Section A-Research paper

Prediction of Compressive Strength of Concrete with Rice husk Ash by using ANN Model

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Abstract: Both the problem of disposing of agricultural waste and the production of carbon dioxide are reduced by the use of rice husk ash and ordinary concrete. The evaluation of the compressive strength of rice husk ash concrete has, however, presented additional difficulties. In order to forecast the compressive strength of RHA concrete, this research suggests a brand-new hybrid artificial neural network model that has been optimised utilising a reptile search method with circle mapping. The suggested model was trained using 192 concrete data with 6 input parameters (age, cement, rice husk ash, super plasticizer, aggregate, and water) and its prediction performance was compared to that of five existing models. To assess the accuracy of the produced models' predictions, four statistical indicators were used. According to the performance evaluation, the suggested hybrid artificial neural network model had the best prediction accuracy in terms of R2, VAF, RMSE, and MAE (0.9709, 3.4489, 2.6451), all of which were highly satisfactory. The suggested model outperformed previously created models on the same data in terms of predicted accuracy. Age is the most crucial factor for predicting the compressive strength of RHA concrete, according to the results of the sensitivity analysis.

Keywords: rice husk ash; concrete; compressive strength; reptile search algorithm with circle mapping; artificial neural network

1. Introduction

Concrete continues to be one of the materials that is most in demand worldwide in the building and other sectors [1]. Concrete was produced in excess of 10 billion cubic metres by 2018 [2]. The manufacturing of cement increased to 4 billion tonnes in as a major component in 2020 [3]. Although cement gives concrete the strength it needs, the carbon dioxide (CO2) that is created during the forging process puts a significant environmental load (about 7%) on the atmosphere. Energy conservation and emission reduction have evolved into common objectives with practical applications in light of the harm that CO2 does to the environment and people. One of the best solutions to this issue is to look for alternative materials, namely supplemental cementitious materials (SCMs), to substitute cement in some areas. The majority of SCM choices now on the market come from waste materials produced during industrial and agricultural activities, including fly ash, silica fume, seed shells, scattered coconut fibres, and palm oil fuel (4,5,6,7,8,9). talc [14–20]. The rick husk ash (RHA) and standard concrete combination is one of these unique SCMs that has drawn a lot of interest [21–23]. First, one of the major byproducts of agricultural output is RHA. By contrast, mixing it with concrete is a sensible and creative approach to recycle, as opposed to conventional stacking, which might contaminate the air and groundwater [24]. Second, RHA's pozzolanic properties contribute to the strength and durability of concrete [25]. RHA, however, has a significant impact on the performance of concrete [26], particularly compressive strength, which has a direct impact on the resilience and stability of buildings in the construction and other sectors. RHA was utilised to replace 20% of the cement by Madandoust et al. [27] in order to examine the strength of concrete. According to their findings, RHA concrete's short-term compressive strength decreased but its long-term compressive strength increased. Cement performance at two different RHA replacement rates (10% and 20%) was studied by Ahsan and Hossain [28]. They discovered that substituting 10% of cement with RHA was ideal because the silica component of RHA more efficiently densified the interfacial transition zone. However, Noaman et al. [29] demonstrated that 15% RHA might be used in place of cement to increase the compressive strength of concrete. Determining the strength of concrete is both vital and difficult since it is difficult to calculate the ratio of other ingredients to cement and RHA while producing concrete. The laboratory compressive test is the most precise way to assess the strength of concrete. However, creating and maintaining concrete examples is difficult, time-consuming, and wasteful of labourers and resources [30]. For instance, two to three experts are needed to execute a set of experiments. A method based on an empirical formula was created to estimate compressive strength in order to increase computation efficiency and site limitation. This approach was highly commended by field workers. By calculating the compressive strength of RHA concrete using the least-squares method, Islam et al. [31] created an empirical formula. Their findings demonstrated that the formula performed well in terms of prediction, with a correlation coefficient (R) of 0.816. To calculate the compressive strength of concrete containing RHA with various replacement levels, Liu et al. [32] used six empirical equations. The empirical formula's drawback, however, is that it cannot fully capture the intricate nonlinear relationship between the factors that were taken into consideration and compressive strength. [33]

In recent years, machine learning (ML), a commonplace technology, has been widely applied in artificial intelligence approaches to answer the challenge of predicting concrete strength [34–40]. Four different support vector machine (SVM) models were used by Azimi-Pour et al. [41] to forecast the compressive strength of fly ash concrete. According to the performance findings, the radial basis function (RBF)-based SVM model achieved the maximum accuracy for an R2 coefficient of 0.9932. The random forest (RF) model was enhanced by Zhang et al. [42] to forecast the compressive strength of lightweight concrete (LWC). The compressive strength of lightweight foamed concrete was predicted using the extreme learning machine (ELM) model [43]. In comparison to these models, an artificial neural network (ANN) model is more preferred in forecasting the actual strength of RHA [44–47]. It has a simple structure, strong capabilities for processing high-dimensional data, and complicated parameter interactions. To predict the 28-day compressive strength of a composite concrete mixture using RHA and reclaimed asphalt pavement (RAP), Getahun et al. [48] created an ANN model. According to the prediction results' good performance indices—R was 0.9811 and the root mean square error (RMSE) was 0.648—the ANN model could successfully match the relationship between the strength and the investigated components. Many researchers modified this model using different optimisation algorithms for predicting concrete strength, such as grey wolf optimisation (GWO) [49,50], particle swarm optimisation (PSO) [51,52], the genetic algorithm (GA) [53], the whale optimisation algorithm (WOA) [54], and simulated annealing (SA) with PSO [55]. The goal of these modifications was to optimise the selection scheme of the ANN model on weight and bias values and further improve model performance. Andalib et al. [56] optimised the ANN model for forecasting compressive strength for RHA concrete using the bat algorithm (BA), PSO, and teaching-learning-based optimisation (TLBO) method.

