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Concrete Mixture Compressive Strength Estimation Using Interpretable Tree-Based Machine Learning Models

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Abstract

Compressive strength is a critical property of concrete, influencing its performance and durability. Accurate prediction is essential for optimizing mix designs and ensuring construction safety. The aim of this study is to evaluate the effect of varying material compositions on the mechanical performance of concrete, aiming to assess their potential as sustainable alternatives in structural applications. This work focuses on evaluating the 28-day compressive strengths of concrete mixtures that include waste brick aggregates, with particular attention to its compression strength after 28 days of curing. Several machine learning models were used to estimate the strength of a concrete mixture that incorporated crushed brick as a partial or complete replacement for conventional aggregates. Then, the explainable tool SHapley Additive exPlanations was employed to interpret the models and analyze the contribution of each input feature to the predictions.

Keywords: compressive strength, reinforced concrete, waste brick aggregates, explainability, predictive modelling, machine learning.

1 Introduction

The selection of construction materials plays a crucial role in ensuring the structural integrity, durability, and sustainability of wall systems in modern buildings. Among these materials, concrete remains a fundamental component due to its versatility and high compressive strength. However, the growing demand for environmentally responsible construction practices has led to increasing interest in alternative and supplementary materials. Concrete is extensively utilized as a construction material because of its robust durability, adaptability, and affordability [5]. A fundamental attribute of concrete is its compressive strength, which plays a vital role in its capacity to endure loads and perform efficiently within structural applications. Compressive strength is a key quality measure for masonry units like blocks. Higher compressive strength ensures greater reliability in load-bearing applications and long-term stability of structures [24]. The incorporation of alternative materials, such as crushed brick, aims to enhance sustainability and reduce construction waste [30]. Traditional strength prediction methods rely on empirical formulas and laboratory testing, which can be time-consuming and costly. Additionally, variations in material properties, curing conditions, and external environmental factors further complicate the prediction process. Machine learning (ML) offers a data-driven alternative, enabling accurate and efficient compressive strength prediction. ML models, when applied to extensive datasets of concrete mixtures, can discern relationships between input variables and compressive strength, resulting in quicker and more accurate forecasts [13, 19].

This work focuses on evaluating the effect of varying material compositions on the mechanical performance of concrete, with particular attention to its compressive strength after 28 days of curing. Specifically, the study investigates the 28-day compressive strength of concrete mixtures that include waste brick aggregates, aiming to assess their potential as sustainable alternatives in structural applications. Different machine learning (ML) techniques were applied to predict the compressive strength of the mixtures in the selected dataset. Subsequently, SHapley Additive exPlanations (SHAP) was employed to interpret the models and analyze the contribution of each input feature to the predictions. Then, the results are interpretable by domain experts, facilitating a better understanding of the influence of each input parameter on the predicted compressive strength. The ultimate goal is to develop a web-based application where users can input the relevant mixture parameters and obtain a prediction of the compressive strength.

The remainder of this paper is structured as follows. An overview of the data collected and modeled is provided in Section 3. Section 4 presents the methodology employed in this study. The results are then discussed in Section 5. Finally, the main conclusions and contributions of the work are summarized in Section 6.

2 State of the art

This section presents a summary of ML methods used to predict the compressive strength of concrete when crushed brick partially or fully replaces standard aggregates. Initially, prevalent trends in concrete strength forecasting are discussed using a bibliometric analysis [22]. Traditional and ML-based methods exist, becoming more popular because of their ability to model intricate input-output relationships in concrete characteristics.

For example, the work by [32] aimed to predict compressive strength, flexural strength, and slump based on mix composition, using data from an Spanish company, Cementos Argos S.A., over five years. Models such as XGBoost and neural networks were applied. The study showed that ML can optimize concrete mix design, improving performance and reducing costs. Additionally, the authors in [14] used ML for material characterization, finding that random forests outperformed other models.

