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Predictive Analysis of Ceramic Waste Modified Concrete Properties Using ANN and Linear Regression Algorithm

Abdullah Asiri
Department of Civil Engineering, King Khalid University, Abha, Saudi Arabia
https://orcid.org/0009-0000-8592-4314

corresponding author's e-mail: anmasiri@kku.edu.sa

Abstract: In this study, concrete modified with ceramic waste was modelled. The ceramic waste percentage ranged from 2.5% to 5% to 10% to 12.5% to 15% to 17.5% to 20%. Modelling was done for the concrete's tensile strength and compressive strength. Regression modelling and artificial neural networks were used as prediction methods for concrete strength. The models developed in this study to predict the mechanical properties of concrete were evaluated using Mean absolute error, coefficient of determination and root mean square error. The R^2 value for the ANN model was determined to be 0.97, compared to 0.95 for the linear regression model. For the one-week, two-week, and four-week prediction models, RMSE values were 1.1 MPa, 1.15 MPa, and 1.05 MPa for the ANN model for one-week, two-week and four-week, respectively, while the linear regression model displayed the RMSE values of 1.08 MPa, 1.22 MPa, and 1.25 MPa. The R^2 values for ANN and LR models were estimated to be 0.87 and 0.7, respectively, for predicting split tensile strength. This study will conclude that the artificial neural network model has high accuracy. It can be employed in modelling the mechanical properties of ceramic-modified concrete.

Keywords: compressive strength, ceramic waste, split tensile strength, artificial neural network, linear regression

1. Introduction

According to several studies (Ahmad et al. 2022, Zegardo 2022), concrete is a vital building material because of its significance and the sheer volume at which it is used in the construction industry. It has called for many research works to upgrade the concrete material with additives and newly developed materials. The most well-known method for obtaining environmentally friendly, sustainable, and green materials is to produce building materials using waste materials (Kuruc & Štefunková 2024). It renders concrete as a green and sustainable building material. Recently, attention has been drawn to using ceramic waste instead of sand and gravel in traditional concrete as a building ingredient.

Using various machine learning algorithms, Javed et al. (2024) modelled the strength properties of eco-friendly concrete produced from waste foundry sand in terms of split tensile strength and compressive strength. Singh et al. (2024) assessed machine learning efficiency in predicting the compressive strength of concrete used for road construction using red mud mixed with fly ash. Rajagopal et al. (2024) employed machine learning and artificial intelligence approaches to predict self-compacting concrete strength properties. It renders concrete as a green and sustainable building material. Recently, attention has been drawn to using ceramic waste instead of sand and gravel in traditional concrete as a building ingredient. Brekailo et al. (2022) looked into the effects of using ceramic waste instead of cement while making concrete. Meena et al.'s review of ceramic use as a sustainable concrete medium was published in 2022. The durability and sustainability of self-curing concrete made using ceramic waste were assessed by Younis et al. in 2022. Zegardo (2022) examined the heat resistance of carbon fiber from the sailing industry's trash and concrete made from ceramic waste. From current literature, it may be deduced that study has recently focused on ceramic waste. However, in recent years, the emphasis of study has also switched to the prediction and modeling of concrete's mechanical properties.

Zheng et al. (2022) employed ANN and other numerical approaches to predict concrete properties. The compressive strength of eco-friendly concrete was measured using a multivariate adaptive regression splines model by Naser et al. (2022). Ekanayake et al. (2022) used a shapely additive explanation machine learning in terms of a black box approach to forecasting the compressive strength of concrete. Residual tensile strength under severe alkaline conditions was modelled for glass fibre-reinforced concrete by Iqbal et al. (2022) using a fuzzy metaheuristic model. As seen in Table 1, numerous other studies have lately used various models to anticipate and model concrete's properties.

Table 1. Research studies modelling concrete mechanical properties using different approaches

