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Harnessing AI For Sustainable Construction: Predicting and Optimizing Recycled Aggregate Concrete with Krn-PSO

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Abstract:
This study presents an AI-driven approach to optimize recycled aggregate concrete (RAC) mixes reinforced with glass fibers (GF). A suite of machine learning (ML) models – including a Keras Recurrent Neural Network (kRN), Multilayer Perceptron (MLP), Back Propagation Neural Network (BPNN), Residual Neural Network (ResNet), and stacked Long Short-Term Memory (LSTM) – was developed to predict the 28-day compressive strength of RAC and identify optimal mix proportions. A comprehensive dataset of RAC mix designs (incorporating up to 100% recycled coarse aggregate replacement and various GF dosages) was compiled from literature and experimental results. Data were preprocessed (normalized and analyzed for correlations), and model hyperparameters were tuned via Bayesian optimization to maximize predictive performance. The best model (kRN) achieved near-perfect accuracy, with an $R^2 \approx 1.0$ on compressive strength prediction. Results confirm an inverse relationship between recycled aggregate content and compressive strength (e.g. 50% RCA caused ~8.9% strength reduction), while the inclusion of GF significantly improved mechanical performance. A small GF addition (0.5% by volume) enhanced compressive strength (e.g. from 35.9 MPa to 37.9 MPa in 0% RCA mixes) and recovered much of the strength lost to RCA, whereas excessive fiber content (>2% GF) led to diminished returns. The optimized ML-guided mix – using 50% recycled aggregate and 0.5–1.0% GF – achieves comparable strength to natural aggregate concrete, with a ~22% boost in tensile strength at 2% GF . These findings demonstrate that ML optimization can effectively balance performance and sustainability in concrete design, enabling high predictive accuracy in compressive strength and guiding the development of greener, fiber-reinforced RAC mixtures.
Keywords: *ai, predictive modeling, concrete, compressive strength, recycled aggregates, performance evaluation, cost savings*

1. INTRODUCTION

Construction and demolition waste have spurred interest in **recycled aggregate concrete (RAC)** as a sustainable alternative to conventional concrete. In Iraq and elsewhere, large stocks of discarded concrete blocks can be crushed into recycled concrete aggregate (RCA) for new concrete production [1-3]. Reusing RCA reduces landfill waste and preserves natural aggregates, but often at the cost of reduced mechanical properties. Studies have shown that RAC tends to have lower compressive strength than natural aggregate concrete (e.g. full replacement of coarse aggregate can reduce strength by ~23%) [4-6]. Even at 50% replacement, compressive strength may drop around 14%. This strength deficit is attributed to old adhered mortar on RCA, higher porosity, and weaker interfacial zones. However, the sustainability benefits of RAC – such as lower CO_2 footprint, conservation of raw materials, and cost savings – often justify moderate use of RCA if performance can be maintained [7,8]. To improve RAC performance, fiber reinforcements like steel or glass fibers have been explored. **Glass fiber (GF)** in particular is an attractive additive to enhance tensile/flexural behavior and mitigate the brittleness of RAC. Prior research indicates that adding small fractions of GF (≤1%) can improve concrete's tensile and flexural strength by bridging micro-cracks. For example, steel fibers have been reported to raise RAC compressive strength by 8–12% and tensile strength by 35–44% [9-11]. Glass fibers similarly can compensate for strength loss: **Babar Ali et al. (2020)** found that 0.5% GF mitigated the drop in compressive strength for 50% RCA concrete, improving tensile strength by >16% and flexural strength by >26% [14]. However, fiber benefits are non-linear – higher fiber volumes (>1–2%) can lead to fiber clumping, increased voids, and reduced workability, ultimately **diminishing compressive strength at excessive dosages** [15]. Thus, an optimal fiber content exists that maximizes strength gain before negative effects set in.

2. LITERATURE REVIEW

This paper discusses recent developments in the field of recycled concrete (RAC) and the application of artificial intelligence (AI) methods to estimate its properties. It also discusses the impact of recycled aggregates on concrete performance, as well as improving concrete mix design to improve its strength and durability, its environmental impacts and cost, and the addition of glass fiber (GF) to improve its mechanical properties. It also discusses the introduction of AI models, such as artificial neural networks (ANNs), adaptive neuro-fuzzy inference systems (ANFIS), and other machine learning algorithms.

2.1. The Past Record of Recycled Aggregate Concrete

RAC began to be used in the post-World War II period as a means of recycling the rubble of destroyed cities. Initial research indicated that GFRC exhibited lower water absorption, compressive strength, and freeze-thaw resistance compared to natural concrete. The recent addition of GF has improved the durability of GFRC in terms of cracking resistance, ductility, and overall mechanical performance. The reinforcing capacity of GFs in GFRC is significantly influenced by fiber length, diameter, aspect ratio, and dispersion methods.

2.2. Previous Studies

Various researchers have studied RAC and its mechanical properties:

- **Bravo et al. (2015)** [16]: Examined durability variations based on recycled aggregate sources.
- **Kishore and Gupta (2019)** [17]: Highlighted environmental benefits and challenges of increasing recycled content.
- **Ali and Qureshi (2019)** [18]: Explored combining GFs with recycled aggregates to improve durability.
- **Paluri et al. (2020)** [19]: Compared strengths and weaknesses of recycled vs. natural aggregates.
- **Mahakavi et al. (2020)** [20]: Investigated fly ash and GF influence on lightweight concrete properties.
- **Ali et al. (2020)** [21]: Studied combined effects of fly ash and GFs on recycled concrete.
- **Lavado et al. (2020)** [22]: Assessed workability changes when replacing natural coarse aggregate with recycled materials.
- **Małek et al. (2021)** [23]: Investigated the effect of GFs on cement mortar.
- **Liang et al. (2021)** [24]: Analyzed RAC's compressive and shear strength over time.
- **Thomas et al. (2020)** [25]: Explored multi-aggregate RAC using microtomography.
- **Rashid et al. (2020)** [26]: Used decision-making techniques to assess RAC's sustainability and mechanical properties.

2.3. AI and Recycled Aggregate Concrete

AI's role in RAC property prediction has grown significantly:

- **Behnood et al. (2015)** [27]: Used the M5 algorithm to improve prediction accuracy.
- **Khademi et al. (2016)** [28]: Compared ANNs, ANFIS, and regression for strength prediction.
- **Duan et al. (2020)** [29]: Developed a hybrid algorithm combining gradient boosting and imperialist competitive algorithm.
- **Nunez et al. (2020)** [30]: Applied Gaussian processes, deep learning, and gradient boosting regression trees.
- **Chen et al. (2020)** [31]: Predicted compressive strength based on water-cement ratio and replacement levels.
- **Zhu et al. (2022)** [32]: Used ML algorithms to predict tensile strength with superior accuracy.
- **Yuan et al. (2022)** [33]: Compared random forest and gradient boosting models for RAC quality assessment.

