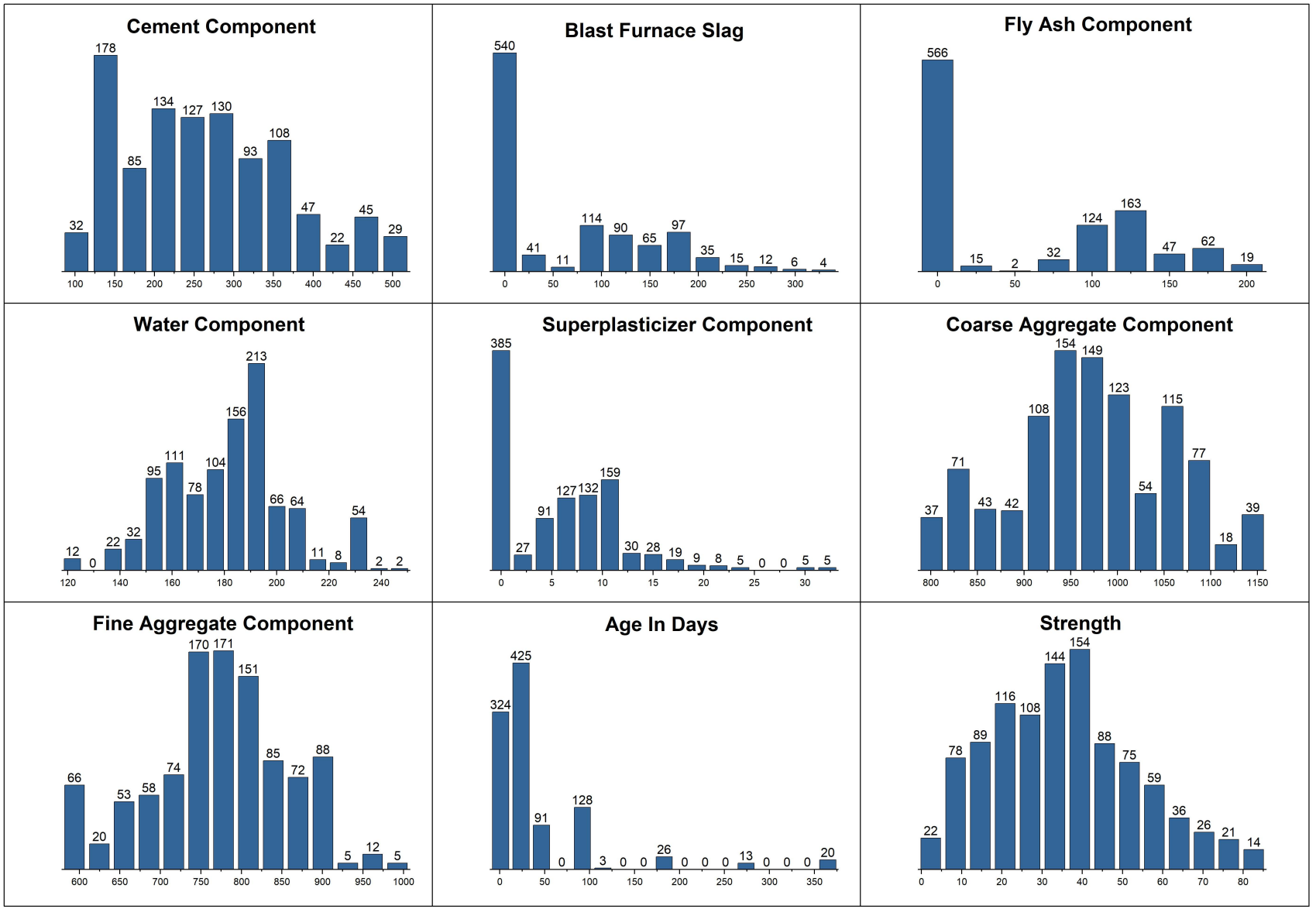

Figure 3. Visualized attributes for the concrete strength systems prediction model