Type of concrete	Properties of concrete	Modelling approach	Reference
Waste foundry sand concrete	Split tensile strength and compressive strength	Support vector regression, decision tree and Adaboost regressor	(Javed et al. 2024)
Red-mud concrete	Compressive strength	Machine Learning	(Singh et al. 2024)
Self-compacting concrete	Compressive strength	Regression trees, support vector regression, ANNs, gaussian process regression	(Rajagopal et al. 2024)
Aggregate (ceramic waste)	Split tensile strength and compressive strength	SVM (support vector machine)	(Ray, Haque et al. 2021)
Concrete mixed with bacteria	Compressive strength	Mathematical modelling	(Algaifi et al. 2021)
FRC (fibre reinforced concrete)	Split tensile strength (post cracking)	Prediction (artificial neural network)	(Ikumi et al. 2021)
Nanomaterial	Concrete compressive strength	GEP (gene expressing programming)	(Yasmin 2021)
Reactive powder	Concrete shear strength	Linear mathematical modelling	(Ridha et al. 2018)
FRC (ceramic waste)	Concrete tensile and compressive strength	GBM (gradient boosting machine) and SVM (Support vector machine)	(Ray, Rahman, et al. 2021)
RCC (corrosion resistant)	Concrete shear strength	Chord capacity model (compression)	(Cladera et al. 2021)
LWC (Lightweight concrete)	OPS (Optimum compressive strength)	Mathematical linear modelling	(Oyejobi et al. 2020)
Column to beam joints (RCC)	Concrete (shear strength)	GEM (Gene expression modelling)	(Murad et al. 2020)
Normal concrete	Concrete compressive strength	RSM (response surface modelling)	(Poorarbabi et al. 2020)

From Table 1, it can be inferred that the research shift has tilted towards forecasting and modelling concrete properties employing various approaches. However, the full potential of predicting and modelling ceramic waste concrete characteristics has not yet been discovered. As a result, the study aims to evaluate the prediction performance of linear regression model and artificial neural networks and compare their performance accuracy.

2. Methods and Data Used

2.1. Laboratory investigation

Laboratory investigation was carried out to determine the concrete's compressive strength, split tensile strength and workability. The correlation matrix of the concrete characteristics utilized in this work to simulate concrete properties is presented in Figure 1.

2.2. Compressive Strength

Concrete's ability to withstand loads applied to its surface without deflecting or cracking is known as its compressive strength. Concrete's ability to endure compressive pressures that cause it to shrink in size under compression is called its compressive strength.

2.2.1. Tensile Strength

When a force tends to draw on concrete, it can resist any elongation due to its tensile strength.

2.2.2. Water cement ratio

It refers to the ratio of cement to water used to make concrete. Typically, the acceptable range of water-to-cement ratio is 0.4-0.45. Concrete strength is inversely related to the w/c ratio.

Workability indicates how simple it is to spread, position, and compact concrete on site. A greater workability score suggests that placing concrete will be simpler.

2.2.3. Ceramic waste

Ceramic waste was added with a 2.5% percentage fluctuation between 0 and 20%. Ceramic powder was created by using ceramic waste.

Input for the prediction models came from 150 tested sample readings in total. Incorporating ceramic waste at different rates into concrete was examined, including 2.5%, 5%, 7.5%, 10%, 12.5%, 15%, 17.5% and 20% by the weight of cement. To assess the influence of ceramic waste on the characteristics of concrete, a control specimen of concrete that included no ceramic waste was evaluated. Concrete cube specimens of 150 mm x 150 mm x 150 mm were cast to estimate the compressive strength. Cylinders of 150 mm in diameter and height of 300 mm were cast to evaluate the split tensile strength of ceramic concrete. Workability, split tensile strength, and compressive strength were the mechanical properties of concrete that were evaluated. In addition to altering the amount of ceramic waste for sand replacement, the w/c ratio varied from 0.4 to 0.44. Table 2 details the chemical composition of Portland cement and ceramic powder. Table 3 details the mix type used in this study for mechanical property analysis.

Table 2. Binding materials (ceramic powder and Portland cement) Chemical composition

Chemical composition	Cement (%)	Ceramic (%)
Silica dioxide	22.10	67.10
Calcium oxide	64.98	3.74
aluminum trioxide	5.87	17.89
Iron trioxide	2.65	4.01
Magnesium oxide	2.98	3.52
Potassium oxide	0.75	3.38

Table 3. The design mix used and its component proportions

Mix type	W/c ratio	Cement (kg/m^3)	Sand	Ceramic	% Replaced	Coarse aggregate
1	0.45	415	654.00	0.00	0.0	1158
2	0.45	415	637.65	16.35	2.5	1158
3	0.45	415	621.30	32.70	5.0	1158
4	0.45	415	604.95	49.05	7.5	1158
5	0.45	415	588.60	65.40	10.0	1158
6	0.45	415	572.25	81.75	12.5	1158
7	0.45	415	555.90	98.10	15.0	1158
8	0.45	415	539.55	114.45	17.5	1158
9	0.45	415	523.20	130.80	20.0	1158