The research demonstrates significant advances in understanding and improving RAC properties using GF models. AI methods, such as artificial neural networks (ANNs), ANFIS, and ensemble models, demonstrate better accuracy than traditional regression analysis methods. Further research into the predictive power of AI and ways to improve it is needed to promote its sustainable use in RAC development.

3. EXPERIENTIAL WORKS

This article discusses the process of developing an AI model for optimizing recycled concrete (RAC) mixes using machine learning (ML). This includes selecting AI algorithms, data preprocessing, hyperparameter tuning, and model building using the Keras library. Recurrent neural network (RNN), multilayer perceptron (MLP), backpropagation neural network (BPNN), residual neural network (ResNet), and stacked long short-term memory (StackedLSTM) techniques were used.

3.1. Hybrid DL-ML Model for Optimizing RAC Mixture

Machine learning (ML) has transformed numerous disciplines, such as concrete optimization. The three categories of ML algorithms are supervised learning (regression problems), unsupervised learning (clustering data), and reinforcement learning (optimal solutions based on feedback) [34-37]. Five strong models were created that could be used for the prediction of compressive strength of RAC:

1. **Keras Recurrent Neural Network (kRN)**: Excels in analyzing sequential data.
2. **Multilayer Perceptron (MLP)**: Handles large datasets with non-linear transformations.
3. **Back Propagation Neural Network (BPNN)**: Utilizes gradient descent for error minimization.
4. **Residual Neural Network (ResNet)**: Addresses the vanishing gradient problem with skip connections.
5. **StackedLSTM**: Captures long-term dependencies in hierarchical patterns.

These models leverage unique capabilities for data analysis, enabling precise compressive strength predictions for RAC.

3.1.1. Recurrent Neural Networks (RNNs)

Deep learning algorithms like RNNs are widely applied in domains such as image recognition and civil engineering for tasks like structural monitoring [38-40]. RNNs feature internal memory loops that process sequential data, but they face challenges such as vanishing gradients. To mitigate this, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) introduce gated mechanisms to improve older data retention [41-42].

Keras and RNNs:

Keras simplifies RNN implementation with layers like Simple RNN, LSTM, and GRU, suitable for tasks involving time series and other sequential data [41, 43].

3.1.2. Alternative AI Models

- **Multilayer Perceptron (MLP)**: Composed of input, hidden, and output layers, MLPs use backpropagation to minimize errors through gradient adjustments [45, 46].
- **Back Propagation Neural Network (BPNN)**: An ANN variant that uses gradient descent and automatic differentiation for error correction [44-46].
- **Residual Neural Network (ResNet)**: Simplifies deep network training by bypassing certain layers, enhancing gradient flow and performance [47].
- **StackedLSTM**: Extends LSTM architecture with hierarchical memory layers, enabling complex pattern recognition [48-49].

3.2. Data Collection and Preprocessing

The dataset, derived from 42 peer-reviewed publications, includes 799 examples of RAC mixture designs, ensuring diversity and robustness (Table 3). It consists of nine input parameters—water-cement ratio, quantities of water, cement, sand, gravel, RCA, superplasticizer, specimen type, and age—and one output parameter, compressive strength [50].

Data Preprocessing:

Data cleaning involved removing outliers, normalizing values, and calculating correlations. These steps prepared the data for ML analysis, ensuring accurate predictions of RAC properties.

Table 3 Sources of the Dataset

No.	Reference		Samples No.
1	(Manzi et al., 2013)	[51]	10
2	(Ajdukiewicz & Kliszczewicz, 2007)	[52]	4
3	(Gómez-Soberón, n.d.)	[53]	15
4	(Sheen et al., 2013)	[54]	57
5	(Lin et al., 2004)	[55]	48
6	(Poon et al., 2004)	[56]	36
7	(Ulloa et al., n.d.)	[57]	25
8	(Matias et al., 2013)	[58]	11
9	(Taffese, 2018)	[59]	6
10	(Etxeberria, Marí, et al., 2007)	[60]	3
11	(Andreu & Miren, 2014)	[61]	27
12	(Etxeberria, Vázquez, et al., 2007)	[62]	3
13	(Beltrán, Agrela, et al., 2014)	[63]	18

14	(Cong Kou et al., n.d.)	[64]	90
15	(Beltrán, Barbudo, et al., 2014)	[65]	6
16	(Poon et al., 2007)	[66]	16
17	(Carneiro et al., 2014)	[67]	3
18	(Dilbas et al., 2014)	[68]	3
19	(Casuccio et al., 2008)	[69]	6
20	(Duan & Poon, 2014)	[70]	24
21	(Kou et al., 2008)	[71]	60
22	(Folino & Xargay, 2014)	[72]	3
23	(Yang et al., 2008)	[73]	54
24	(López Gayarre et al., 2014)	[74]	12
25	(Domingo-Cabo et al., 2009)	[75]	6
26	(Medina et al., 2014)	[76]	10
27	(Corinaldesi, 2010)	[77]	10
28	(Kumutha & Vijai, 2010)	[78]	20
29	(Pepe et al., 2014)	[79]	10
30	(Malešev et al., 2010)	[80]	6
31	(Haitao & Shizhu, 2015)	[81]	16
32	(Fathifazl et al., 2011)	[82]	4
33	(Tam et al., 2015)	[83]	16
34	(Abdel-Hay, 2017)	[84]	9
35	(Somna et al., 2012)	[85]	36
36	(Abd Elhakam et al., 2012)	[86]	12
37	(Nepomuceno et al., 2018)	[87]	12
38	(Butler et al., 2013)	[88]	6
39	(Thomas et al., 2018)	[89]	18
40	(Ismail & Ramli, 2013)	[90]	12
41	(Younis & Pilakoutas, 2013)	[91]	32
42	(Kim et al., 2013)	[92]	24

Data analysis and preprocessing were performed using Python libraries such as **pandas**, **numpy**, **seaborn**, **matplotlib.pyplot**, and **scipy.stats** [93,94]. These libraries provided efficient tools for data manipulation, statistical computations, and visualization.
The preprocessing involved:
1. **Outlier Removal**: Ensured all parameters remained within realistic ranges to avoid distorted statistical analyses.
2. **Parameter Ranges**: Determined using domain knowledge and industry standards.
3. **Visualization**: Box plots were employed to identify outliers and assess data distribution.
4. **Cost Analysis**: The cost of each concrete mixture was calculated based on component prices, adding an economic dimension to the analysis [95].

These steps ensured robust and meaningful insights, aligning the analysis with real-world cost-effectiveness considerations.

