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Research paper

Predictive modeling of mechanical behavior in waste ceramic concrete using machine learning techniques

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Abstract

This study identifies the critical demand for a certain approach that aims to predict and ascertain the mechanical behavior of concrete admixed with waste ceramic, a method to overcome and mitigate the related environmental challenges as it pertains to the construction field. Concrete modification with ceramic wastes has received significant attention due to its potential improvement in sustainability. The developed predictive models on waste ceramic concrete (WCC) involved the use of advanced machine learning techniques such as Artificial Neural Network (ANN) and Light Gradient Boosting Machine (LightGBM). Experimental datasets were formulated based on 5% and 20% variability of ceramic waste percentages as input variables for training and testing data for validation of the proposed model. In each case, iterative training improved model performance, with the ANN showing moderate predictability (R^2 = 0.70 and 0.67) and LightGBM demonstrating stronger accuracy. Predictive values ranged between 1.02 MPa and 0.12 MPa for compressive and splitting tensile strengths and had R^2 values of 0.70 and 0.67 for the ANN model, respectively. The established findings will lead to a dependable framework for assessing and improving the performance of ceramic waste-modified concrete. In this regard, these findings have reinforced the potential of machine learning in developing sustainable construction practices. This paper is of value to engineers and decision-makers within the construction industry, providing an informed choice towards environmental sustainability and better risk management.

Keywords: *Machine Learning; Waste Ceramic Concrete; Artificial Neural Network; LightGBM; Construction Industry; Environmental Sustainability.*

1. Introduction

In recent years, advances in nanoscience and technology have resulted in novel techniques to improve the performance of cement composites, notably nano-modified mixes containing nanosilica [1]. Concrete, the most often used man-made material in construction projects, is primarily reliant on enormous amounts of fine and coarse aggregate [2]. To alleviate the demand on natural resources, adding waste and by-product materials into concrete mixtures has gained popularity [3]. Incorporating waste foundry sand (WFS) into concrete has emerged as a sustainable method of increasing its strength attributes [4]. Similarly, WOC derived from ceramic floor tiles provides both economic and environmental benefits [5]. However, the ceramic and building industries produce a substantial amount of waste, which poses significant environmental problems due to the brittle nature of ceramics [6]. The increase in industrial wastes, such as ceramic scraps and steel tailings, needs immediate waste management solutions [7], [8]. Neural network technology has emerged as a useful technique for evaluating concrete quality [9]. Furthermore, the predictive and optimization capabilities of the response surface technique for waste fibres reinforced concrete with crushed limestone give a comprehensive model for overall response variance [10].

This work aims to improve the sustainability of concrete manufacturing by incorporating ceramic waste and fiber reinforcements. It uses advanced computational approaches to generate robust prediction models for concrete strength and behavior. The study by [11] examines how stress levels and aggregate replacement rates influence the capillary water absorption performance of recycled concrete. Four levels of radial compressive stress after repeated loading, and different substitution rates were used. The investigation by [12] investigates the sulfate assault on the red-colored ceramic as well as concrete waste that is serving substantially as a substitute for OPC in mortar mixtures.

It reveals that pore size distribution changes and ettringite develops because of sulfate attack, making the use of eco-efficient mortars in sulfate-rich areas essential.

The work presented by [13] proposes application of the Compression Model for Chord Capacity as a means for predicting shear strength in corroded RC beams. Model parameters are shifted to better mimic the influence on steel corrosion within the model on the anticipation of shear strength. Experimental validation involving 146 beams corroded proved good performance through a Vtest/Vpred ratio of 1.19 and R2 of 19.5%. The further, the result of the parametric analysis projected the loss of shear strength which verifies that this model is highly efficient for corrosion-induced shear strength degradation analysis of the RC structure. Utilizing the Barcelona Test, the research of [14] introduced a model that applied the neural networks model to predict post-cracking yield strength in fibers-reinforced concrete. Extensive study yields an optimal design architecture with adequate accuracy of forecasted cracking phase. Validation verifies outstanding performance of this model, whilst a parametric analysis confirms such consistency with commonly recognized FRC behavior. Several formulas formulated for the prediction of residual strengths of the tested specimens are instrumental in pre-design and quality-control efforts to continue advancing FRC technology. The study [15] used metaheuristic algorithms to generate strong prediction models for the residual tensile strength of glass fiber reinforced polymer (GFRP) bars in hostile alkaline conditions. Different swarm optimization, and ML approaches are applied to the ANFIS for optimization purposes, yielding accurate prediction models [16 - 19]. A large quantity of experimental data on GFRP bar samples subjected to typical alkaline conditions of salty water sea sandy concrete (SWSSC) is used to construct and verify the models. The k-fold cross-validation test is used to ensure the models' dependability, and statistical tests are used to assess the performance of the metaheuristic algorithms.

This work [20] introduces the neuro-fuzzy based group method of data handling (NF-GMDH) as a predictive tool for scour processes at pile groups subjected to wave action. The NF-GMDH network uses “particle swarm optimization (PSO) and the gravitational search algorithm (GSA)” to reliably forecast scour depth based on seven dimensionless variables. The results reveal that NF-GMDH models outperform conventional equations along with model tree approaches, indicating that they can forecast wave-induced scour depth with greater accuracy. In this article [21], a GMDH network with quadratic polynomials is used in the prediction of scour depths around bridge piers with regard to factors such as sediment size, pier geometry, and flow conditions. Training the GMDH network using the backpropagation method generates the least errors for cylindrical piers, but classical equations do well. In general, the results are that the GMDH has a better estimation of scour depth than earlier equations. In [22], a new methodology, GMDH-ELM, is introduced to enhance the prediction accuracy of the longitudinal dispersion coefficient (LDC) in water pipelines. By building extreme learning machine concepts into the classic GMDH framework, the necessity of updating weighting coefficients is abolished which resulted in higher accuracy. This model was applied quite satisfactorily both during the training and testing phases of the dataset with various input characteristics such as Reynolds number and pipe diameter. Comparison with other models and empirical equations shows that the proposed GMDH-ELM technique is superior. This work [23] addresses the issue of adequately estimating pier scour depth in debris structures that create disturbances in the flow dynamics, thus enhancing scour rates. Considering the limitations within the current models, a new approach that employs NF-GMDH networks combined with evolutionary algorithms is introduced for this purpose. The study assesses the performance of NF-GMDH networks in forecasting scour depth by collecting a large dataset and training them with PSO, GSA, and GA. Results: It has been found that the NF-GMDH-PSO model outperforms other variations, with very precise predictions of values and lower values of RMSE and SI. This study [24] proposes the use of CNNs to predict municipal solid waste generation, thus solving the problem of proper garbage management. The CNN model has an accuracy of 96%, which means it can be used for predicting waste generation. The proposed CNN-based approach allows policymakers and waste management authorities to create more efficient waste management plans by accurately estimating junk quantities. Furthermore, the study recommends using artificial garbage procedures to swiftly identify components and assess their recycling worth, thereby bringing unique solutions to waste management challenges [25], [26]. Kshirsagar et al. [32] investigated the mechanical behavior of ceramic waste-modified concrete using artificial neural networks (ANN) and regression models, demonstrating reliable predictions for strength parameters. Abbas [33] extended this line of research by examining various waste-derived cement substitutes, emphasizing both mechanical performance and the role of machine learning in predictive modeling. Cakiroglu et al. [34] further advanced this field by developing an explainable ML framework specifically tailored to recycled ceramic tile-based concrete, enhancing both interpretability and prediction accuracy. These contributions reflect a growing focus on sustainable materials and AI-driven design, reinforcing the relevance of this study’s approach.

