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Predictive modelling of concrete tensile strength using ANN and Supplementary Cementitious Materials (SCMs)

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ABSTRACT

The global construction industry's rapid growth has led to a substantial increase in construction and demolition waste, necessitating sustainable solutions. Supplementary Cementitious Materials (SCMs) derived from waste materials have emerged as eco-friendly alternatives, improving concrete's mechanical properties and durability while reducing its Footprint of carbon. The goal of this study is to use artificial neural networks (ANNs) to predict the tensile strength of concrete that contains SCMs. A robust ANN model was developed using a dataset of 440 entries, encompassing various SCM types such as waste glass powder, ceramic waste powder, and marble powder. The Levenberg-Marquardt algorithm was employed to optimize ANN architectures, achieving high predictive accuracy. The best-performing model demonstrated an excellent correlation coefficient ($R = 1$) and minimal Mean Squared Error (MSE), validating the efficacy of ANNs in forecasting concrete properties. The findings highlight the potential of SCMs and ANNs in advancing sustainable construction practices by reducing reliance on physical testing and accelerating mix design optimization. The approach becomes even more practical thanks to an developed application provided that shall be able to give, on-spot optimization of the mixture.

1. Introduction

In many regions of the world, the amount of construction and demolition waste produced by fast urbanization and industrial activity has significantly grown, it reached approximately 3 billion tonnes the annual generation of C&D waste [1,2] is estimated to be as high as 14 million tons [3–5]. Thus such a huge amount of it can not be avoided from creating a serious environmental impact if not disposed of. Similarly keeping the aforementioned facts in consideration, landfill sites more frequently later on within a time interval will not be enough, it is thus necessary to find out suitable means for reusing such domestic wasters [6].

Due to SCMs containing extremely low embodied CO₂ whereas cement industries contribute approximately 5% of total human CO₂ emissions, as calculated by the total CO₂ released in raw material extraction and transportation and their production into their end product, They can potentially make concrete sustainable [7]. There are several SCMs with distinct qualities, each of which contributes differently to the improvement of concrete's mechanical qualities.

Several researchers have used various techniques over the last few decades to forecast the characteristics of concrete made with varying

mix amounts. Among them, artificial neural network-based methods are highly favored. This is mostly because of ANN's clear benefits: Because ANN can learn directly from examples—that is, the associations between input and output variables are created by the data itself—it is (1) simple to use. (2) High accuracy, ANN is even less susceptible to outliers and can handle jobs that are somewhat imprecise or partial, as well as approximation outcomes [8]. Some researches used ANN approaches to forecast concrete performance because of the aforementioned characteristics [9–19].

By applying ANN in the prediction of tensile strength This will help reduce much time that is wasted in making concrete test samples. It will eliminate long curing and physical testing processes by directly assessing the quality of concrete. Using a well-trained ANN model, we can make fast decisions on optimizing mix designs in real time and hence enhance project efficiency overall.

The goal of the current study is to create an artificial neural network (ANN)-based model that can forecast the tensile strength of concrete with different kinds of SCMs. 440 data points from earlier studies have been carefully chosen for this purpose, and factors including cement, coarse and fine particles, water, and specimen curing age, a number of these parameters have been regarded as significant determinants of conventional concrete's tensile strength.

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List of notations	
SCMs	Supplementary Cementitious Materials
ANN	Artificial neural network
R	R correlation coefficient
MSE	MSE Mean Squared Error
FA	FA fine aggregate
CA	CA coarse aggregate
WGP	WGP waste glass powder
CWP	CWP ceramic waste powder
WGD	WGD waste granite dust
WBP	WBP waste brick powder
WMP	WMP waste marble powder
μ	Combination coefficient
w	weight vector
J_0	Jacobi matrix
T	Transpose
e	error vector
I	Identity matrix

2. Methodology

2.1. Research and data retrieval strategy

The ANN Data were collected manually by observing a multiple publication on SCMs [20–68,6], To establish a robust framework for predicting concrete tensile strength using artificial neural networks (ANNs) Fig. 1, a comprehensive literature review was conducted. Key studies focusing on supplementary cementitious materials (SCMs) were targeted, emphasizing their role in sustainable construction. The data collection adhered to the following criteria:

- Peer-reviewed articles published.
- Research published within twenty years to maintain relevance and currency.
- Studies that specifically examined the use of ANNs in predicting the mechanical properties of concrete incorporating SCMs such as marble powder, ceramic waste powder, and waste glass powder.

Using this retrieval approach, a dataset comprising 440 entries was compiled from various scholarly publications.

2.2. Data selection criteria

The inclusion of studies in this domain was guided by several key criteria:

2.2.1. Relevance to sustainable construction

- The research must address critical issues such as the incorporation of SCMs for enhanced concrete durability, mechanical strength, and eco-friendliness.
- Studies providing insights into optimizing concrete mix designs using ANNs were prioritized.

2.2.2. Methodological consistency

- The selected studies needed to employ robust and replicable methodologies, including ANN models, predictive analytics, and advanced data science techniques.
- Research demonstrating innovative applications of ANNs to capture complex nonlinear relationships in concrete properties was highly valued.

2.2.3. Significance and Practical Impact

Preference was given to studies offering practical solutions, such as reducing reliance on physical testing or enhancing real-time decision-making in concrete mix design.

2.3. Information sources

The following sources were considered reliable and relevant for the study:

- Research conducted in real-world or laboratory-controlled settings, provided the studies adhered to rigorous quality standards.
- Studies from recognized academic journals, conferences, and institutions specializing in civil engineering and sustainable construction.

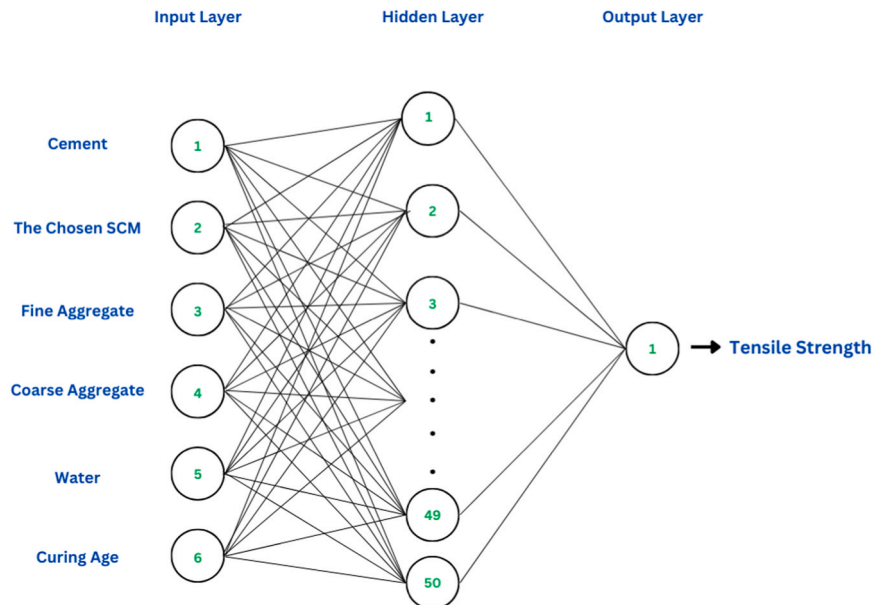


Fig. 1. Artificial neural network architecture.

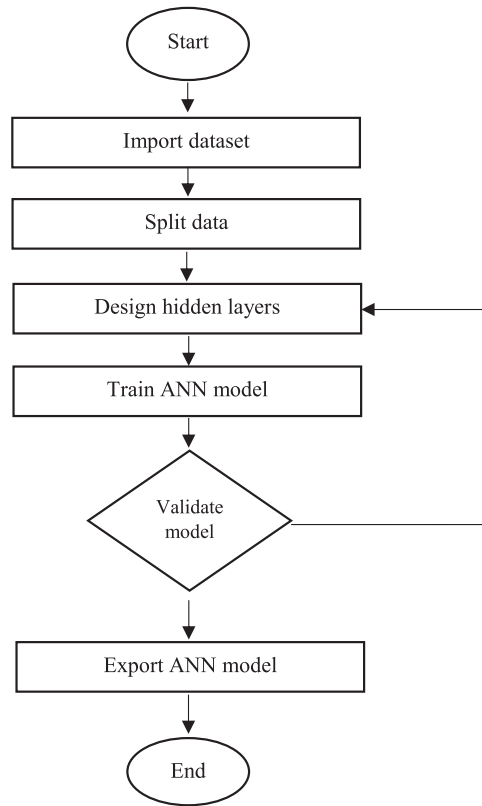


Fig. 2. Flowchart of training.

Table 1
Artificial neural network Layers data.

Neural Network	Input Layer	Hidden Layer	Output Layer
ANN-I	6	30	1
ANN-II	6	23	1
ANN-III	6	50	1
ANN-IV	6	50	1
ANN-V	6	50	1

- Publicly available reports and data from accredited organizations, including environmental agencies and industry standards committees.

2.4. Algorithm

The algorithm used is Levenberg-Marquardt which is driven from Gauss Newton method the algorithm workflow shown in Fig. 2.

J_0 The Jacobian matrix:

Table 2
Dataset samples.