Table 3.1 Dataset's statistical attributes

Input Features	**count**	**mean**	**sd**	**min.**	$\frac{25}{100}$	$\frac{50}{100}$	$\frac{75}{100}$	**max**
w/c	799	0.521	0.101	0.3	0.45	0.5	0.55	0.8
water	799	193.3	28.25	137.1	175	190	212.1	304
cement	799	377.2	55.62	250	350	380	404	650
sand	799	666.7	175.5	0	625	668	730	1315
gravel	799	374.4	389.3	0	0	319	736.2	1287.7
ra.	799	699.3	381.1	0	300	750.6	1017	2040

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sp.	799	1.834	2.874	0	0	0	3.4	20.74
specimen	799	2.811	1.575	1	1	3	4	5
age	799	27.58	25.87	1	7	28	28	91
Output Features	**count**	**mean**	**sd**	**min.**	**$\frac{25}{100}$**	**$\frac{50}{100}$**	**$\frac{75}{100}$**	**max**
strength	799	36.2	16.97	4.8	25	34.7	44.89	108.5

a) Normalization

Normalization is a method of rescaling data such that its standard deviation is one and mean value is zero, was done using the *z*-score method. Normalization is an important preprocessing step for most algorithms in AI since it normalizes all features to be of the same magnitude and therefore avoids domination of any feature by virtue of its scale.

The findings of a correlation analysis were explored to illustrate the relationships between all the varying parameters Figure 3.1 It is possible through such analysis to observe dependencies between variables of concern for the selection of models and model simplification. Observing such relationships can assist in establishing which features play the most critical roles in modelling concrete strength.

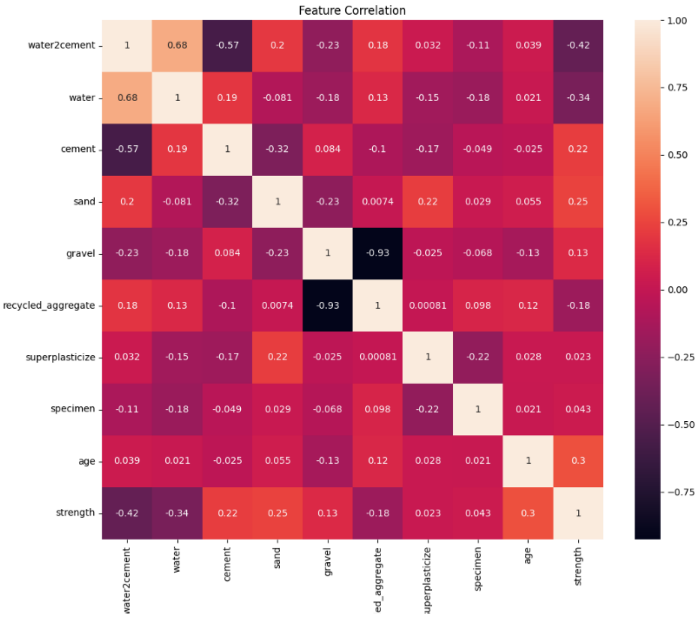

Figure 3.1 Feature Correlation

Lastly, graphical representation of each function with the use of histograms Figure 3.2 Histograms supply an elementary but very useful tool for the interpretation of data distributions, which helps us recognize skewness, kurtosis, and other notable features of data. [96]

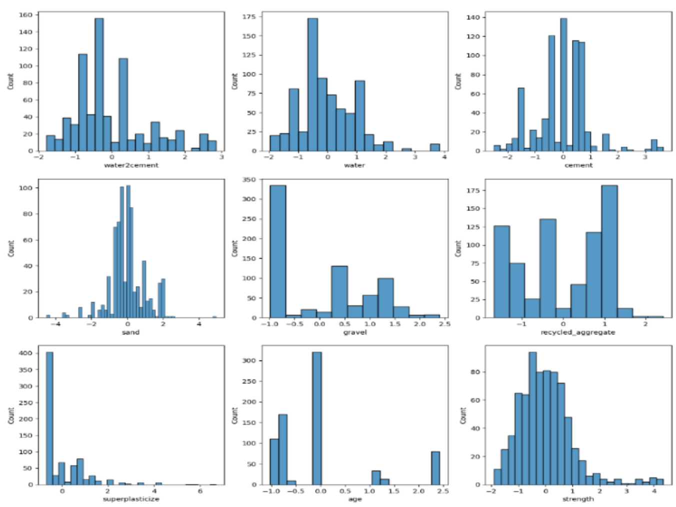

Figure 3.2 Histogram Analysis

3.3. Hyperparameter Tuning

Hyperparameters significantly influence AI model performance. This study utilized the Keras Tuner library and Bayesian Optimization to automate hyperparameter tuning, efficiently exploring various configurations to enhance predictive accuracy.
Key steps involved in hyperparameter tuning comprised
1. Model Architecture: A single RNN layer with two dense layers was specified with each layer's unit count considered as an adjustable hyperparameter.
2. Search Strategy: The hyperparameter space was set by the HyperModel class in Keras Tuner, with Bayesian Optimization iteratively improving it based on performance observations.
3. Evaluation Measure: The objective function used was the mean absolute error (MAE).
4. Cross-Validation: Training and test groups of the data split over multiple folds for ensuring robustness
The optimized model bested the lowest MAE with improved convergence speed as well as generalization. Automated hyperparameter tuning with Keras Tuner made it easier for researchers to execute the process.

3.4. Model Development

a) Keras in Recurrent Neural Networks (RNNs)

The developed RNN architecture comprised:

- Single RNN Layer: Used the SimpleRNN function with 32 hidden neurons and the ReLU activation function.
- Dense Layers: The first dense layer included 8 neurons with ReLU activation, while the final layer had 1 neuron with linear activation.

b) Hyperparameters:

- **Learning Rate**: Tuned from [1e-2, 1e-3, 1e-4] using Bayesian Optimization.
- **Optimizer**: **Adam**, known for combining AdaGrad and RMSProp benefits.
- **Loss Function**: Mean Absolute Error (MAE), which minimizes sensitivity to extreme values compared to mean squared error (MSE).

c) Evaluation Metrics:

The model was assessed using metrics such as MAE, MSE, Mean Absolute Percentage Error (MAPE), and the **R^2 score** (coefficient of determination). R^2 represents the variance in the dependent variable explained by independent variables in regression models.

d) Training and Validation:

- **Early Stopping**: Halted training after 20 epochs with no improvement in validation loss.
- **k-Fold Cross-Validation**: Used 10 folds, training the model 10 times with 9 folds for training and 1 for testing, enhancing generalization and minimizing overfitting.
- **Training Duration**: Limited to 500 epochs, with batch size determined through Bayesian Optimization.

3.4Implementation:

The RNN model was built and fine-tuned using **TensorFlow**, **Keras**, and **Keras Tuner** libraries.
This comprehensive hyperparameter tuning and model development approach ensured high predictive performance, as detailed in **Figure 3.3** and **Table 3.2**.