The performance results revealed that all improved ANN models, particularly the BA-ANN model (RMSE = 5.898), had acceptable prediction accuracy;

Four hybrid ANN models were put out by Hamidian et al. [33] to calculate the compressive strength of RHA concrete. The PSO-with-two differential-mutations (PSOTD)-based ANN model outperformed other models based on the findings of the performance study of all models, as shown by the higher R2 values (0.9697). Numerous recently created and good populations based on optimisation algorithms have yet to be used to forecast the strength of RHA concrete. To maximise the prediction power of ANN models, population initialization also has to be taken into consideration.

2. Data and Methods

2.1. Rice Husk Ash Concrete

Without the usage of additional materials, RHA concrete cannot be formed. For instance, cement is necessary to make concrete strong enough, water is essential for regulating concrete compactness during mixing, and aggregate preserves concrete's volume stability. Iftikhar et al. [57] produced a number of concrete samples to test the compressive strength of RHA concrete by mixing cement (kg/m3), RHA (kg/m3), a superplasticizer (kg/m3), an aggregate (kg/m3), and water (kg/m3). Concrete that has just been poured has to cure, and after it has, its strength needs to be assessed. Age (days) is thus a significant factor in estimating the strength of concrete. This study evaluated RHA concrete using 192 compressive strength data from Iftikhar et al. [57].

Table 1. Statistical information on each variable for predicting RHA concrete strength.

Variables	Statistical Indices				
	Min	**Max**	**Mean**	**Median**	**St. D**
Cement	249.0	783.0	409.02	400.00	105.47
RHA	0.0	171.0	62.33	57.00	41.55
Superplasticizer	0.0	11.3	3.34	1.85	3.52
Aggregate	1040.0	1970.0	1621.51	1725.00	267.77
Water	120.0	238.0	193.54	203.00	31.93
Age	1.0	90.0	34.57	28.00	33.52
Compressive strength	16.0	104.1	48.14	45.95	17.54

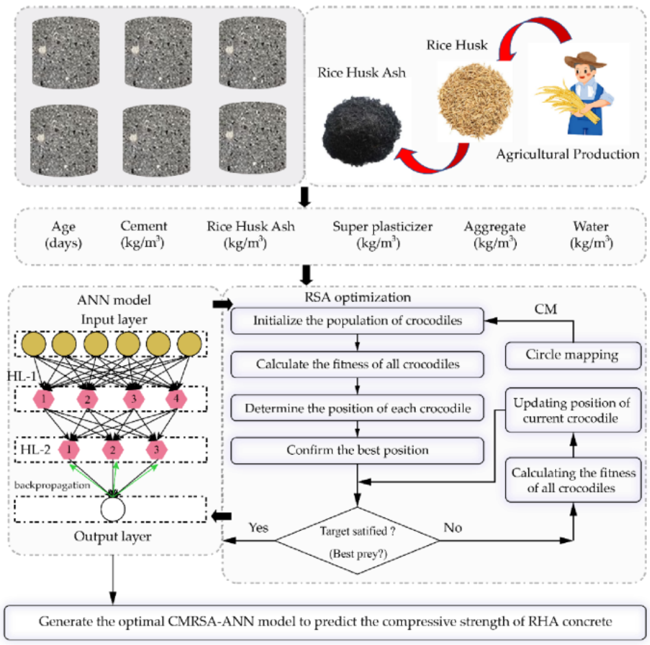
Note: Min, minimal values; Max, maximal values; St. D, standard deviation.

2.2. Reptile Search Algorithm

Abualigah et al. [61] presented the unique metaheuristic optimization-based method known as RSA. The crocodile's hunting style served as the model for this algorithm's approach to the optimisation challenge. Scientists have long been interested in the behaviour of crocodiles since they are the top predators in aquatic habitats. Due to their excellent mobility, crocodiles may easily pursue and attack prey, especially at night. This characteristic is benefited by the crocodile's superior night vision and its body structure, which offers less resistance [61]. Second, because crocodiles are exceptionally intelligent creatures, they have excellent recognition and perceptive skills. For instance, crocodiles lurk around rivers or other areas where prey is often present. Crocodile hunting is another example of group behaviour, and teams that have a distinct division of labour allow people to have adequate food. This process is based on a random initialization method, but it has limitations regarding population diversity and the potential search area [62]. The diverse distributions of people in the search area were established using a combination of different methods of chaos mapping to tackle this challenge [63,64]. In this research, circle mapping was used to optimise the population initialization of RSA, which has the benefits of stability and coverage rate.

3. Development of the Novel CMRSA–ANN Model

The ANN model used in this study was created to precisely forecast the strength of RHA concrete. However, the effectiveness of prediction is significantly impacted by the design of an ANN structure. It is particularly tough and difficult to determine the weights and biases between the input, hidden, and output layers [65]. The ideal weights and biases for the ANN model were determined using the enhanced RSA with Circle mapping (CM). In order to estimate the compressive strength of RHA concrete, a novel prediction model called the CMRSA-ANN model was put out. A total of 192 data points were randomly split into training and test sets at a 4 to 1 ratio before the model was run, meaning that 154 data points were used to train the model and 38 data points were used to test it. You can find all the information in the Supplementary materials. This influence on performance development might be avoided by the requisite normalisation because the units of all employed parameters varied. As a result, every parameter was normalised to lie between 1 and 1. Population size is the most crucial internal parameter that must be established throughout iterations for the optimisation algorithm-based population [66-68]. Six population sizes (25, 50, 75, 100, 125, and 150) were used to perform the optimisation process for the ANN model in order to identify the global optimal solution. To make sure the best solution could be identified and remained stable, we set up 300 iterations. In general, the solution determined by the optimisation method was represented by the fitness value.