ML approaches have also been applied to sustainable materials like Compressed Earth Blocks (CEB). In [25], classification models were trained to predict CEB compressive strength. After, SHAP analysis was used to identify compaction pressure and soil granularity as key factors. In addition, authors in [28] applied ML-based quality monitoring to CSEBs using cement content, electrical resistivity, and UPV as input variables, with a dataset of 180 samples. The results highlighted ML's potential to improve quality control in sustainable masonry materials. Similarly, the study in [12] proposed several models, including ANN, GMDH-Combi, and GEP, to estimate the compressive strength of hollow concrete block masonry prisms. The model was trained and tested with 102 samples, and used inputs such as the height-to-width ratio of the prisms and the compressive strength of mortar and concrete blocks. Finally, the study in [21] developed three ML models (DNN, KNN, and SVM) to predict geopolymer concrete's compressive strength. The results showed strong accuracy across all models, with DNN achieving the best performance.

The reviewed studies demonstrate the versatility of ML in predicting concrete compressive strength, improving accuracy while minimizing the need for extensive testing. ML approaches have been successfully applied to traditional concrete [22, 32], geopolymer concrete [21], and compressed earth blocks [25]. Additionally, ML has been used to assess the quality of cement-stabilized earth blocks [11] and grouted masonry [12, 28], with ANN models showing strong predictive performance. Ensemble models, such as XGBoost and voting classifiers, exhibit robust predictive power, while deep learning excels with larger datasets [14]. Feature selection and hyperparameter tuning, including genetic algorithms [32] or SHAP analysis [25], further enhance model interpretability. Overall, ML proves valuable for optimizing mix design, reducing over-engineering, and advancing material characterization

3 Data collected

The data analyzed in this study were drawn from a series of experimental investigations reported in the scientific literature, as listed in Table 1.

Reference	Year
Pei Ge, Wei Huang, Jiarui Zhang, Wenli Quan, Yuting Guo. Microstructural analysis of recycled brick aggregate concrete modified by silane. *Structural Concrete* [15]	2022
Ksenija Janković, Dragan Bojović, Dragan Nikolić, Ljiljana Lončar, Zoran Romakov. Frost resistance of concrete with crushed brick as aggregate. *Facta Universitatis* [16]	2010
J.M. Khatib. Properties of concrete incorporating fine recycled aggregate. *Cement and Concrete Research* [18]	2005
Paulo B. Cachim. Mechanical properties of brick aggregate concrete. *Construction and Building Materials* [7]	2009
Tara L. Cavalline, David C. Weggel. Recycled brick masonry aggregate concrete. *Structural Survey* [8]	2013
Juntao Dang, Jun Zhao. Influence of waste clay bricks as fine aggregate on the mechanical and microstructural properties of concrete. *Construction and Building Materials* [10]	2019
Syed Ishtiaq Ahmad, Mohammad Anwar Hossain. Water Permeability Characteristics of Normal Strength Concrete Made from Crushed Clay Bricks as Coarse Aggregate. *Advances in Materials Science and Engineering* [3]	2017
Alaa Abdeltawab Aboalella, Abeer Elmalky. Use of crushed bricks and recycled concrete as replacement for fine and coarse aggregates for sustainable concrete production. *Challenge Journal of Concrete Research Letters* [1]	2023
H. Adem, E. Athab, S. Thamer, A.T. Jasim. The behavior of Lightweight Aggregate Concrete Made with Different Types of Crushed Bricks. *IOP Conference Series: Materials Science and Engineering* [2]	2019
T. Vieira, A. Alves, J. de Brito, J.R. Correia, R.V. Silva. Durability-related performance of concrete containing fine recycled aggregates from crushed bricks and sanitary ware. *Materials & Design* [33]	2016
R.Kumutha Rathinam, Kumutha Vijai. Strength of concrete incorporating aggregates recycled from demolition waste. *Journal of Engineering and Applied Sciences* [20]	2010
Ihab S. Saleh, Saddam Kh Faleh, Aqeel H. Chkheiwer. Flexural Behavior of RC Two Way Slabs Made With Crushed Melted Bricks as Coarse Aggregate. *Springer Nature* [27]	2019
Ahmed T. Noaman, Ghassan S. Jameel, Shamil K. Ahmed. Producing of workable structural lightweight concrete by partial replacement of aggregate with crushed clay brick (CCB) aggregate. *Journal of King Saud University - Engineering Sciences* [26]	2021
Chunlin Su, Jinyan Shi, L.U.D. Tambara Jr, Yuanxia Yang, Baoju Liu, Víctor Revilla-Cuesta. Improving the mechanical properties and durability of steam-cured concrete by incorporating recycled clay bricks aggregates. *Powder Technology* [31]	2024
Farid Debieb, Said Kenai. The use of coarse and fine crushed bricks as aggregate in concrete. *Construction and Building Materials* [11]	2008
Ali A. Aliabdo, Abd-Elmoaty M. Abd Elmoaty, Hani H. Hassan. Utilization of crushed clay brick in concrete industry. *Alexandria Engineering Journal* [4]	2014
Yongcheng Ji, Dayang Wang. Constitutive model of waste brick concrete based on Weibull strength theory. *Case Studies in Construction Materials* [17]	2023