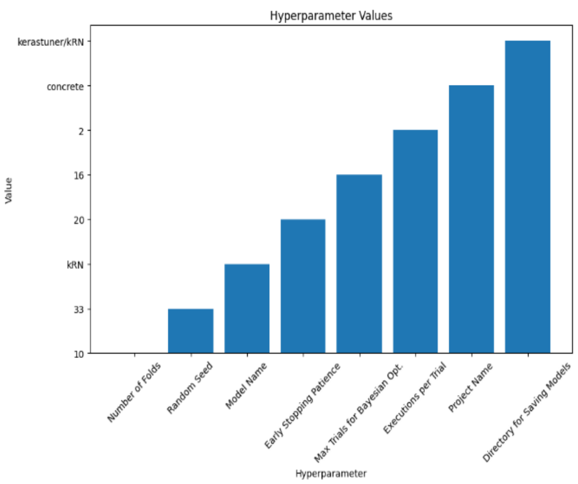

Figure 3.3 Hyperparameters Information for KRN

Table 3.2 Hyperparameters Information for KRN

Hyperparameter	Value
Number of Folds	10
Random Seed	33
Model Name	kRN
Early Stopping Patience	20
Max Trials for Bayesian Opt.	16
Executions per Trial	2
Project Name	concrete
Directory for Saving Models	kerastuner/kRN

a) Multilayer Perceptron

The architecture of the MLP model implemented with the TensorFlow and Keras libraries comprises dense layers activated with ReLU activation functions that lead to an output layer for prediction. Hyperparameters such as the number of units in each layer and learning rates were optimized using Keras Tuner's Bayesian Optimization. The process involved k-fold cross-validation iteration to narrow configurations until the lowest value of MAE was obtained. The metrics used for evaluation comprised MAE, RMSE, MAPE, and R^2 that are illustrated in scatter plots of actual versus predicted values of strength along with annotated progression graphs.

b) Backpropagation Neural Network Model

The BPNN model utilized TensorFlow as well as Keras with dense layers activated by ReLU and batch normalization to improve the stability of the training process. The hyperparameters were tuned with Bayesian Optimization through Keras Tuner. The model was tested using k-fold cross-validation with accurate performance on datasets. The most important metrics like MAE, RMSE, MAPE, and R^2 were utilized in complement with graphical analysis such as prediction error distributions as well as scatter plots of the price versus predicted strength.

c) Residual Neural Network

The ResNet model incorporated a convolutional layer with 64 filters, kernel size 2, batch normalization, and max pooling. Data was preprocessed and split using scikit-learn's train_test_split function. The ResNet architecture was refined through **Bayesian Optimization** and evaluated via k-fold cross-validation to minimize MAE. Visualization included training/validation MAE vs. epoch graphs and scatter plots of actual vs. predicted strength values, confirming the model's efficacy.

d) Stacked Long Short-Term Memory

The Stack-LSTM model architecture, specified by the stackedLSTMHyperModel class, contained layers that could learn long-range dependencies in sequential data. Data preparation involved scikit-learn's train_test_split utility function, along with evaluation metrics like MAE, RMSE, MAPE, and R^2. Visualization involved scatter plots of predicted strength versus actual price along with learning curve plots (training/validation MAE versus epoch), which guaranteed high performance and flexibility for multiple datasets.

3.2.1. RCA Mixture Optimization

The optimization of RCA mixtures was performed using the **Particle Swarm Optimization (PSO)** algorithm to develop cost-efficient RAC designs for various compressive strength grades. PSO simulates the collective behavior of organisms, where "particles" iteratively adjust their positions based on individual and group best-known solutions.

- **Objective**: Minimize the production cost of RAC while meeting strength requirements.
- **Data Source**: Material costs were sourced from suppliers in Iraq (Table 3.3), providing flexibility to adjust for other locations.
- **Solution Space**: Defined by upper and lower bounding vectors to constrain possible solutions.

The PSO algorithm effectively reduced production costs while optimizing the mixture proportions, emphasizing its applicability in developing economically viable and sustainable RAC mixtures.

Table 3.3 Price Data

Component	Price ($/kg)
water	$ 0.0002703
Cement	$ 0.0878378

Sand	$ 0.0090090
Gravel	$ 0.0054650
RCA content	$ 0.0026464
Superplasticizer	$ 3.2000000

The vectors described in Table 3.4 are meticulously formulated, drawing upon a real-world experimental case from the dataset that exhibits a distinct compressive strength, thereby enabling an apt evaluation and verification of the algorithm's efficacy.

Table 3.4 Bounder vectors for mixture optimization.

Features		**Water 2cement**	**water**	**cement**	**sand**	**gravel**	**recycled aggregate**	**superplasticizer**	**specimen**	**age**
Mpa	**Unit**	-	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	**Type**	**Day**
25	Lower	0.55	201	300	598	0	971	0	1	28
	Upper	0.77	232	410	795	0	1027	13.5	1	28
30	Lower	0.47	159.8	300	556	0	497	1.24	1	28
	Upper	0.78	234	340	846	537	1037	13.5	1	28
35	Lower	0.45	153	300	556	0	204	0	1	28
	Upper	0.76	247	410	868	1020	1154	9	1	28
40	Lower	0.4	140	300	556	0	202	0	1	28
	Upper	0.768	271	537	941.72	886	1400	4.2	1	28
45	Lower	0.4	140	300	556	0	204	0	1	28
	Upper	0.683	241	537	948.92	1020	1524	5.2339	1	28
50	Lower	0.41	159.8	323.08	556	0	138	0	1	28
	Upper	0.68	220	537	948.92	1020	1075	5.6	1	28

Key concrete components, including sand, cement, and water, were assigned minimum and maximum threshold values, fluctuating approximately 20% above and below the base mixture values. To encourage the use of RCA materials, the upper and lower limits for RCA were deliberately set high, while gravel values were minimized due to associated economic considerations. For superplasticizer, a notable cost factor, boundary values were kept at the lowest practicable levels.

The compressive strength of standard 15 × 15 cm specimens after a 28-day curing period served as the benchmark for comparison. The optimized mixture proportions and results are detailed in Table 3.5.

The Keras Recurrent Neural Network (kRN), identified as the most accurate predictive model, evaluated the optimized mixture. These kRN outcomes were then compared against an actual concrete sample from the dataset to confirm alignment with predefined compressive strength parameters, as shown in Table 3.6.

Table 3.5 Optimized Mixture Proportions

Optimized Mix Mpa			**25**	**30**	**35**	**40**	**50**
water2cement		N/A	0.68	0.6	0.68	0.493	0.68
water		kg/m^3	205	186	205	148	219.35
cement		kg/m^3	300	310	300	300	323.08
sand		kg/m^3	697	702	697	600	948.92
gravel		kg/m^3	0	531	0	0	771
recycled aggregate		kg/m^3	1027	501	1075	1400	257.69
superplasticizer		kg/m^3	0	1.24	0	0	0
specimen		Type	1	1	1	1	1
age		Day	28	28	28	28	28

The employed AI model, a variant of the **Recurrent Neural Network (RNN)** integrated with the **Particle Swarm Optimization (PSO)** algorithm and referred to as 'krnn,' was implemented using **Python**, leveraging the **TensorFlow** and **Keras libraries** for model construction and training.