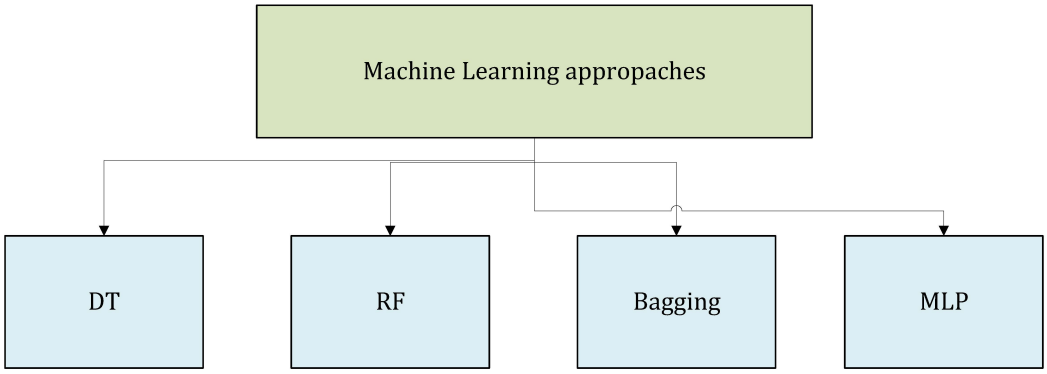

Figure 4. Machine learning approaches of the proposed model

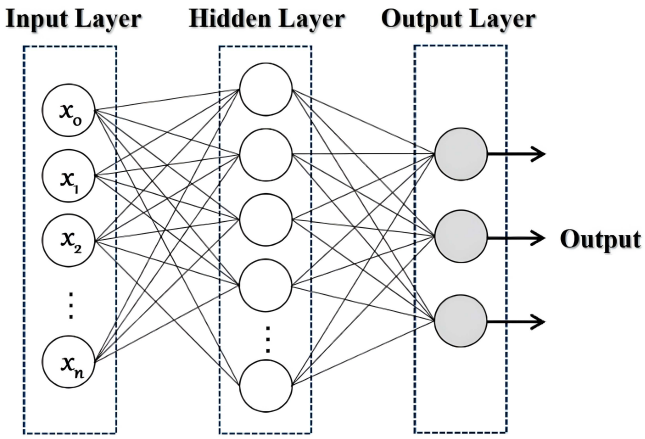

Figure 5. MLP diagram. [34]

2.2.2. Random Forest (RF)

A reliable method for both classification and regression, the RF algorithm was created by Ho in 1995 and then refined by Breiman in 2001. By generating an ensemble of trees by bootstrap aggregating trees as shown in Figure 6, it reduces model variance and guarantees accuracy and stability [34]. However, each tree is trained on a random sample using a decision, and the original set's data is substituted. RF is a non-parametric supervised learning approach that combines multiple weak classifiers to achieve good performance in terms of accuracy and generalization [35,36]. The main rules used to binary divide data of such suggestions in classification problems are the towing rule, deviation, and Gini index; the Gini index in Equation "(1)", which quantifies the node impurity, is most frequently applied:

$$\mu = \sum_{a=1}^{A} \quad P_a(1 - P_a) \tag{1}$$

With a sample fraction of Pa, the target class is A. A pure node primarily comprising single-class observations has an acceptable μ value. X, n data dimensions, and T trees make up the RF structure [37].

2.2.3. Decision Tree (DT)

For problems with prediction and classification, DT is a non-parametric supervised learning technique. The predictive information is extracted using a Boolean function and a tree structure. To choose the best-fit variable, DTs begin with training samples. The leaves display the predictions that are tested along with the middle nodes. Error is quantified by standard deviation using the split criteria [39, 40].

2.2.4. Bagging

Breiman's Bagging technique is a simple and effective integration approach that makes use of a weak classification algorithm and an original training set. It entails several rounds of training, with each cycle using bootstrap techniques and put-back sampling to rebuild a new set. The training pattern of prediction functions is classified by using the straightforward voting approach to ensure base classifier variability [41,42]. On the other hand, Bagging is used for combining numerous versions of an imbalanced estimator from a bootstrap sample to produce a composite predictor via majority voting. Its goal is to improve the underlying classifier's performance by reducing variance and preventing overfitting [43]. However, by separating samples from a training dataset, using bagging allows for the creation of distinct classifiers with differing attention to detail and viewpoints on the issue at hand.