Table 1: Summary of references where the data come from.

These studies encompass a broad range of concrete mixtures incorporating waste brick aggregates, including both fine and coarse fractions, and explore their mechanical behavior under various conditions. The primary focus is on the 28-day compressive strength — a widely accepted benchmark for assessing the structural performance of concrete. The selected publications span nearly two decades (2005–2024) and reflect diverse experimental designs, geographical contexts, and methodological approaches. Collectively, they provide a comprehensive overview of how recycled brick materials influence the strength development of concrete and offer valuable insights into the potential of such materials for sustainable construction practices.

The data collected for this study consists of 156 samples, each containing eight features, with seven input attributes and the target value (28-day compressive strength). Six of the input attributes are numerical, while one is categorical. The input attributes are described as follows, and a brief statistical overview of the data collected is presented in Table 2.

- **Water to Cement Ratio**: This numerical variable represents the ratio of water to cement used in the mixture, which plays a critical role in the hydration process and overall strength development.
- **Cement Content (kg/m³)**: The amount of cement in the mix, expressed in kilograms per cubic meter. Cement content is a key factor influencing the compressive strength of concrete.
- **Fine Aggregate (Natural + Waste Bricks) (kg/m³)**: The amount of fine aggregate in the concrete mix, which includes both natural and recycled waste bricks, measured in kilograms per cubic meter.
- **Coarse Aggregate (Natural + Waste Bricks) (kg/m³)**: The quantity of coarse aggregate in the mix, similarly consisting of both natural and recycled waste bricks.
- **Waste to Natural Fine Aggregate Ratio**: The ratio of recycled waste to natural fine aggregate in the mix, influencing the overall properties of the concrete.
- **Waste to Natural Coarse Aggregate Ratio**: The ratio of recycled waste to natural coarse aggregate, which impacts the material's structural integrity.
- **Type of the Sample**: A categorical variable that classifies the shape of the sample (cube 100, cube 150, or cylinder), which affects the curing process and strength testing.

Parameter	**Min**	**Max**	**Mean**	**Std.**
Water to Cement Ratio	0.3	1.08	0.53	0.14
Cement [kg/m³]	250	514	382.65	64.74
Fine Aggregate (Natural + Waste Bricks) [kg/m³]	506	960	695.77	89.85
Coarse Aggregate (Natural + Waste Bricks) [kg/m³]	480	1309	992.70	200.32
Waste to Natural Fine Aggregate Ratio	0	1	0.22	0.33
Waste to Natural Coarse Aggregate Ratio	0	1	0.45	0.45
Compressive Strength [MPa]	11.05	67.50	32.39	12.90

Table 2: Summary statistics of the collected data.