4. Prediction Model Development

4.1. ANN Model

The fundamental layers for a typical ANN model are input, hidden, and output layers. In single-target regression problems, one input layer and one output layer are fixed collocations relative to the quantity of hidden layers. Similar prediction problems are frequently solved using two hidden layers [71–73]. The performance of the ANN model is also significantly impacted by the number of neurons in each hidden layer. In order to choose the best ANN structure and matching neurons for forecasting the compressive strength of RHA concrete, a number of tests were conducted. In this study, the activation function was adjusted to sigmoid, the hidden layers were either 1 or 2, the number of neurons ranged from 2 to 12, and the backpropagation technique was used to increase prediction accuracy. As a consequence, ten tests employing various ANN models were developed, and Table 3's representation of their performance using R2 and RMSE. With a better R2 (0.8772) and lower RMSE (5.8632) than other models, the ANN model with two hidden layers—four neurons in the first hidden layer and three neurons in the second hidden layer—performed the best.

Performance of the ANN model with different hidden layers and neuron numbers.

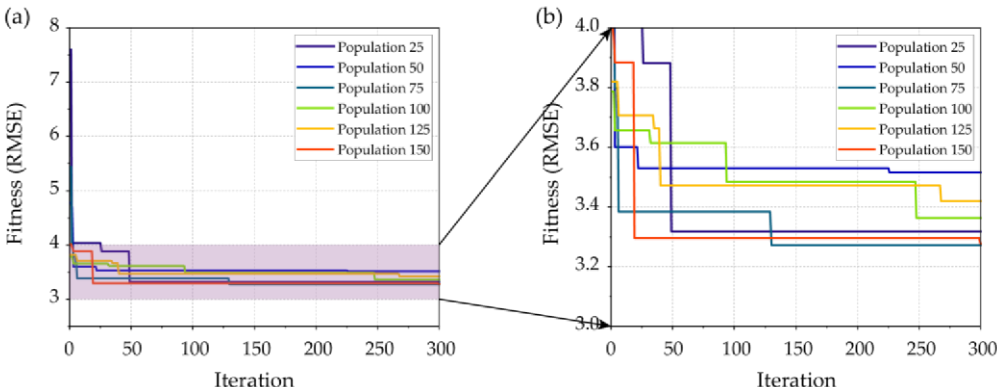
Tests	Structure		Performance	
	HL-1	HL-2	R2	RMSE
1	2	/	0.8322	6.8525
2	4	/	0.7839	7.7690
3	6	/	0.8100	7.2921
4	8	/	0.8225	7.0476
5	10	/	0.8554	6.3611
6	4	3	0.8772	5.8632
7	4	6	0.8312	6.8726
8	6	8	0.8025	7.4350
9	8	10	0.8143	7.2101
10	10	12	0.8338	6.8193

Note: HL-1, first hidden layer; HL-2, second hidden layer.

4.2. CMRSA–ANN Model

Even if the optimum structure was identified during the ANN model construction, selecting the weights and biases between layers to reduce prediction error might be challenging.

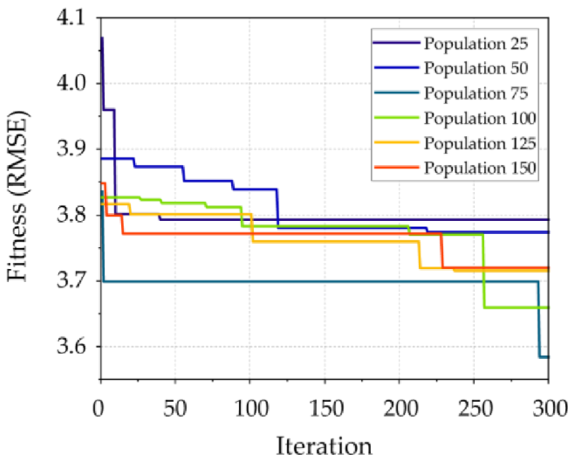
Therefore, the basic ANN model with two hidden layers (four neurons in the first hidden layer and three neurons in the second hidden layer) was optimised using the CMRSA optimisation technique; the resulting framework is illustrated in Figure 2. 300 iterations of six hybrid CMRSA-ANN models with various population sizes were performed. Figure 3a displays each model's iteration curve. Figure 3b demonstrates that, out of all hybrid ANN models, the CMRSA-ANN model with a population size of 75 had the lowest fitness value. This model was therefore utilised to forecast the compressive strength of RHA.



CMRSA–ANN model development: (**a**) iteration curves; (**b**) local comparison.

4.3. SOA–SVM Model

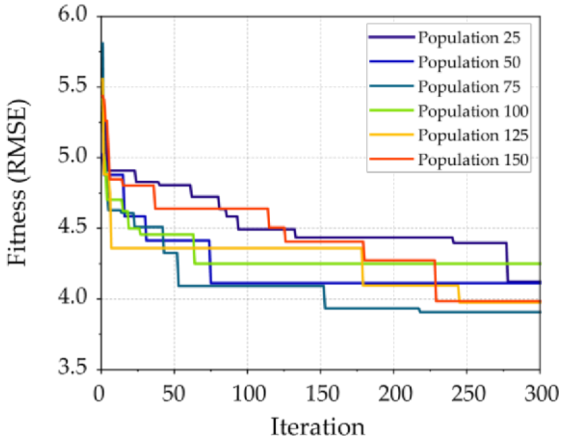
The SOA-SVM model's evolution is comparable to that of the CMRSA-ANN model. The regularisation parameter (C) and kernel coefficient () of the used kernel function are the two basic hyperparameters for the SVM model that are crucial for enhancing model performance [74,75]. The well-known radial basis function (RBF) was used in this study as the SVM model's kernel function. The range of these values was 0 to 100 in order to find the best hyperparameter combination for the SVM model. Population sizes and the number of iterations for SOA were set to match those for CMRSA. Figure 4 displays the SOA-SVM models' development outcomes. 75 people made up the training population of the top SOA-SVM model.



