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Predicting Compressive Strength of Advanced Bricks with Rice Husk Ash Using Feedforward Neural Network

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Abstract—**Rice husk ash (RHA) is a sustainable alternative to Portland cement in construction applications. A byproduct from rice milling, RHA is rich in silica and, when properly burned, exhibits pozzolanic properties that enhance the performance of concrete. The study examines the transformation of rice husk into RHA, emphasizing its composition of opaline silica and lignin, which contributes to improved bonding between cement paste and aggregate, ultimately resulting in enhanced concrete strength, waterproofing, and chemical resistance. In contrast, the production of Portland cement is energy-intensive, significantly contributing to carbon emissions. A neural network model was developed to predict the compressive strength of advanced bricks incorporating RHA. The model, trained on a dataset segmented into training, validation, and test subsets, demonstrated strong predictive capability with a high correlation coefficient (R = 0.9594) during training, showcasing its effectiveness in capturing underlying data patterns. Validation metrics improved further, achieving an R-value of 0.9714, indicating vigorous generalization to unseen data and confirming that the model is not overfitting. Experimental testing corroborated these findings, with measured stress values—4.69508 MPa for 20%, 7.58838 MPa for 15%, and 3.51326 MPa for 10% RHA—demonstrating effective load resistance across different material configurations. The model's performance on the test set, with an R-value of 0.9521, reflects the bricks' above-average durability and reinforces the model's reliability in predicting compressive strength. The consistent performance of the neural network model not only mirrors the actual material behavior observed in the tests but also highlights its significant potential as a powerful tool for both research and practical applications. Overall, these findings support the case for RHA as a valuable resource in sustainable construction. The findings emphasize RHA's potential as an eco-friendly and effective substitute for traditional Portland cement, promoting sustainable construction methods while improving structural efficiency and safety.**

Keywords—Enhanced Material Selection; Knowledge Advancement; Neural Network Applications; Practical Implementation; Rice Husk Ash; Structural Performance.

I. Contextual Framework & Literature Overview

The growing demand for sustainable, durable, and efficient construction materials has prompted extensive research into alternative resources and innovative technologies that reduce environmental impact without sacrificing quality. Enhanced material selection has become a focal point in civil engineering, with an emphasis on eco-friendly alternatives like RHA, which can partially replace traditional components such as Portland cement. By incorporating such sustainable materials, construction practices not only contribute to waste reduction but also enhance the strength, durability, and longevity of concrete structures, addressing environmental challenges in the sector.

RHA is an agricultural outcome generated through rice mills. The rice husk is the outer layer of rice seeds or grains. During the growing season, this covering sustains the germinated seed or grain. The husk transforms into dense substances such as opaline silica and lignin. Rice husk consists of a lot of silica when effectively scorched. Utilizing it as a stabilizing agent for soil is an ecologically sustainable substitute for the final disposition. As a pozzolanic reactive material, RHA can increase the surface area of the transition zone between the microscopic structure of cement paste and aggregate in high-performance concrete. RHA is an additional green component with functions that range from small to large. It is suitable for waterproofing. It is also used as an admixture in concrete to render it resilient to the permeation of chemicals [1].

Conversely, Portland cement is a fine powder produced by heating limestone and clay minerals in a kiln enough to form clinker. The clinker is ground to a fine powder with a small number of additional elements indicated. It is one of the most frequently utilized types of cement in the world. Portland cement is composed of tri- and dicalcium silicates, tricalcium aluminate, tetracalcium aluminoferrite, and gypsum. It has adhesive and cohesive properties and is capable of binding mineral fragments together in an environment of water, resulting in a constant compact mass of masonry. Portland cement is applied in all types of buildings in which special properties are not necessary. It is frequently employed in reinforced concrete constructions, bridges, and roads, and additionally in locations with normal soil properties [2].

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A. Systemize Improved Structural Performance

RHA's surface texture and area exhibit a higher absorption trait and require more water to maintain its specific consistency. The figure indicates that at a specific water-cement ratio value, the structural performance tends to rise. The incorporation of RHA impacts the total spread of concrete. The preservation of a given consistency while decreasing the need for water will be beneficial in enhancing the mix's all-around building qualities. The granularity of the cement, in addition to the coarse and fine aggregates, are going to affect the number of gaps visible in the fresh and later stages of the concrete. This granulometric property has a major impact on the existence or lack of gaps in concrete. The addition of any mineral admixture with a size in the range of 20 micrometers will help the mix by reducing its total voids. This mineral admixture contributes to the supplementation of cement grains. This would end up resulting in a mix that requires less water to attain the right consistency. The densification of a RHA concrete mixture enhances performance. This approach employs cement and RHA to fill the pores with the aid of water. Within the compacted aggregates, this occurs [1].