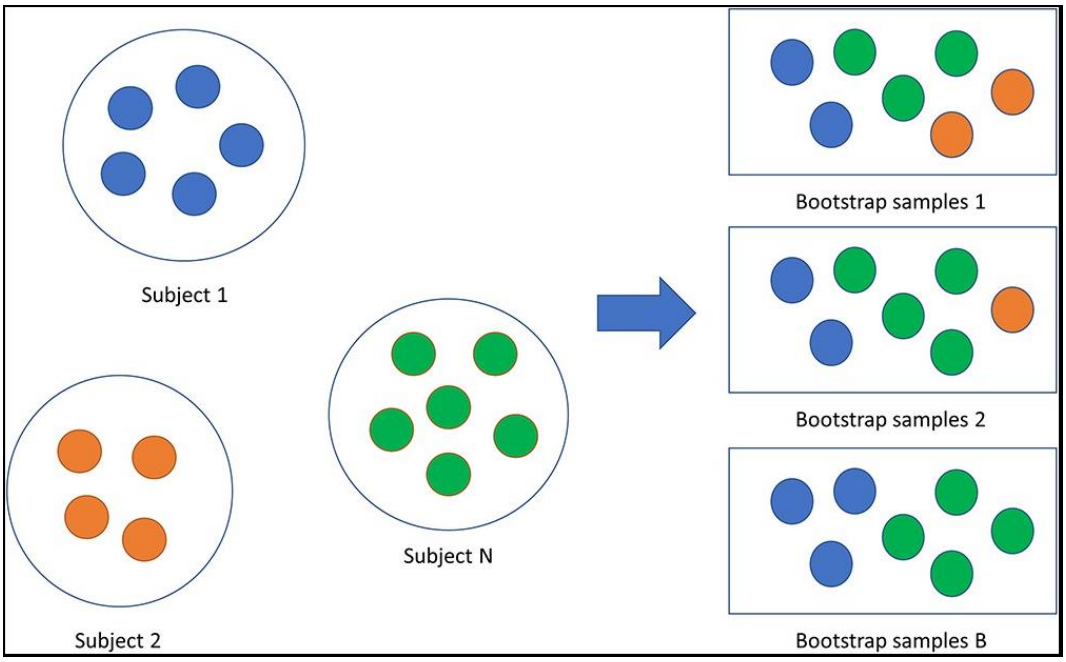

Figure 6. Bootstrap samples to construct the DT in standard RF [38]

3. Performance Evaluation

3.1. Cross-Validation

In statistics and machine learning, cross-validation is a common approach for selecting models and parameters. It entails fitting and testing prospective models on various data sets to guarantee accuracy. Models are frequently overfitted using conventional strategies such as V-fold and leave-one-out. For low-dimensional linear models, which are used by the majority of statistical software applications due to greater training samples, cross-validation necessitates a zero training-testing split ratio [44,45]. However, in this study, the model was evaluated using the 10-fold cross-validation method. Ten groups of data were randomly assigned, nine for training and one for validation. The procedure was carried out ten times to get the average value. This technique confirmed the models' most accurate performance.

3.2. Performance Matrices

Regression and correlation are methods for prediction and association, respectively; regression is concerned with the forecasting of data, while correlation measures the strength of the connection between them [46,47]. In supervised machine learning, regression analysis plays a vital role in forecasting a continuous independent variable based on predictor variables. There is, however, no agreement on a single criterion to evaluate regression findings. While MAE and MSE are frequently used in research, they have problems [48]. This study is focused on four metrics: R^2, MAE, RMSE, and RAE, which were used to evaluate the algorithm's performance. On the other hand, the lower RMSE and MAE values imply better accuracy, and higher R^2 values suggest a better fit. By comparing and choosing the best model based on quality of fit and prediction accuracy, these metrics improve in the process. MAE and RMSE are two often-used metrics for model evaluation. The RMSE, MAE, MSE, and R^2 are shown in Equations "(2)" to "(6)" when n observations are sampled and n corresponding model predictions are obtained [49,51]. The following metrics were used to assess the accuracy of the regression models that were produced:

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

$$MAE = \sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

$$RAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{\sum_{i=1}^{n}(y_j - \bar{y}_i)} \quad (4)$$

$$MSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \quad (6)$$

Also, another matrix is used to evaluate the result in the model, as demonstrated in Equation "(7)" [52]

$$RRSE = \sqrt{\sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)^2}{(y_i - \bar{y})^2}} \quad (7)$$

In this case, equal to the number of observations, yi denotes the actual value, $\hat{y}i$ the predicted value, and $\bar{y}$ the average value for yi [20]

4. Results and Discussions

The study evaluated several prediction models, such as DT, MLP, RF, and Bagging. With the lowest MAE of 4.7449 and RMSE, as well as the best correlation coefficient, RF had the strongest predictive performance and was the most dependable model, with a RAE of 24.3348%. However, with a high RAE of 52.8796% and an MAE of 8.9398, the MLP model showed considerable limitations in producing reliable predictions, which raised questions about its suitability for the dataset. Despite their reasonable performance, the DT and Bagging models lacked the predictive capability needed for high-precision applications. Because of its strong accuracy, the study concludes that RF is the best option for predictive analytics, highlighting the significance of choosing models based on performance indicators. To improve prediction efficacy, future studies should concentrate on feature selection, hyperparameter optimization, and sophisticated ensemble approaches. Table 1 summarizes the performance evaluation of all classifiers, and Table 2 contrasts the performance of the suggested model with previous studies. Figure 7 shows a comparative assessment of various classifiers.