SOA–SVM model development.

4.4. SOA–RF Model

In tackling classification and regression issues, ensemble models, such the RF model, might perform well; a thorough introduction to the RF model can be found in the literature [58,76]. All trees can assess RF performance and resist overfitting thanks to the distinctive tree structure and bootstrap sampling [74]. The basic goal of developing SOA-RF models is to identify the ideal RF model hyperparameter combination, which includes the number of trees (Nt) and the depth of random features (Maxdepth). The tree number range in this paper was 1 to 100, while the random feature range was 1 to 10. After 300 iterations, Figure 5 displays the optimisation outcomes for the SOA-RF models based on various population sizes.



SOA–RF model development.

4.5. ELM Model

The ELM model is a unique neuron network with a single hidden layer designed specifically to address regression issues. Only the number of neurons chosen for the hidden layer controls how well the ELM model predicts outcomes. In order to estimate concrete strength, 10 ELM models with different hidden layer neuron counts were created. The prediction effectiveness of each ELM model during the training phase is listed in Table 4. Large ELM models outperformed models with lesser numbers of neurons in terms of performance. The 9th test, with 100 neurons, included the best ELM model, though. R2 is equivalent to 0.8932 and RMSE, which are more dependable performance metrics for this model than for other models.

Performance of an ELM model with different neuron numbers.

Tests	Neuron Numbers	Performance	
		R2	**RMSE**
1	20	0.5268	11.5078
2	30	0.6460	9.9534
3	40	0.7327	8.6492
4	50	0.7595	8.2046
5	60	0.7851	7.7555
6	70	0.7997	7.4873
7	80	0.8589	6.2835
8	90	0.8373	6.7479
9	100	0.8932	5.4682
10	110	0.8788	5.8235

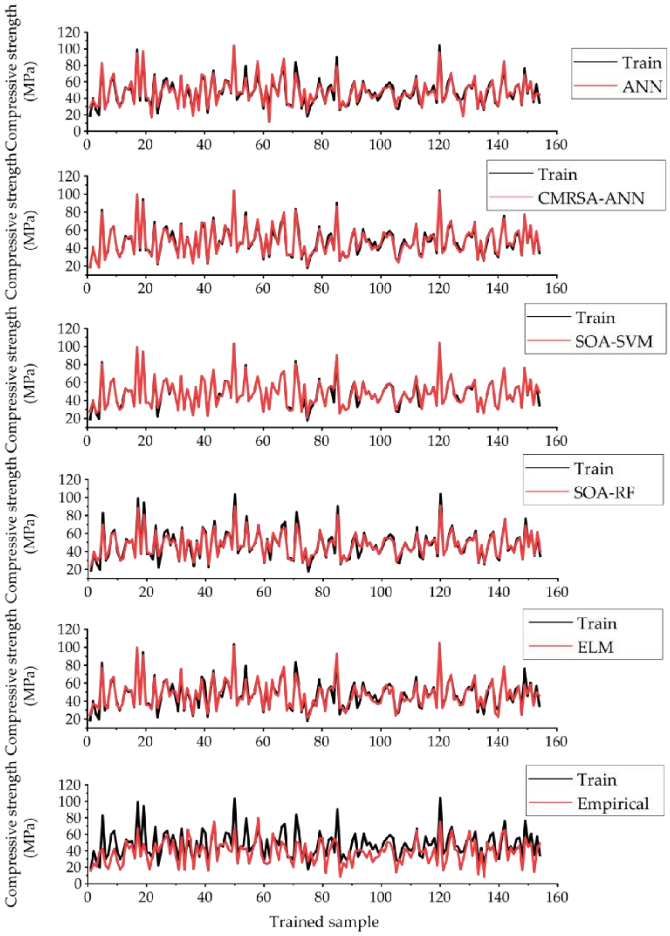
5. Results and Discussion

Each suggested model's prediction performance was thoroughly assessed following training. The prediction curves for each model used to forecast the compressive strength of RHA concrete during the training phase are shown in Figure 7. The empirical model's prediction curve and training curve had the most discrepancy of all the models. Particularly in the CMRSA-ANN model, there was a substantially larger similarity between the training and prediction curves of the three hybrid models.

