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ORIGINAL PAPER

Prediction and modeling of mechanical properties of concrete modified with ceramic waste using artificial neural network and regression model

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Abstract
Over two centuries, concrete has been crucial to building. Thus, eco-friendly concrete is being developed. Emulating these tangible traits has recently gained popularity. Ceramic waste concrete's mechanical properties were modeled in this study. Ceramic waste percentages ranged from 5 to 20%. Compressive and tensile concrete strengths were modeled. To predict concrete hardness, regression modeling and artificial neural network (ANN) were used. Model performance was evaluated using prediction coefficients and root-mean-square error (RMSE). ANN models outperformed linear prediction with a coefficient for determination (R^2) of 0.97. ANN models achieved root-mean-square errors (RMSEs) of 1.22 MPa, 1.21 MPa, and 1.022 MPa after 7, 14, and 28 days of retraining, respectively. Linear regression model showed RMSE values of 1.21, 1.32, and 1.27 MPa at 7, 14, and 28 days, respectively. In determining the compressive and tensile strength, the R^2 was 0.70, meanwhile the ANN model achieved 0.87. Given its accuracy in predicting the strength qualities of ceramics cement and structural stiffness, the ANN model presents a promising tool for representing various types of concrete.

Keywords Rejected ceramics · Compressive strength · Splitting tensile strength · ANN · LR

1 Introduction

The use of waste resources to create environmentally friendly and recyclable components is becoming more common, notably in the building industry [70]. Cement, a key component of construction materials worldwide, is being investigated for prospective upgrades [4–10], such as reinforced aggregate substituting natural sands and rock pieces [55]. Recent research has looked into the possibilities of adding ceramics into concrete compositions to ensure long-term sustainability [70]. Furthermore, studies have looked into the efficacy and durability of ceramic waste-cured self-curing aggregates [113], as well as the use of waste ceramics and synthetic fibers from the windsurfing industry in high-temperature concrete building [115]. Notably, recent academic research has concentrated on predicting and modeling concrete's tensile modulus [100]. Neural networks (NNs) and computational techniques have been used to predict concrete dynamics [100], while multimodal adaptive logistic b-spline models have been used to predict environmental aggregate compressive strengths [76]. Furthermore, research has used machine learning approaches, such as fuzzy evolving algorithms, to forecast the mechanical properties of cement-based materials [61, 67].

The objectives of this research are to use regression modeling and artificial neural network (ANN) approaches to

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simulate the mechanical properties of ceramic waste concrete [13–16], such as compressive and tensile strengths. The performance of these models is assessed using prediction coefficients and root-mean-square error [21]. The study evaluates the accuracy and effectiveness of ANN models in forecasting [23, 24] concrete strength to classic linear regression methods. Furthermore, the study aims to investigate the capability of [27, 29] ANN models in modeling various types of concrete and their use in real-world construction settings.

2 Literature review

The study [118] offered empirical models for predicting the compressive strength of plastic sand paver blocks (PSPB) constructed from plastic, sand, and fiber [36, 39, 40]. The results revealed substantial connections between predicted and real values, with R^2 values of 0.87 for GEP and 0.91 for MEP, demonstrating MEP's superior performance. Sensitivity study revealed that sand grain size and fiber percentage play an important impact in compressive strength, accounting for about 50% of the total [41–50]. These findings point to PSPB's potential [51–60] in sustainable construction, which promotes environmental preservation while also providing economic benefits.

The study [119] advocated using waste-derived cement-based composites (CBCs) to address environmental issues. Its goal was to evaluate eggshell and glass powder-modified cement mortar (EG-CM) in acidic environments using machine learning techniques [61–70]. SVM emerged as the best accurate predictor, with an R^2 value of 0.88. SHAP study revealed that glass powder is critical for EG-CM's acid resistance.

The article [120] describes a unique approach that uses gene expression programming (GEP) to estimate the compressive strength (CS) of plastic sand paver blocks (PSPB), with the goal of improving waste management and eco-friendly building [71–80]. Using a dataset of 135 compressive strength findings and seven input factors, including sand size and fiber percentage [81–88], GEP models show promising predictive accuracy, with R^2 values of 0.89 (training) and 0.88 (testing). Sensitivity analysis identifies sand size and fiber percentage as critical elements in PSPB CS [100–120], demonstrating the models' accuracy and potential for wider use.

The study [121] suggests employing machine learning approaches, notably MEP and GEP, to forecast the compressive strength (CS) and slump of alkali-activated concrete (AAC). MEP models surpass GEP in terms of expediting AAC proportion determination for construction projects while also taking environmental sustainability and adaptability into account, with R2 values of 0.92 and 0.93 for slump and CS prediction, respectively. The models demonstrate strong correlations with expected outcomes following hyperparameter fine-tuning and validation, with sensitivity analysis providing insights into factors influencing AAC characteristics.

The study [122] seeks to create machine learning models for forecasting the compressive strength (CS) of self-compacting concrete (SCC) by gene expression programming (GEP) and multi-gene expression programming (MEP). It fills a gap in previous studies by introducing mathematical formulae for estimating SCC strength. The results show that MEP outperformed GEP, with an R^2 of 0.89 against 0.85. Sensitivity analysis identifies superplasticizer as the most influential element, providing important insights into raw material effects on SCC strength.