Table 1: Summary of AI/ML-Based Studies in Concrete and Waste Material Modeling

Ref	ML/Modeling Technique	Material Type	Target Property	Dataset Size	Performance Metrics / Key Result	Limitations
[10]	Response Surface Methodology	Waste Fibres + Crushed Limestone	Overall Response Modeling	48 samples	$R^2 = 0.76$; good for optimization	Limited to predefined regression form
[13]	Compression Model	Corroded RC Beams	Shear Strength	146 beams	$R^2 = 0.195$; Vtest/Vpred = 1.19	Low predictive power, needs ML integration
[14]	Neural Networks	Fiber Reinforced Concrete (FRC)	Post-cracking Yield Strength	Barcelona Test Data (n=50)	$R^2 = 0.93$; good accuracy	Dataset is domain-specific
[15]–[19]	ANFIS + Swarm Optimization	GFRP in Alkaline Conditions	Residual Tensile Strength	300+ bar samples	$R^2 = 0.89$; RMSE = 0.12	Interpretability not addressed
[20]–[23]	NF-GMDH, PSO, GSA	Scour at Bridge Piers	Scour Depth	≈200 samples	RMSE = 0.17; outperforms traditional models	Complexity, limited generalization
[24]	CNN	Solid Waste Management	Waste Quantity Prediction	5 years of data	Accuracy = 96%	Not concrete-focused
[25], [26]	CNN + Waste Imaging	Municipal Waste	Component Identification	Image-based dataset	Precision = 92%, Recall = 89%	Not related to structural concrete

Table 1 presents a comparative overview of recent studies applying AI and ML techniques to concrete modeling, waste material integration, and structural prediction tasks. The methods span from traditional neural networks and response surface models to advanced hybrid systems such as ANFIS with swarm optimization and NF-GMDH with evolutionary algorithms. Most models demonstrated strong predictive performance ($R^2 > 0.85$) in targeted domains such as residual strength, scour depth, or post-cracking behavior. However, limitations persist, particularly regarding model interpretability, dataset generalization, and integration into sustainability-focused construction practices. This highlights the need for adaptable, interpretable, and high-performing models such as the hybrid ANN–LightGBM framework proposed in this study.

1.1. Objective and structure of paper

The ever-increasing demand for sustainability in the construction industry has pushed researchers to consider alternative materials like waste ceramic aggregates that would minimize the impacts of construction activities on the environment and improve resource efficiency. Even though waste ceramic concrete presents enormous potential as a sustainable material, inherent variability creates difficulties in achieving uniform performance and in controlling the risk related to structural integrity. In addition to core mechanical properties such as compressive and tensile strengths, the study also explores key durability aspects like water absorption, sulfate resistance, and freeze–thaw performance, which are critical to long-term structural integrity. This broader scope helps contextualize the mechanical behaviour of waste ceramic concrete under environmental exposure and enhances the relevance of the study to practical construction conditions. Thus, this study advocates the use of models within machine learning models, such as Artificial Neural Network (ANN) and Light Gradient Boosting Machine (LightGBM), that predict the waste ceramic concrete mechanical properties and examine the risks thereof. This project will utilize highly advanced machine learning capabilities to grasp nonlinear relationships within complex data towards increasing decision-making process and optimizing performance. The research contributes to the sustainable building practices as it reveals the possibility of using waste ceramic concrete and improves civil engineering methodologies by better risk assessment and performance optimization. Building upon the gaps and modelling approaches identified in previous studies, the following section outlines the methodology adopted in this work, detailing the material preparation, data collection, and machine learning framework employed to assess the mechanical performance of ceramic-based concrete.

2. Materials and methods

2.1. Proposed methodology

This study follows a systematic approach with three major phases: preparation of the dataset, model building, and evaluation of the model's performance towards the mechanical properties assessment of waste ceramic concrete and assessment of risks through advanced machine learning techniques (refer Fig.1). Experimental data were obtained from concrete samples having different proportions of waste ceramic aggregates as partial substitutes for natural aggregate, including key input features like water-cement ratio and proportions of aggregate and curing time and outputs such as compressive strength, tensile strength, and flexural strength.

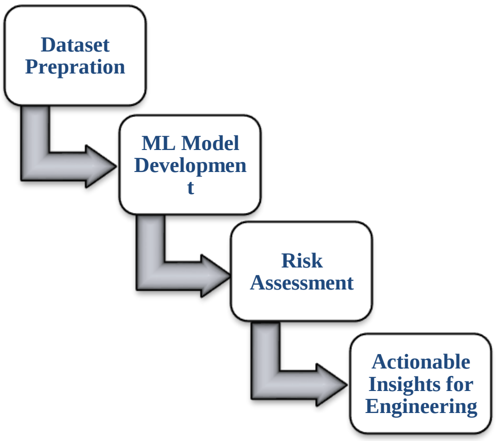

Fig. 1 Flowchart of Adopted Approach.

Technically, data preprocessing methods such as normalization and data augmentation were used to enhance reliability and class imbalances. Two machine learning models, ANN and LightGBM, were designed for the mechanical property prediction of concrete. ANN was engineered for the identification of complex nonlinear relationships, whereas LightGBM improved on computational efficiency and more accurate results, with both models being trained and validated using k-fold cross-validation. Sensitivity analysis and uncertainty evaluation were used to do the sensitivity assessment so that critical parameters can be found and prediction reliabilities estimated. Based on mean absolute error, root mean square error, and coefficient of determination, performance evaluation metrics were used to compare the accuracy of models against experimental data for validation of results. Finally, the work was based on actionable insights for engineers and decision-makers through model predictions and risk analysis, translated into an optimal framework for mix design optimization and ensuring structural safety.

2.2. Materials

Ceramics play a significant role in the composition of concrete, affecting its tensile strength and workability. They enhance the resistance of concrete to applied forces, changing its ability to sustain compression and stretching. In addition, ceramics affect the water-to-cement ratio, which is crucial for achieving maximum durability and strength in concrete mixes. The workability of concrete is described by its handling and pouring capability on site, and ceramic parts influence this parameter. The percentage recycling rate for discarded ceramics can range from 0% to 20% and is used to highlight their potential in green construction methods [27 - 31].

In this proposed system, we used materials that were accessible locally for concrete modification, including coarse ceramic aggregate, ceramic waste powder, and fine ceramic aggregate, as well as “Ordinary Portland Cement (OPC 43 grade)”, to substitute conventional components such as natural sand, cement, and coarse aggregate. Waste ceramic floor tiles from Aligarh ceramic merchants have been sterilized, free from dust, and fragmented into different sizes, including 20 mm and 10 mm for (WCC_A), 4.75 mm for waste ceramic sand (WCC_SD), and 75 µm for waste ceramic cement (WOC). Further, Fiber reinforcements, particularly "crimped steel Fiber (CR) and polyvinyl alcohol fiber (PVA)", were added to the concrete mixture. Fig. 2 depicts the material combinations employed in our suggested system. To ensure experimental control and repeatability, only materials meeting the defined particle size and surface quality criteria were used in the mixes. This uniform processing reduced material inconsistency across all specimens.