The target variable in this study is the Compressive Strength of the samples, measured in megapascals (MPa) after 28 days of curing. This is a standard measure used in the concrete industry to assess the load-bearing capacity of concrete and determine its suitability for various structural applications.

4 Methods

A variety of approaches were employed to model the relationship between the input attributes and the target variable, compressive strength. Three tree-based machine learning (ML) models were used to attempt to model the relationship between the input attributes and the target variable (compressive strength). These approaches included Decision Tree (DT), Random Forest (RF) [6], and Extreme Gradient Boosting (XGB) [9].

One hot encoding was used for the categorical input variable (Sample Type). 80% of the data was randomly selected to serve as the training dataset and the remaining 20% was used as the test dataset. In this split, the data was split in a stratified manner to ensure, as far as possible, the same proportion of Sample Type data in both datasets.

A SHAP (Shapley Additive ExPlanations) [23] analysis was also performed on each of the models created to determine how each input attribute or feature affected the output of the model. SHAP is grounded in Shapley values from cooperative game theory [29]. Shapley values quantify the marginal contribution of each feature by considering all possible subsets of features, thereby offering both local and global interpretability.

Formally, given a model f and input features X, the Shapley value ϕ_i for feature x_i represents the average contribution of that feature to the prediction $f(X)$, across all subsets $S \subseteq X \setminus \{x_i\}$, as expressed in Eq. 1:

$$\phi_i(f) = \sum_{S \subseteq X \setminus \{x_i\}} \frac{|S|!(|X| - |S| - 1)!}{|X|!} \left[f(S \cup \{x_i\}) - f(S) \right] \tag{1}$$

To obtain a robust estimate of feature importance, SHAP averages the Shapley values across multiple permutations, as shown in Eq. 2, where M is the number of permutations and $\phi_{x_i}^k$ is the Shapley value for feature x_i in permutation k:

$$\phi_{\{x_i\}}(f) = \frac{1}{M} \sum_{k=1}^{M} \phi_{x_i}^k(f) \tag{2}$$

This method not only highlights the most relevant features but also quantifies their overall contribution to the model's predictions.

5 Results

The results obtained using the optimal configurations for each of the tree-based regression models, as well as the results of the SHAP analysis, are presented in this section.

5.1 ML models

As mentioned in Section 4, the ML models implemented were DT, RF, and XGB. In order to determine the most suitable structure of the model, hyperparameter tuning was performed using grid search. The list of model parameters, the corresponding possible values, as well as the values obtained for the optimal configuration are provided in Tables 3, 4 and 5.

Table 3: List of configuration parameters for Decision Tree model.

Parameter name	**Brief description**	**Possible values of parameters considered**	**Parameter values for optimal configuration**
max_depth	the maximum depth of each tree	(3, 5, 10, None)	10
min_samples_split	the minimum number of samples required to split an internal node	(2,5,10)	2
min_samples_leaf	the minimum number of samples required to be at a leaf node	(1,2,4)	2
max_features	the number of features to consider when looking for the best split, i.e., when splitting a node	(None, 'sqrt', 'log2')	'sqrt'

Table 4: List of configuration parameters for Random Forest model.

Parameter name	**Brief description**	**Possible values of parameters considered**	**Parameter values for optimal configuration**
n_estimators	the number of trees in the forest	(5,10,15)	5
max_depth	the maximum depth of each tree	(3, 5, 10, None)	10
min_samples_split	the minimum number of samples required to split an internal node	(2,5,10)	2
min_samples_leaf	the minimum number of samples required to be at a leaf node	(1,2,4)	1
max_features	the number of features to consider when looking for the best split, i.e., when splitting a node	(None, 'sqrt', 'log2')	'log2'

Table 5: List of configuration parameters for XGBoost model.