The study [123] seeks to predict the compressive strength (CS) of preplaced aggregate concrete (PAC) utilizing machine learning approaches such as gene expression programming (GEP) and random forest. The complexity of PAC, which involves injecting cement–sand grout after laying coarse aggregate, needs good CS predictions. Machine learning minimizes the requirement for significant experimental testing. The results reveal a significant agreement between predicted and experimental CS values, with R^2 values of 0.94 for GEP and 0.96 for RF, indicating that the latter performs better. Lower statistical error values further support RF's superiority.

The study [123] proposes utilizing machine learning (ML) methods to estimate concrete compressive strength (CS) at high temperatures (HT), with the goal of streamlining SCM integration and achieving CS in concrete. Results show that the bagging regressor (BR) model outperforms the decision tree (DT) and AdaBoost (ADB) models, with the highest coefficient of determination (R^2) at 0.92. Statistical analysis and cross validation corroborate the BR model's reliability, revealing decreased error metrics and a closer alignment with actual values. Sensitivity research demonstrates temperature's considerable impact on CS, confirming ML's efficacy in forecasting CS for SCM concrete under HT circumstances.

Table 1 demonstrates the use of newer technologies to forecast and recreate ceramic qualities in current research.

Table 1 shows the recent emphasis on predicting and estimating properties of concrete utilizing a wide variety of approaches and technology. [1–3]. This can be observed as a result of the fact that however, the full potential of predictions and modeling of the features of concrete made from pozzolanic ingredients have not yet been used. In light of this, the following objectives for the study are intended: 1. to forecast the mechanical properties of concrete by using ANNs and a coefficient of determination. Following this, we will evaluate the two models' capacity for prediction in order to establish which of the two is more accurate.

Table 1 Classification techniques for properties of concrete that have stood the test of time

Several ceramic types	Indicators of concrete's physical properties	Method for predicting the future	References
The Sum Total of Ceramics Garbage	Durability in compression and tension	Support Vector Machine (SVM)	[19]
Bacteria Concrete	Resistance to stress in a materials	Simulation in Mathematical	[52]
Composite fiber-reinforced concrete	Force of tensile recovery after a delay	NN predictive aids	[64]
Small-Scale Materials, or Nanomaterials	Pressure resistance	The Synthesis of a Computer Program to Express Genes	[109]
pulverized Reactive Substance	Resistance to damage tolerance in tension	Simulation in Mathematical	[106]
Garbage made of ceramics and synthetic fibers	Maximum compressive forces	SVM and gradient boosting machine	[102]
Reinforcement was weakened by oxidation	Solidity under tension	Calculating the Limits of Compression Chords	[58]
Light weight concrete	Strongest possible compression	Simulation in Mathematical	[85]
Connection of a reinforcement ratio to a columns	Tensile rigidity	The Synthesis of a Computer Program to Express Genes	[74]
Regular cementations material	Toughness under pressure	Methodologies based on the reaction surfaces	[90]

3 Proposed methodology

3.1 Methods and data used

Extensive testing conducted in a laboratory. The samples containers used for the compressive and tensile evaluations are shown in Fig. 1 (as cubes and cylinders, respectively), and Fig. 2 shows the cointegration test of the cementations composites used to simulate the effectiveness of concrete faith and tensile properties in this research (as shown in Tables 2 and 3). Figure 1 shows the cubes and cylinders samples holders employed for the compressive and tensile tests.

Table 2 The cement used in these studies was regular Portland cement, and the concrete mixture was of a specified kind

Product requ	OPC	Ceramic crystals
SiO2	31.8	69.49
CaO	61.38	9.55
AL2O3	7.58	19.87
Fe2O3	5.22	3.88
MgO	2.98	5.01
K2O	0.89	3.99

The concrete's resistance refers to the amount of force that may be applied to a floor foundation before enabling the slab to crack or buckle [11, 14]. The mechanical properties of concrete are used to evaluate the material's ability to withstand the shrinkage that results from being compressed. Hardness may be thought of as another name for biomechanical qualities. Concrete's tensile strength is measured by its ability to resist further stretching when subjected to pulling forces [15, 17].

The ratio of water to cement in a concrete mix denotes the percentage of water to cement that will be present in the finished product. In most circumstances, the best w/c ratio is between 0.40 and 0.45 [18–20]. Increases in the percentage of water to cement may decrease the durability of cementitious materials.

The term "workability" is used in the context of concrete to refer to the ease with which the material may be poured, disseminated, and crushed on the building site [22, 25, 26, 28]. When the workability value is higher, it implies that the concrete may be poured with less difficulty.

Discarded ceramics: Recycling rates for ceramic ranged from 0 to 20%, with a 2.5% margin of error for any number somewhere in. In additional, powdered ceramics fragments were included [30].