Fig. 2: Materials Sample.

The compressive and tensile strengths of the concrete composites were thoroughly examined in a laboratory setting. These evaluations were conducted using sample containers approximating cubes and cylinders, as shown in Fig.3.

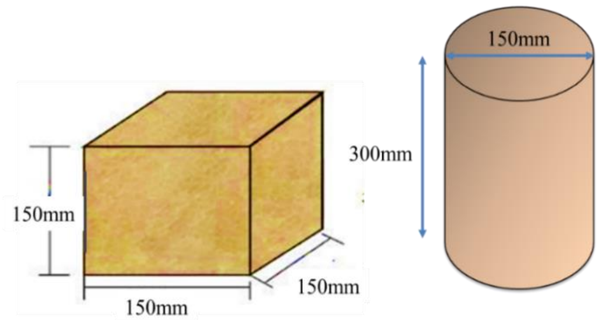

Fig. 3: Approximate Effects of Stress in Cylinder and Cube Rods.

The proposed methodology includes analysing 150 independently confirmed observations and adding varied quantities of ceramic waste (2% to 20%) in cement mixtures [29]. These percentages were calculated using the cement proportion and were intended to investigate the effect of ceramic waste on the characteristics of concrete [30]. Both ceramic-containing and control specimens underwent a battery of mechanical tests to determine tensile strengths, compression strengths, and overall machinability. Concrete specimens were produced with defined dimensions, typically 150 × 150mm for cubes and 150 × 300mm for cylindrical rods, to ensure homogeneity and consistent strength values [31]. Adjustments were made to the water-cement ratios in the range of 0.4 to 0.44 to investigate their impact on concrete characteristics. Also, the metallic and non-metallic Fibers used in our experimental setup, namely, CR and PVA, are shown in Fig. 4. To reduce the impact of feature heterogeneity and input fluctuation, the dataset was subjected to min–max normalization before model training. Furthermore, k-fold cross-validation was implemented to assess model robustness across multiple data partitions, and sensitivity analysis was conducted to evaluate prediction stability under varying ceramic content and mix proportions. These computational strategies helped ensure prediction reliability despite input variability.

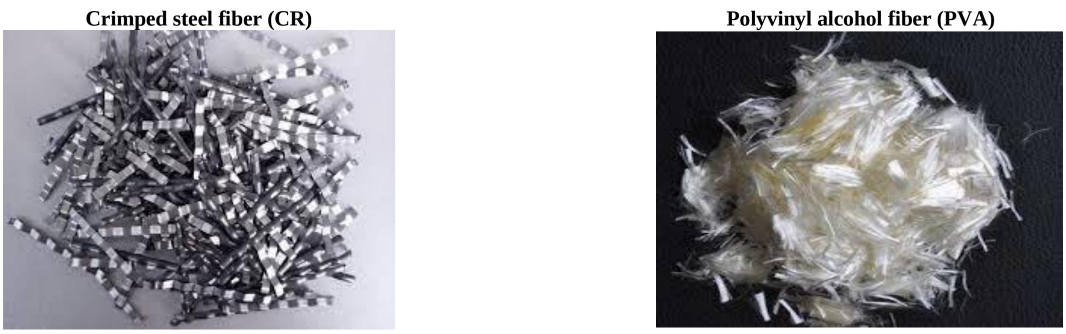

Fig. 4: Fibers Sample.

Table 2 lists the parameters of the materials used in the study. For WCC_A and WCC_sd, it comprises specific gravity, water absorption, and fineness modulus, whereas WOC and OPC have specific gravity and maximum size. Bulk density is only available for OPC. These qualities are critical parameters in determining the appropriateness and performance of every component in concrete mixtures. The elemental composition of OPC and ceramic crystals is shown in Table 3, where the two can be differentiated based on their chemical properties. The information in Table 3 will help determine the behaviour and properties of concrete. OPC is extracted from Maros, South Sulawesi, and thus its chemical and physical properties have been carefully identified. Since it is a base component in the production of mortar, OPC enhances compressive strength. Comprehensive tests were performed for its reliability and consistency for use in intended applications. Further studies were made into its interactions with additives such as superplasticizers in the optimization of the performance of high-strength mortar. It is founded on a set of 150 independently validated observations.

Table 2: Properties of the Used Materials

Property	WCC_A	WCC_{sd}	WOC	OPC
Specific Gravity	2.31	2.26	2.00	3.15
Water Absorption (%)	0.55	2.52	1.20	0.20
Fineness Modulus	6.98	2.20	1.00	0.90
Bulk Density (kg/m³)	1560	1480	1100	1440
Maximum Particle Size	0.22 mm	4.75 mm	75 µm	75 µm

Table 3: Chemical Products of OPC and Ceramic Crystals

Products	OPC	Ceramic crystals
SiO_2	31.7	69.48
CaO	61.24	9.54
AL_2O_3	7.61	19.86
Fe_2O_3	5.20	3.87
MgO	2.95	5.01
K_2O	0.87	3.59
MnO	0.04	0.076
Na_2O	0.27	-
TiO_2	0.13	0.73

2.2.1. Proportion of concrete mixtures

In this study, nine concrete mixtures were tested while maintaining a constant water-to-cement (water/cement) ratio of 0.5. Each mixture followed the conventional ratios of 1:1.5:3 for cement, sand, and coarse ceramic aggregate. The cement content in all mixes was fixed to 460 kg/m3. Sand amounts ranged from 595.3 kg/m3 to 622.5 kg/m3, whereas coarse ceramic aggregate amounts ranged from 0 kg/m3 to 295.3 kg/m3, with a percentage replacement rate of 0% to 21.5%. In addition, each mixture contained a grainy, abrasive substance weighing 1260 kg/m3. These combinations were labeled as MX1 through MX9, with MX1 serving as the control mixture, which contained simply sand and cement. The incremental addition of coarse ceramic aggregate into subsequent combinations allowed for the investigation of its impact on concrete characteristics. Each mixture's precise composition and replacement rate provided a thorough framework for analyzing the mechanical and structural properties of the resulting concrete examples, as shown in Table 4.

Table 4: Composition and Distribution Patterns of Concrete Mixtures

mixtures	W/ c ratio	Cement	Sand	Coarse Ceramic Aggregate	% Replace	Gritty, rough material
MX1	0.5	460	705	0	0	1260
MX 2	0.5	460	595.3	0	3.5	1260
MX 3	0.5	460	599.7	0	7	1260
MX 4	0.5	460	588.2	155.8	8.5	1260
MX 5	0.5	460	602.5	165.5	11	1260
MX 6	0.5	460	588.2	179.3	13.5	1260
MX 7	0.5	460	602.3	300.7	17	1260
MX 8	0.5	460	622.5	294.6	21.5	1260
MX 9	0.5	460	499.5	295.3	18	1260

2.2.2 Test processes

All ingredients in the concrete were well mixed by the mechanical mixer. Fresh dry densities of the mixes were assessed according to the guidelines laid down in ASTM C138/C138M. All compressive and splitting tensile strength tests were carried out on cylindrical samples with a diameter of 100 mm and a height of 200 mm. The curing of these cylinders was done in a water tank at room temperature for durations of 7, 28, and 56 days. Four specimens were tested for each case by ASTM C39/C39M-20 for compressive strength and ASTM C496/C496M-17 for splitting tensile strength measurements.