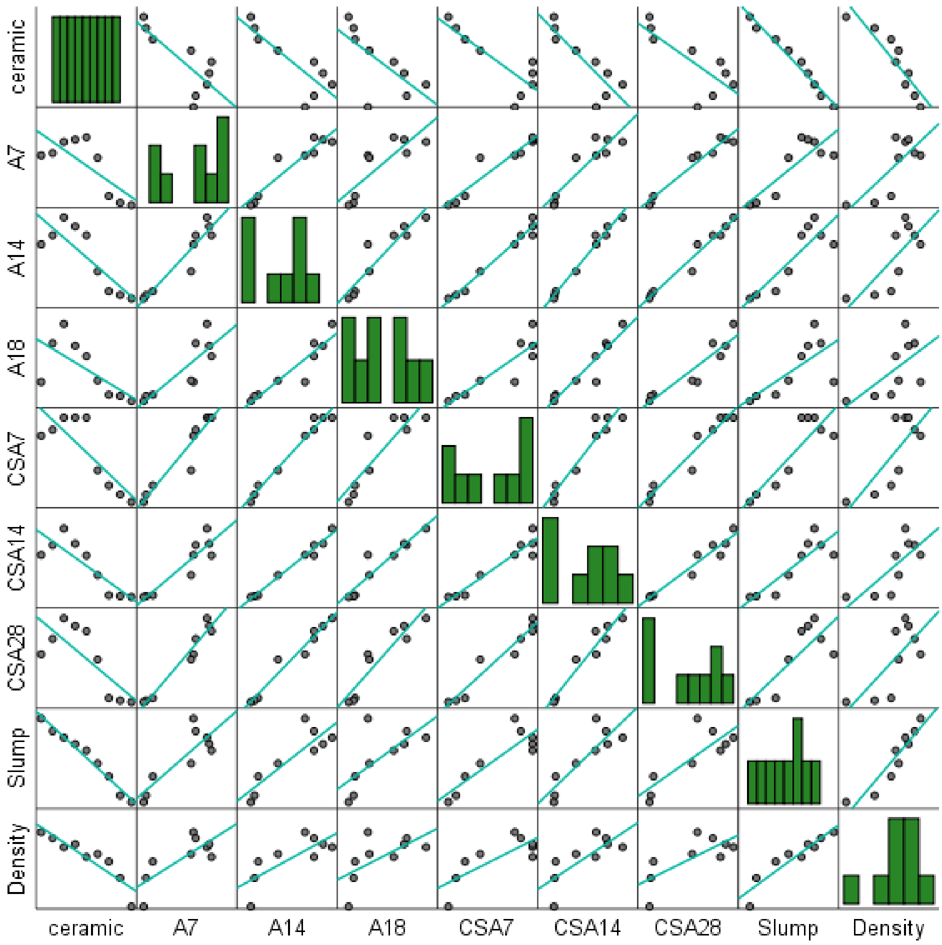

Fig. 1. Correlation between split tensile strength and compressive strength of concrete specimen with no ceramic powder (split tensile strength at A7, A14 and A28 days, and CSA7, CSA14 and CSA28 = compressive strength for one-week, two-week and four-week respectively)

2.4. Linear regression (LR)

Linear regression establishes correlations between several variables in a set of data. Equation 1 is a presentation of a linear regression model. The dependent variable a is here, and the independent variable b. The line's intercept is shown by the number 0. One of the most crucial factors in any given regression modelling is the line's slope, or 1. While a bigger positive value suggests a greater positive relationship and vice versa, a value close to zero indicates no or little link.

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

2.5. Artificial Neural Network (ANN)

ANN is an approach which imitates actual neurons. Simple pieces that operate in tandem make up neural networks. Single activation function, threshold, and weights are the three fundamental factors determining how a neuron works. The three essential layers of ANN comprise a hidden layer, an output layer and an inner layer. The input layer corresponds to the passive node-based inputs to the neural network. It serves as a signal transmitter and alters the signals received from passive nodes and n number of neurons corresponding to n number of layers, and the hidden layer is an active component. In addition, the output layer is an active component with n neurons for n layers. The foundation of artificial neural networks is optimum weight values. Learning is the process of weight optimization. The ANN creates an output of specified level accuracy corresponding to a given input value based on the learning. The ANN model used in this study is presented in Figure 2.