The ordinary Portland cement (OPC) from Maros, South Sulawesi, was comprehensively analyzed for chemical and physical qualities. It is a significant element in mortar manufacturing, influencing compressive strength properties. Rigorous testing ensured that OPC's properties were consistent and trustworthy for their intended use. The compatibility of additives such as superplasticizers was explored in order to increase performance in high-strength mortar production. The proposed methodology was fed a total of 150 independently confirmed data observations. 2 percent, 5 percent, 7

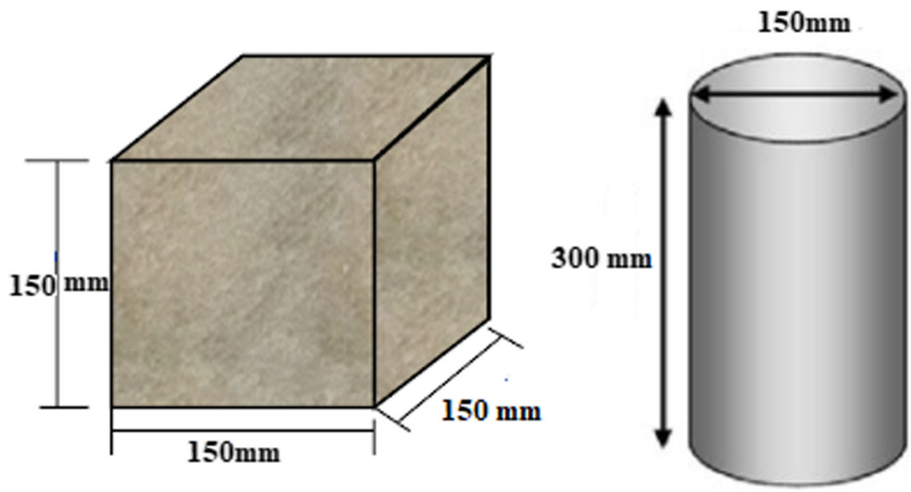

Fig. 1 Crushing and tension test specimen dimensions for cubes and cylindrical rods

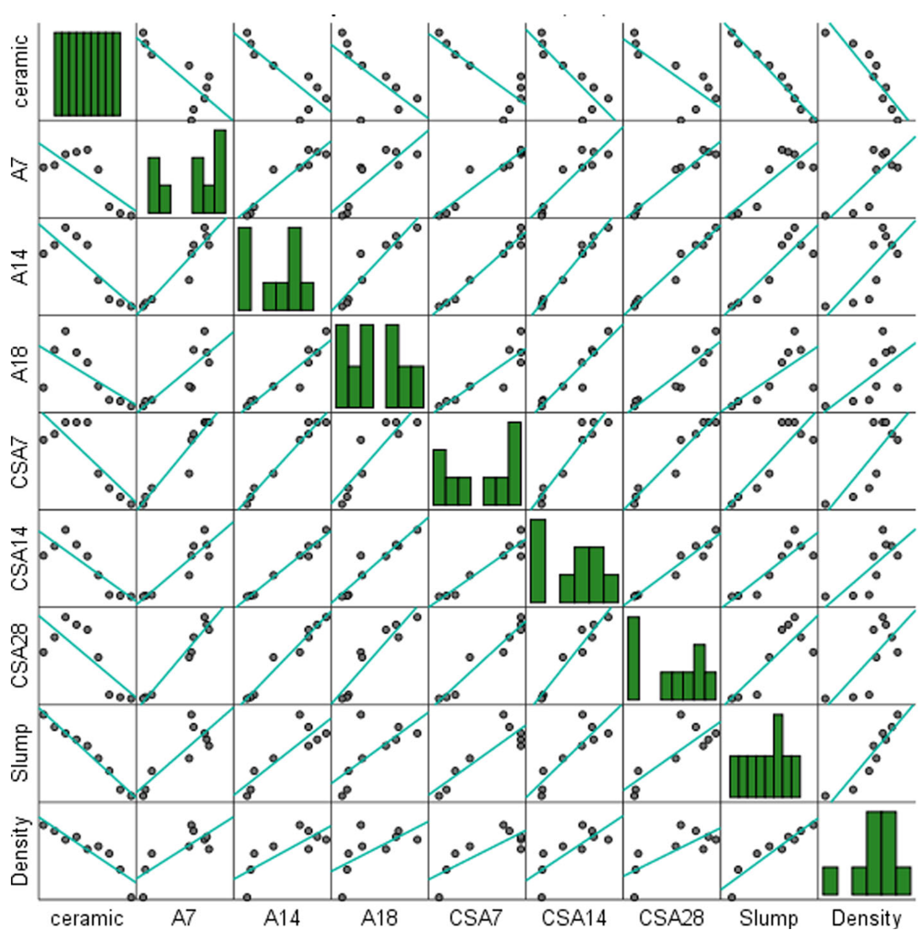

Fig. 2 Actual tangible quality real correlation tensile strength at 7, 14, and 28 days during drying (CSA7, CSA14, and CSA28) equates to optimum tensile capacity of the concrete

percent, 10 percent, 12 percent, 15 percent, 17 percent, and 20 percent ceramics garbage were combined with cement to see what would happen [31, 32] and [34]. These percentages of ceramic wastes were all used as a percentage of cement. In order to explore the effect that ceramic waste has on the properties of concrete, specimens containing ceramic waste as well as those that did not include any ceramic waste were put through a series of tests. The mechanical qualities of cement were evaluated by casting a concrete mixture with dimensions of 150 mm on a side, 150 mm on a length, and 150 mm on a height [1, 36, 47]. The split tensile strength of the material was evaluated using concrete cylinder specimens with dimensions of 300 mm by 150 mm. Concrete's machinability, along with its compressive strength, flexural strength,

Table 3 Elements of concrete mixtures and their distribution patterns

Mixtures	W/c ratio	Cement (kgm^3)	Soil	Concrete	Percents replace	Gritty, rough material
MT1	0.52	455	705	0	0	1258
MT2	0.52	455	595.63	20.36	3.5	1258
MT3	0.52	455	599.87	29.56	7	1258
MT4	0.52	455	588.12	55.58	8.5	1258
MT5	0.52	455	602.5	65.5	11	1258
MT6	0.52	455	588.32	79.33	13.5	1258
MT7	0.52	455	602.3	88.78	17	1258
MT8	0.52	455	622.55	104.23	21.5	1258
MT9	0.52	455	499.25	125.33	18	1258

and overall strength, was one of the properties that was evaluated [37]. In addition to the incorporation of ceramic waste in place of coarse aggregates, the water–cement ratios had also been adjusted to a range between 0.4 and 0.44 [54]. The chemical components of both the powder combination and the compound are listed in Table 2 [55]. The precise sorts of mixtures that were used in this investigation are detailed in Table 3, which can be seen here.