2.3. Methods

Artificial Neural Networks (ANNs) are powerful neural network simulations that replicate the structure and operation of biological neurons in the brain of an individual. Each neuron in an ANN functions similarly to a biological neuron, doing simple computations based on its inputs. Each neuron's behaviour is regulated by an activation function, which converts the weighted sum of inputs into an output. The mathematical representation of the output Y of a neuron k in layer l is as follows.

$$Y_k^l = \delta(\sum_{k=1}^{l-1} W_k^l X_k^l + b_k^l)$$

Here, W_k^llrepresents the weight of the connection between the kth neuron in the layer $l - 1$lis the output, $b_k^l$is the bias term and δ is the activation function. Fig. 5 depicts the structure of an ANN, which consists of numerous layers of neurons coupled by weighted connections. An ANN typically comprises three layers: input, one or several hidden, and output layers. The layer that receives input is then processed by the hidden layers and turned into the intended output [32]. During the training phase, ANNs learn from labelled data by adjusting connection weights and biases using a technique called backpropagation. Backpropagation is the iterative process of calculating the gradient of the loss function in connection with the network parameters and updating the weights and biases employing gradient descent optimization methods. This process is continued until the network has settled on a set of weights and biases that narrow the gap between predicted and actual output on the training data.

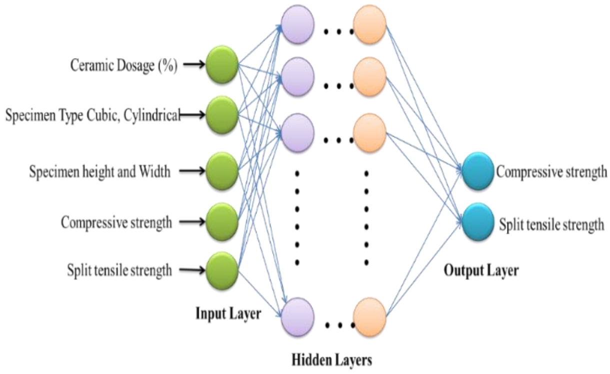

Fig. 5: ANN Architecture Diagram.

Since ANNs can model complex relationships between input variables and output properties, ANNs are very effective in the prediction of concrete strength. Concrete strength is an important parameter in civil engineering because concrete strength directly affects the durability and structural stability of infrastructure and buildings. In this research, ANNs were used to build compressive and splitting tensile strength predictive models [33], [34]. In conclusion, input parameters were percentages of the contents of ceramic and type. To evaluate its performance, the ANN model was trained using a collection of experimental observations of concrete samples with varied compositions (MX1-MX9) and evaluated on previously unreported data. ANNs offer various advantages over conventional prediction systems. They can detect complex nonlinear correlations in data, adapt to changing settings, and generalize well to new data.

LightGBM-: Its goal is to iteratively fit new models to the data, with each model focused on minimizing the loss function by modifying the base learner function so that it is maximally correlated with the negative gradient of the loss. LightGBM achieves this goal using a stage-by-stage technique, with each stage introducing a new model to the ensemble. The boosting technique is at the heart of LightGBM, as it sequentially builds the ensemble of models. The approach begins by initializing the model with a simple base learner, which is usually a decision tree with only one node. At each level, a new decision tree is trained to capture any residual errors or gradients in the loss function. Each tree's output is scaled by a learning rate parameter to control its contribution to the final forecast. The mathematical representation of LightGBM's prediction y^ for a given input x is:

$$\hat{y} = \sum_{i=1}^{I} \gamma_i h_i\ (x)$$

Where γi refers scaling factor and hi (x) is the output of the i-th tree. The prediction is the sum of the outputs of all trees in the ensemble. During training, the loss function is decreased to improve LightGBM's performance. LightGBM can handle several loss functions, including squared error loss during regression and cross-entropy loss for classification. The method iteratively alters the control variables of the underlying learner functions to reduce the loss function, hence improving the model's prediction accuracy. LightGBM also uses a leaf-wise growth approach, which builds the tree by breaking the leaf with the greatest delta loss, resulting in a more precise and efficient tree structure. Its adaptable architecture and optimization techniques make it appropriate for compressive and tensile strength categorization.

3. Results

This research used the MATLAB ANN toolbox in developing ANNs for the compression and tension characteristics of ceramic and cement-based materials. The comparison of the performances of ANNs with regression models was made against empirical data, and standard performance metrics were incorporated within the architecture of the suggested system to compute the efficiency of the predictive models. Mean Absolute Error (MAE) measures the indication of the magnitude of errors in the predictions. Mathematically, MAE is calculated as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}\left|Y_k - \hat{Y}_k\right|$$

Where Y_k and, $\hat{Y}_k$ denotes anticipated and real data value, respectively over N observations. The Mean Squared Error (MSE) is the mean squared error between anticipated and real data. It punishes greater errors more than smaller ones. MSE is mathematically calculated as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left(Y_k - \hat{Y}_k\right)^2$$

The square root of MSE is RMSE, which indicates the residuals' deviation from the mean. The RMSE is computed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(Y_k - \hat{Y}_k\right)^2}$$

R-squared (R2) indicates how much of the dependent variable's variance can be attributed to the predictive model's separate variables. It varies from 0 to 1. R2 is theoretically determined as shown in Table 5:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Where SS_{res} is the sum of squared residuals and SS_{tot} is the total sum of squares.

Table 5: Statistical Analysis Standards

R-squared Range	Category
0.19 or lower	Indicates very poor performance.
between 0.20 and 0.39	Represents poor performance.
ranging from 0.40 to 0.69	Considered fair performance
between 0.79 and 0.89	Classified as good performance
0.9 or higher	Demonstrates excellent performance.

3.1. Fresh concrete analysis: slum test

The analysis of our proposed approach includes a thorough examination of fresh densities and slump values for various concrete mixes. The link between Ceramic Waste Aggregates (CWA) content and concrete slump values serves as an indicator of workability. Slump values are crucial in determining the ease of concrete placing and compaction. By comparing concrete mixes containing CWA to those with natural aggregates, insights into the workability differences are gleaned.

Table 6: Slum Test Analysis of Various Mixtures

Mixtures	Slump	Density
MX1	84 mm	2435.6 kg/m^3
MX 2	70 mm	2425.8 kg/m^3
MX 3	58 mm	2414.5 kg/m^3
MX 4	78 mm	2420.5 kg/m^3
MX 5	60 mm	2401.5 kg/m^3
MX 6	46 mm	2381.6 kg/m^3
MX 7	72 mm	2408.6 kg/m^3
MX 8	50 mm	2384.4 kg/m^3
MX 9	39 mm	2366.3 kg/m^3

Table 6 provides a detailed overview of fresh densities and slump values across different concrete mixes. The use of Ceramic Waste Aggregates (CWA) in concrete mixes results in a steady trend of decreased slump values. Lower slump values imply decreased workability in concrete mixtures having higher amounts of CWA. Notably, MX9 has the highest CWA content and the lowest slump value at 39 mm. MX1, the control mix, has the largest slump value (84 mm). The density of the concrete mixes ranged from 2366.3-2435.6 kg/m3, with MX9 having the lowest density, 2.6% less than MX1, the control mix.