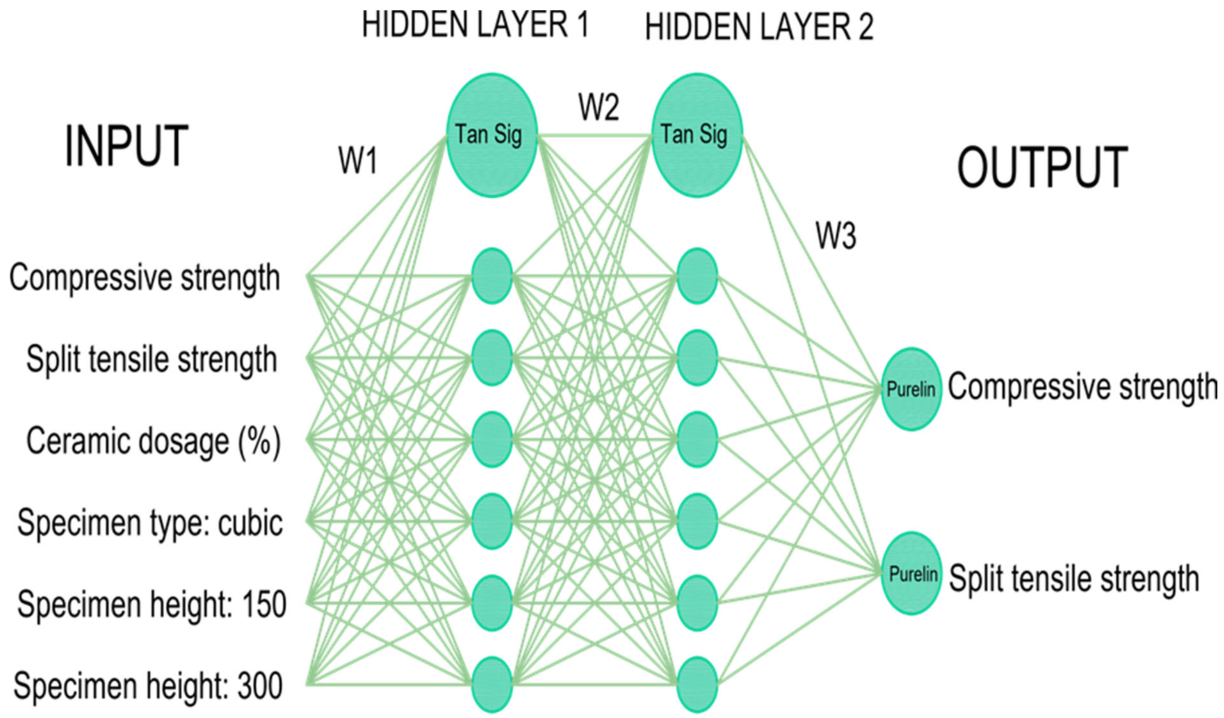

Fig. 2. Artificial neural network architecture used in this study with all given inputs

2.6. Evaluation of model performance

The model performance was evaluated based on a data set that was not used during the models' training. This dataset was termed as testing dataset. It aided in selecting the most optimized parameter for the model to increase the prediction accuracy of the models. The indicators used in the literature for model evaluation are Mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). These three indicators were employed to evaluate the model performance, which was calculated using the following equations:

$$\text{Coefficient of determination, } R^2 = \frac{\sum_1^n (x_i - y_i)^2}{\sum_1^n (x_i - \ddot{h}_i)^2} \tag{2}$$

$$\text{Root mean square error, RMSE} = \sqrt{\frac{1}{n}\sum_1^n (x_i - y_i)} \tag{3}$$

$$\text{Mean Absolute error, MAE} = \frac{1}{n}\sum_1^n |x_i - y_i| \tag{4}$$

3. Results and Discussion

The predictive accuracy of artificial neural network and linear regression models was assessed based on the lab testing of concrete specimens regarding compressive and split tensile strength. Based on (RMSE), the prediction accuracy is further validated. R^2 was estimated to examine the performance of both the models used in this study. The following information was gathered for the statistical parameter that was used to assess the model's precision and accuracy:

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^N (a_i - b_i)^2}{N}} \tag{5}$$

$$\text{Coefficient of determination } (R^2) = \frac{1}{N}\sum_{i=1}^N \left|a_i - b_i\right|^2 \tag{6}$$

RMSE found the residual standard deviation in the difference between expected and actual values. It shows the separation between the regression and the data points. In other words, RMSE stands for root mean square error. The density of data points surrounding the best-fit line is implied. The degree of fit, often known as the degree of coefficient or R^2, represents the function of data change.