Table 1. Performance evaluation comparison of all classifiers

Model	R^2	MAE	RMSE	RAE	RRSE
RF	0.9604	3.2794	4.7449	24.3348%	28.3898%
DT	0.9238	4.1918	6.5107	31.1052%	38.9550%
MLP	0.8722	7.1261	8.9398	52.8796%	53.4889%
Bagging	0.9384	4.2874	5.8435	31.8152%	34.9630%

RF was determined to be a highly dependable model for predictive tasks due to its ensemble learning method, ability to manage non-linear interactions, and effectiveness in minimizing overfitting. During training, RF automatically assesses feature importance, focusing on relevant predictors, and its resilience to missing data enhances its utility in real-world applications. This robustness is reflected in RF's lowest MAE and RMSE, supporting its superior performance over DT, MLP, and Bagging in evaluating concrete strength. However, considerable error margins in concrete strength forecasts are indicated by the Mean Absolute Error (MAE) of 3.2794 and the Root Mean Square Error (RMSE) of 4.7449. Because the MAE shows a 3.28 MPa difference from the actual values, the design must include safety margins and quality control. Greater errors are suggested by the RMSE, suggesting either an underestimation or an overestimation of strength. To verify forecasts versus actual performance, field testing must be done regularly. These mistakes demonstrate how important it is to do thorough validation, maintain quality control, and continuously modify construction methods. On the other hand, the increased prediction errors of the MLP highlight the necessity of careful model selection. Given the potential for further fine-tuning and optimization, the study recommends using RF for forecasting concrete strength in future research and practical applications.

Comparing the RF model to comparable state-of-the-art models in Table 2 reveals significant advantages both qualitatively and quantitatively. With a competitive MAE of 3.2794 and RMSE of 4.7449, the RF model outperforms several models, including AutoML-SHAP (R^2: 0.96) and XGBoost (R^2: 0.84), with an R^2 of 0.9604. RF model's ensemble method, which improves robustness and lowers overfitting, especially in different datasets, is one of its main qualitative advantages. On the other hand, even though they perform well statistically, models like CatBoost and PSO-XGBoost could have trouble handling data noise. Because of its superior ability to capture non-linear correlations and interactions, the RF model is ideally suited to the intricacies involved in predicting concrete strength. Additionally, by using feature importance assessments, the RF model provides increased interpretability, enabling users to determine which variables have the most effect on strength results. In other models, as EBM with Bayesian Optimization, this interpretive ability is frequently constrained. In addition to being robust against outliers and flexible to different kinds of data, the RF model offers practical advantages for real-world applications.

Table 2. Comparison of the classifier's performance metrics of previous research and the proposed model

Study/ Year	Model	Result
[32]/2024	CatBoost	MAE: 0.89, MSE: 4.37, RMSE: 2.09, MAPE: 2%, R ² 0.94
[33]/2024	PSO-XGBoost	R ² 0.9072, MSE: 11.4546
[34]/2023	AutoML-SHAP	R ² 0.96, RMSE: 3.63, MAE: 2.41
[35]/2023	XGBoost	Mean ratio: 0.956, 95% accuracy, majority within 15% error range
[36]/2013	GB-RS DT, GB-GB DT, Bag-Bag DT	GB-RS DT: R ²=0.9520, GB-GB DT: R ²=0.9456, Bag-Bag DT: R ²=0.9368
[37]/2024	XGBoost	R ² 0.84
[38]/2024	EBM with Bayesian Optimization	R ² 0.9293, MAE: 35.42, RMSE: 50.99
Proposed Model	**RF, MLP, DT and Bagging**	**R ²0.9604, MAE: 3.2794, RMSE: 4.7449**