Key implementation details include:

- **Data Preprocessing**: Incorporated necessary steps for cleaning and preparing the data.
- **Determination Coefficient Function**: Calculated the R^2 score.
- **PSO Algorithm Class**: Integral for optimization tasks.
- **Cross-Validation**: A 10-fold cross-validation technique was used to enhance reliability and stability.
- **Reproducibility**: Random seeds were set to constant values.

The model's **training and optimization** utilized the **Bayesian Optimization** method from the Keras Tuner API, with the objective of minimizing the **MAE** (mean absolute error), ensuring alignment between forecasted and actual compressive strength values.

Evaluation Metrics

The model's proficiency was evaluated using:

- **MAE** (mean absolute error)
- **RMSE** (root mean square error)
- **MAPE** (mean absolute percentage error)

The model achieving the lowest MAE across all folds was deemed the most effective.

Table 3.6 Comparison of Optimized Mixture with Base Mixture.

Features		Water/Cement	Water	Cement	Sand	Gravel	Recycled Aggregate	Super Plasticizer	Specimen	Age	Strength	Price
Mpa	Unit	-	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	$\frac{Kg}{m^3}$	Type	Day	Mpa	USD
25	Base	0.77	232	300	795	0	994	13.5	1	28	27.5317	79.40
	Opt.	0.68	205	300	697	0	1027	0	1	28	29.2645	35.40
30	Base	0.47	159.8	340	556	319	767	3.4	1	28	33.0518	49.57
	Opt.	0.6	186	310	702	531	501	1.24	1	28	34.6454	41.80
35	Base	0.76	228	300	868	0	985	9	1	28	35.0397	65.63
	Opt.	0.68	205	300	697	0	1075	0	1	28	35.0583	35.53
40	Base	0.47	159.8	340	556	319	894	3.4	1	28	43.9453	49.90
	Opt.	0.493	148	300	600	0	1400	0	1	28	44.0740	35.50
50	Base	0.45	180	400	708	0	1075	5.6	1	28	52.0540	62.32
	Opt.	0.68	219.35	323.08	948.92	771	257.69	0	1	28	52.1908	41.88

4. RESULTS AND DISCUSSIONS

4.1. Mixture Optimization Using AI.

4.1.1. AI Models Prediction Performance

The study evaluated five machine learning models: kRN, MLP, BPNN, ResNet, and Stacked LSTM, using multiple metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2.

a) Keras Recurrent Neural Network (kRN)

The Keras Recurrent Neural Network (kRN) demonstrated outstanding performance based on multiple evaluation metrics, as detailed in Table 4.1:

 Achieved the best performance across all metrics:

- **MAE**: 0.1793
- **RMSE**: 0.2473
- **MAPE**: 0.77%
- **R^2**: 99.98%

 Its precision and reliability make it ideal for forecasting RAC compressive strength.

Table 4.1 Keras Recurrent Neural Network (kRN) Performance

Keras Recurrent Neural Network (kRN)		
	Train	**Test**

Random Seed	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
RS=33	0.1910	0.2040	0.6410	**1.0000**	0.1960	0.2400	0.7730	**1.0000**
RS=365	0.1900	0.2500	0.7880	**1.0000**	0.2060	0.2650	0.8460	**1.0000**
RS=678	0.2140	0.2800	0.5430	**1.0000**	0.1900	0.2400	0.4850	**1.0000**
RS=2023	0.1380	0.1660	0.6060	**1.0000**	0.1520	0.2020	0.7550	**1.0000**
RS=3084	0.1660	0.2040	0.6830	**1.0000**	0.1690	0.2360	0.8120	**1.0000**
Rs=4042	0.1390	0.1990	0.5290	**1.0000**	0.1630	0.3010	0.9750	**0.9990**
MEAN	**0.1730**	**0.2172**	**0.6317**	**1.0000**	**0.1793**	**0.2473**	**0.7743**	**0.9998**
SD	**0.0281**	**0.0372**	**0.0878**	**0.0000**	**0.0192**	**0.0302**	**0.1477**	**0.0004**

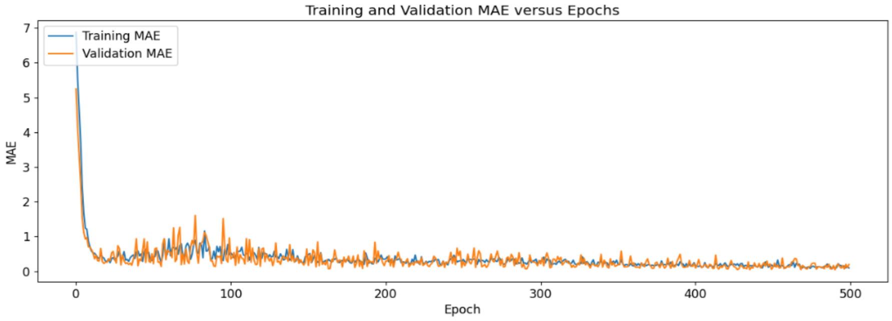

Figure 4.1 kRN Training and Validation MAE Versus Epochs

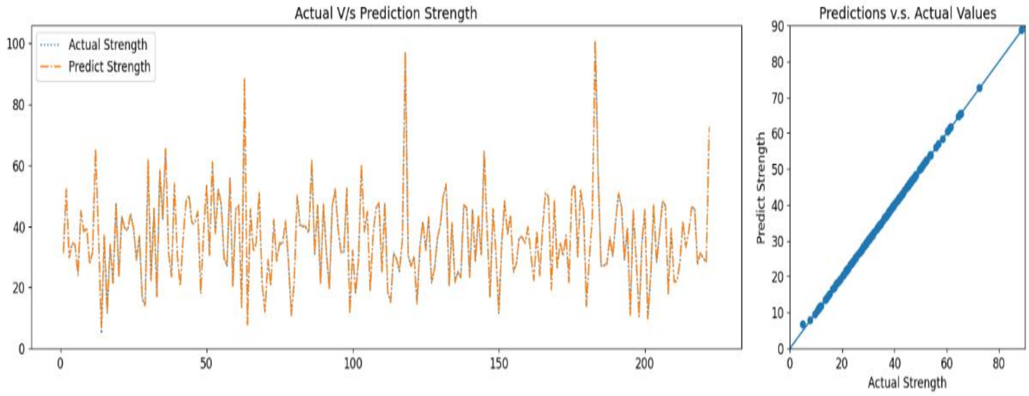

Figure 4.2 kRN Actual Versus Prediction

b) Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) model demonstrates versatility in handling complex patterns but underperforms compared to the kRN model for this dataset, as indicated in Table 4.2 Demonstrated strong but slightly lower performance than kRN:

- **MAE**: 0.2812
- **RMSE**: 0.4138
- **MAPE**: 1.03%
- **R^2**: 99.90%

Table 4.2 Multilayer Perceptron (MLP) Performance

Multilayer Perceptron (MLP)								
Random Seed	Train				Test			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
RS=33	0.1110	0.2090	0.4020	1.0000	0.3010	0.4420	0.9540	0.9990
RS=365	0.1110	0.1990	0.3700	1.0000	0.2720	0.4050	1.0620	0.9990
RS=678	0.1090	0.1910	0.3970	1.0000	0.3010	0.4510	1.1030	0.9990
RS=2023	0.1270	0.2200	0.4550	1.0000	0.2880	0.4280	1.0510	0.9990
RS=3084	0.1410	0.2400	0.5380	1.0000	0.2720	0.3970	1.0830	0.9990
Rs=4042	0.1230	0.2250	0.4310	1.0000	0.2530	0.3600	0.9240	0.9990
MEAN	**0.1203**	**0.2140**	**0.4322**	**1.0000**	**0.2812**	**0.4138**	**1.0295**	**0.9990**
SD	**0.0114**	**0.0164**	**0.0544**	**0.0000**	**0.0173**	**0.0306**	**0.0666**	**0.0000**

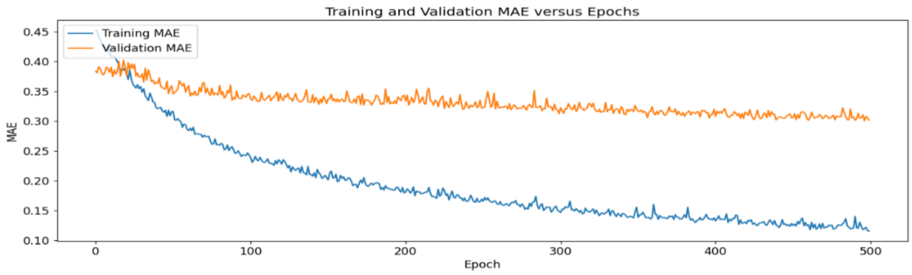

Figure 4.3 MLP Training and Validation MAE Versus Epochs

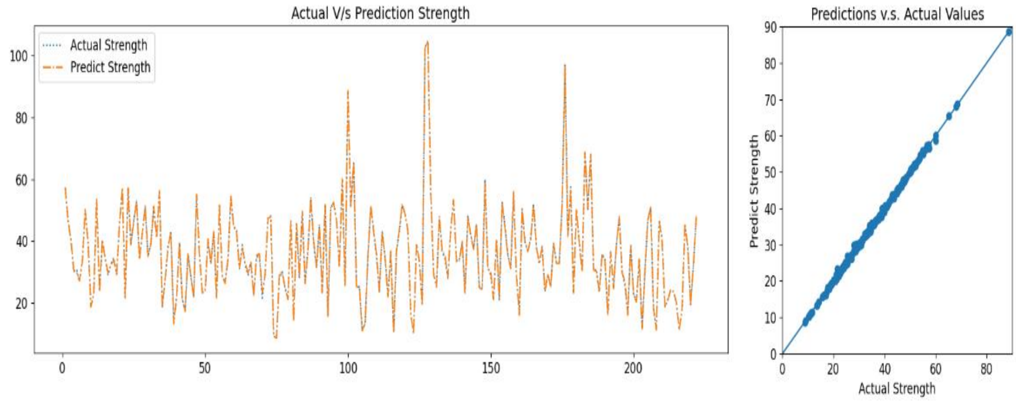

Figure 4.4 MLP Actual Versus Prediction

c) Back Propagation in Neural Network (BPNN)

The Backpropagation Neural Network (BPNN) model displayed significantly higher prediction errors compared to the kRN and MLP models, as outlined in Table 4.3:

- **MAE**: 2.1695
- **RMSE**: 3.9063
- **MAPE**: 8.87%
- **R^2**: 92.72%.

Table 4.3 Back Propagation in Neural Network (BPNN) Performance

Back Propagation in Neural Network (BPNN)								
Random Seed	**Train**				**Test**			
	MAE	**RMSE**	**MAPE**	**R2**	**MAE**	**RMSE**	**MAPE**	**R2**
RS=33	2.1940	4.0280	8.9690	0.9310	2.7610	7.1690	7.6560	0.8230
RS=365	2.4150	2.9220	8.5310	0.9570	2.5490	3.1400	9.3160	0.9630
RS=678	1.5910	1.9580	5.6610	0.9790	1.6080	1.9850	5.6590	0.9840
RS=2023	2.4400	4.1670	13.0010	0.9100	2.7820	5.0350	14.4200	0.8680
RS=3084	1.9990	3.3280	9.6060	0.9420	1.9340	2.3640	7.3300	0.9750
Rs=4042	1.2840	3.1560	8.8360	0.9640	1.3830	3.7450	8.8290	0.9500
MEAN	**1.9872**	**3.2598**	**9.1007**	**0.9472**	**2.1695**	**3.9063**	**8.8683**	**0.9272**
SD	**0.4247**	**0.7345**	**2.1491**	**0.0226**	**0.5565**	**1.7608**	**2.7434**	**0.0601**

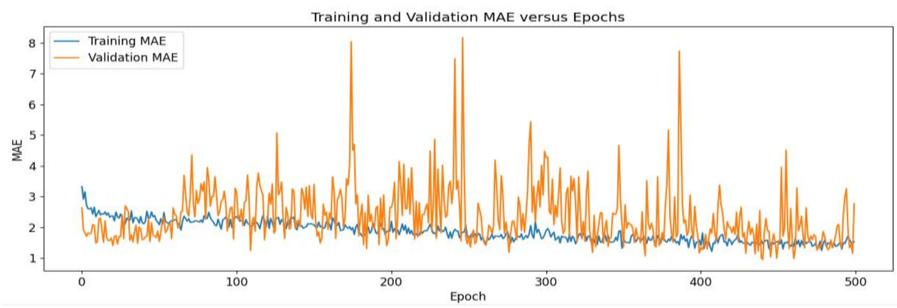

Figure 4.5 BPNN Training and Validation MAE Versus Epochs

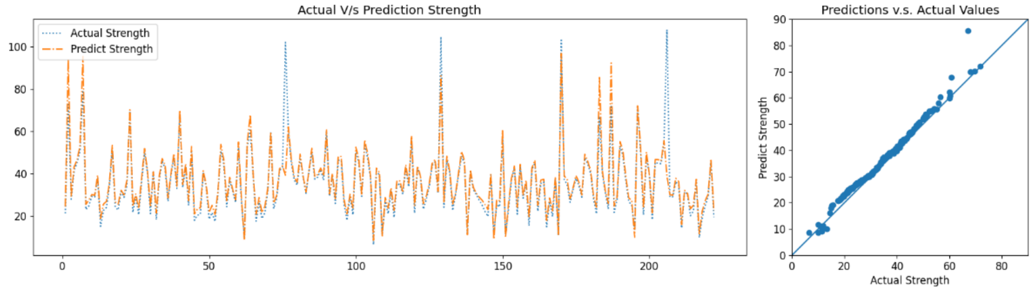

Figure 4.6 BPNN Actual Versus Prediction

d) Residual Neural Network (ResNet)

The Residual Neural Network (ResNet) model demonstrated the least optimal performance among all models evaluated, as shown in Table 4.4:

- **MAE**: 4.1057
- **RMSE**: 5.7212
- **MAPE**: 13.10%
- **R^2**: 84.47%.