CEMENT (Kg/ m ³)	CWP(Kg/ m ³)	WGP (Kg/ m ³)	WGD (Kg/ m ³)	WMP (Kg/ m ³)	WBP (Kg/ m ³)	FA (Kg/ m ³)	CA (Kg/ m ³)	Water (Kg/ m ³)	age (Days)	Tensile Strength (Kg/ m ³)
310	-	-	-	-	-	700	1050	124	7	4.8
279	31	-	-	-	-	700	1050	124	7	3.9
279	31	-	-	-	-	700	1050	124	28	4.9
248	62	-	-	-	-	700	1050	124	28	4.6
350	-	-	-	-	-	723	1084	175	7	2.61
332.5	-	17.5	-	-	-	721	1082	175	7	3.04
262.5	-	87.5	-	-	-	716	1074	175	28	2.72
350	-	-	-	-	-	723	1084	175	56	3.67
325.5	-	-	24.5	-	-	755	1135	140	7	3.15
318.5	-	-	31.5	-	-	755	1135	140	7	3.08
350	-	-	0	-	-	755	1135	140	28	2.95
346.5	-	-	3.5	-	-	755	1135	140	28	3.03
405.34	-	-	-	21.33	-	671.87	1093	192	7	3.61
384	-	-	-	42.66	-	671.87	1093	192	14	4.35
362.67	-	-	-	64	-	671.87	1093	192	28	5.13
260	-	-	-	-	100	600	1200	200	7	1.414
320	-	-	-	-	40	600	1200	200	14	2.645
340	-	-	-	-	20	600	1200	200	28	3.38

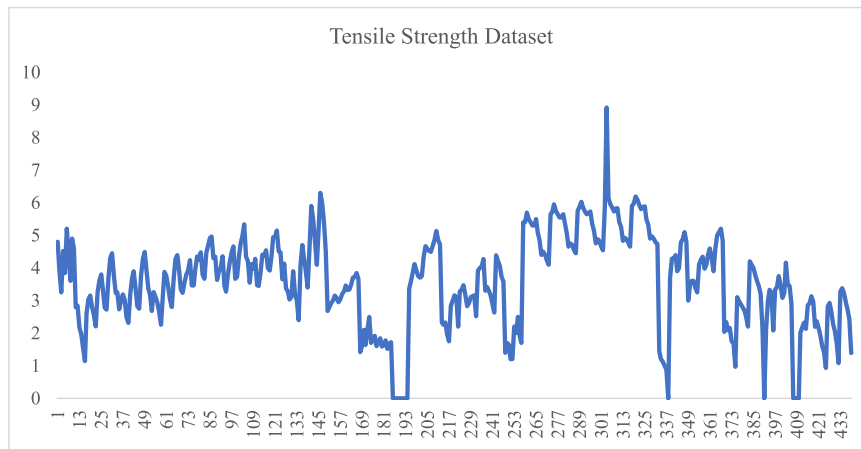


Fig. 3. Graphical presentation of the dataset.

Table 3
ANN training results.

ANN	Training (MSE)	Validation (MSE)	Test (MSE)	Training (R)	Validation (R)	Test (R)
I	0.0325	1	0.0046	0.9899	Not a Number (NaN)	Not a Number (NaN)
II	0.0077	1.25E+04	0.0437	0.9958	0.243	0.9448
III	0	0.073	0.0317	1	1	1
IV	0.0373	0.0459	0.0288	0.9933	0.9966	0.9944
V	0.0042	0.2857	0.0559	0.9978	1	1

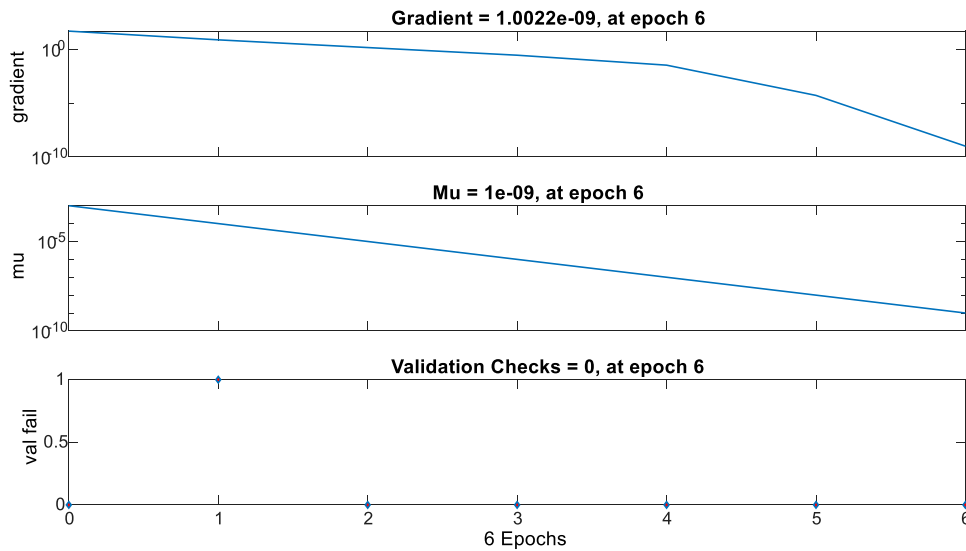


Fig. 4. Training state plot of ANN-I.

$$J_0 = \begin{bmatrix} \frac{\partial f}{\partial \beta_1}(x_1, b_0) & \dots & \frac{\partial f}{\partial \beta_p}(x_1, b_0) \\ \vdots & \ddots & \vdots \\ \frac{\partial f}{\partial \beta_1}(x_n, b_0) & \dots & \frac{\partial f}{\partial \beta_p}(x_n, b_0) \end{bmatrix}$$

Levenberg–Marquardt algorithm:

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k$$

The ability of the ANN to map complex nonlinear relations has made it particularly applicable in applications like engineering and material science, such as concrete property prediction. The number of hidden layers shown in Table 1 where chosen for best performance of the

algorithm, and neurons in each layer problem-dependent, where more complex problems are modeled using deeper architectures. The synergy of modern concrete materials and artificial intelligence technologies enhances the resilience of urban infrastructure [69], while sustainability for buildings concerns environmental impacts and energy consumption by means of construction, operation, and demolition of the structure. It also encompasses those that come from raw materials used during the process [70–72].

Overall, the training of the ANN should be done on a partition of the data into training, validation, and testing subsets in order not to have any generalization problem or overfitting. The model generalization might get improved by applying some regularization techniques, including dropout, or L2 regularization methods. More sophisticated optimization algorithms such as Adam or RMSprop adaptive methods

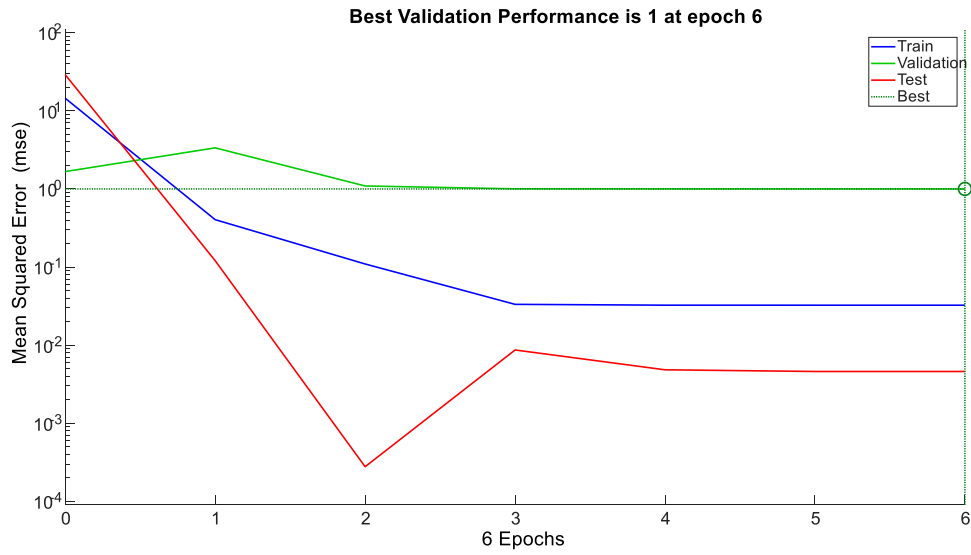


Fig. 5. Performance plot of ANN-I.

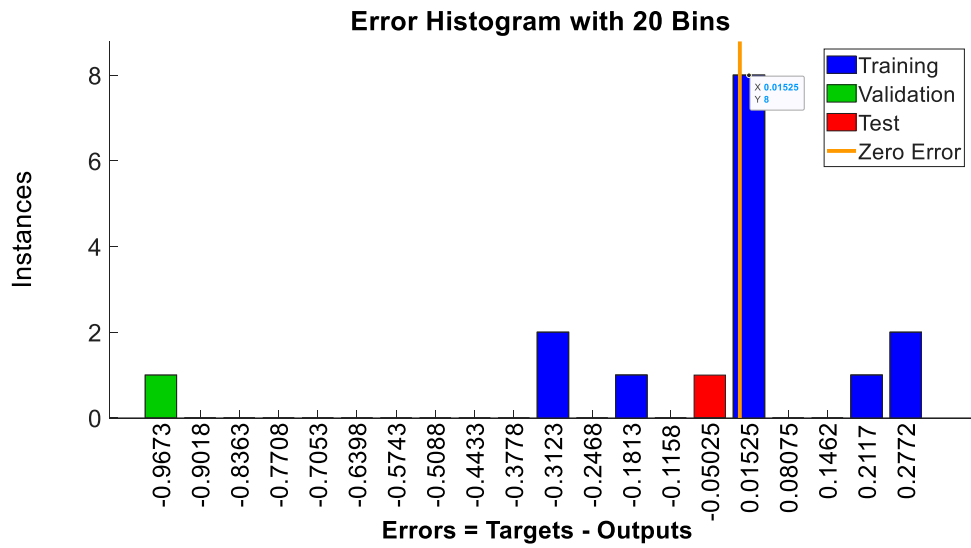


Fig. 6. Error histogram plot of ANN-I.