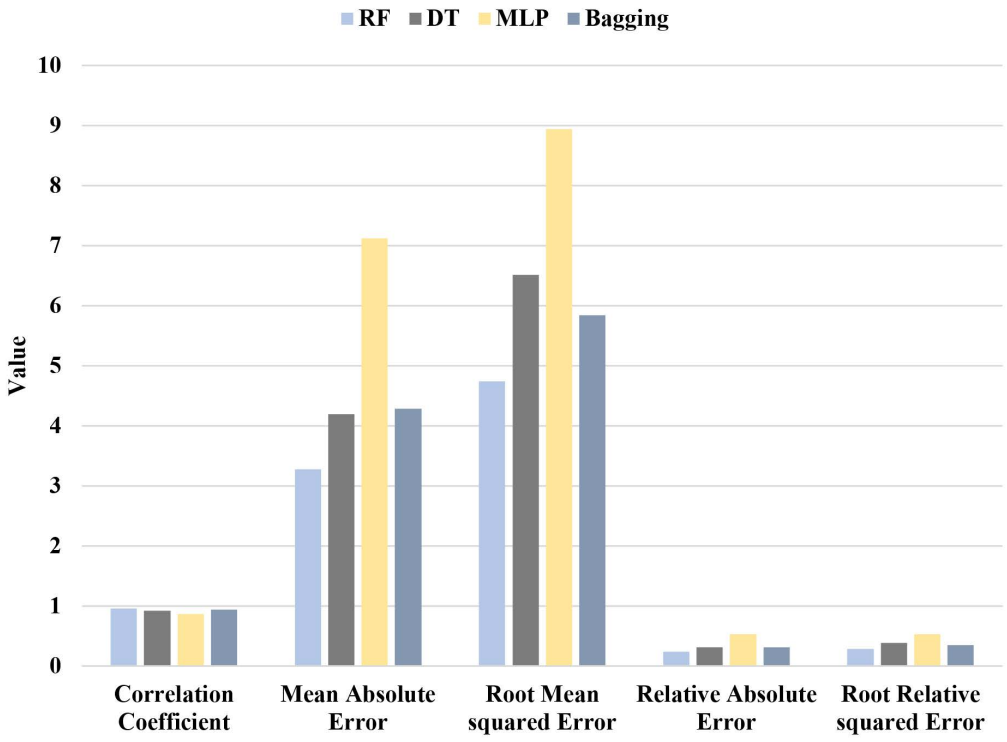

Figure 7. Comparative analysis of different classifiers' performances

5. Conclusions

Despite being an essential building material, concrete's effects on the environment are a concern. Sustainable substitutes such as slag and fly ash can be employed. In this study, the prediction of concrete compressive strength has been entirely transformed by the development of ML and AI, which have surpassed conventional empirical techniques that frequently produce inaccurate findings. The studies assess ML methods such as RF, DT, MLP, and Bagging to forecast the compressive strength of concrete. These methods provide accurate initial predictors of desired outcomes using metrics such as R^2, MAE, RMSE, RAE, and RRSE. We assessed the efficacy of several approaches, including RF, DT, MLP, and Bagging. Also, overfitting is avoided by using 10-fold cross-validation in this model to enhance the prediction method. However, the effectiveness RF classifier in predicting concrete strength was demonstrated in this study with an R^2 of 0.9604; the RF model showed remarkable predictive accuracy and a robust relationship between expected and actual values. With an RMSE of 4.7449 and an MAE of 3.2794, it demonstrated a high degree of prediction accuracy. Its reliability in comparison to other models was further confirmed by the RAE of 24.3348% and the RRSE of 28.3898%. In the end, the results support the incorporation of cutting-edge ML methods into civil engineering procedures. To increase accuracy in forecasting and contribute to safer and more resilient concrete structures, future research should focus on improving existing models and investigating hybrid techniques.

6. Future Work

Future research on machine learning applications for concrete technology should focus on enhancing sustainability, efficiency, and accuracy in the building sector. This requires developing sophisticated ensemble methods like boosting and stacking in addition to hybrid models that integrate the advantages of multiple algorithms. Furthermore, real-time data collecting with IoT technology might improve predictive skills, and deep learning techniques will help decipher intricate patterns in the data. Future research should also thoroughly examine sustainable components and alternative materials, assessing their effects on performance and environmental sustainability. However, experts will need to work across disciplines to address these issues. Predictive models can be improved by developing machine learning tools that are easy to use and by carrying out field testing to validate laboratory results. Such interdisciplinary collaborations involving data scientists, civil engineers, and environmental scientists may result in better concrete mix designs and more environmentally friendly construction methods. Any comments and suggestions are welcomed so that we can constantly improve this template to satisfy all authors' research needs.

REFERENCES

[1] M. Nithurshan and Y. Elakneswaran, "A systematic review and assessment of concrete strength prediction models," Case Studies in Construction Materials, vol. 18, p. e01830, 2023, DOI: 10.1016/J.CSCM.2023.E01830.

[2] M. N. Amin, W. Ahmad, K. Khan, and A. F. Deifalla, "Optimizing compressive strength prediction models for rice husk ash concrete with evolutionary machine intelligence techniques," Case Studies in Construction Materials, vol. 18, p. e02102, 2023, DOI: 10.1016/J.CSCM.2023.E02102.

[3] G. Liu and B. Sun, "Concrete compressive strength prediction using an explainable boosting machine model," Case Studies in Construction Materials, vol. 18, p. e01845, 2023, DOI: 10.1016/J.CSCM.2023.E01845.

[4] K. K. Yaswanth, V. Sathish Kumar, J. Revathy, G. Murali, and C. Pavithra, "Compressive strength prediction of ternary blended geopolymer concrete using artificial neural networks and support vector regression," Innovative Infrastructure Solutions, vol. 9, no. 2, pp. 1–24, 2024, DOI: 10.1007/S41062-023-01343-Y/METRICS.