Table 4.4 Residual Neural Network (ResNet) Performance

Residual Neural Network (ResNet)								
Random Seed	Train				Test			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
RS=33	2.3320	3.5670	7.6030	0.9520	3.9560	5.3480	12.5860	0.8500
RS=365	2.5470	3.5770	8.8020	0.9340	4.2630	6.1820	14.3550	0.8390
RS=678	2.2380	3.4570	7.7410	0.9520	3.8400	5.2840	12.4300	0.8960
RS=2023	3.1750	4.6980	9.1870	0.9200	4.3080	5.9220	13.3250	0.8130
RS=3084	2.3320	3.5670	7.6030	0.9520	3.9560	5.3480	12.5860	0.8500
Rs=4042	2.4190	3.3260	8.2480	0.9540	4.3110	6.2430	13.2960	0.8200
MEAN	**2.5072**	**3.6987**	**8.1973**	**0.9440**	**4.1057**	**5.7212**	**13.0963**	**0.8447**
SD	**0.3134**	**0.4556**	**0.6140**	**0.0127**	**0.1929**	**0.4072**	**0.6635**	**0.0269**

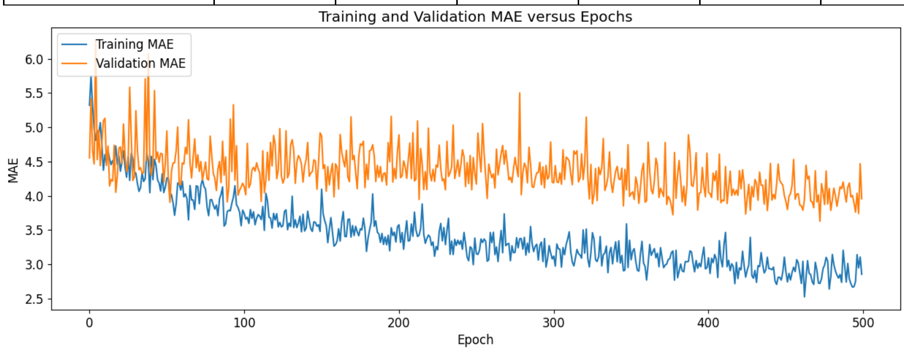

Figure 4.7 ResNet Training and Validation MAE Versus Epochs

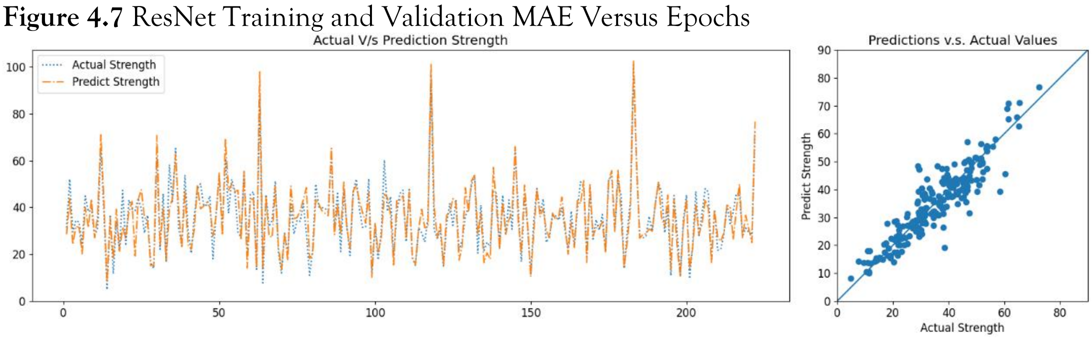

Figure 4.8 ResNet Actual Versus Prediction

e) Stacked Long Short-Term Memory Neural Network (StackedLSTM)

The Stacked Long Short-Term Memory (Stacked LSTM) model exhibited the poorest performance among all models evaluated, as shown in Table 4.5:

- **MAE**: 6.1137
- **RMSE**: 8.8100

- **MAPE**: 20.86%
- **R²**: 62.60%.**Table 4.5** stackedLSTM Performance

Stacked Long short-term memory Neural Network (stackedLSTM)								
Random seed	Train				Test			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
RS=33	4.8400	8.8610	14.4540	0.7590	4.4750	7.0070	14.5060	0.7610
RS=365	6.9550	10.5830	24.2020	0.6110	7.5840	10.6850	26.9040	0.4760
RS=678	4.5310	8.8860	12.2390	0.7760	3.8630	5.9490	11.6650	0.8260
RS=2023	8.0500	11.5540	27.3240	0.5280	9.5710	12.4540	31.4560	0.3600
RS=3084	5.6290	9.3200	17.8110	0.7370	6.6170	9.3750	22.2320	0.5900
Rs=4042	5.6340	9.6450	17.2360	0.7230	4.5720	7.3900	18.3710	0.7430
MEAN	5.9398	9.8082	18.8777	0.6890	6.1137	8.8100	20.8557	0.6260
SD	1.2157	0.9713	5.2783	0.0894	2.0206	2.2571	6.8533	0.1666

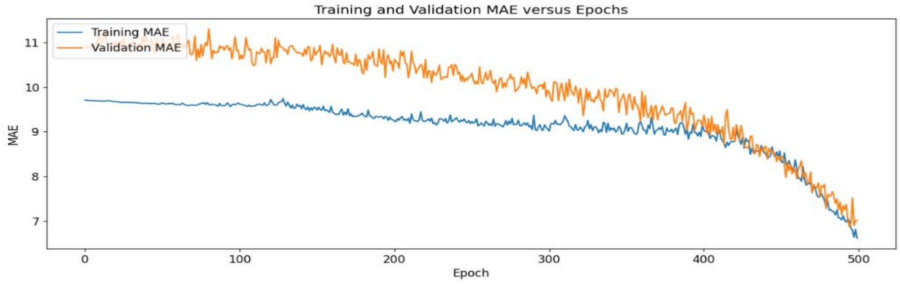

Figure 4.9 stackedLSTM Training and Validation MAE Versus Epochs

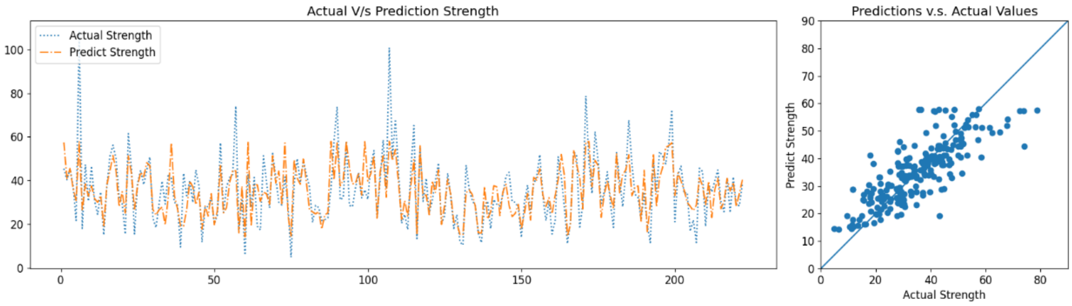

Figure 4.10 stackedLSTM Actual Versus Prediction

4.1.2. Contrasting with Prior Research

Table 4.6 compares the performance of various AI models for predicting compressive strength. This study's **kRN-PSO** model achieved:

- **R²**: 1.000
- **RMSE**: 0.2087

These metrics outperformed all prior techniques, including MLP, GB, and ANN. While earlier models like ANFIS and traditional regression methods exhibited lower accuracy, the kRN-PSO model demonstrated its ability to handle complex datasets effectively, even with fewer samples.