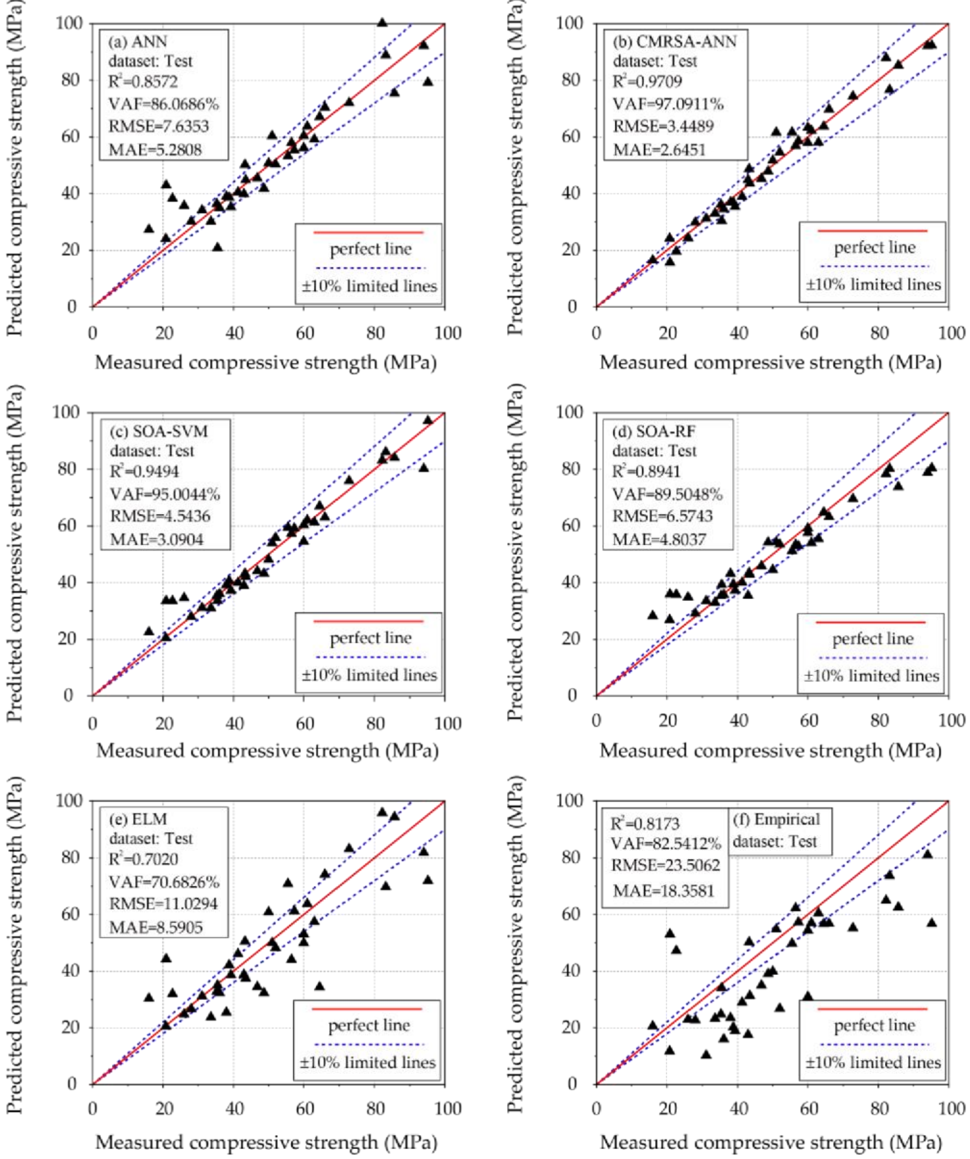
To assure the continued preservation of the strong predictive capacity, further testing was required for all trained models. The assessment results of each model utilising four performance indicators throughout both the training and testing periods are shown in Table. The CMRSA-ANN model was the best prediction model, according to the performance results obtained using the training set, as it had the greatest values of R2 and VAF (0.9679 and 96.7884%) and the lowest values of RMSE and MAE (2.9991 and 2.3169). Following this approach, two further hybrid models (SOA-SVM and SOA-RF) also outperformed unoptimized ML (ANN and ELM) and empirical models in terms of prediction accuracy. However, the suggested CMRSA-ANN model still outperformed other models in terms of predictive performance, as shown by the higher values of R2 and VAF (0.9709 and 97.0911%) and the lower values of RMSE and MAE (3.4489 and 2.6451) than those of other models.

Performance evaluation of prediction models using training and test sets.

Model		**ıce (Training Set)**			**Model**	**Performance (Test Set)**			
	R2	**VAF %**	**RMSE**	**MAE**		**R2**	**VAF %**	**RMSE**	**MAE**
ANN	0.8772	87.7619	5.8632	4.1423	ANN	0.8572	86.0686	7.6353	5.2808
CMRSA–ANN	0.9679	96.7884	2.9991	2.3169	CMRSA–ANN	0.9709	97.0911	3.4489	2.6451
SOA–SVM	0.9595	96.0957	3.3651	1.2528	SOA–SVM	0.9494	95.0044	4.5436	3.0904
SOA–RF	0.9224	92.2384	4.6610	3.2359	SOA–RF	0.8941	89.5048	6.5743	4.8037
ELM	0.8932	89.3163	5.4682	4.0644	ELM	0.7020	70.6826	11.0294	8.5905
Empirical	0.2023	50.0783	14.9418	12.0202	Empirical	0.3716	57.3263	16.0169	13.1709

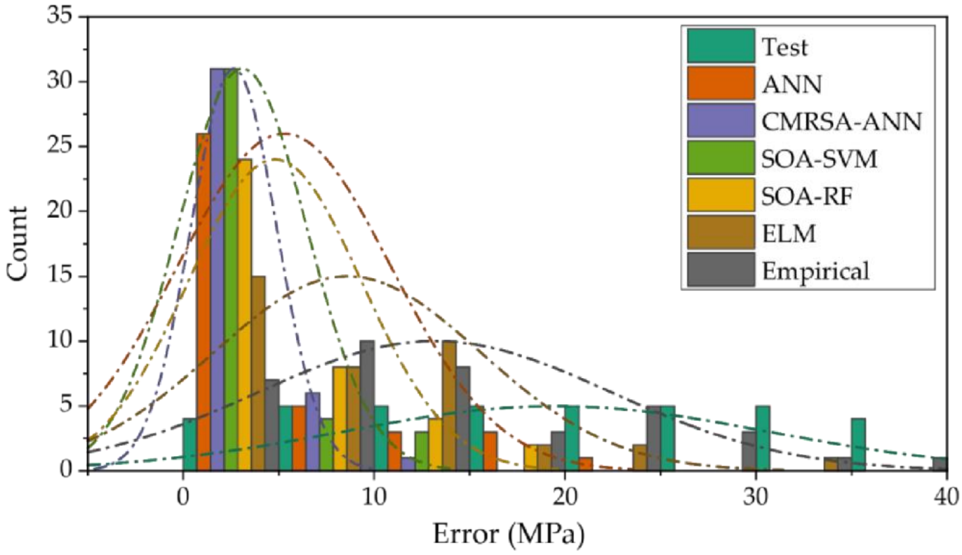


Regression connections may also be used to assess and compare a model's capability to predict outcomes. The regression outcomes for each model using the test set are displayed in Figure 8. To assess the regression connection between the values from the prediction model and the measured values, one perfect and two restricted lines were employed in each regression plot. The best model's predicted data point, for instance, may be on the ideal line if it has a prediction accuracy of 100%. The more data points that were close to the ideal line and within the restricted lines, as shown by the observations based on this criterion, demonstrate that the CMRSA-ANN model outperformed other models in terms of predictive ability.