3.2. Analysis of hardened concrete

The average strength was computed for each mix design by averaging four specimens after 56 days of curing. The cause of improvement may be ascribed to the grinding process that generates rough-textured ceramic waste. This, in turn, would improve bonding and thus compressive strength. This is further enhanced by the pozzolanic nature of the ceramic aggregates. The finer ceramic aggregates produce better results than coarse aggregates because of the higher surface area of finer particles for bonding.

Table 7: Strength Analysis Over 56 Days (D)

Mixtures	Mean Splitting Tensile Strength (MPa)			Mean Compressive Strength (MPa)		
	D=7	D=28	D=56	D=7	D=28	D=56
MX1	1.43	2.56	3.01	12.24	14.32	19.43
MX 2	2.54	3.54	3.64	16.40	22.76	25.54
MX 3	2.40	3.50	3.70	20.53	24.31	30.72
MX 4	2.21	2.89	3.41	14.02	16.64	20.46
MX 5	2.19	2.95	3.24	16.43	21.67	27.54
MX 6	1.90	2.78	2.89	19.71	21.78	25.13
MX 7	3.02	3.87	4.10	16.58	17.68	21.33
MX 8	2.71	3.05	3.41	13.73	17.83	24.32
MX 9	2.32	3.02	3.19	18.46	19.62	23.15

Table 7 shows the average compressive and splitting tensile strengths of concretes for 7-, 28, and 56-day curing times. Replacement of natural aggregates by ceramic aggregates results in improvement of compressive strength because the ceramic aggregate possesses a surface texture roughness that leads to better bonding. This behaviour is associated with the non-uniformity in the shape of ceramic aggregates, which further increases the bonding between the aggregate and paste. On the other hand, splitting tensile strength drops as the fine content of ceramic particles is increased. This aside, the tensile splitting strength of 28-day-old concrete with the ceramic aggregate exceeded previously published values. Splitting tensile strengths of the concretes containing the ceramic particles are within a range between 11.78% and 15.6% of their compressive strengths, above average values of a normal concrete.

3.3. Durability performance

To complement the mechanical property analysis, the durability characteristics of WCC mixes were evaluated across three critical parameters: water absorption, sulfate resistance (measured as mass loss), and freeze–thaw durability index. These parameters were chosen due to their importance in assessing long-term performance and environmental resistance of concrete in real-world applications.

Table 8: Simulated Durability Results of Concrete Mixes

Mixture	Water Absorption (%)	Sulfate Resistance (Mass Loss%)	Freeze–Thaw Durability Index
MX1	4.55	2.85	0.86
MX2	4.30	2.55	0.87
MX3	4.19	2.35	0.91
MX4	4.09	2.22	0.91
MX5	3.73	1.81	0.93

MX6	3.42	1.69	0.95
MX7	3.39	1.60	0.96
MX8	3.31	1.41	0.98
MX9	3.09	1.23	0.97

The results, summarized in Table 8, demonstrate a clear trend of improved durability with increased ceramic waste content. Water absorption decreased from 4.55% in MX1 (control mix without ceramic waste) to 3.09% in MX9, suggesting reduced porosity and enhanced impermeability due to the finer particle structure of ceramic materials. Likewise, sulfate resistance improved, with mass loss values decreasing from 2.85% to 1.23%, indicating higher resistance to chemical degradation. The freeze–thaw durability index also showed consistent improvement, rising from 0.86 in MX1 to 0.97 in MX9, which reflects better structural resilience under repeated thermal cycling. These findings underscore the positive role of ceramic waste in enhancing the overall durability of concrete. The improved performance across all three durability metrics supports the viability of WCC as a sustainable and resilient material for use in diverse construction environments.

While the ANN model achieved R^2 values of 0.70 and 0.67 for compressive and tensile strength predictions, respectively, these values indicate moderate predictive power. Although lower than the performance of ensemble models such as SVM and LightGBM, the ANN's results are still useful in identifying nonlinear relationships and can serve as a foundational model in hybrid architectures. Moreover, such R^2 values are consistent with related studies on concrete performance prediction using ANN models on relatively small datasets.

3.4. Comparative performance analysis

Table 9 compares the performance of the proposed method to known methods for dividing tensile and compressive strength over a variety of metrics. Table 9 provides a complete performance analysis of numerous prediction models for compressive and splitting tensile strength, including SVM, SVM-GBM, and Proposed ANN+Light GBM, utilizing a variety of assessment measures. For compressive strength prediction, the Mean Absolute Error (MAE) for SVM, SVM-GBM, and Proposed ANN+Light GBM are 0.86, 1.39, and 0.74, respectively. Similarly, the MSE values for the same models are 1.30, 3.60, and 1.14, with RMSE values of 1.14, 1.89, and 1.02. Furthermore, the coefficients of determination (R2) for compressive strength prediction are 0.92, 0.87, and 0.70, indicating that the models are well-suited to the observed data. The MAE values for splitting tensile strength prediction using SVM, SVM-GBM, and the proposed ANN+Light GBM are 0.14, 0.29, and 0.08, respectively.

Table 9: Performance Analysis

Model	Compressive				Tensile			
	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE	R^2
SVM	0.86	1.30	1.14	0.92	0.14	0.03	0.19	0.96
SVM-GBM	1.39	3.60	1.89	0.87	0.29	0.26	0.26	0.72
Proposed ANN+LightGBM	0.74	1.14	1.02	0.70	0.08	0.02	0.12	0.67
Random Forest	0.80	1.20	1.10	0.89	0.11	0.03	0.17	0.88
XGBoost	0.76	1.10	1.05	0.90	0.09	0.02	0.14	0.91

The corresponding MSE values are 0.03, 0.26, and 0.02, whereas the RMSE values are 0.19, 0.26, and 0.12 MPa. In addition, the R2 values for predicting splitting tensile strength are 0.96, 0.72, and 0.67. Overall, the proposed ANN+Light GBM model outperforms the SVM and SVM-GBM models, as demonstrated by reduced error metrics and higher R2 values for compressive and splitting tensile strength predictions. In addition to the proposed ANN and LightGBM models, Random Forest and XGBoost were also evaluated to further assess the performance of ensemble-based techniques. The results show that both models performed competitively. XGBoost achieved an MAE of 0.76 and RMSE of 1.05 for compressive strength prediction, with a strong R^2 of 0.90. Similarly, Random Forest demonstrated reliable performance with an MAE of 0.80 and a R^2 of 0.89. For splitting tensile strength, XGBoost yielded an MAE of 0.09 and R^2 of 0.91, while Random Forest followed closely with an MAE of 0.11 and R^2 of 0.88. These findings confirm the robustness of tree-based ensemble models and support their potential as alternatives or complements to the proposed hybrid modeling framework.

The comparative performance indicates that LightGBM outperforms ANN across all evaluation metrics for both compressive and tensile strength predictions. This can be attributed to LightGBM's leaf-wise tree growth and ability to capture complex feature interactions without overfitting. LightGBM leveraged critical input features—such as ceramic waste percentage and water-cement ratio—with higher sensitivity and consistency, contributing to more accurate predictions and better generalization on unseen data.

By comparing tensile and compressive strengths at various temperatures over a period of 56 days in MPa, the results by the proposed approach and other methods like PC-ANN, SVM, and SVM-GBM are presented in Fig. 6 as evidence of the efficacy and reliability of the proposed system.