Parameter name	**Brief description**	**Possible values of parameters considered**	**Parameter values for optimal configuration**
max_depth	the maximum depth of each tree	(3, 5, 10, None)	3
learning_rate	the learning rate used to weight each model	(0.01, 0.1, 0.2)	0.1
n_estimators	the number of trees in the ensemble	(100, 200, 300)	200
subsample	the fraction of samples (rows) used in each tree	(0.8, 0.9, 1.0)	0.9
colsample_bytree	the fraction of features (columns) used in each tree	(0.8, 0.9, 1.0)	0.9

The results of the ML models on the test data set are provided in Table 6. Based on the performance of the models obtained during training, the best model was XGB followed by RF and then DT. However, this order is reversed when the results of the performance of the models on the test dataset are analyzed (Table 6). Based on this, it can be concluded that the more complex the model, the better the results on the training set and the poorer the results on the test set. In other words, the more complex models seem to overfit on the training set, leading to poor generalization capabilities on the test data set. Hence we decided to use the DT model.

Table 6: ML models performance.

Model	MSE	MAE	R^2
DT	22.28	3.41	0.88
RF	31.59	3.58	0.82
XGB	37.96	4.02	0.79

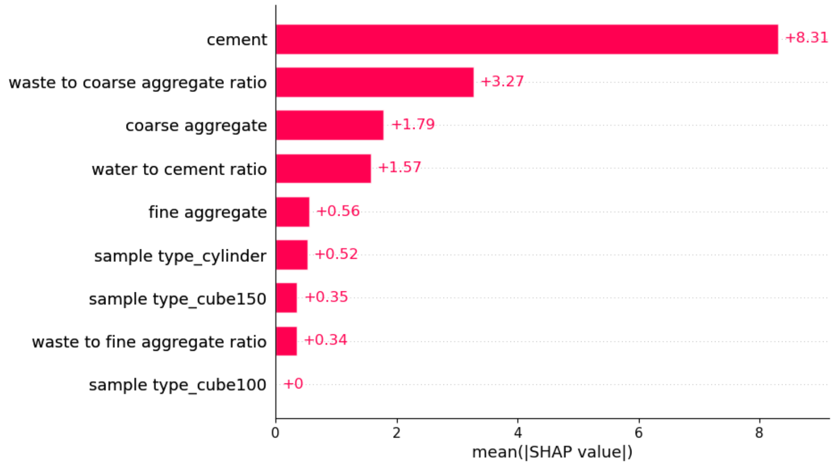
5.2 Explainable AI: SHAP

The SHAP method is employed to evaluate the contribution of each input attribute or parameter to the model's predictions. SHAP enables both global and local interpretability of the model. On a global level, feature importance values derived from SHAP indicate the overall impact of each feature across all predictions. These are typically visualized in a bar plot, where features are ranked from highest to lowest according to their influence on the model output. In contrast, local feature contributions are illustrated using a beeswarm plot, where each point represents an individual data instance. This plot not only preserves the ranking of features by their effect on the model but also shows how high or low values of a given feature influence the prediction. Additionally, the distribution of SHAP values for each feature can be further explored using violin plots, which provide a complementary perspective on the variation and density of local explanations.