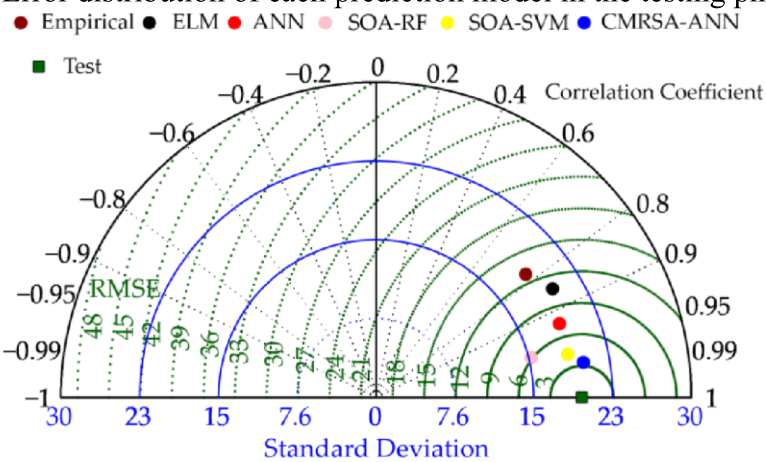


Regression results of all developed models using the test set.

Taylor diagrams are used to compare several models' prediction abilities graphically. A model with a high prediction accuracy will be near the target value in a Taylor diagram. Three indices—St. D., RMSE, and R—are used to establish each model's position. As a result, the model's performance may be assessed and measured against many indices. The Taylor diagram in Figure 10 shows the evaluation findings for each built model. The test set's location was most closely approximated by the CMRSA-ANN model. Models ranked by distance after this model are SOA-SVM, SOA-RF, ANN, ELM, and empirical. According to these findings, the CMRSA optimisation technique is effective in raising the predictive capability of ANN models.

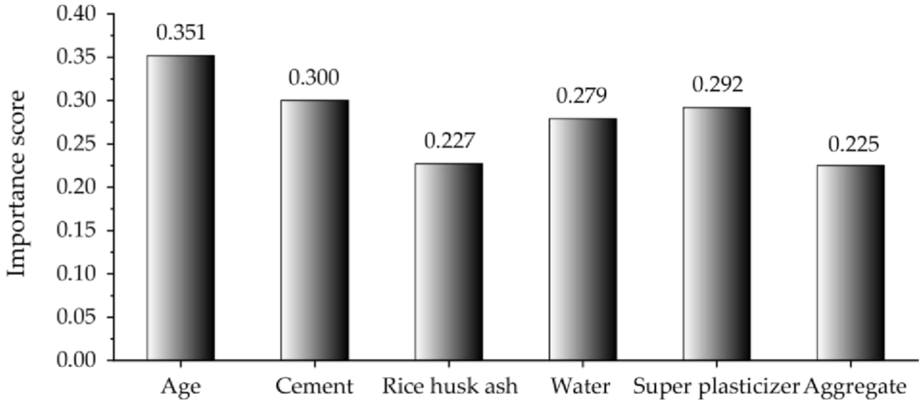


Error distribution of each prediction model in the testing phase.



Performance comparison between prediction models using a Taylor diagram.

Nevertheless, it is difficult to further enhance the qualities of concrete since it is unclear how important or sensitive each input parameter is to the prediction of compressive strength. Sensitivity analysis was thus performed to assess the effect of each input parameter on the result. In this study, the Pianosi and Wagener (PAWN) calculation technique was used to determine the relevance score of the input values. The compressive strength prediction of the CMRSA-ANN model is shown in Figure 11 with the results of the sensitivity analysis. The most significant factor for predicting the compressive strength of RHA concrete was age, with the highest score (0.351). In order of effect, the following factors come after age: cement (0.300), superplasticizer (0.292), water (0.279), RHA (0.227), and aggregate (0.225). This outcome is congruent with that which was found.



Importance score of each parameter based on the CMRSA-ANN model.

The predictive performance of the other models created using the same database was compared with that of the CMRSA-ANN model suggested in this study in order to confirm the efficacy and superiority of the prediction model. The results are displayed in Table 7. The higher R2 value indicates that the proposed model performed better in terms of prediction than the published models. These findings also suggest that the CMRSA-ANN model might provide a more comprehensive explanation of how the input parameters and the compressive strength of RHA concrete relate to one another.

Performance comparison of previous works and the proposed model.

Reference	**Model**	**Performance (R^2)**
Iftikhar et al. [57]	GEP	0.9670
	RFR	0.9130
Amin et al. [79]	DT	0.8900
	BgR	0.9200
	ADB	0.9100
This paper	CMRSA–ANN	0.9709

Note: GEP, gene expression programming; RFR, random forest regression; DT, decision trees; BgR, bagging regressors; ADB, AdaBoost regressors.

6. Conclusion

In addition to addressing the issue of carbon dioxide emissions from cement manufacturing and easing the strain of waste accumulation, the combination of RHA with concrete has the potential to be extensively employed as a green construction material. We suggested a unique hybrid CMRSA-ANN model to forecast the compressive strength of RHA concrete in order to assess the performance of RHA concrete. In order to train the model and evaluate its effectiveness, we used 192 concrete data. The prediction outcomes of four ML models and an empirical model were also created, and they were contrasted with those of the suggested model. The following are this paper's primary conclusions:

(1) In both the training and testing phases, the proposed hybrid CMRSA-ANN model outperformed all other models in terms of prediction accuracy for R2 (0.9679 and 0.9709), VAF (96.7884% and 97.0911%), RMSE (2.9991 and 3.4489), and MAE (2.3169 and 2.6451). The performance comparison of the suggested and optimised ANN models showed that the CMRSA may significantly increase the ANN model's capacity for prediction.