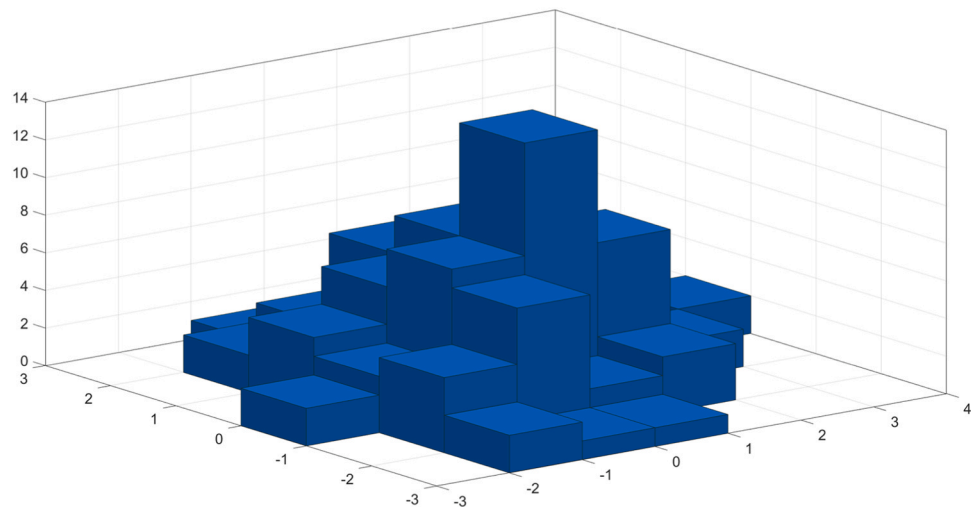


Fig. 7. Bivariate Histogram plot of ANN-I.

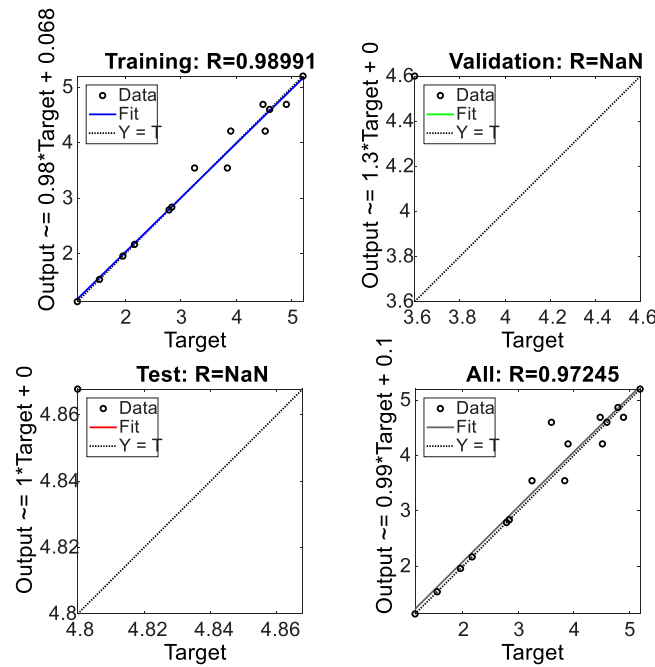


Fig. 8. Regression plot of ANN-I.

should be applied for speedier convergence and overall improvement of general performance. ANNs are flexible and can be adapted for a wide range of problem domains by adjusting their architecture and hyper-parameters, making them a powerful tool for predictive modeling and pattern recognition Levenberg-Marquardt was used in this research.

3. Construction digitalization

Numerous innovations have been revealed, and researchers from a variety of communities are excited. These include the development of deep learning, the availability of large datasets for benchmarking, and algorithm improvements like activation functions, weight-initialization schemes, and better optimization schemes. In order to detect damage to structures [73,74], concrete cracks [75,76], bridge structural elements [77], asphalt [78], tunnels [79], towers of transmission [80], and ceiling [81], civil engineering researchers have used this new computer technology. The construction industry lags behind other industries due to a

lack of creativity and innovation, and most importantly, poor sustainability outcomes [82]. Innovations include a wide range of transformative systems like artificial intelligence (AI) and artificial neural networks (ANN), which can help the construction sector develop, but this opportunity is undermined by the lack of online data.

A dataset of 440 entries gathered from earlier studies on the effects of different Supplementary Cementitious Materials (SCMs) and their contributions to the durability of cement and concrete was used in this investigation. Waste glass powder (WGP), Waste granite dust (WGD), Waste marble powder (WMP), Waste brick powder (WBP), and Ceramic waste powder (CWP) were among the SCMs. To improve concrete’s mechanical qualities and sustainability, cement was used in different amounts to partially replace these materials. The tensile strength of the concrete was the dataset’s output parameter, and the input parameters were the amounts of cement, fine aggregate (FA), coarse aggregate (CA), water, SCMs, and curing age. Examples of the dataset used are displayed in Table 2.

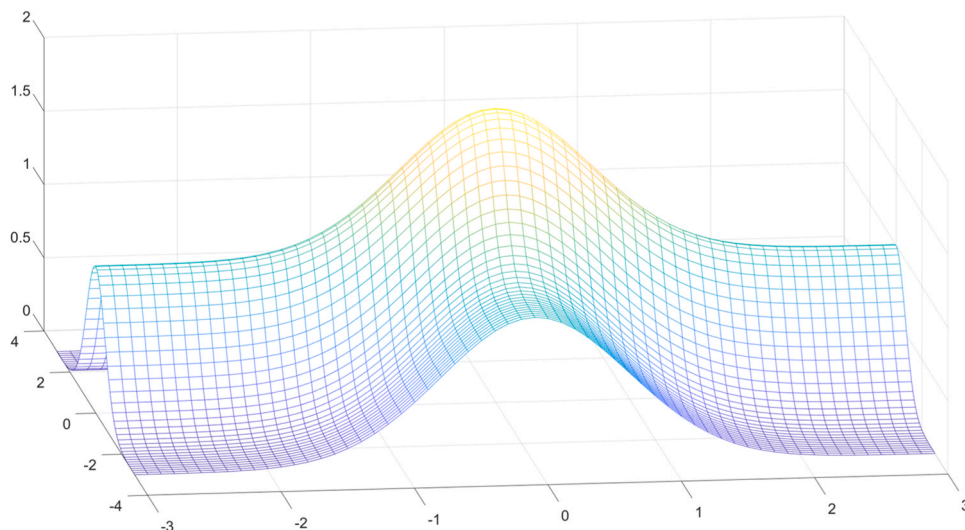


Fig. 9. Surface plot of ANN-I.

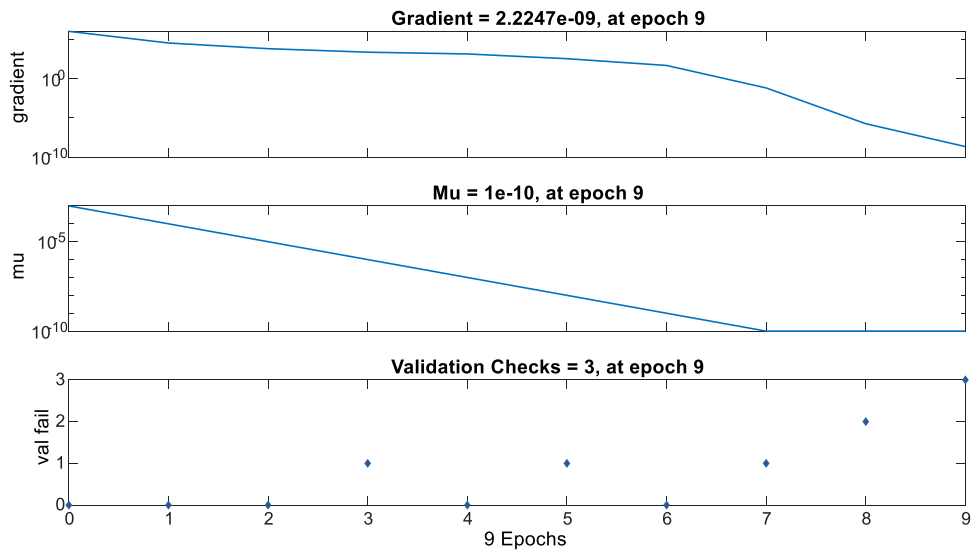


Fig. 10. Training state plot of ANN-II.

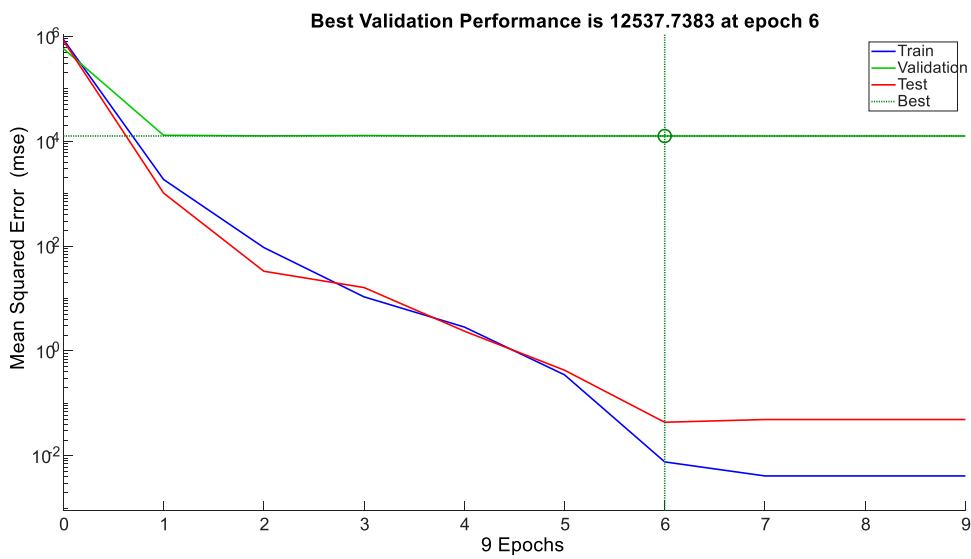


Fig. 11. Performance plot of ANN-II.