Table 3 shows the design mixtures utilized in the dataset, as well as the distribution patterns of major concrete mixture components. Each mixture is labeled MT1 to MT9. The water-to-cement (w/c) ratio in all mixes is constant at 0.52. All combinations have a cement content of 455 kg/m^3. The table also includes data on the distribution of soil and concrete components, as well as the percentage replacement of gritty, abrasive material. The amounts of soil and concrete components vary among combinations, with varied ratios of replacement for gritty, abrasive material. Overall, these design combinations serve as the foundation for analyzing the performance and properties of concrete compositions in the dataset.

It is possible to find connections between sets of data by using a technique called quadratic regression [96, 107, 108]. The fundamental procedure of linear regression may be written as (1). Which means that (*a*) is both the result of (and the main cause of) (*b*). The number 0 represents the point where the two lines meet is α_0 [12, 109]. The slope of a line (α_1), represented by the number 1, is a crucial part of every dependent variable (*b*). There is a positive connection if the quantity is more than zero, and a negatives one if it is less than zero [54, 94].

$$a = \alpha_0 + \alpha_1 b \tag{1}$$

3.2 ANN

Artificial Neural Networks (ANNs) outperformed other robust AI models such as ANFIS, M5, GEP, MARS, EPR, and SVM due to their shown ability to handle complicated, nonlinear interactions inherent in concrete material qualities. ANNs provide versatility in modeling varied datasets and can capture subtle patterns without requiring explicit mathematical formulations.

Furthermore, ANNs support iterative learning and modification, allowing for refining and adaptability to a variety of experimental settings, making them ideal for the delicate nature of empirical research [55, 86, 115]. A neural network consists of a collection of simple components that carry out related tasks. Each neuron's functions are dependent on its own unique perceptron, thresholds, and weights [98, 99]. The input data, the hidden layers, as well as the output layers are indeed the three major components of any given ANN model. In a NN, the nodes stand in for the data that have been input into the network. As the name suggests, it transfers messages without changing them in any manner [92]. With n levels to correspond to the number of neurons in the network, the layer is a crucial component that modifies the signals given by the passive node. The output layer plays a crucial role in networks with n layers and n neurons per layer [41, 75, 100]. Weighting levels are the backbone of every artificial neural network, and they are often adjusted according to a specific formula [33, 54, 91]. This action of fine-tuning existing settings is known as learning. After being trained, an ANN is able to make predictions about the output values of a given input sequence [55, 100]. The ANN structures shown in Fig. 3 were developed in the following ways:

1. Neural network type, 2. hidden layer, 3. Neurons in layer, 4. number of output

To enhance model performance, hyperparameters such as the learning rate (0.001), batch size (32), and the number of hidden layers (2–3) can be adjusted. Additionally, incorporating a dropout rate of 0.5 can help prevent overfitting and

Table 4 Estimating the efficacy of ANN-LR: a look at the factors borne by empirical research

		$A=7$	$A=14$	$A=28$	NN = 7	NN = 14	NN = 28	LR = 7	LR = 14	LR = 28
Tensile strengths	Min	02.53	02.85	02.53	02.52	02.73	02.638	02.31	02.22	02.33
	Max	03.12	4	4.21	3.41	3.21	4.13	3.11	2.98	4.12
	Mean	2.98	2.85	3.45	3.01	2.78	2.56	3.45	3.22	2.98
	Study	0.31	0.28	0.35	0.30	0.26	0.35	0.34	0.28	0.23
	Skewness	− 0.82	− 0.29	0.41	− 0.92	0.28	0.92	− 0.51	0.20	− 0.61
	Kurtosis	− 1.35	− 1.55	− 1.63	− 0.77	− 1.77	0.33	− 1.45	− 2.15	0.81
Compressive strength	Min	27.99	31.88	28.9	25.3	30.21	29.9	31.6	31	29.5
	Max	29	34.6	33	31.7	37.8	39.3	31.3	38	41
	Mean	31.2	33.55	29.9	27.33	32.44	36.89	28.32	33.74	36.88
	Study	2.43	02.35	02.63	02.52	02.83	02.55	02.77	02.62	02.55
	Skewness	− 0.62	− 0.42	− 0.55	− 0.78	− 0.45	− 0.68	− 0.55	0.19	− 0.59
	Kurtosis	− 3.12	− 2.88	− 2.55	− 3.44	− 1.78	− 3.12	− 1.96	− 3.02	− 2.01

Table 5 Comparing the accuracy of NN and LR models for predicting compressive and tensile forces at 7, 14, and 28 days