(2) The empirical model was unable to more adequately describe how the input variables and the compressive strength of RHA concrete relate to one another. As a result, the empirical model proved inadequate as a traditional method of assessing tangible performance.

(3) As shown by greater R2 (0.9491 and 0.8941) and VAF (95.0044% and 89.5048%), as well as lower RMSE (4.5436 and 6.5743) and MAE (3.0904 and 4.8037) in the testing phase, the hybrid SOA-SVM and SOA-RF models outperformed the unoptimized ANN and ELM models in terms of performance. Using an optimisation approach, such a population-based one, to boost the performance of ML models is both useful and required.

(4) The most crucial factor used to estimate the compressive strength of RHA concrete was age. However, high priority should also be given to other input factors with comparable relevance ratings.

This paper's goal was to provide a novel approach for estimating RHA concrete strength and to explore the potential relationships between the data by combining and optimising hybrid algorithms. However, this paper's main drawback is the fact that there was never enough data to train and evaluate the models. The capacity of the model to understand the possible link between input and output parameters may be improved by increasing the amount of useful data, and the model's performance may be more accurately verified by diversifying the test data. Therefore, increasing the amount of experimental data is a useful strategy to raise the model's prediction accuracy. Combining several ML models and other optimisation strategies to forecast RHA performance.

References

1. Mei, X.; Cui, Z.; Sheng, Q.; Zhou, J.; Li, C. Application of the Improved POA-RF Model in Predicting the Strength and Energy Absorption Property of a Novel Aseismic Rubber-Concrete Material. *Materials* **2023**, *16*, 1286. [CrossRef] [PubMed]
2. Thomas, B.S. Green concrete partially comprised of rice husk ash as a supplementary cementitious material–A comprehensive review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3913–3923. [CrossRef]
3. Sheheryar, M.; Rehan, R.; Nehdi, M.L. Estimating CO_2 emission savings from ultrahigh performance concrete: A system dynamics approach. *Materials* **2021**, *14*, 995. [CrossRef] [PubMed]
4. Hamada, H.M.; Thomas, B.S.; Yahaya, F.M.; Muthusamy, K.; Yang, J.; Abdalla, J.A.; Hawileh, R.A. Sustainable use of palm oil fuel ash as a supplementary cementitious material: A comprehensive review. *J. Build. Eng.* **2021**, *40*, 102286. [CrossRef]

5. Amran, M.; Murali, G.; Fediuk, R.; Vatin, N.; Vasilev, Y.; Abdelgader, H. Palm oil fuel ash-based eco-efficient concrete: A critical review of the short-term properties. *Materials* **2021**, *14*, 332. [CrossRef]
6. Tayeh, B.A.; Hadzima-Nyarko, M.; Zeyad, A.M.; Al-Harazin, S.Z. Properties and durability of concrete with olive waste ash as a partial cement replacement. *Adv. Concr. Constr.* **2021**, *11*, 59–71.
7. Hakeem, I.Y.; Agwa, I.S.; Tayeh, B.A.; Abd-Elrahman, M.H. Effect of using a combination of rice husk and olive waste ashes on high-strength concrete properties. *Case Stud. Constr. Mater.* **2022**, *17*, e01486. [CrossRef]
8. Herath, C.; Gunasekara, C.; Law, D.W.; Setunge, S. Performance of high volume fly ash concrete incorporating additives: A systematic literature review. *Constr. Build. Mater.* **2020**, *258*, 120606. [CrossRef]
9. Teixeira, E.R.; Camões, A.; Branco, F.G. Synergetic effect of biomass fly ash on improvement of high-volume coal fly ash concrete properties. *Constr. Build. Mater.* **2022**, *314*, 125680. [CrossRef]
10. Mehta, A.; Ashish, D.K. Silica fume and waste glass in cement concrete production: A review. *J. Build. Eng.* **2020**, *29*, 100888. [CrossRef]
11. Khan, M.; Ali, M. Improvement in concrete behavior with fly ash, silica-fume and coconut fibres. *Constr. Build. Mater.* **2019**, *203*, 174–187. [CrossRef]
12. Beskopylny, A.N.; Shcherban, E.M.; Stel'makh, S.A.; Meskhi, B.; Shilov, A.A.; Varavka, V.; Özkılıç, Y.O.; Aksoylu, C.; Karalar, M. Composition Component Influence on Concrete Properties with the Additive of Rubber Tree Seed Shells. *Appl. Sci.* **2022**, *12*, 11744. [CrossRef]
13. Shcherban, E.M.; Stel'makh, S.A.; Beskopylny, A.N.; Mailyan, L.R.; Meskhi, B.; Shilov, A.A.; Chernil'nik, A.; Özkılıç, Y.O.; Aksoylu, C. Normal-Weight Concrete with Improved Stress–Strain Characteristics Reinforced with Dispersed Coconut Fibers. *Appl. Sci.* **2022**, *12*, 11734. [CrossRef]
14. Zeybek, Ö.; Özkılıç, Y.O.; Karalar, M.; Çelik, A.I.; Qaidi, S.; Ahmad, J.; Burduhos-Nergis, D.D.; Burduhos-Nergis, D.P. Influence of replacing cement with waste glass on mechanical properties of concrete. *Materials* **2022**, *15*, 7513. [CrossRef] [PubMed]
15. Karalar, M.; Bilir, T.; Çavus¸lu, M.; Özkiliç, Y.O.; Sabri Sabri, M.M. Use of recycled coal bottom ash in reinforced concrete beams as replacement for aggregate. *Front. Mater.* **2022**, *9*, 1064604. [CrossRef]
16. Qaidi, S.; Najm, H.M.; Abed, S.M.; Özkılıç, Y.O.; Al Dughaishi, H.; Alosta, M.; Sabri, M.M.S.; Alkhatib, F.; Milad, A. Concrete containing waste glass as an environmentally friendly aggregate: A review on fresh and mechanical characteristics. *Materials* **2022**, *15*, 6222. [CrossRef] [PubMed]
17. Çelik, A.I.; Özkılıç, Y.O.; Zeybek, Ö.; Karalar, M.; Qaidi, S.; Ahmad, J.; Burduhos-Nergis, D.D.; Bejinariu, C. Mechanical Behavior of Crushed Waste Glass as Replacement of Aggregates. *Materials* **2022**, *15*, 8093. [CrossRef] [PubMed]