[5] M. A. Abuhussain, A. Ahmad, M. N. Amin, F. Althoey, Y. Gamil, and T. Najeh, "Data-driven approaches for strength prediction of alkali-activated composites," Case Studies in Construction Materials, vol. 20, p. e02920, 2024, DOI: 10.1016/J.CSCM.2024.E02920.

[6] C. Li, X. Mei, D. Dias, Z. Cui, and J. Zhou, "Compressive Strength Prediction of Rice Husk Ash Concrete Using a Hybrid Artificial Neural Network Model," Materials, vol. 16, no. 8, p. 3135, 2023, DOI: 10.3390/MA16083135/S1.

[7] D. C. Feng et al., "Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach," Construction and Building Materials, vol. 230, p. 117000, 2020, DOI: 10.1016/J.CONBUILDMAT.2019.117000.

[8] A. Behnood and E. M. Golafshani, "Artificial Intelligence to Model the Performance of Concrete Mixtures and Elements: A Review,"Archives of Computational Methods in Engineering, vol. 29, no. 4, pp. 1941–1964, 2022, DOI: 10.1007/s11831-021-09644-0.

[9] A. Hendi, D. Mostofinejad, A. Sedaghatdoost, M. Zohrabi, N. Naeimi, and A. Tavakolinia, "Mix design of the green self-consolidating concrete: Incorporating the waste glass powder," Construction and Building Materials, vol. 199, pp. 369–384, 2019, DOI: 10.1016/j.conbuildmat.2018.12.020.

[10] E. Ford, S. Kailas, K. Maneparambil, and N. Neithalath, "Machine learning approaches to predict the micromechanical properties of cementitious hydration phases from microstructural chemical maps," Construction and Building Materials, vol. 265, p. 120647, 2020, DOI: 10.1016/j.conbuildmat.2020.120647.

[11] A. Behnood, V. Behnood, M. Modiri Gharehveran, and K. E. Alyamac, "Prediction of the compressive strength of normal and high-performance concretes using M5P model tree algorithm," Construction and Building Materials, vol. 142, pp. 199–207, 2017, DOI: 10.1016/j.conbuildmat.2017.03.061.

[12] E. M. Golafshani, A. Behnood, and M. Arashpour, "Predicting the compressive strength of eco-friendly and normal concretes using hybridized fuzzy inference system and particle swarm optimization algorithm," Artificial Intelligence Review, vol. 56, no. 8, pp. 7965–7984, 2023, DOI: 10.1007/s10462-022-10373-4.

[13] A. Dinesh and B. Rahul Prasad, "Predictive models in machine learning for strength and life cycle assessment of concrete structures," Automation in Construction, vol. 162, p. 105412, 2024, DOI: 10.1016/J.AUTCON.2024.105412.

[14] Y. Yang, J. Zhang, F. Huang, Z. Chen, R. Qiu, and S. Wu, "Effect of structural parameters on compression performance of autoclaved aerated concrete: Simulation and machine learning," Construction and Building Materials, vol. 423, p. 135860, 2024, DOI: 10.1016/J.CONBUILDMAT.2024.135860.

[15] M. Alfouneh, M. E. A. Ben Seghier, B. Keshtegar, and S. A. Tabatabaie Shojah, "A new formulation for predicting the ultimate capacities of FRP-confined concrete using advanced machine learning framework: Developed structural reliability analysis," Structures, vol. 68, p. 107158, 2024, DOI: 10.1016/J.ISTRUC.2024.107158.

[16] S. Zhang, W. Chen, J. Xu, and T. Xie, "Use of interpretable machine learning approaches for quantificationally understanding the performance of steel fiber-reinforced recycled aggregate concrete: From the perspective of compressive strength and splitting tensile strength," Engineering Applications of Artificial Intelligence, vol. 137, p. 109170, 2024, DOI: 10.1016/J.ENGAPPAI.2024.109170.

[17] T. Huang, C. Wan, T. Liu, and C. Miao, "Degradation law of bond strength of reinforced concrete with corrosion-induced cracks and machine learning prediction model," Journal of Building Engineering, p. 111022, 2024, DOI: 10.1016/J.JOBE.2024.111022.

[18] M. Z. Akber, "Improving the experience of machine learning in compressive strength prediction of industrial concrete considering mixing proportions, engineered ratios and atmospheric features," Construction and Building Materials, vol. 444, p. 137884, 2024, DOI: 10.1016/J.CONBUILDMAT.2024.137884.

[19] P. Swamy Naga Ratna Giri and P. Rathish Kumar, "Enhancing concrete strength prediction models with advanced machine-learning regressors," Proceedings of the Institution of Civil Engineers - Construction Materials, 2024, DOI: 10.1680/JCOMA.23.00096.