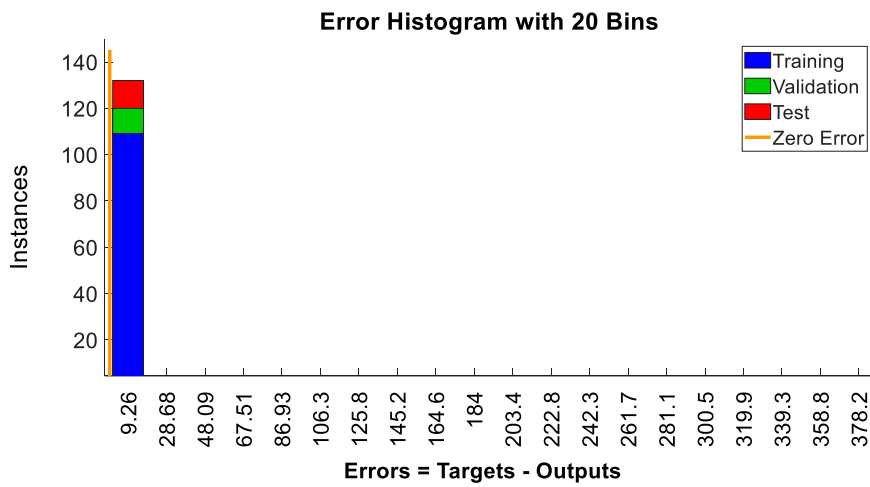


Fig. 12. Error histogram plot of ANN-II.

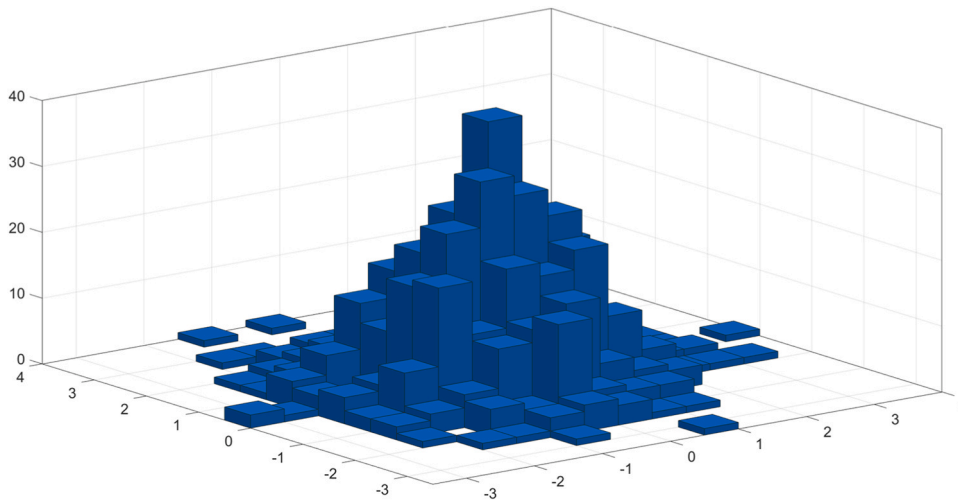


Fig. 13. Bivariate Histogram plot of ANN-II.

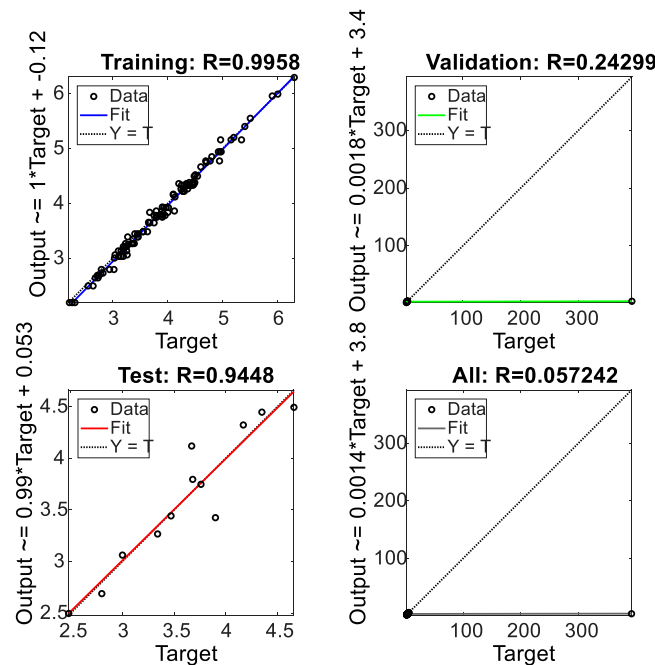


Fig. 14. Regression plot of ANN-II.

Fig. 3 graphical presentation of the data collected SCMs were replaced with different percentage of cement in studies and subsequently, the properties tested include the compressive strength test, the tensile strength test, and the flexural test for their concrete samples. Such tests had indicated the potential of SCM usage as a means to enhance eco-friendliness in structural concretes by demonstrating even longer service life.

4. Results & discussion

ANN models with architectures ranging from ANN-I to ANN-V were trained and tested using the Mean Squared Error (MSE) and correlation coefficient metrics. Among them, model ANN-III, with 50 hidden neurons, gave the best performance, Validation and Training results shown in Table 3 with minimum MSE and maximum predictive accuracy.

Results show that the addition of waste-derived SCMs enhances the tensile strength of concrete and enhances concrete durability generally, Other significant analytical researches was found the benefit effect of

using SCMs [83–87]. Curing time and water-to-cement ratio were critical factors in controlling the tensile strength. The ANN performance with testing data was excellent, indicating that this approach is applicable.

4.1. ANN-I

The gradient coefficient varies according to the number of epochs, as seen in Fig. 4. At epoch number 6, the gradient coefficient’s final value is 1.0022e-09, which is very close to zero. Epoch indicates that every sample in the training dataset has had a chance to update the internal model parameters; the lower the gradient coefficient value, the better the network training and testing will be.

Fig. 5 illustrates how the network’s error changes over training epochs for different data subsets—typically training, validation, and testing sets. This plot is instrumental in assessing the network’s learning progress and its ability to generalize to new, unseen data, At epoch 6, the validation dataset achieved its MSE, which is 1. This indicates the

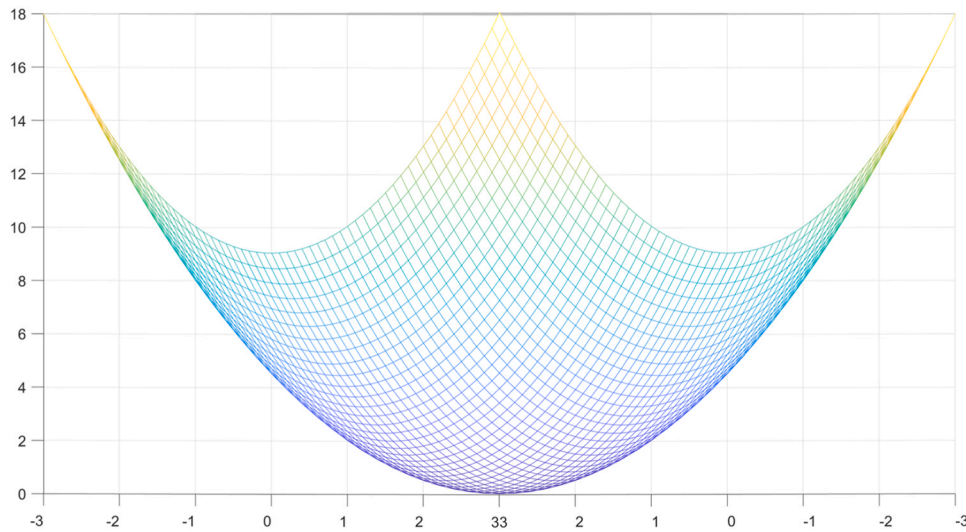


Fig. 15. Surface plot of ANN-II.

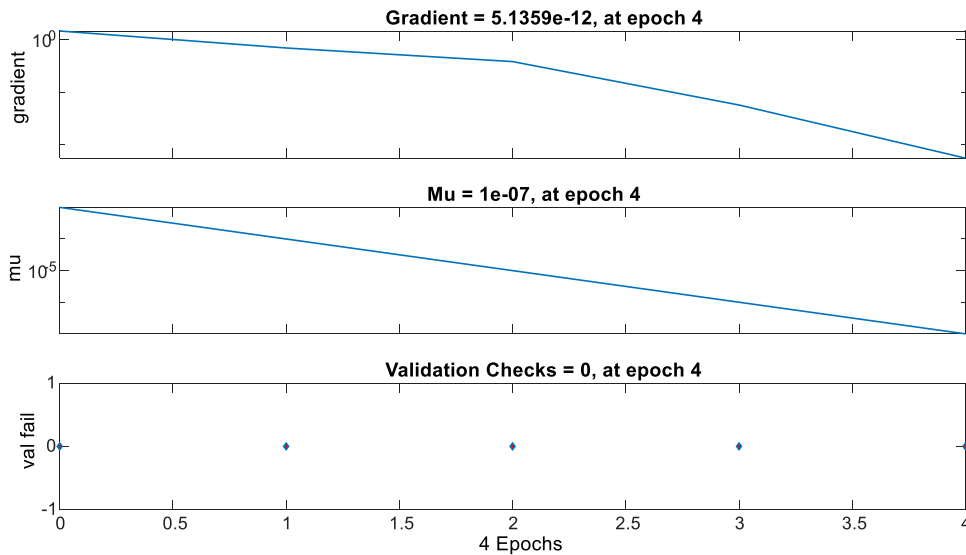


Fig. 16. Training state plot of ANN-III.

network’s best generalization ability to unseen data during training.

An Error Histogram Plot shown in Fig. 6 visually represents the distribution of errors between the network’s predicted outputs and the actual target values. This plot is instrumental in assessing the performance and accuracy of the ANN, which in this case it suggest that the data is more closer to the actual value.

Fig. 7 visualizes the joint distribution of variables by dividing the data into bins along two dimensions and representing the frequency of data points within each bin. Analyzing relationships between pairs of variables.