Table 4. Correlation of MAE with evaluated ANN models

MAE		Number of Hidden Layers								
		Linear activation function			Logistic activation function			Tanh activation function		
		1	3	5	1	3	5	1	3	5
No. of Neurons for each hidden layer	1	3.65	3.75	2.98	2.75	2.63	3.42	2.45	2.87	2.78
	2	2.13	2.23	2.75	3.1	3.01	3.14	2.88	2.99	2.25
	3	2.09	2.01	2.54	3.26	3.17	3.21	3.42	3.54	2.15
	4	1.98	1.78	2.38	2.89	2.93	3.05	3.65	3.7	2.43
	5	2.43	2.25	2.43	2.64	2.65	2.89	3.28	3.5	3.65
	6	2.67	3.17	2.16	2.43	2.74	2.54	2.97	3.9	3.81
	7	3.12	2.89	2.12	2.36	2.69	2.41	3.26	3.82	4.52
	8	2.22	2.12	2.17	2.28	2.31	2.25	3.15	4.25	3.76
	9	2.12	1.98	1.98	2.54	2.25	2.43	4.12	4.05	4.79
	10	2.53	2.07	2.01	2.72	2.43	2.53	3.98	4.59	4.61

Table 5. Correlation of R^2 with evaluated ANN models

R^2		Number of Hidden Layers								
		Linear activation function			Logistic activation function			Tanh activation function		
		1	3	5	1	3	5	1	3	5
No. of Neurons for each hidden layer	1	0.765	0.587	0.683	0.781	0.81	0.899	0.59	0.783	0.852
	2	0.853	0.742	0.796	0.912	0.729	0.72	0.857	0.882	0.813
	3	0.91	0.834	0.88	0.893	0.672	0.816	0.762	0.643	0.823
	4	0.811	0.853	0.832	0.785	0.893	0.693	0.834	0.783	0.785
	5	0.818	0.879	0.798	0.813	0.903	0.839	0.784	0.867	0.682
	6	0.785	0.739	0.687	0.834	0.709	0.851	0.812	0.915	0.567
	7	0.913	0.87	0.565	0.765	0.784	0.877	0.914	0.823	0.539
	8	0.893	0.887	0.91	0.805	0.843	0.785	0.759	0.848	0.675
	9	0.743	0.896	0.921	0.887	0.887	0.736	0.857	0.708	0.567
	10	0.731	0.892	0.874	0.935	0.89	0.897	0.694	0.783	0.574

Table 6. Root mean square error (RMSE) with evaluated ANN models

RMSE		Number of Hidden Layers								
		Linear activation function			Logistic activation function			Tanh activation function		
		1	3	5	1	3	5	1	3	5
No. of Neurons for each hidden layer	1	3.59	4.13	3.27	4.87	3.52	5.12	4.09	3.68	2.87
	2	2.85	3.37	2.75	2.57	3.38	2.67	3.21	4.03	3.19
	3	2.57	3.84	3.09	3.78	4.12	2.95	3.69	5.17	3.56
	4	2.95	2.98	3.24	3.28	3.11	4.56	3.21	3.53	6.7
	5	3.17	3.54	4.49	2.85	2.89	3.37	4.53	3.21	5.73
	6	3.62	5.37	3.13	4.35	3.65	3.74	5.4	3.23	4.65
	7	3.78	4.72	5.38	3.84	3.17	4.17	3.45	5.89	6.91
	8	4.14	2.93	2.81	3.05	2.93	3.87	4.36	4.05	6.38
	9	3.19	3.27	2.73	2.94	4.36	4.12	4.87	5.67	7.23
	10	4.07	2.81	2.67	4.31	3.62	3.15	5.86	6.86	7.27

3.1. Compressive strength

In the lab, compressive strength was obtained for concrete specimens mixed with Ceramic waste at varying degrees of percentage. The compressive strength test after 7 days, a 1.5% increment and 2.5% increase in ceramic waste were noted. Compressive strength increase was observed to increase by more than 4.5% concrete mix with 5%, 7.5%, and 10% ceramic waste. Concrete specimens that contained more than 10% ceramic waste showed a reduction in the compressive strength of the concrete. Concrete specimens decreased by 8%, 12%, 14%, and 16%, and trash increased by 12.5%, 15%, 17.5%, and 20%. During two-week and four-week tests, similar trends were observed. It was discovered that the compressive strength for 14 days was higher at 5% by 11%. It also showed that concrete with 5% ceramic waste increased in strength at a significant pace. Additionally, for 5% ceramic waste, an increase of 8% was seen after 28 days of testing. The concrete specimen's best dose was discovered to be 5% ceramic waste in place of sand.