[20] A. N. Beskopylny et al., "Prediction of the Compressive Strength of Vibrocentrifuged Concrete Using Machine Learning Methods," Buildings, vol. 14, no. 2, p. 377, 2024, DOI: 10.3390/BUILDINGS14020377.

[21] Y. Yang, G. Liu, H. Zhang, Y. Zhang, and X. Yang, "Predicting the Compressive Strength of Environmentally Friendly Concrete Using Multiple Machine Learning Algorithms," Buildings, vol. 14, no. 1, p. 190, 2024, DOI: 10.3390/BUILDINGS14010190.

[22] B. Sun, W. Cui, G. Liu, B. Zhou, and W. Zhao, "A hybrid strategy of AutoML and SHAP for automated and explainable concrete strength prediction," Case Studies in Construction Materials, vol. 19, p. e02405, 2023, DOI: 10.1016/J.CSCM.2023.E02405.

[23] M. I. Khan, Y. M. Abbas, G. Fares, and F. K. Alqahtani,

"Strength prediction and optimization for ultrahigh-performance concrete with low-carbon cementitious materials – XG boost model and experimental validation," Construction and Building Materials, vol. 387, p. 131606, 2023, DOI: 10.1016/J.CONBUILDMAT.2023.131606.

[24] H. I. Erdal, "Two-level and hybrid ensembles of decision trees for high performance concrete compressive strength prediction," Engineering Applications of Artificial Intelligence, vol. 26, no. 7, pp. 1689–1697, 2013, DOI: 10.1016/J.ENGAPPAI.2013.03.014.

[25] R. Karim, M. H. Islam, S. D. Datta, and A. Kashem, "Synergistic effects of supplementary cementitious materials and compressive strength prediction of concrete using machine learning algorithms with SHAP and PDP analyses," Case Studies in Construction Materials, vol. 20, p. e02828, 2024, DOI: 10.1016/J.CSCM.2023.E02828.

[26] J. Shu et al., "Proposing an inherently interpretable machine learning model for shear strength prediction of reinforced concrete beams with stirrups," Case Studies in Construction Materials, vol. 20, p. e03350, 2024, DOI: 10.1016/J.CSCM.2024.E03350.

[27] Mayur, "Concrete Strength Prediction." Accessed: Oct. 13, 2024. [Online]. Available: https://www.kaggle.com/datasets/mchilamwar/predict-concrete-strength

[28] M. Castelli, F. M. Clemente, A. Popovič, S. Silva, and L. Vanneschi, "A Machine Learning Approach to Predict Air Quality in California," Complexity, vol. 2020, no. 1, p. 8049504, 2020, DOI: 10.1155/2020/8049504.

[29] M. Erkinay Ozdemir, Z. Ali, B. Subeshan, and E. Asmatulu, "Deep Convolutional Neural Networks Object Detector for Real-Time Waste Identification," Appl Sci, vol. 10, no. 20, p. 7301, 2020, DOI: 10.1007/s10163-021-01182-y.

[30] M. A. Setitra, M. Fan, B. L. Y. Agbley, and Z. E. A. Bensalem, "Optimized MLP-CNN Model to Enhance Detecting DDoS Attacks in SDN Environment," Network, vol. 3, no. 4, pp. 538–562, 2023, DOI: 10.3390/NETWORK3040024.

[31] S. Ahmed, "A Software Framework for Predicting the Maize Yield Using Modified Multi-Layer Perceptron," Sustainability, vol. 15, no. 4, p. 3017, 2023, DOI: 10.3390/SU15043017.

[32] A. Naseer and A. Jalal, "Multimodal Objects Categorization by Fusing GMM and Multi-layer Perceptron," 2024 5th International Conference on Advancements in Computational Sciences, ICACS 2024, 2024, DOI: 10.1109/ICACS60934.2024.10473242.

[33] E. B. Moustafa and A. Elsheikh, "Predicting Characteristics of Dissimilar Laser Welded Polymeric Joints Using a Multi-Layer Perceptrons Model Coupled with Archimedes Optimizer," Polymers, vol. 15, no. 1, p. 233, 2023, DOI: 10.3390/POLYM15010233.

[34] H. Lee, D. Kim, and J. H. Gu, "Prediction of Food Factory Energy Consumption Using MLP and SVR Algorithms," Energies, vol. 16, no. 3, p. 1550, 2023, DOI: 10.3390/EN16031550.

[35] A. Lachaud, M. Adam, and I. Mišković, "Comparative Study of Random Forest and Support Vector Machine Algorithms in Mineral Prospectivity Mapping with Limited Training Data," Minerals, vol. 13, no. 8, p. 1073, 2023, DOI: 10.3390/MIN13081073.