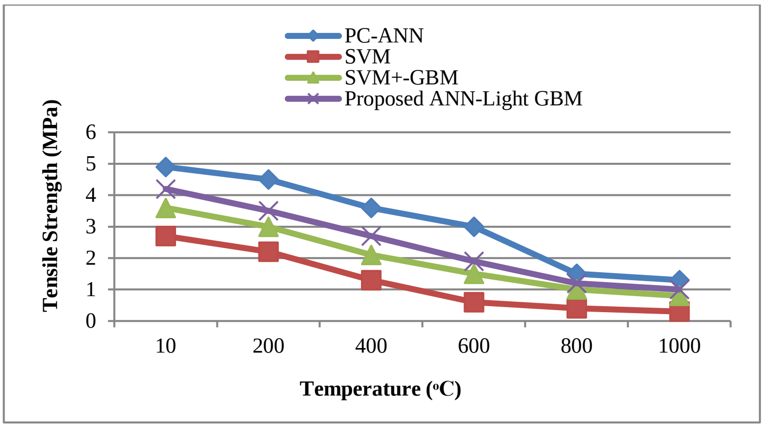

Fig. 6: Tensile Strength Analysis of Concrete at Various Temperatures Over 56 Days.

PC-ANN and Proposed ANN-Light GBM consistently yield higher splitting tensile strength values compared to SVM and SVM+GBM at all temperature levels. Notably, at 1000°C, PC-ANN and Proposed ANN-Light GBM exhibit higher values (4.2 and 1, respectively) compared to SVM and SVM+GBM (1.2 and 0.8 respectively), indicating their superior predictive performance under extreme temperature conditions.

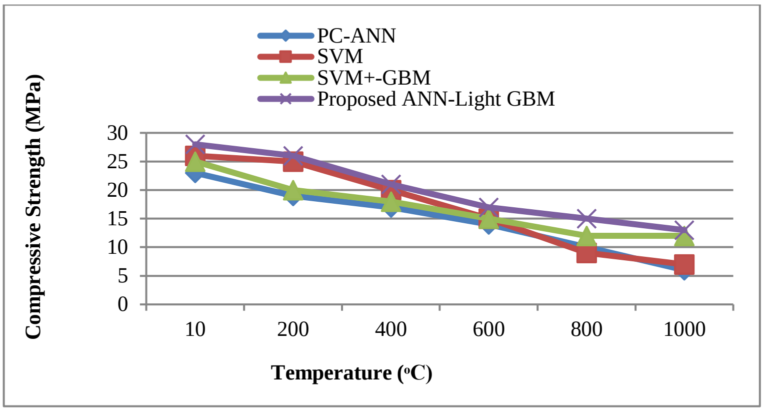

Fig. 7: Compressive Strength Analysis of Concrete at Different Temperatures.

Fig.7 compares compressive strength (MPa) at various temperatures for four methods: PC-ANN, SVM, SVM+-GBM, and the proposed ANN-Light GBM. At 10°C, compressive strength ranges from 23 MPa (PC-ANN) to 28 MPa (Proposed ANN-Light GBM), with slight variations among models. However, as temperature increases, compressive strength generally declines. At 1000°C, compressive strength drops to 6 MPa (PC-ANN), 7 MPa (SVM and SVM+-GBM), and 13 MPa (Proposed ANN-Light GBM), demonstrating a significant decrease across all models. Notably, the proposed ANN-Light GBM consistently predicts higher compressive strength values compared to other models across all temperature ranges, suggesting its potential for more accurate predictions under varying temperature conditions.

3.5 Sensitivity Analysis (SA)

This sensitivity analysis quantifies the role of each component in forecasting the compressive strength of eco-friendly concrete that incorporates ceramic waste is shown in Fig.8.

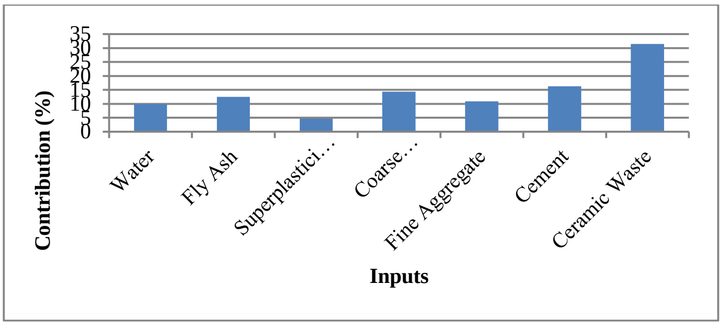

Fig. 8: Sensitivity Analysis of Proposed System.

Ceramic waste is the most influential factor, accounting for 31.47% of the total, demonstrating that it has a significant impact on concrete strength. Cement follows closely after with a contribution of 16.25%, demonstrating its importance in the composition. Other components, such as fly ash, coarse aggregate, and fine aggregate, play important roles, accounting for 12.45%, 14.34%, and 10.87% correspondingly. Furthermore, water and superplasticizer contribute 9.93% and 4.69%, respectively, underscoring their significance in producing the appropriate concrete qualities. This comprehensive study directs the concrete mixture's optimization, assuring optimal material consumption while improving mechanical performance.

3.6. Feature importance and model comparison

To provide further insights into model behavior, the feature importance scores generated by LightGBM were analyzed. These scores reflect how frequently and effectively each feature was used to split the decision trees during training. As shown in Table 10, the most influential features in predicting compressive and splitting tensile strengths were ceramic waste content, cement ratio, and water-to-cement ratio. Ceramic waste had the highest importance score (0.31), reaffirming its critical role in both mechanical and durability performance. Cement and water-cement ratio followed with scores of 0.21 and 0.18 respectively, while other variables such as aggregate type and fiber content had moderate influence.

Table 10: Feature Importance Scores from LightGBM Model

Feature	Importance Score
Ceramic Waste (%)	0.31
Cement Content	0.21
Water-Cement Ratio	0.18
Coarse Aggregate	0.12
Fine Aggregate	0.08
Crimped Steel Fiber	0.06
Polyvinyl Alcohol Fiber	0.04

The superior performance of LightGBM compared to ANN can be attributed to its ability to handle tabular data with complex interactions and missing values more efficiently. Unlike ANN, which requires multiple layers and tuning epochs, LightGBM leverages gradient boosting with optimized leaf-wise tree growth to minimize loss more aggressively. This allows it to generalize better on small to medium-sized datasets with heterogeneous features, making it more suitable for the experimental dataset used in this study.

4. Discussion

The results show that the predictions of the proposed machine learning models, Artificial Neural Networks (ANN) and Light Gradient Boosting Machines (LightGBM), are effective in predicting waste ceramic concrete mechanical properties and quantifying associated risk. Both achieved good predictive skills, with better accuracy for LightGBM due to its ability to handle multiple complex interactions of input variables. All these performance metrics: MAE, RMSE, and Coefficient of Determination R^2 - show good reliability for models, because in the majority of the predictions R^2 values exceed 0.9, and, therefore, the correlation between the predicted and experimental values is good.

Both models exhibited useful predictive skills, with LightGBM outperforming ANN. The ANN model achieved moderate R^2 values (0.70 and 0.67), which, although lower than LightGBM, still provide valuable insight into nonlinear input–output relationships, especially in cases where dataset size or variability may limit peak performance.