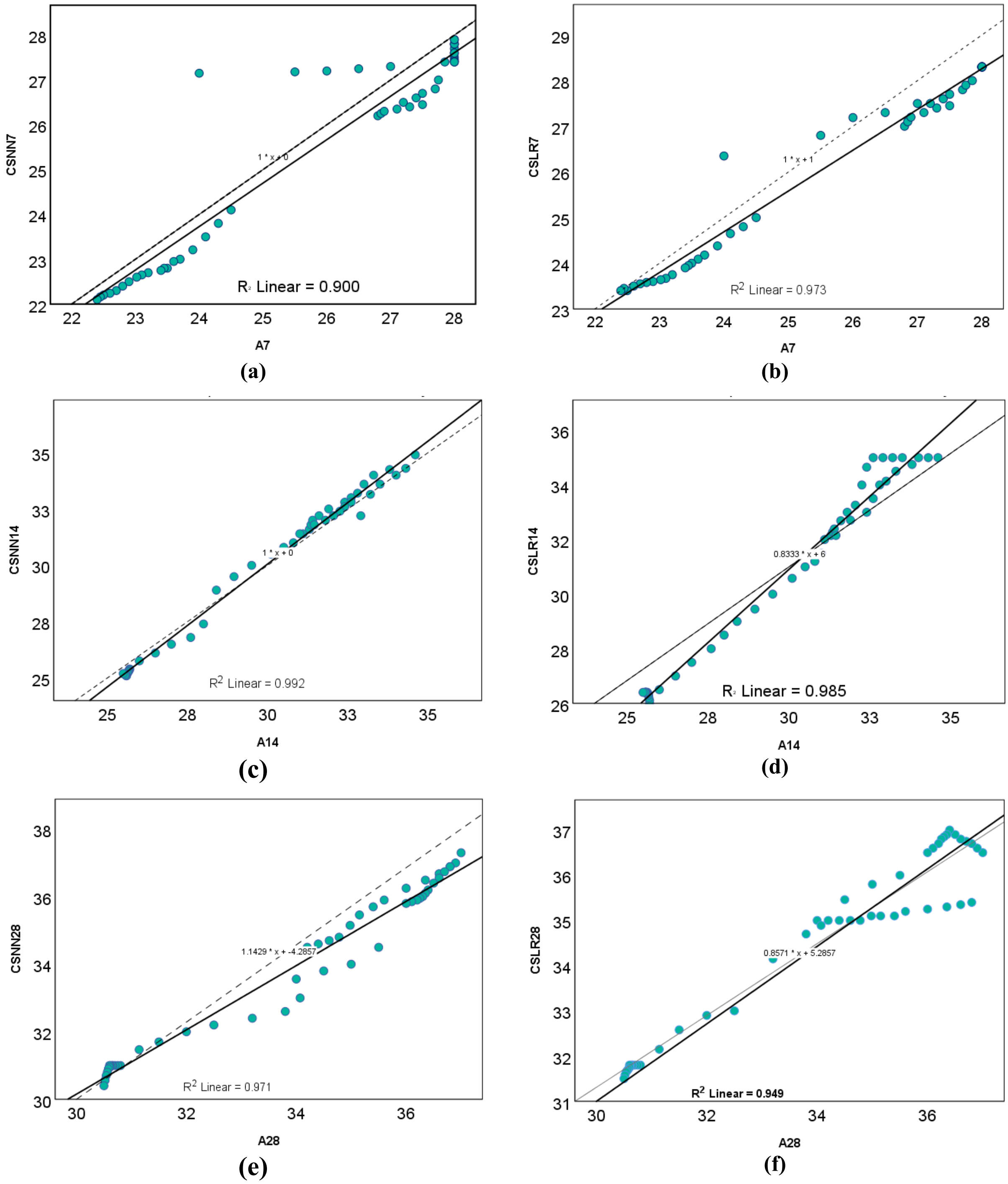

Fig. 3. Ceramic waste concrete specimen compressive strength actual (A7, A14 and A28) versus predicted for one week, two weeks and four weeks

Both algorithms used to forecast compressive strength were accurate for seven days. The linear regression and ANN models were accurate, with R2 values of 0.97 and 0.9, respectively, for the prediction of concrete compressive strength in one week. However, the linear regression model was better at forecasting compressive strength over seven days than the ANN. Both models' accuracy was shown to be higher at a 14-day compressive strength forecast than it was at a 7-day prediction. The ANN model depicted an R^2 value of 0.99, and the linear regression model depicted an R^2 value of 0.985. Even though both models' accuracy was high, the ANN model was observed to be more accurate in the prediction of compressive strength at two weeks. After two weeks of prediction accuracy, this study evaluated the prediction efficiency of both models at compressive strength at 4 weeks. ANN model depicted the R^2 value to be 0.97 as compared to 0.95 R-2-value for the linear regression model.