A regression plot shown in Fig. 8 illustrates the relationship between actual target values and the model’s predicted outputs, aiding in performance evaluation. In the provided plot, the training data shows a high correlation coefficient ($R = 0.98991$), indicating accurate predictions during training. However, the validation and test plots display R values as Not a Number (NaN), suggesting issues such as missing or insufficient data in these phases. The overall plot maintains a strong correlation ($R = 0.97245$).

Surface plot in Fig. 9 provides insights into the decision boundaries and functional mappings learned by the ANN, offering a visual understanding of how the network distinguishes between different classes or

predicts continuous outcomes, These applications demonstrate the ANN’s ability to model complex surfaces and predict intermediate values.

4.2. ANN-II

Fig. 10 illustrates the training process over 9 epochs. The gradient decreases steadily to 2.2247×10^{-92} , indicating successful convergence. The μ parameter decreases exponentially to 1×10^{-101} , reflecting fine-tuning by the Levenberg-Marquardt algorithm. Validation checks occur intermittently, with 3 checks by epoch 9, showing efforts to monitor and prevent overfitting. Overall, the low gradient value highlights the model’s convergence.

Test datasets over 9 epochs shown in Fig. 11. The best validation performance is achieved at epoch 6 with an MSE of 12,537.7383. After epoch 6, the validation error stabilizes, while the training error continues to decrease slightly, indicating potential overfitting. The test error closely follows the validation error, confirming consistent performance across datasets.

Most errors in Fig. 12 are concentrated near zero, indicating good model performance. The training dataset has the highest instance count,

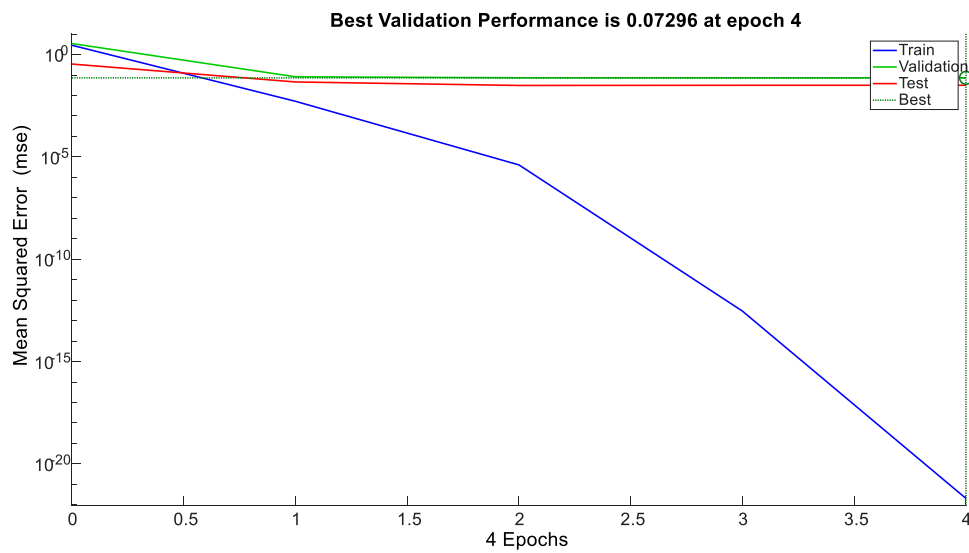


Fig. 17. Performance plot of ANN-III.

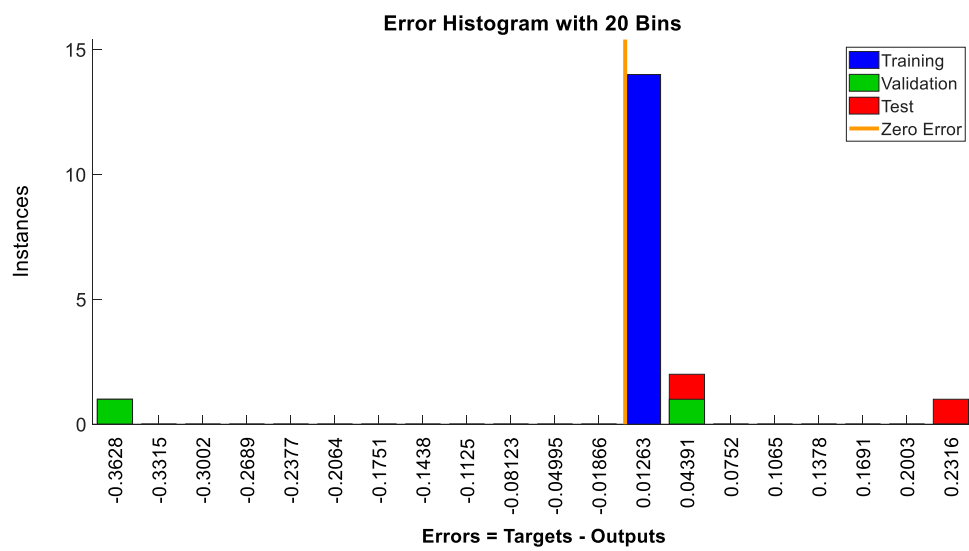


Fig. 18. Error histogram plot of ANN-III.

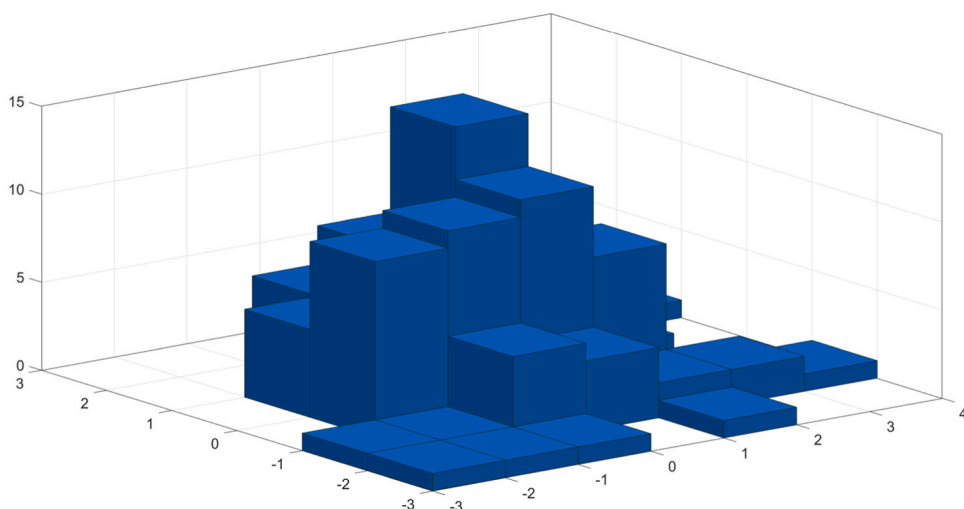


Fig. 19. Bivariate Histogram plot of ANN-III.

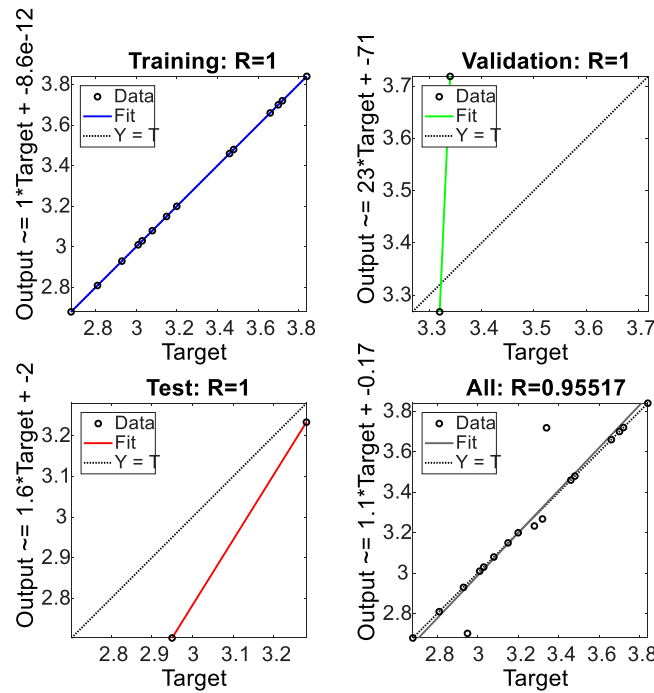


Fig. 20. Regression plot of ANN-III.

followed by validation and test, with minimal outliers. The concentration of errors near zero suggests the model predicts accurately across datasets (Fig. 13).

The regression plots in Fig. 14 show the performance on the training ($R = 0.9958$) and test sets ($R = 0.9448$) and validation performance ($R = 0.24299$). The overall performance ($R = 0.057242$) (Figs. 15 and 16).

4.3. ANN-III

The training metrics show a steady decrease in the gradient ($5.1359e-12$ at epoch 4) and the learning rate parameter ($1e-07$ at 4 epoch), indicating convergence. No validation failures occurred, suggesting stable validation performance during training.

The Validation Performance in Fig. 17 is 0.07296 at epoch 4.

Test and validation shown in Fig. 18 shows wider error range than the Training which is closer to the best value (Fig. 19).

Achieving a correlation coefficient (R) of 1 for the training in Fig. 20,

validation, and test datasets, indicating perfect agreement between the predicted and actual target values for each phase. The combined data, comprising all three datasets, achieves an R-value of 0.95517 , showcasing the model's strong predictive capability across diverse data points. This slight reduction in R for the overall dataset may suggest minor variability or noise across the data splits (Fig. 21).

4.4. ANN-IV

In Fig. 22 Over 14 epochs, the gradient steadily decreases, reaching a value of 0.45856 , indicating effective minimization of the loss function. The Mu parameter stabilizes at 0.001 , confirming that the Levenberg-Marquardt algorithm reached convergence. Validation checks reached 6 by epoch 14, triggering the stopping criterion to prevent overfitting and ensure the model's generalization capability (Figs. 23–25).