		NN = 7	NN = 14	NN = 28	LR = 7	LR = 14	LR = 28
Tensile strength	MAE	0.24	0.45	0.51	0.33	0.42	0.21
	MSE	0.15	0.10	0.19	0.11	0.29	0.17
	RMSE	0.07	0.14	0.24	0.18	0.19	0.7
	MAPE	5.12	8.89	13.01	6.87	9.88	12.01
Compressive strength	MAE	0.71	0.38	0.46	0.49	0.88	0.91
	MSE	0.28	0.19	0.39	0.43	1.55	0.99
	RMSE	0.30	0.19	0.26	0.31	0.39	0.38
	MAPE	3.08	3.21	0.89	5.01	1.77	2.88

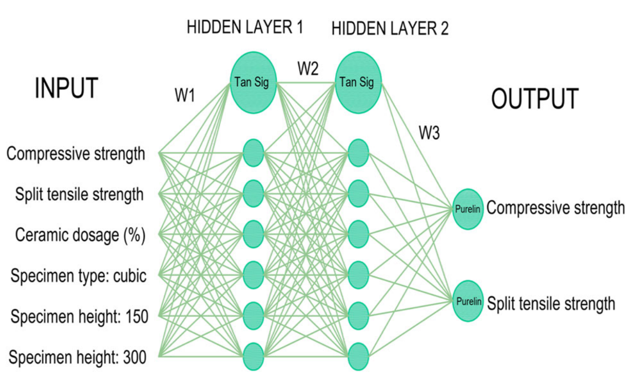

Fig. 3 In this investigation, we used a standard ANN setup with all inputs

improve generalizability. Mathematical features from measured, predicted ANN values and logistic R (LR) [73, 89, 101] are included in Table 4. Table 5 displays the absolute percentage error (APE), mean absolute error (MAE), root-mean-squared error (RMSE), and mean absolute percentage error (MAPE) numbers used to assess the precision of the models.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_e - y_p\right| \tag{2}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_e - y_p\right)^2 \tag{3}$$

$$\mathrm{RMSE}\frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(y_e - y_p\right)^2} \tag{4}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_e - y_p}{y_p}\right| * 100 \tag{5}$$

One takes the real value y_e and subtracts it from the predicted value y_p. APE measures the absolute difference between y_p and y_e. MAE calculates the average magnitude of errors between y_p and y_e. RMSE is calculated as the square root of the average of squared discrepancies between y_p and y_e, and it is used to assess the model's prediction ability. MAPE estimates the average percentage difference between

y_p, providing insight into the degree of mistakes relative to y_e.

4 Results and discussion

Here, empirical data are used to compare the performance of artificial neural networks (ANNs) and regression techniques for forecasting the tensile and compressive characteristics of ceramics and cementitious materials. The accuracy of the forecasts is measured in several ways, including by the root-mean-square error (RMSE). Both models' efficacy were evaluated using the measurement coefficient (R^2). By calculating the root-mean-squared error, we could evaluate how far off we really were. It is a statistical indicator of the deviation from the mean of standardized residuals. Distance from the mean value of your residuals is quantified by the RMSE. A high value for this metric indicates that a large number of data points are clustered close to the best fit line. A measure of how well the data fits is provided by the R^2 statistic.

Stress in a compressed state.

Multiple compression tests were performed on various laboratory combinations to measure their strength growth. There is a 1.5% improvement in concrete strength after 7 days when using 2.5% ceramic waste. There was an increase of 4.5 percentage points in strength over the control specimens when ceramic waste was added to the cured concrete at the rates of 5%, 7.5%, and 10%. When more than 10% ceramics debris was mixed in with the concrete, the specimen's compressive strength dropped. Reductions of 8%, 14%, and 16% were recorded, in that order, in concrete samples containing 12%, 14.5%, 16.5%, and 20% waste. After 14 and 28 days, there were persistent patterns in the concrete's workability. There was an 11% increase in concrete strength at 5% after 14 days. Further, adding 5% pozzolanic ingredients significantly increased the concrete's strength. Also, after 28 days of testing, the 5% cementations material exhibited an increase of 8%. The best result was achieved by replacing sand in the concrete specimen with ceramic waste at a 5 percent dosage.

The compressive strength estimates made using either approach were accurate for a week. With an R^2 of 0.97 for the linear regression and 0.9% for the ANN model, the linear regression was clearly superior. The results show that although both methods are correct, the linear regression method outperformed the ANN when estimating the activity after 7 days. After 14 days, both the ANN model ($R^2 = 0.97$ for predictions) and the regression model ($R^2 = 0.96.5$ for coefficient of determination) were significantly better than the 1-week baseline at predicting strength growth. In forecasting the strength attributes after 14 days, the inferential ANN model performed better than the linear regression models. Both models performed similarly when asked to forecast concrete strength after 28 days. When compared to a linear regression model, the ANN approach had an R^2 of 0.97, meanwhile the regression model approach had an R^2 of 0.95. The RMSE for ANN models was 1.2 Mpa after 7 days, 1.1 Mpa after 14 days, and 1.02 Mpa after 4 weeks (28 days). Values among 1.3 and 15.2 Mpa for various artificial intelligence approaches used to forecast the tensile properties of fly ash geopolymer concrete mixtures, and adjusted r^2 around 0.70 and 0.98 for linear model at 1, 2, and 28 days.. report. A coefficient of determination of 0.88 and a RMSE of 0.98 were obtained when the ultimate strength of polypropylene pp composite materials recycled accumulated material was modeled using an SVM classifiers and a shading pumping up supervised learning methodology.