Table 4.6 Comparison of Metric Outcomes with Prior Research

AI Learning Technique	Testing R^2	Testing RMSE	Total Samples	Reference	Year
ANN	0.998	2.395	210	[97]	2008
FL	0.996	3.866			
ANN	0.995	3.6804	168	[98]	2013
ANN	0.971	-	1178	[99]	2013
ANN	0.903	-	257	[100]	2014
MT	0.757	-			
NLRM	0.74	-			
MLR	0.609	9.975	257	[28]	2016
ANN	0.919	4.446			
ANFIS	0.908	5.045			

ANN	0.688	-	139	[101]	2018
MARS	-	8.75	650	[102]	2020
M5MT	-	8.25			
LSVR	-	7.55			
ANN	0.894	0.066	12,168	[103]	2020
GB	0.919	5.076	1134	[30]	2020
DL	0.868	6.502			
SVM	0.879	-	81	[104]	2021
GBM	0.981	-			
ANN	0.96240	-	-	[105]	2021
SVR_PSO	0.862	8.198	721	[106]	2022
XGB_PSO	0.934	5.391			
GB_PSO	0.936	5.56			
ANN	0.975	0.028	333	[107]	2023
MLR	0.893	0.178			
kRN_PSO (DL)	1.0000	0.2087	799	This Study	2023
kRN (DL)	0.9998	0.2473			
MLP (ML)	0.9990	0.4138			
BPNN (ML)	0.9272	3.9063			
ResNet (DL)	0.8447	5.7212			
stackedLSTM (DL)	0.6260	8.8100			

4.1.3. RAC Mixture Proportioning and Optimization
The Keras Recurrent Neural Network integrated with Particle Swarm Optimization (KRN-PSO) was employed to optimize the mixture design process while predicting the compressive strength of concrete with recycled concrete aggregate (RCA). The primary goal was to determine cost-effective mixtures that met required compressive strength classes while considering material costs.

Key Outcomes and Insights

- Superior Performance: The kRN model outperformed all other models, prioritizing reductions in the use of costly components such as cement, leading to more economically viable and environmentally friendly mixtures with reduced CO_2 emissions.
- RCA Maximization: High RCA limits ensured its maximum utilization, enhancing sustainability.
- Cost Savings: As shown in Table 3.6, the KRN-PSO model achieved significant cost reductions, such as a 45% cost reduction for the 35 MPa strength class while maintaining similar compressive strength levels.
- Material Redistribution: The water-to-cement ratio (0.68) remained constant between base and optimized mixtures; however, the optimized mixture redistributed materials, adjusting quantities of sand and RCA for improved performance.

Optimization Effectiveness

- Identifying Complex Relationships: The model effectively determined optimal proportions for water-to-cement ratio, recycled aggregate quantities, and target compressive strength (Table 4.7), demonstrating its ability to handle intricate interdependencies within the dataset.
- Enhanced Properties: Despite reducing cement content, the optimized mixtures met or slightly exceeded compressive strength requirements, improving RCA's quality, durability, and strength.

This validates the effectiveness of KRN-PSO in optimizing RCA mixtures for sustainable construction. By balancing economic and environmental considerations, this innovative approach enables the development of cost-efficient, high-performance concrete mixtures that contribute to sustainable construction practices.

Table 4.7 Keras Recurrent Neural Network & Particle Swarm Optimization

Random Seed	**Train**				**Test**			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
RS=33	0.113	0.155	0.376	1	0.114	0.166	0.339	1

RS=365	0.142	0.19	0.523	1	0.165	0.22	0.663	1
RS=678	0.123	0.175	0.539	1	0.16	0.244	0.593	1
RS=2023	0.121	0.169	0.416	1	0.139	0.194	0.481	1
RS=3084	0.141	0.186	0.479	1	0.151	0.211	0.488	1
Rs=4042	0.144	0.191	0.438	1	0.157	0.217	0.442	1
MEAN	0.1307	0.1777	0.4618	1	0.1477	0.2087	0.501	1
SD	0.0121	0.0129	0.0578	0	0.0171	0.0241	0.1041	0

5. Conclusions and Recommendations

5.2. Conclusions

The purpose of this work was to assess and contrast the performances of different AI models for predictive work with an emphasis on their use in optimizing recycled aggregate concrete (RAC) mixtures. The main findings are:

1. **AI Model Performance**:

- The kRN model had the greatest efficiency with the optimal performance metrics it achieved, thus making it ideal for datasets of comparable characteristics.
- Models such as MLP, BPNN, and ResNet also demonstrated considerable performance, making them viable options based on setting and dataset characteristics.
- The Stacked LSTM model performed poorly in this research, emphasizing the need for model selection and that highly complex or popular models are not the best for every dataset.
- Model performance is highly dependent on the nature of the dataset, and the results cannot necessarily be translated to datasets with different characteristics.

2. **AI in Concrete Production**:

- AI and deep learning methods provide immense advantage in creating improved concrete mixtures with high accuracy in forecasting properties such as compressive strength.
- The recycling of RAC promotes environmental sustainability through minimizing the use of materials, carbon footprint, and expenses.

Recycling of concrete blocks, particularly in such environments as Iraq, helps in preserving natural resources and lowering environmental effects while cutting back on production expenses of protective concrete blocks.

5.3. Recommendations

For AI Models:

1. Evaluate a range of AI models for predictive tasks, as model selection significantly impacts prediction accuracy.
2. Leverage the **kRN model** for datasets with similar characteristics, given its superior performance.
3. Investigate the underperformance of **Stacked LSTM** in this scenario to uncover potential improvements or limitations.
4. Conduct additional comparative studies across diverse domains and datasets to further generalize these findings.

For Optimizing Concrete Production:

1. Use AI to optimize RAC production processes, maximizing the value and applications of recycled concrete.
2. Focus future research on practical implementations of optimized processes in real-world scenarios, such as recycling protective concrete blocks in Iraq.
3. Explore the environmental, economic, and practical impacts of AI-optimized RAC production across varying contexts and environments.

This study underscores the transformative potential of AI in sustainable construction, emphasizing both economic benefits and environmental responsibility.

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