The linear regression model exhibited RMSE values of 1.28 MPa, 1.23 MPa and 1.1 MPa for four weeks, two weeks and one week, respectively. For ANN, the RMSE values were 1.02 MPa, 1.1 MPa and 1.2 MPa for four weeks, two weeks and one week, respectively. Ahmed et al. (2022) reported comparable accuracy of the machine learning algorithm with R^2 values of 0.7-0.98 and RMSE values of 1.3-15.2 MPa. This is in a similar range of results obtained in this study, which was evaluated for geopolymer fly ash concrete. The compressive strength of nylon fibre-reinforced ceramic waste concrete was modelled by Ray, Rahman et al. (2021). They employed gradient-boosting machine learning and support vector machine for prediction, and they reported values of 0.88 and 0.98 for R^2 and RMSE, respectively. Javed et al. (2024) observed an RMSE value of 2.153 for the support vector regression model, 3.28 for the decision tree model, and 0.435 for the autoregression model for compressive strength modelling. Singh et al. (2024) reported an R^2 value of 0.44 for the linear regression model, 0.99 for the linear gradient boost model, 0.99 for the gradient boosting regressor model and 0.98 for the decision tree model for compressive strength prediction.

3.2. Ceramic waste concrete split tensile strength

The split tensile strength increased by 3.16%, 2.76%, 2.37%, and 0.39% when mixed with ceramic wasteway at the rate of 10%, 7.5%, 5% and 2.5%, respectively. At the seven-day testing, there was a decrement of 8.7%, 8.3%, 7.11% and 0.39% when concrete specimen was modified with 10%, 17.5%, 15%, 12.5% and 10%, respectively. Nonetheless, after 14 days split tensile strength of concrete increased by 1.75%, 3.5%, 5.26% and 1.75% when modified with ceramic waste at rates of 10%, 7.5%, 5% and 2.5%, respectively. Similarly, after four weeks of testing, the split tensile strength of concrete increased by 10%, 15%, 9.3%, and 6.6% for 2.5%, 5%, 7.5%, and 10% of the ceramic waste in concrete.

ANN model and linear regression model prediction results obtained in this study for split tensile strength of concrete are presented in Figure 4. The modelling was carried out for one, two, and four weeks split tensile reading obtained in this study for ceramic waste-modified concrete. The accuracy of a one-week prediction using the ANN and LR models was very poor, with R2 values of 0.11 and 0.09 for each model. The two-week prediction model depicted improved accuracy but was still far from satisfactory. The R^2 values obtained were 0.54 and 0.3 for LR and ANN models, respectively. This revealed that the LR prediction accuracy was higher than the ANN model. The prediction accuracy further increased when the prediction was considered for four-week readings of concrete specimen for split tensile strength. The LR model depicted an R^2 value of 0.7, while the ANN model reached satisfactory performance with an R^2 value of 0.87. The ANN model significantly outperformed the linear regression model in terms of accuracy. Ray, Rahman et al. (2021) observed a similar result difference in R2 values (0.7 and 0.92) for ceramic waste fibre-reinforced concrete. Javed et al. (2024) observed an RMSE value of 0.318 for the support vector regression model, 0.373 for decision tree model, and 0.152 for the autoregression model for compressive strength modelling.