4.1 Tensile strength

The elasticity of the concrete samples was improved by 0.39%, 2.37%, 2.76%, and 3.16% when recycled predication was added at 2.5%, 5%, 7.5%, and 10%, respectively. Consistent with the results of the compressive strength test, the compressive modulus decreased by 0.39 percentage points, 7.11%, 8.3%, and 8.7% after 7 days of testing for 12.5%, 15%, 17.5%, and 20%, respectively. After 14 days, all percentages of ceramic waste examined showed increased compressive characteristics (2.5%, 5%, 7.5%, and 10%). After 28 months, the structural stress was increased by 10%, 15%, 9.3%, and 6.6% when ceramic waste was added to concrete at a 2.5%, 5%, 7.5%, and 10% concentration, respectively. Figure 4 shows the ANN and linear regression models' respective detection accuracies for split tensile strengths in this study. The same methodology used to predict compressive strength was used to model split tensile modulus for 7, 14, and 28 days. With an R^2 of 0.11 and 0.09, respectively, the ANN and logistic regression models performed poorly 7 days out. Improvements in methodology for the 14-day split tensile results are shown by R^2 values of 0.3 and 0.54 for the ANN and logistic prediction techniques, respectively. It has been established that a linear regression model is superior to even an ANN model for predicting the modulus of rupture over a 14-day period [86–95]. Utilizing ANN and linear regression analysis, it was shown that predictions of 28-day divided tensile strength were more accurate than those using 1-week and 14-day results. When compared with multiple linear regression, the ANN model's R^2 of 0.87 much outpaced that of 0.70. After 28 days, in order to estimate the dividing compressive modulus of ceramic recycling aggregates, the ANN method performs noticeably better than the linear regression technique. Comparing the R^2 values of SVM with GBM analysis tools for green glass 7 characteristics concrete, Ray, Rahman, et al., (2021) observed a comparable difference, using R^2 values of 0.70 as well as 0.92.

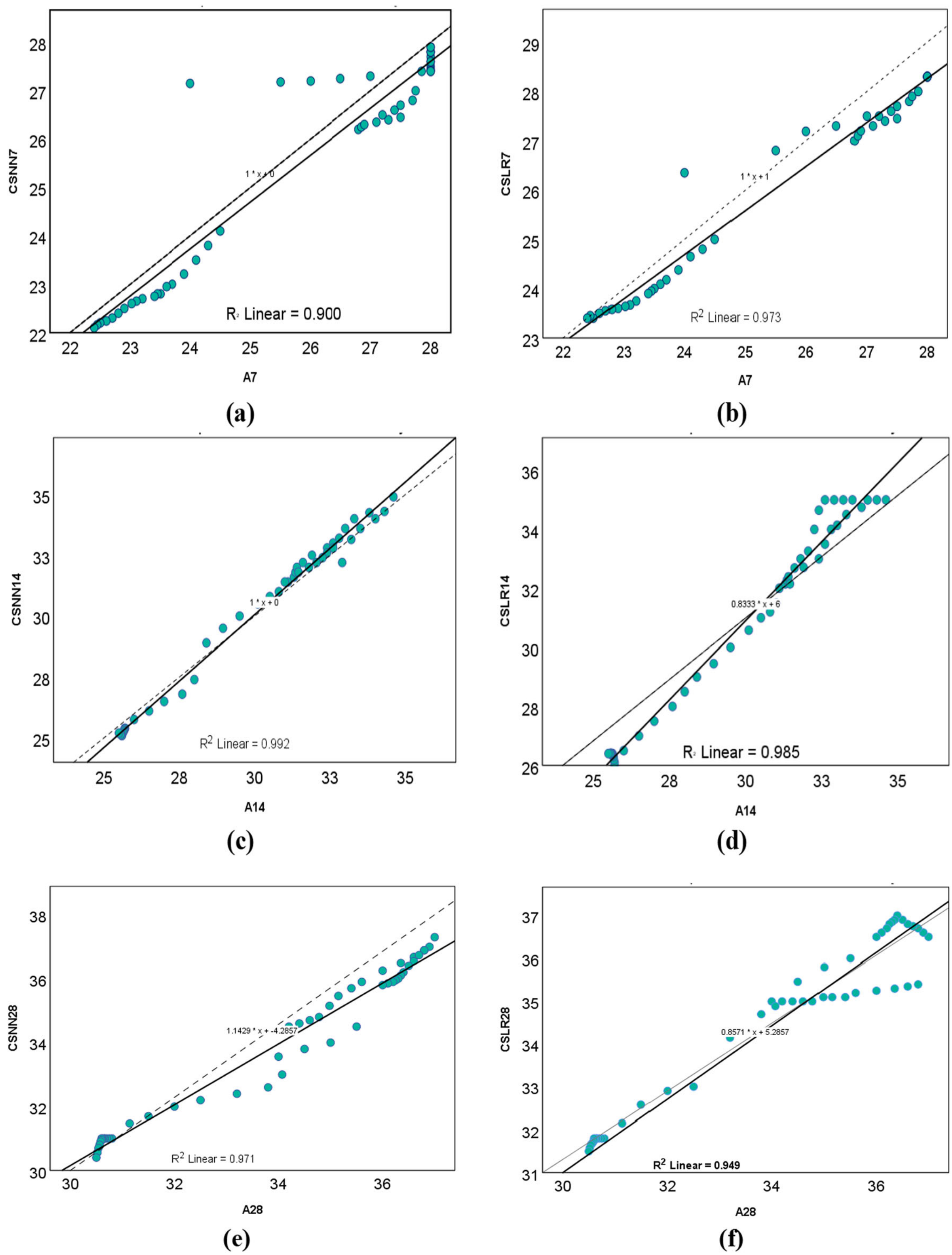

Fig. 4 Examining the tensile qualities of ceramic materials and bricks and comparing them to their predicted values