18. Karalar, M.; Özkılıç, Y.O.; Aksoylu, C.; Sabri MM, S.; Beskopylny, A.N.; Stel'makh, S.A.; Shcherban, E.M. Flexural behavior of reinforced concrete beams using waste marble powder towards application of sustainable concrete. *Front. Mater.* **2022**, *9*, 1068791. [CrossRef]
19. Çelik, A.L.I.; Özkılıç, Y. Geopolymer concrete with high strength, workability and setting time using recycled steel wires and˙ basalt powder. *Steel Compos. Struct.* **2023**, *46*, 689–707.
20. Acar, M.C.; Çelik, A.I.; Kayabas¸ı, R.; S¸ener, A.; Özdöner, N.; Özkılıç, Y. Production of perlite-based-aerated geopolymer using˙ hydrogen peroxide as eco-friendly material for energy-efficient buildings. *J. Mater. Res. Technol.* **2023**, *24*, 81–99. [CrossRef]
21. Santhosh, K.G.; Subhani, S.M.; Bahurudeen, A. Recycling of palm oil fuel ash and rice husk ash in the cleaner production of concrete-A review. *J. Clean. Prod.* **2022**, *354*, 131736. [CrossRef]
22. Amin, M.N.; Ahmad, W.; Khan, K.; Sayed, M.M. Mapping research knowledge on rice husk ash application in concrete: A scientometric review. *Materials* **2022**, *15*, 3431. [CrossRef] [PubMed]
23. Li, Q.; Song, Z. Prediction of compressive strength of rice husk ash concrete based on stacking ensemble learning model. *J. Clean. Prod.* **2023**, *382*, 135279. [CrossRef]
24. Ihedioha, J.N.; Ukoha, P.O.; Ekere, N.R. Ecological and human health risk assessment of heavy metal contamination in soil of a municipal solid waste dump in Uyo, Nigeria. *Environ. Geochem. Health* **2017**, *39*, 497–515. [CrossRef] [PubMed]
25. He, Z.H.; Yang, Y.; Yuan, Q.; Shi, J.Y.; Liu, B.J.; Liang, C.F.; Du, S.G. Recycling hazardous water treatment sludge in cement-based construction materials: Mechanical properties, drying shrinkage, and nano-scale characteristics. *J. Clean. Prod.* **2021**, *290*, 125832. [CrossRef]
26. Paris, J.M.; Roessler, J.G.; Ferraro, C.C.; DeFord, H.D.; Townsend, T.G. A review of waste products utilized as supplements to Portland cement in concrete. *J. Clean. Prod.* **2016**, *121*, 1–18. [CrossRef]
27. Madandoust, R.; Ranjbar, M.M.; Moghadam, H.A.; Mousavi, S.Y. Mechanical properties and durability assessment of rice husk ash concrete. *Biosyst. Eng.* **2011**, *110*, 144–152. [CrossRef]
28. Ahsan, M.B.; Hossain, Z. Supplemental use of rice husk ash (RHA) as a cementitious material in concrete industry. *Constr. Build. Mater.* **2018**, *178*, 1–9. [CrossRef]
29. Noaman, M.A.; Karim, M.R.; Islam, M.N. Comparative study of pozzolanic and filler effect of rice husk ash on the mechanical properties and microstructure of brick aggregate concrete. *Heliyon* **2019**, *5*, e01926. [CrossRef]
30. Mei, X.; Li, C.; Sheng, Q.; Cui, Z.; Zhou, J.; Dias, D. Development of a hybrid artificial intelligence model to predict the uniaxial compressive strength of a new aseismic layer made of rubber-sand concrete. *Mech. Adv. Mater. Struct.* **2022**, 1–18. [CrossRef]
31. Islam, M.N.; Mohd Zain, M.F.; Jamil, M. Prediction of strength and slump of rice husk ash incorporated high-performance concrete. *J. Civ. Eng. Manag.* **2012**, *18*, 310–317. [CrossRef]

32. Liu, C.; Zhang, W.; Liu, H.; Lin, X.; Zhang, R. A compressive strength prediction model based on the hydration reaction of cement paste by rice husk ash. *Constr. Build. Mater.* **2022**, *340*, 127841. [CrossRef]
33. Hamidian, P.; Alidoust, P.; Golafshani, E.M.; Niavol, K.P.; Behnood, A. Introduction of a novel evolutionary neural network for evaluating the compressive strength of concretes: A case of Rice Husk Ash concrete. *J. Build. Eng.* **2022**, *61*, 105293. [CrossRef]
34. Ozcan, G.; Kocak, Y.; Gulbandilar, E. Estimation of compressive strength of BFS and WTRP blended cement mortars with machine learning models. *Comput. Concr* **2017**, *19*, 275–282. [CrossRef]
35. Deshpande, N.; Londhe, S.; Kulkarni, S. Modeling compressive strength of recycled aggregate concrete by Artificial Neural Network, Model Tree and Non-linear Regression. *Int. J. Sustain. Built Environ.* **2014**, *3*, 187–198. [CrossRef]