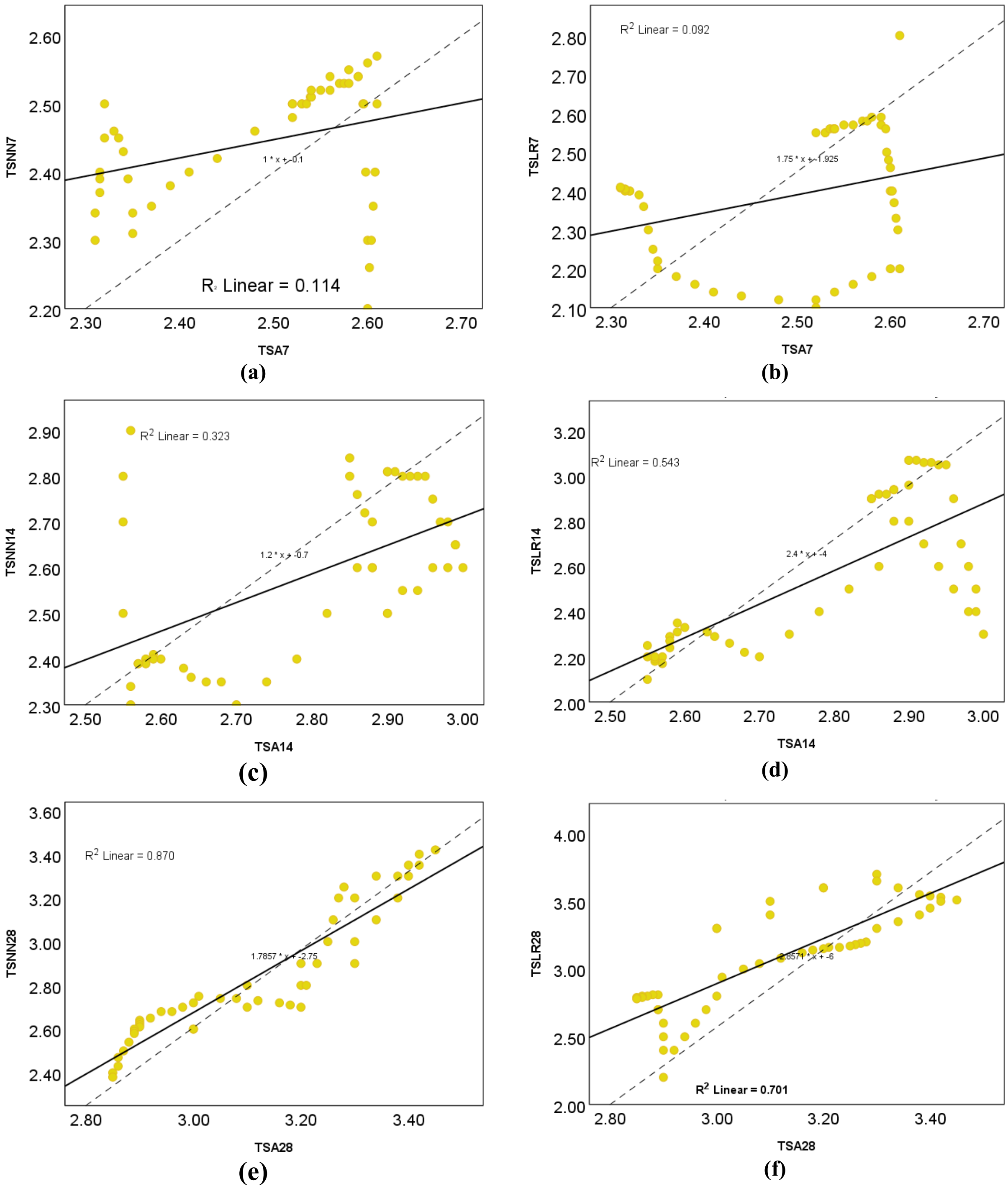

Fig. 4. Ceramic waste concrete specimen Split Tensile strength actual (A7, A14 and A28) versus predicted for one week, two week and four weeks

4. Conclusion

This study evaluated the impact of ceramic waste incorporation in concrete regarding compressive and tensile strength. The sand was replaced by ceramic waste to develop the concrete mix. The modelling used linear regression and an artificial neural network approach. The study's conclusion is as follows:

- Ceramic waste incorporated in place of sand in the concrete matrix was varied at a concentration of 0-10% with each increment of 2.5%. The compressive strength of the modified concrete increased by 3.5-8%. Any increase in the percentage of ceramic waste results in the decrement of compressive strength of ceramic-modified concrete by 1-10%.
- Similarly, for 2.5%, 5%, 7.5% and 10% dosage of ceramic waste, split tensile strength rose by 10%, 15%, 9% and 6%. Any further increase in ceramic proportion led to a 0.3-5% loss in split tensile strength, mirroring results for compressive strength.
- The ideal dosage of ceramic waste to boost concrete's compressive strength is 2.5-10%. However, from the results, 5% of ceramic waste was the ideal dose to use in place of sand.
- Both models appear rather accurate in their predictions of ceramic-modified concrete mechanical properties. Regarding compressive strength forecasting of ceramic concrete after seven days, the linear regression model was more reliable than the ANN model. For twenty-eight days, compressive is standardized worldwide; this study would advise using artificial neural networks for modelling.
- In split tensile strength, ANN and linear regression prediction models performed badly. Both models' performances for split tensile prediction over 7 and 14 days were quite inaccurate. However, the ANN model did quite well regarding 28-day prediction accuracy.
- This study will conclude that the artificial neural network model has high accuracy. Therefore, it can be employed to model the mechanical properties of ceramic-modified concrete.
- Additional research is needed to assess more prediction models available regarding Machine learning, deep machine learning and other AI tools to identify and optimize the best-fitted model for concrete strength prediction, which can be used for developing a framework to evaluate the existing buildings and remaining service life of concrete structure.

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