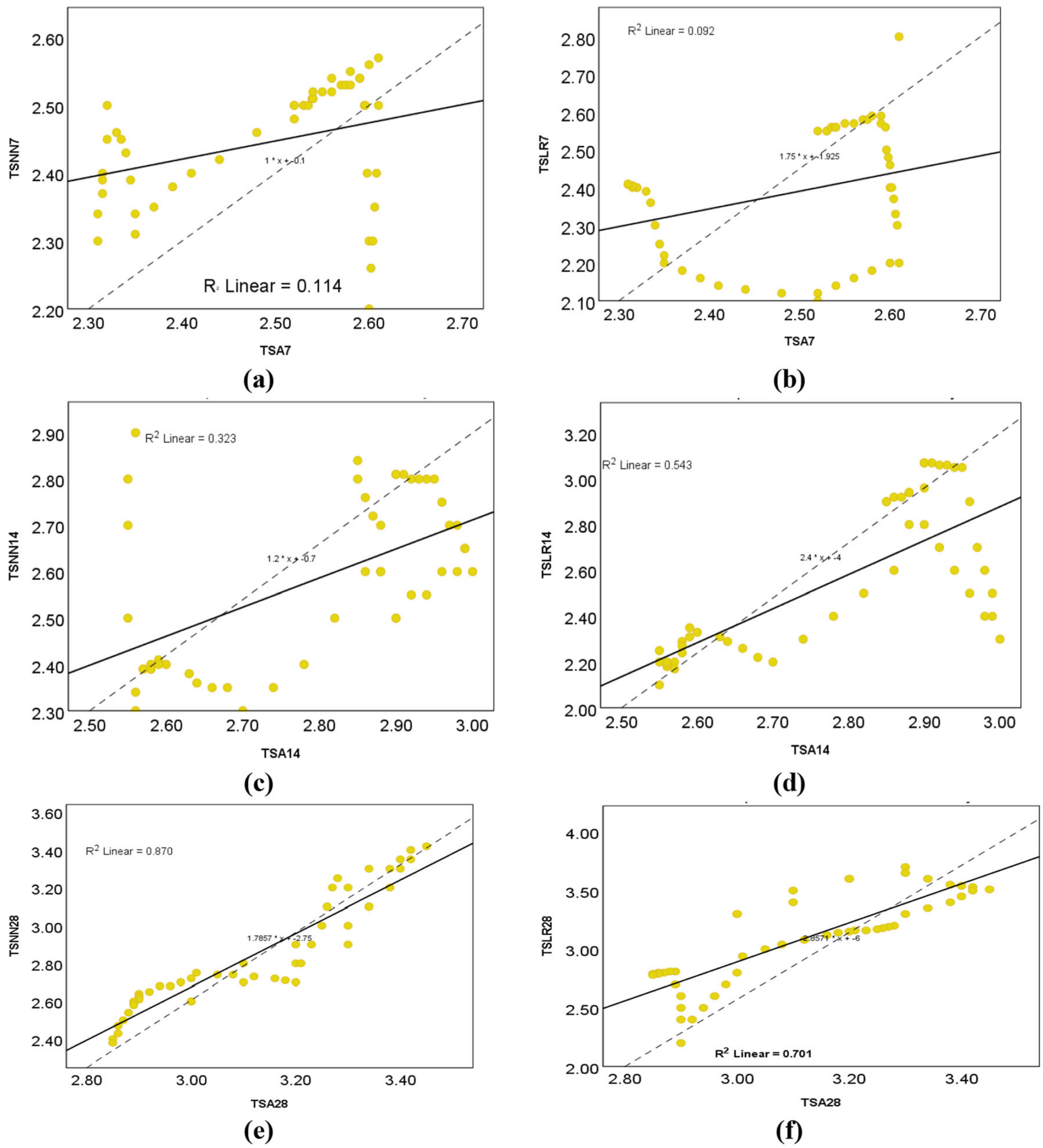

Fig. 5 Comparison of experimental and computational bending and tensile results for ceramics and cement debris

Figure 5 shows the comparative analysis of tensile and compressive strengths at different temperatures over 28 days (MPa) for various methods PC-ANN, hybrid ANN, and WOC-ANN with the proposed method shows the effectiveness of the system.