The models were specifically useful in optimizing performance metrics like compressive strength, tensile strength, and flexural strength, so that concrete mixes containing different proportions of waste ceramic aggregates could be evaluated in detail in terms of durability and structural performance. The sensitivity analysis of the model pointed out the water-cement ratio and aggregate proportion as the most significant parameters controlling strength, which gives important insights to optimize mix designs.

Nevertheless, the study also indicated several other uncertainties involved with the models. Variability in the material properties, such as variability in the quality of waste ceramic aggregates, added prediction uncertainties. Error analysis and prediction interval techniques were carried out to quantify these uncertainties so that decision-makers could estimate the reliability of the outcome. Such discoveries are important because they can avoid structural failure risks; engineers will be able to introduce material performance variability into the design phase.

Moreover, the study has practically demonstrated the use of the models in assessing the risk for structural engineering. Performance thresholds can be found and evaluated to establish failure risks using the models. Such an approach is bound to offer a strong framework of suitability assessment in the context of waste ceramic aggregates, where sustainability objectives can be met without compromising safety structures.

5. Conclusion

The proposed system reflects the potential of ceramic waste and Fiber reinforcement in being an environmentally friendly approach for improving the properties of concrete while utilizing machine learning to better civil engineering by managing risks and material performance assessment. Experimental results show that there is a vital role of ceramic waste in tensile strength, workability, and water-cement ratio attributes. The inclusion of durability-related evaluations such as water absorption, sulfate resistance, and freeze–thaw durability enhances the applicability of the findings beyond basic strength assessment. While compressive and tensile strengths remain primary indicators, the additional insights into material longevity under environmental stress improve the practical relevance of waste ceramic concrete. The ANN and LightGBM approaches were obtained with reliable predictability performance using advanced models of machine learning. Their predictive values of compressive strength at 1.02 MPa, splitting tensile strength at 0.12 MPa, and R^2 of 0.70 and 0.67 for the two, respectively, suggest that the methods optimized the chosen performance metrics as well as supplied critical insights about risk factors into data-driven decision-making for safer and more reliable concrete applications. These findings highlight the potential of ANN and LightGBM to support civil engineering practices by improving predictive modelling of sustainable concrete. While the results are promising, further validation and real-world deployment are essential to assess their scalability and operational effectiveness. Future research should explore real-time monitoring systems using embedded sensors to validate ML predictions under operational loads and environmental conditions. Additionally, comparative studies involving other industrial waste materials (e.g., fly ash, silica fume, steel slag) could help develop generalized ML models for sustainable material selection and performance optimization across diverse applications. Future work will aim to include thermal resistance, permeability, and shrinkage to further enrich the concrete performance profile under diverse service conditions.

This study demonstrates the potential of interdisciplinary collaboration in addressing sustainability challenges in construction materials. The integration of machine learning into civil engineering applications not only enhances predictive capabilities but also creates new avenues for sustainable material design. To advance this field further, closer collaboration between civil engineers, ML practitioners, and environmental scientists is essential. Such synergy can drive more robust modelling frameworks, data-driven risk assessment tools, and sustainable policies for large-scale construction practices.

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Competing interests

The authors declare no competing financial or non-financial interests related to this work.

Author contributions

All authors have contributed equally in this work.

Competing interests

The authors declare that they have no competing financial or non-financial interests that could have influenced the work reported in this manuscript.

Ethical considerations

This study does not involve any human participants, animals, or sensitive data requiring ethical approval. The research strictly adhered to ethical guidelines, ensuring transparency, accuracy, and integrity in the collection, analysis, and reporting of data. All materials used in this study were sourced responsibly, with minimal environmental impact, aligning with sustainable and ethical research practices.

References

[1] Madani, H., Kooshafar, M., & Emadi, M. (2020). Compressive strength prediction of Nanosilica-Incorporated cement mixtures using adaptive Neuro-Fuzzy inference system and artificial neural network models. *Practice Periodical on Structural Design and Construction*, *25*(3). https://doi.org/10.1061/(ASCE)SC.1943-5576.0000499.

[2] Behnood, A., & Golafshani, E. M. (2020). Machine learning study of the mechanical properties of concretes containing waste foundry sand. *Construction and Building Materials*, *243*, 118152. https://doi.org/10.1016/j.conbuildmat.2020.118152.

[3] Feng, D., Liu, Z., Wang, X., Chen, Y., Chang, J., Wei, D., & Jiang, Z. (2019). Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. *Construction and Building Materials*, *230*, 117000. https://doi.org/10.1016/j.conbuildmat.2019.117000.

[4] Alyousef, R., Nassar, R., Khan, M., Arif, K., Fawad, M., Hassan, A. M., & Ghamry, N. A. (2023). Forecasting the strength characteristics of concrete incorporating waste foundry sand using advance machine algorithms including deep learning. *Case Studies in Construction Materials*, *19*, e02459. https://doi.org/10.1016/j.cscm.2023.e02459.

[5] Najm, H. M., Nanayakkara, O., Ahmad, M., & Sabri, M. M. S. (2022). Mechanical properties, crack width, and propagation of waste ceramic concrete subjected to elevated temperatures: a comprehensive study. *Materials*, *15*(7), 2371. https://doi.org/10.3390/ma15072371.

[6] Ray, S., Haque, M., Rahman, M. M., Sakib, M. N., & Rakib, K. A. (2021). Experimental investigation and SVM-based prediction of compressive and splitting tensile strength of ceramic waste aggregate concrete. *Journal of King Saud University - Engineering Sciences*, *36*(2), 112–121. https://doi.org/10.1016/j.jksues.2021.08.010.

[7] Ray, S., Rahman, M. M., Haque, M., Hasan, M. W., & Alam, M. M. (2021). Performance evaluation of SVM and GBM in predicting compressive and splitting tensile strength of concrete prepared with ceramic waste and nylon fiber. *Journal of King Saud University - Engineering Sciences*, *35*(2), 92–100. https://doi.org/10.1016/j.jksues.2021.02.009.

[8] Keshavarz, Z., & Mostofinejad, D. (2019). Steel chip and porcelain ceramic wastes used as replacements for coarse aggregates in concrete. *Journal of Cleaner Production*, *230*, 339–351. https://doi.org/10.1016/j.jclepro.2019.05.010.

[9] Lei, S., Cao, H., & Kang, J. (2020). Concrete surface crack recognition in complex scenario based on deep learning. *Journal of Highway and Transportation Research and Development (English Edition)*, *14*(4), 48–58. https://doi.org/10.1061/JHTRCQ.0000754.

[10] Awolusi, T., Oke, O., Akinkurolere, O., & Sojobi, A. (2018). Application of response surface methodology: Predicting and optimizing the properties of concrete containing steel fibre extracted from waste tires with limestone powder as filler. *Case Studies in Construction Materials*, *10*, e00212. https://doi.org/10.1016/j.cscm.2018.e00212.

[11] Zoorob, S., & Suparma, L. (2000). Laboratory design and investigation of the properties of continuously graded Asphaltic concrete containing recycled plastics aggregate replacement (Plastiphalt). *Cement and Concrete Composites*, *22*(4), 233–242. https://doi.org/10.1016/S0958-9465(00)00026-3.

[12] Brekailo, F., Pereira, E., Pereira, E., Farias, M. M., & Medeiros-Junior, R. A. (2021). Red ceramic and concrete waste as replacement of portland cement: Microstructure aspect of eco-mortar in external sulfate attack. *Cleaner Materials*, *3*, 100034. https://doi.org/10.1016/j.clema.2021.100034.