Best validation performance, with an MSE of 0.045857 , is achieved at epoch 8, demonstrating the model's optimal balance of accuracy and

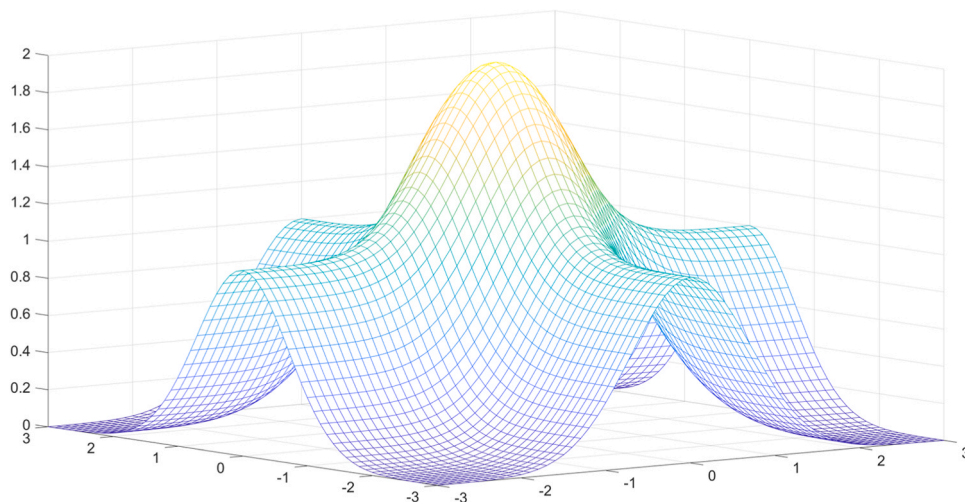


Fig. 21. Surface plot of ANN-III.

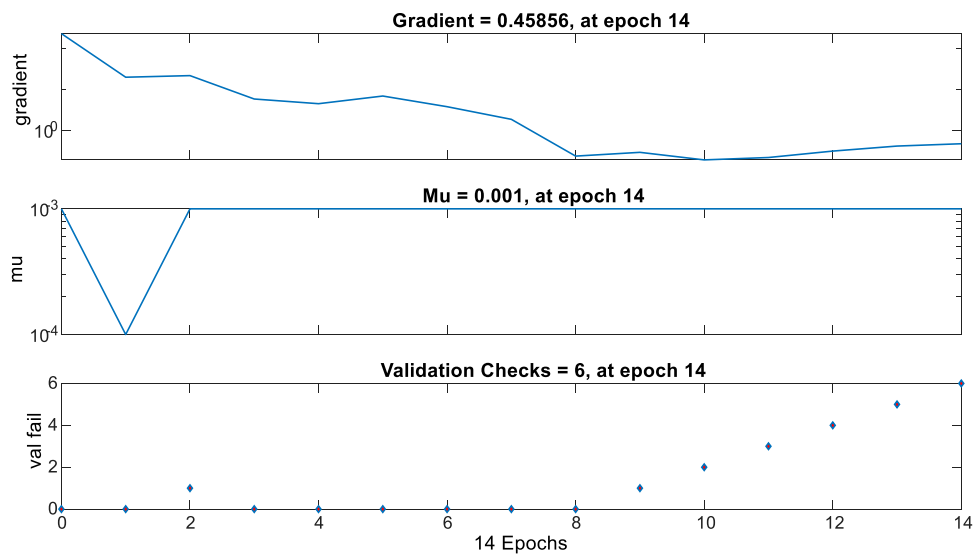


Fig. 22. Training state plot of ANN-IV.

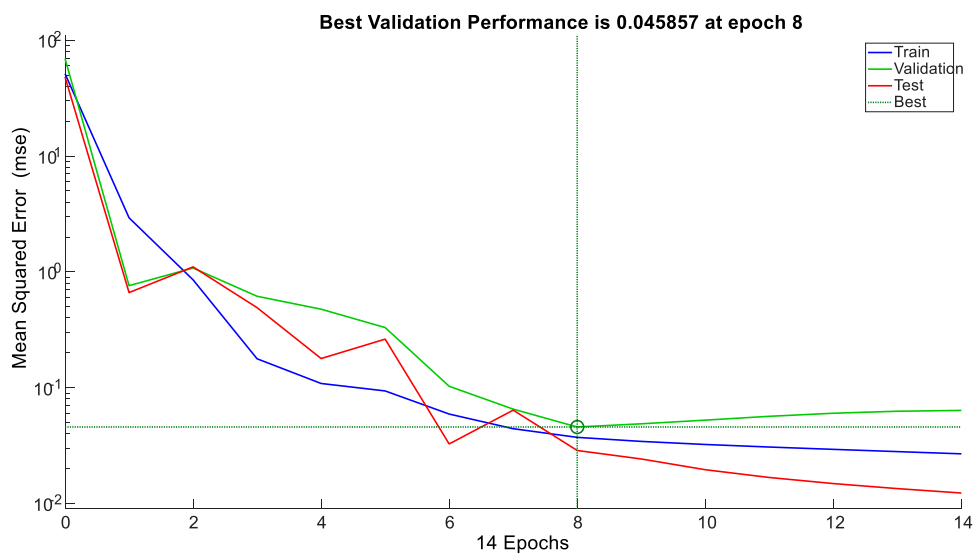


Fig. 23. Performance plot of ANN-IV.

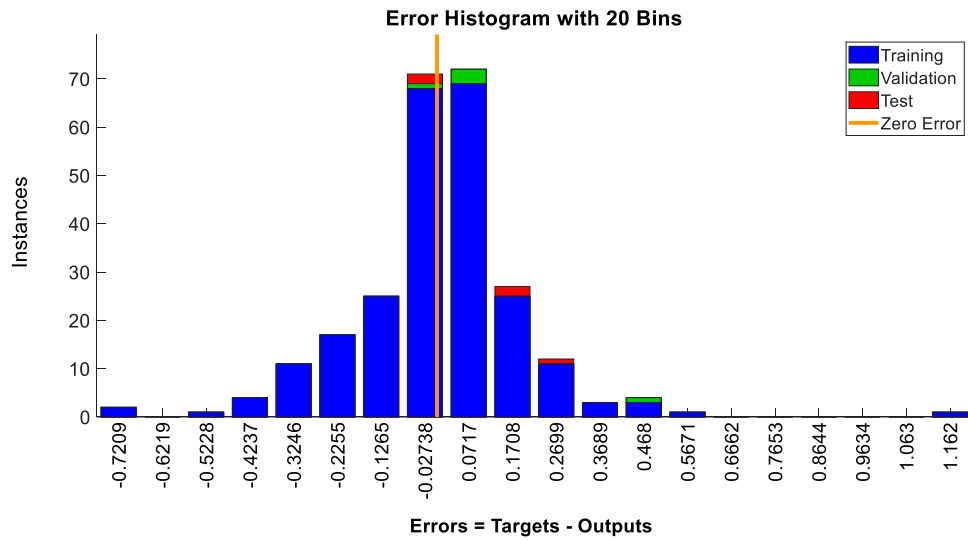


Fig. 24. Error histogram plot of ANN-IV.

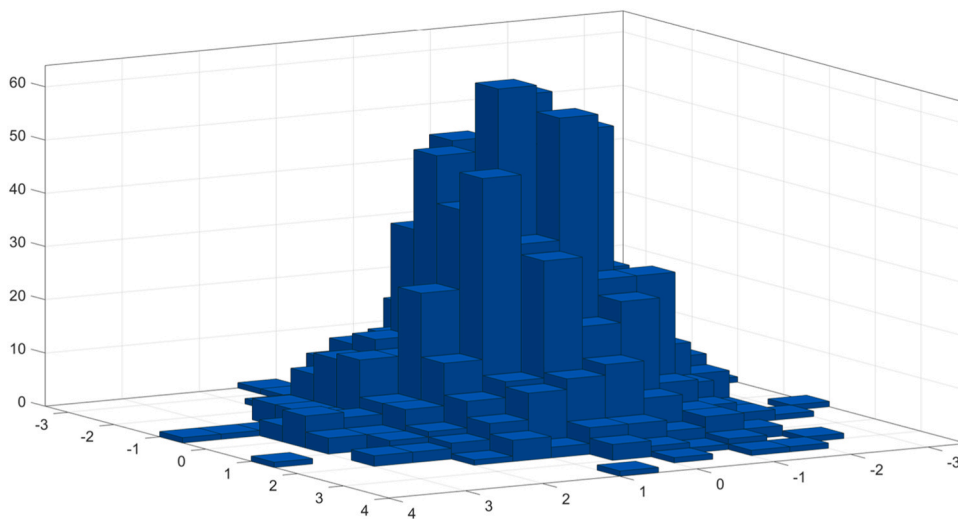


Fig. 25. Bivariate Histogram plot of ANN-IV.

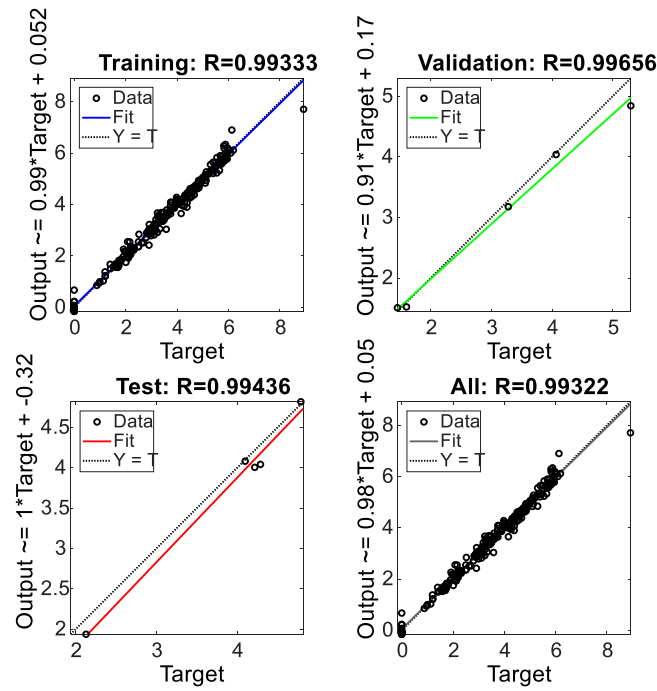


Fig. 26. Regression plot of ANN-IV.

generalization. The MSE in Fig. 22 decreases significantly during the initial epochs, reflecting effective learning. Beyond epoch 8, the validation and test errors plateau, while the training error continues to decline, signaling the potential onset of overfitting. The early stopping criterion, triggered at epoch 14, prevents further overfitting and ensures robust generalization.