Figure 6 for tensile strength, the PC-ANN exhibits decreasing values from 4.2 MPa at 10 °C to 1.0 MPa at 1000 °C, with the proposed method consistently shows the lowest values. In contrast, the hybrid ANN demonstrates superior tensile strength at elevated temperatures. For compressive strength, the PC-ANN method starts at 26 MPa and decreases to 13 MPa, with the proposed method consistently

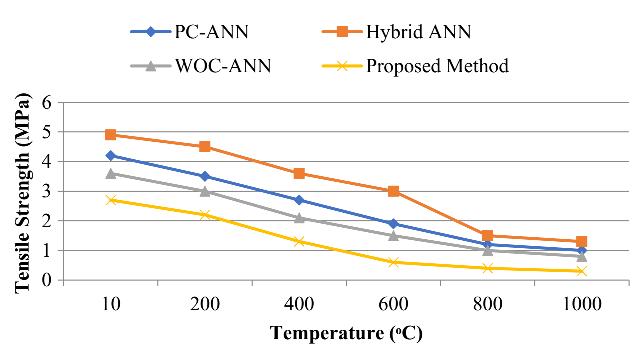

Fig. 6 Temperatures on concrete compressive strength analysis

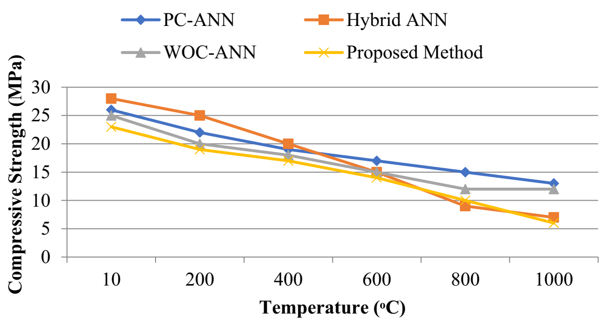

Fig. 7 Temperatures on concrete tensile strength analysis over 28 days

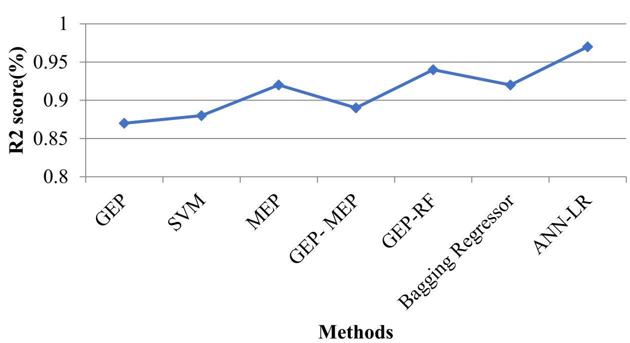

Fig. 8 Comparative analysis of various methods using R^2 score

showing lower values. The hybrid ANN maintains higher compressive strength, indicating its resilience to temperature variations is shown in Fig. 7. The WOC-ANN and the proposed method consistently display the lowest compressive strengths, suggesting the need for further optimization in high-temperature conditions. Overall, the hybrid ANN method appears promising for maintaining mechanical properties at elevated temperatures compared to other approaches.

Figure 8 compares alternative approaches for forecasting concrete qualities, namely (CS), along with their coefficient of determination (R^2) values. Traditional approaches (GEP and SVM) produced reasonable R^2 values ranging from 0.87 to 0.88. More advanced approaches, such as MEP and bagging regressor, demonstrated better performance, with R^2 values of 0.92. Hybrid models that combined GEP with MEP or RF performed even better, with R^2 values as high as 0.94. Notably, the proposed system that uses ANN-LR outperformed all other approaches, with an amazing R^2 value of 0.97. This shows that ANN-LR model outperforms the existing hybrid techniques in predicting concrete qualities, making it a promising solution for real-world applications in construction.

5 Conclusion

This study aims to assess the grade of slabs constructed using Portland cement as a sands alternative and to provide predictions about its strong features and cracking capacity. From what we can tell, adding ceramic waste to concrete at different percentages (2.5–5%, 7.5–10%) may boost its compression strength by 3, 5, and 3.5 percentage points, respectively. The strength of ceramic performance of concrete decreased by 1–10% when additional cementations material was added.

- The ultimate tensile of the material structure by roughly 10%, 15%, 9%, and 6% for 2.5%, 5%, 7.5%, and 10% quantities of blast slag, correspondingly. Similar to the decreases in mechanical properties, decreases in fracturing tensile properties ranged from 0.3 to 5% for each additional decrease in the ceramics proportion. The optimal range for adding pozzolanic ingredients to improve the workability of the concrete capacity is between 2.5 and 10%. The opposite is true for concrete, where 5% ceramic waste in place of sands was shown to maximize both compression and splitting tensile strength.
- These techniques all seem to be about as accurate as one could want for forecasting bearing capacity with ceramic cementitious materials. Regression analysis after 7 days may be useful for predicting earthenware concrete's mechanical characteristics, but an ANN provides more reliable results after 14 and 28 days. Therefore, this study suggests using an ANN model to ascertain strength growth, since cube compressive intensity is a globally accepted proxy for compression strength.
- Both the artificial neural network and the regression model machine learning approaches failed miserably in the ultimate load-carrying capability example. In a test predicting a material's compressive and flexural strength 7 or 14 days in the future, neither model fared well. Following 28 days, the ANN model predicted correctly. This work shows that the proposed model can now accurately forecast strengths growth and split compressibility of porcelain cement hydration components, making it suitable for modeling diverse ceramic kinds. However, both machine learning approaches failed in predicting the ultimate load-carrying capability, showing accuracy only after 28 days. Despite advancements, further study is warranted to enhance prediction accuracy and address limitations. Evidently, further study is include improving ANN models for more precise predictions of mechanical properties, investigating additional variables influencing strength evolution, and assessing other machine learning methodologies. Validation across multiple ceramic types and real-world circumstances is critical to ensuring the proposed model's reliability and usefulness.

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Declarations

Conflict of interest Conflict of interest is not applicable in this work.

Ethics approval and consent to participate No participation of humans takes place in this implementation process.

Human and animal rights No violation of human and animal rights is involved.

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