[36] J. Wang, S. Ma, P. Jiao, L. Ji, X. Sun, and H. Lu, "Analyzing the Risk Factors of Traffic Accident Severity Using a Combination of Random Forest and Association Rules," Applied Sciences, vol. 13, no. 14, p. 8559, 2023, DOI: 10.3390/APP13148559.

[37] K. V. Nikhitha, K. Bhavya, and D. U. Nandini, "Fake Account Detection on Social Media using Random Forest Classifier," Proceedings of the 7th International Conference on Intelligent Computing and Control Systems, ICICCS 2023, pp. 806–811, 2023, DOI: 10.1109/ICICCS56967.2023.10142841.

[38] A. Arabiat and M. Altayeb, "Assessing the effectiveness of data mining tools in classifying and predicting road traffic congestion," Indonesian Journal of Electrical Engineering and Computer Science, vol. 34, no. 2, pp. 1295–1303, 2024, DOI: 10.11591/ijeecs.v34.i2.pp1295-1303.

[39] J. Hu and S. Szymczak, "A review on longitudinal data analysis with random forest," Briefings in Bioinformatics, vol. 24, no. 2, pp. 1–11, 2023, DOI: 10.1093/BIB/BBAD002.

[40] B. T. Pham et al., "Performance Evaluation of Machine Learning Methods for Forest Fire Modeling and Prediction," Symmetry, vol. 12, no. 6, p. 1022, 2020, DOI: 10.3390/SYM12061022.

[41] V. G. Costa and C. E. Pedreira, "Recent advances in decision trees: an updated survey," Artificial Intelligence Review 2022 56:5, vol. 56, no. 5, pp. 4765–4800, 2022, DOI: 10.1007/S10462-022-10275-5.

[42] Y. Dou and W. Meng, "Comparative analysis of weka-based classification algorithms on medical diagnosis datasets," Technology and Health Care, vol. 31, no. Suppl 1, p. 397, 2023, DOI: 10.3233/THC-236034.

[43] C. N. Villavicencio et al., "COVID-19 Prediction Applying Supervised Machine Learning Algorithms with Comparative Analysis Using WEKA," Algorithms, vol. 14, no. 7, p. 201, 2021, DOI: 10.3390/A14070201.

[44] J. M. Gorriz, F. Segovia, J. Ramirez, A. Ortiz, and J. Suckling, "Is K-fold cross validation the best model selection method for Machine Learning?," 2024, Accessed: Oct. 13, 2024. [Online]. Available: https://arxiv.org/abs/2401.16407v1.

[45] D. Rastogi, P. Johri, V. Tiwari, and A. A. Elngar, "Multi-class classification of brain tumour magnetic resonance images using multi-branch network with inception block and five-fold cross validation deep learning framework," Biomedical Signal Processing and Control, vol. 88, p. 105602, 2024, DOI: 10.1016/J.BSPC.2023.105602.

[46] J. Yao and M. Shepperd, "Assessing software defection prediction performance: Why using the Matthews correlation coefficient matters," ACM International Conference Proceeding Series, pp. 120–129, 2020, DOI: 10.1145/3383219.3383232.

[47] O. Almomani, A. Alsaaidah, M. A. Almaiah, A. Alzaqebah, M. M. Abualhaj and W. Jumah Alzyadat, "Evaluating Machine Learning Classifiers for Detecting Distributed Denial of Service Attacks," 2025 12th International

Conference on Information Technology (ICIT), Amman, Jordan, 2025, pp. 134-140, DOI: 10.1109/ICIT64950.2025.11049130.

[48] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," PeerJ. Computer science, vol. 7, pp. 1–24, 2021, DOI: 10.7717/PEERJ-CS.623.

[49] T. O. Hodson, "Root-mean-square error (RMSE) or mean absolute error (MAE): When to use them or not," Geoscientific Model Development, vol. 15, no. 14, pp. 5481–5487, 2022, DOI: 10.5194/GMD-15-5481-2022.

[50] F. A. Awad, D. J. Graham, L. AitBihiOuali, R. Singh, and A. Barron, "Benchmarking the performance of urban rail transit systems: a machine learning application," Transportmetrica a Transport Science, Aug. 2023, DOI: 10.1080/23249935.2023.2241566.

[51] A. Maulana et al., "Optimizing University Admissions: A Machine Learning Perspective," Journal of Educational Management and Learning, vol. 1, no. 1, pp. 1–7, 2023, DOI: 10.60084/JEML.V1I1.46.

[52] S. Emami, V. Rezaverdinejad, H. Dehghanisanij, H. Emami, and A. Elbeltagi, "Data mining predictive algorithms for estimating soil water content," Soft Computing, vol. 28, no. 6, pp. 4915–4931, 2024, DOI: 10.1007/s00500-023-09208-3.