The regression plots Fig. 26 indicate that the model performs exceptionally well across all datasets (training, validation, test, and overall), as evidenced by R-values consistently above 0.99. This reflects a high degree of correlation between predicted and target values, with minimal bias and excellent generalization to unseen data. The near-perfect regression slopes across the datasets suggest the model captures the underlying relationship effectively, with minimal overfitting or underfitting. This performance demonstrates the model's reliability and suitability for predictive tasks in the given context (Fig. 27).

4.5. ANN-V

In Fig. 28 gradient decreases steadily and reaches a near-zero value by epoch 4, indicating successful convergence.

training, validation, and test MSE in Fig. 29 over 4 epochs. The model achieves its best validation performance (MSE = 0.28569) at epoch 1, indicating the optimal trade-off between underfitting and overfitting. While the training MSE continues to decrease, the validation and test MSE stabilize, reflecting excellent generalization and consistency.

Histogram Fig. 30 shows that most errors are concentrated near zero, test and validation datasets have slightly more dispersed errors, suggesting minor generalization gaps. Outliers at the extremes (e.g., -0.7 and 0.17) (Fig. 31).

Fig. 32 shows regression plots for training, validation, test, and overall datasets. The correlation coefficient R is near 1 for all datasets, indicating excellent agreement between predicted and actual values. The training set has R = 0.99783, demonstrating a strong fit, while the

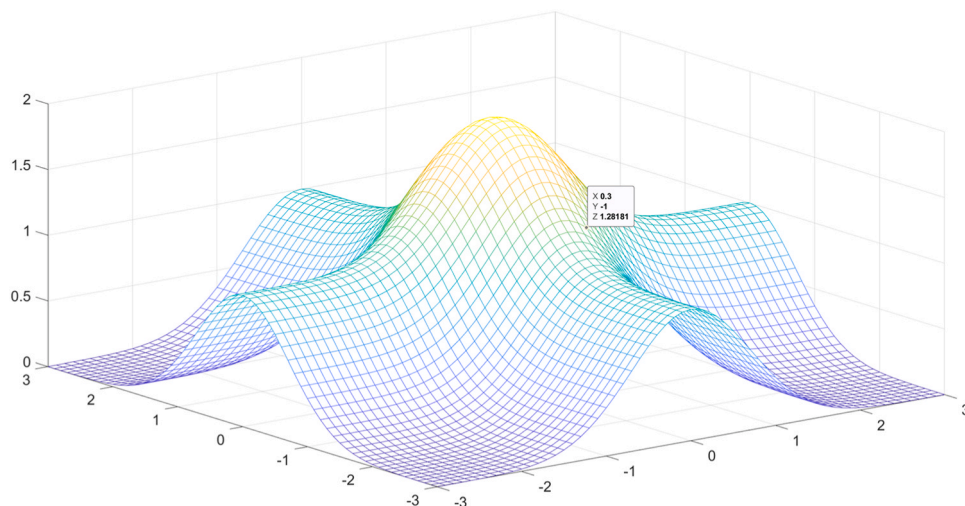


Fig. 27. Surface plot of ANN-IV.

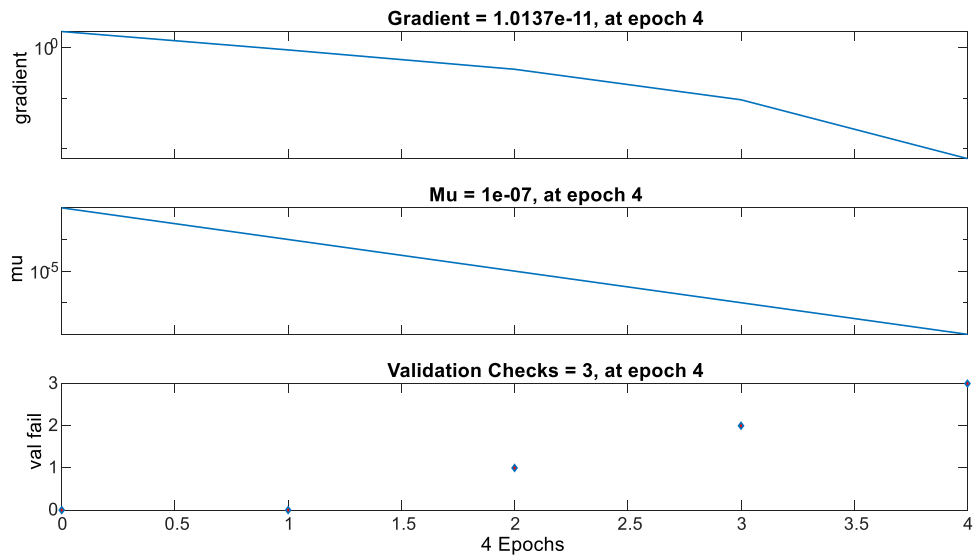


Fig. 28. Training state plot of ANN-V.

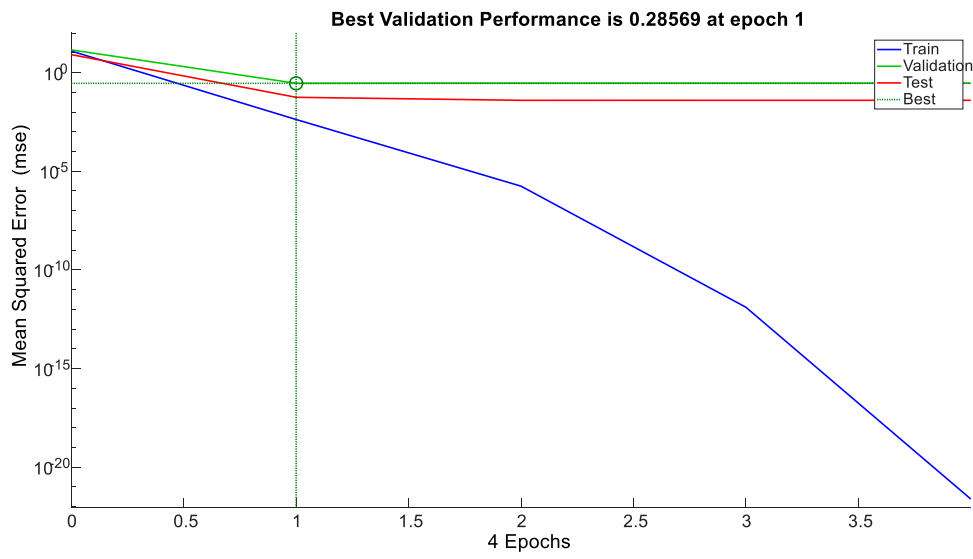


Fig. 29. Performance plot of ANN-V.

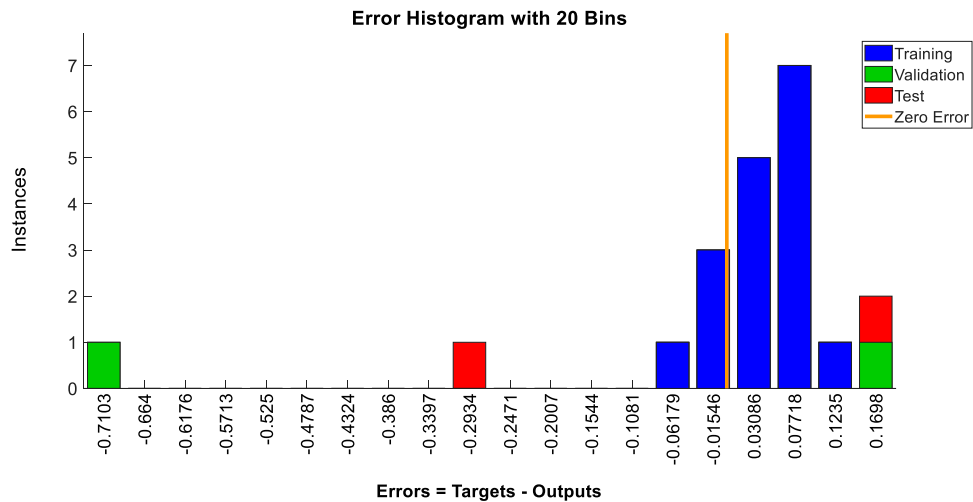


Fig. 30. Error histogram plot of ANN-V.