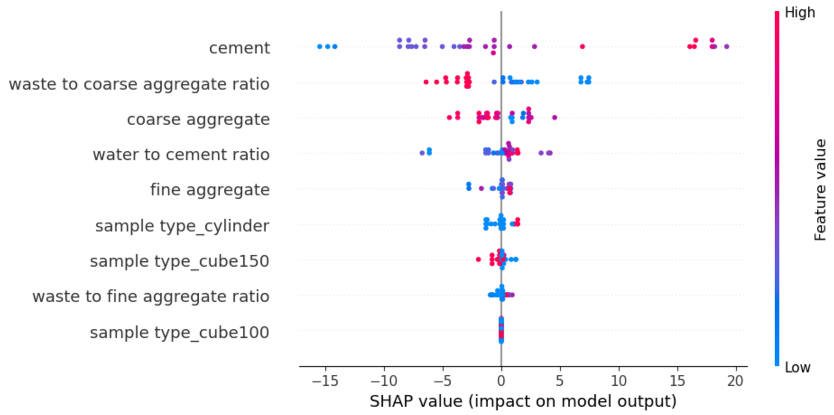
If we ignore the attributes *sample type_cube100*, *sample type_cube150* and *sample type_cylinder* obtained as a result of performing one hot encoding on the attribute **Sample Type** while analysing the results of the SHAP analyses performed using the DT model, it can be concluded that the attributes **cement** and **waste to coarse aggregate ratio** are the most important. These are followed by the attributes **coarse aggregate**, **water to cement ratio** and **fine aggregate**. The least important attribute is the **waste to fine aggregate ratio**. Higher **cement** values have a positive impact on the compressive strength, whereas higher values of **waste to coarse aggregate ratio** have a negative impact on the compressive strength.

6 Conclusions and contributions

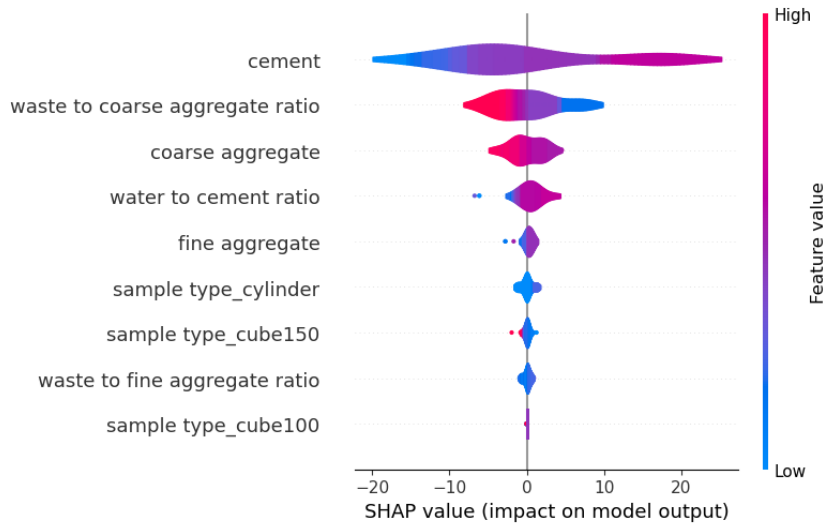
In this study, the influence of different material compositions, in particular the admixture of brick waste aggregates, on the 28-day compressive strength of concrete was successfully investigated. By applying three tree-based machine learning models (Decision Tree, Random Forest and Extreme Gradient Boosting), the potential of data-driven approaches to accurately predict this important mechanical property was demonstrated. While XGBoost performed best on the training data, the decision tree



(a) SHAP Feature importance plot, indicating global influence of input attributes.



(b) SHAP Beeswarm plot indicating local feature contributions per instance.



(c) SHAP Violin plot providing feature-wise SHAP value distributions.

Figure 1: Visualizations based on SHAP values for the DT model: (a) Feature importance ; (b) Beeswarm plot; and (c) Violin plot.

model showed superior generalisation capabilities on the unseen test dataset with an MAE of 3.41 and a determination coefficient R^2 of 0.88.

The application of SHAP analysis (Figure 1) provided valuable insight into the effects of each input feature on the predicted compressive strength. The analysis revealed that cement content had a significant positive correlation with compressive strength, while a higher ratio of waste to coarse aggregate had a notable negative impact.

The study demonstrates the effectiveness of machine learning, in particular the decision tree algorithm, for accurately predicting the compressive strength of concrete using recycled materials.The use of SHAP analysis improves the interpretability of the developed ML models and enables a better understanding of the complex relationships between the parameters of the concrete mix and the resulting strength. This interpretability is crucial for practical application and acceptance by experts.

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