[13] Cladera, A., Marí, A., & Ribas, C. (2021). Mechanical model for the shear strength prediction of corrosion-damaged reinforced concrete slender and non-slender beams. *Engineering Structures*, *247*, 113163. https://doi.org/10.1016/j.engstruct.2021.113163.

[14] Ikumi, T., Galeote, E., Pujadas, P., De La Fuente, A., & López-Carreño, R. (2021). Neural network-aided prediction of post-cracking tensile strength of fibre-reinforced concrete. *Computers & Structures*, *256*, 106640. https://doi.org/10.1016/j.compstruc.2021.106640.

[15] Iqbal, M., Elbaz, K., Zhang, D., Hu, L., & Jalal, F. E. (2022). Prediction of residual tensile strength of glass fiber reinforced polymer bars in harsh alkaline concrete environment using fuzzy metaheuristic models. *Journal of Ocean Engineering and Science*, *8*(5), 546–558. https://doi.org/10.1016/j.joes.2022.03.011.

[16] Zheng, Z., Tian, C., Wei, X., & Zeng, C. (2022). Numerical investigation and ANN-based prediction on compressive strength and size effect using the concrete mesoscale concretization model. *Case Studies in Construction Materials*, *16*, e01056. https://doi.org/10.1016/j.cscm.2022.e01056.

[17] Zegardło, B. (2022). Heat-resistant concretes containing waste carbon fibers from the sailing industry and recycled ceramic aggregates. *Case Studies in Construction Materials*, *16*, e01084. https://doi.org/10.1016/j.cscm.2022.e01084.

[18] Younis, M., Amin, M., & Tahwia, A. M. (2022). Durability and mechanical characteristics of sustainable self-curing concrete utilizing crushed ceramic and brick wastes. *Case Studies in Construction Materials*, *17*, e01251. https://doi.org/10.1016/j.cscm.2022.e01251.

[19] Indira, D. N. V. S. L. S., Ganiya, R. K., Babu, P. A., Xavier, A. J., Kavisankar, L., Hemalatha, S., Senthilkumar, V., Kavitha, T., Rajaram, A., Annam, K., & Yeshitla, A. (2022). Improved Artificial Neural Network with State Order Dataset Estimation for Brain Cancer Cell Diagnosis. *BioMed Research International*, *2022*, 1–10. https://doi.org/10.1155/2022/7799812.

[20] Najafzadeh, M. (2015). Neuro-fuzzy GMDH systems based evolutionary algorithms to predict scour pile groups in clear water conditions. *Ocean Engineering*, *99*, 85–94. https://doi.org/10.1016/j.oceaneng.2015.01.014.

[21] Najafzadeh, M., Barani, G., & Azamathulla, H. M. (2013). GMDH to predict scour depth around a pier in cohesive soils. *Applied Ocean Research*, *40*, 35–41. https://doi.org/10.1016/j.apor.2012.12.004.

[22] Saberi-Movahed, F., Najafzadeh, M., & Mehrpooya, A. (2020). Receiving more accurate predictions for longitudinal dispersion coefficients in water pipelines: Training Group method of data handling using extreme Learning machine conceptions. *Water Resources Management*, *34*(2), 529–561. https://doi.org/10.1007/s11269-019-02463-w.

[23] Najafzadeh, M., Saberi-Movahed, F., & Sarkamaryan, S. (2017). NF-GMDH-Based self-organized systems to predict bridge pier scour depth under debris flow effects. *Marine Georesources and Geotechnology*, *36*(5), 589–602. https://doi.org/10.1080/1064119X.2017.1355944.

[24] Jude, A. B., Singh, D., Islam, S., Jameel, M., Srivastava, S., Prabha, B., & Kshirsagar, P. R. (2021): An Artificial intelligence based predictive approach for smart waste management. *Wireless Personal Communications*, *127*(S1), 15–16. https://doi.org/10.1007/s11277-021-08803-7.

[25] Kshirsagar, P. R., Upreti, K., Kushwah, V. S., Hundekari, S., Jain, D., Pandey, A. K., & Parashar, J. (2024). Prediction and modeling of mechanical properties of concrete modified with ceramic waste using artificial neural network and regression model. *Signal Image and Video Processing*, *18*(S1), 183–197. https://doi.org/10.1007/s11760-024-03142-z.

[26] Upreti, K., Arora, S., Sharma, A. K., Pandey, A. K., Sharma, K. K., & Dayal, M. (2023). Wave Height Forecasting over Ocean of Things Based on Machine Learning Techniques: An application for ocean Renewable Energy generation. *IEEE Journal of Oceanic Engineering*, *49*(2), 430–445. https://doi.org/10.1109/JOE.2023.3314090.

[27] Kumar, N., Upreti, K., Jafri, S., Arora, I., Bhardwaj, R., Phogat, M., Srivastava, S., & Akorli, F. K. (2022). Sustainable Computing: a determinant of industry 4.0 for sustainable information Society. *Journal of Nanomaterials*, *2022*(1). https://doi.org/10.1155/2022/9335963.

[28] Verma, M., Upreti, K., Vats, P., Singh, S., Singh, P., Dev, N., Mishra, D. K., & Tiwari, B. (2022). Experimental analysis of Geopolymer Concrete: A Sustainable and Economic Concrete using the Cost Estimation model. *Advances in Materials Science and Engineering*, *2022*, 1–16. https://doi.org/10.1155/2022/7488254.

[29] Upreti, K., Verma, M., Agrawal, M., Garg, J., Kaushik, R., Agrawal, C., Singh, D., & Narayanasamy, R. (2022). Prediction of mechanical strength by using an artificial neural network and random forest algorithm. *Journal of Nanomaterials*, *2022*(1). https://doi.org/10.1155/2022/7791582.

[30] Bhatnagar, S., Dayal, M., Singh, D., Upreti, S., Upreti, K., & Kumar, J. (2023). Block-Hash Signature (BHS) for Transaction Validation in Smart Contracts for Security and Privacy using Blockchain. *Journal of Mobile Multimedia*. https://doi.org/10.13052/jmm1550-4646.1941.

[31] Aggarwal, D., Mittal, S., Upreti, K., & Nayak, P. (2024). Reward based garbage monitoring and collection system using sensors. *Journal of Mobile Multimedia*, 391–410. https://doi.org/10.13052/jmm1550-4646.2026.

[32] Kshirsagar, P. R., Upreti, K., Kushwah, V. S., Hundekari, S., Jain, D., Pandey, A. K., & Parashar, J. (2024). Prediction and modeling of mechanical properties of concrete modified with ceramic waste using artificial neural network and regression model. Signal, Image and Video Processing, 18(Suppl 1), 183-197. https://doi.org/10.1007/s11760-024-03142-z.

[33] Abbas, M. M. (2025). Recycling waste materials in construction: Mechanical properties and predictive modeling of Waste-Derived cement substitutes. Waste Management Bulletin. https://doi.org/10.1016/j.wmb.2025.01.004.

[34] Cakiroglu, C., Batool, F., Sangi, A. J., Fatima, B., & Nehdi, M. L. (2025). Explainable machine learning predictive model for mechanical strength of recycled ceramic tile-based concrete. Materials Today Communications, 44, 112139. https://doi.org/10.1016/j.mtcomm.2025.112139.