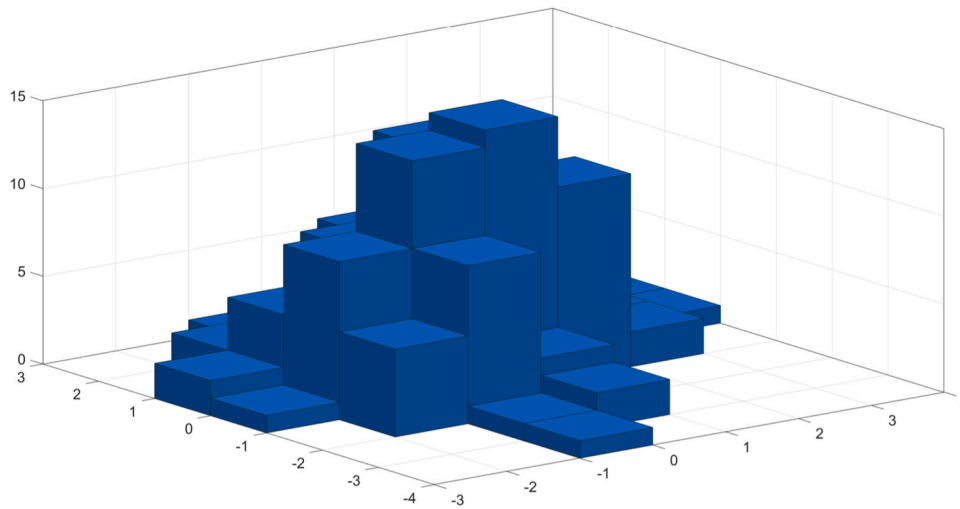


Fig. 31. Bivariate Histogram plot of ANN-V.

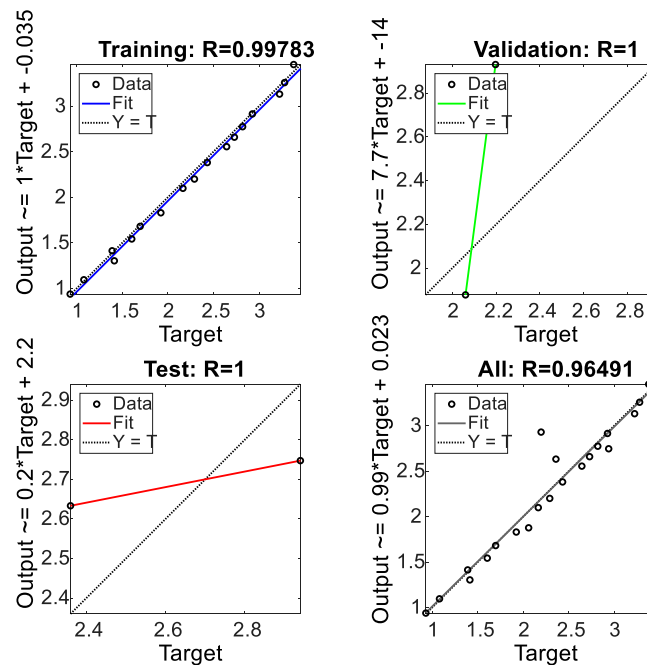


Fig. 32. Regression plot of ANN-V.

validation and test sets achieve perfect fits $R = 1$. The overall $R = 0.96491$ (Fig. 33).

4.6. Graphical user interface

To enhance usability, an application was developed based on the trained ANN model. The application allows users to input parameters such as the type and percentage of cement replacement material, curing time, and water-to-cement ratio to predict concrete tensile strength Fig. 34. This tool provides immediate insights, aiding in the optimization of concrete mix designs and reducing reliance on time-intensive testing methods.

5. Conclusion

The ANN-based model created in the present research showed good performance in its capability to predict the tensile strength of concrete

with various types of waste-derived SCMs. Being non-destructive and general, it has the potential to speed up the processes in concrete testing. The technique is further made highly feasible because of a developed application given that will be able to offer, on-spot optimization of the mix. Such an application of waste material would therefore result in two advantages: on one hand, improvement in properties of concrete and, on the other hand, environmental concerns and sustainable construction.

Future work will be directed towards expanding the data set and including other parameters in an effort to further enhance the performance of the model, the potential influence of cement type variability enhance the model by including cement type as a parameter and other mechanical properties such as compressive and flexural strength tests can be predicted by this model, and its limitation can be overcome by simply developing the database once. It can then be implemented in the application for predicting the optimal value.

Enhance the model by incorporating:

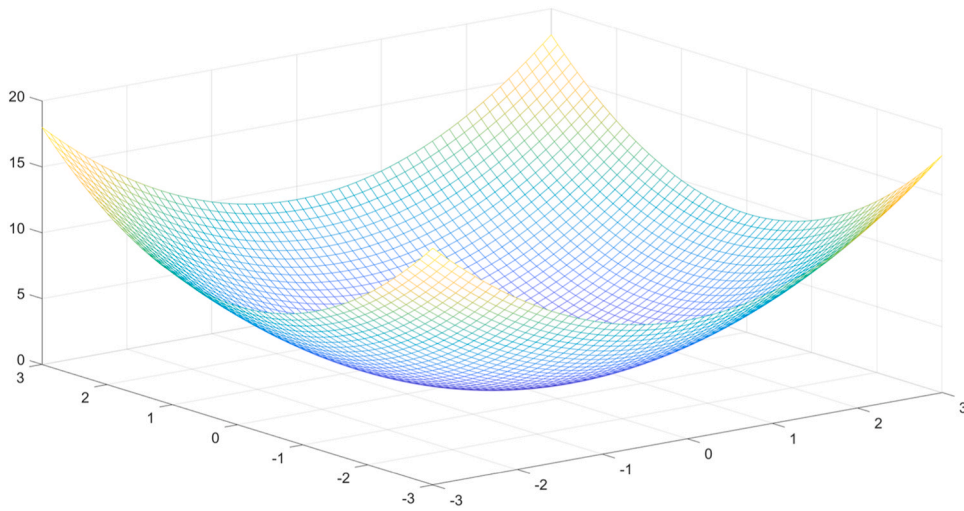


Fig. 33. Surface plot of ANN-V.

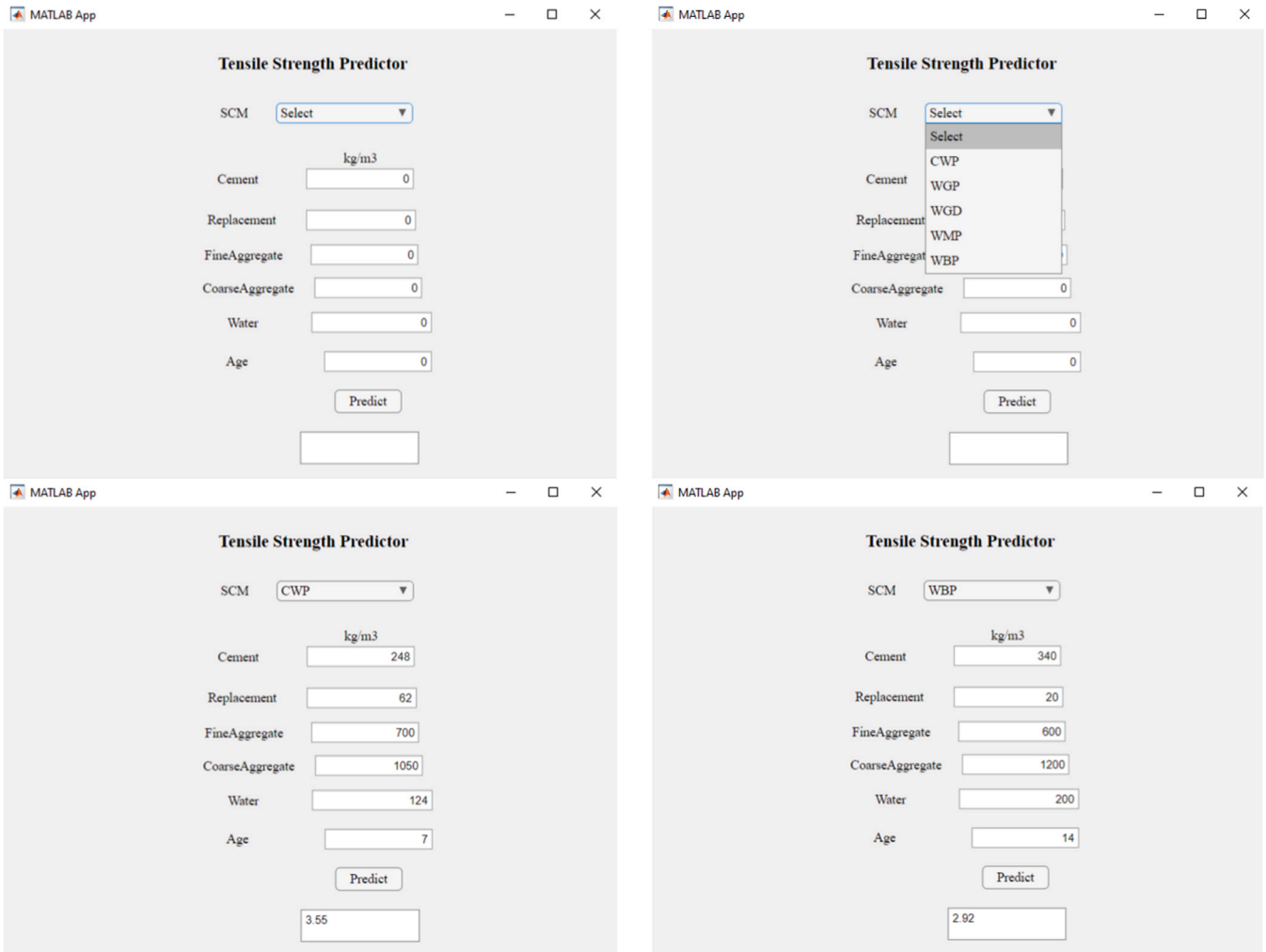


Fig. 34. The developed application for predicting the tensile strength of concrete.

- Expanding the Dataset – Increasing the dataset size by incorporating more experimental results from different concrete mix designs, curing conditions, and SCM types will improve model generalization and accuracy.
- Feature Engineering – Including additional parameters such as cement type, aggregate characteristics, curing temperature, and chemical admixtures could refine the model’s predictive capabilities.
- Hybrid Models – Combining ANN with optimization algorithms.

CRedit authorship contribution statement

Moutaman M. Abbas: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Radu Muntean:** Writing – review & editing, Validation, Supervision, Resources, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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