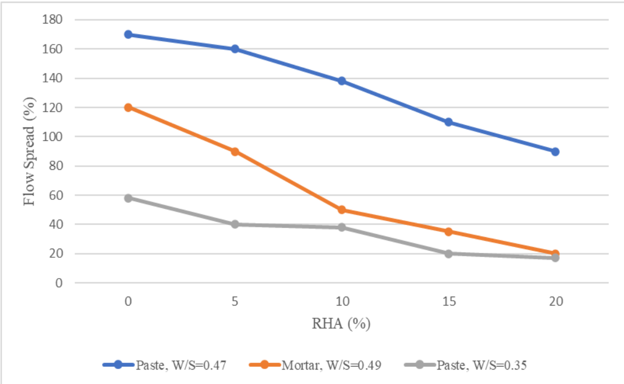

Fig. 1. Flow spread as per the flow table test conducted on mortar with varying water-cement ratio and RHA content [1]

Ordinary Portland cement is costly in developing countries, and there is an abundance of demand for low-cost building materials. Given that cement is the most expensive part of concrete, substituting a portion of it with RHA would substantially decrease the overall price of concrete. Higher-strength concrete with RHA allows the production of lighter-weight products, such as hollow blocks with enhanced thermal insulation properties, that offer lighter walls for steel-framed buildings. It also results in smaller amounts of cement and aggregate [3].

B. Relate Practical Implementation

Using sustainable and energy-efficient building materials is crucial for resolving the environmental issues brought on by conventional construction methods. The use of alternative materials, such as RHA, has attracted a lot of interest recently in the creation of cement-based goods.

The bricks' cement can react and form solid linkages because curing creates the ideal conditions for hydration. The creation of a dense, well-bonded structure and thorough hydration of cement particles are both facilitated by optimal curing conditions. Higher compressive strength, which is necessary for supporting a structure's load-bearing capacity and ensuring its long-term stability, is the result of this. For constructed buildings to be of the highest quality and performance, the curing conditions in cement-based RHA bricks must be optimized. A building's structural integrity and durability are greatly influenced by the bricks' compressive strength, which is maximized by proper curing [1].

The process of curing incorporates steps for regulating temperature during cement hydration and moisture transfer from and into concrete during the initial phases of hardening, in contrast to high water-cement ratio concrete, low water-cement ratio concrete benefits more from early excessive water curing. The hardened silica fume concrete is affected by the curing process as well. In contrast to moist curing, steam curing improves the characteristics of silica fume concrete, whereas air curing has negative consequences. The temperature of the curing water also influences the compressive strength of concrete specimens. The compressive strength of concrete samples that have been cured at temperatures greater than the typical curing water temperature (25°C) has increased. Depending on the type of cement used, this increase in compressive strength varies [4].

C. Enhanced Material Selection for Sustainable Construction

In the construction industry, when making informed decisions regarding the type and quantity of materials for construction projects, it is crucial to evaluate performance, durability, cost, and sustainability. The careful selection and optimization of materials can significantly enhance the overall quality and efficiency of construction endeavors. Concrete, a prevalent construction material, predominantly relies on resources extracted from the earth's crust. This practice contributes to environmental degradation and the depletion of natural resources. In contrast, human activities produce substantial quantities of solid waste annually—exceeding 2.5 billion tons—stemming from industrial, agricultural, and urban sources. Key examples of such wastes include fly ash, blast furnace slag, rice husk (converted into ash), silica fume, and demolition debris. The incorporation of industrial byproducts as partial substitutes for the energy-intensive Portland cement can result in notable energy and cost reductions. For instance, concrete incorporating rice husk exhibits commendable compressive strength and low water absorption characteristics. Although the global production of waste is substantial, the recycling process remains inefficient and energy-demanding. Additionally, unmanaged waste contributes to soil contamination and exacerbates environmental challenges [5].

The integration of waste materials into construction represents a promising solution for waste management, provided that these materials are subjected to rigorous analysis prior to their application. Effectively utilizing waste in new building materials addresses both waste disposal and sustainability issues, offering a viable alternative to conventional construction practices [6].

D. Justify Neural Network Applications

Artificial intelligence is a branch of computer science, involved in the research, design, and application of intelligent computers. Traditional methods for modeling and optimizing complex structure systems require huge amounts of computing resources, and artificial intelligence-based solutions can often provide valuable alternatives for efficiently solving problems in civil engineering [7].

This capability is directly related to the machine learning modeling process, which identifies key variables for Vjh of reinforced concrete beam-column joints (RC BCJ). Key variables include compressive strength, beam longitudinal reinforcement ratio, joint width, joint aspect ratio, and chamfer length, which substitutes for joint transverse reinforcement. Utilizing MATLAB, the study initializes neural network models (NNMs) with a 15% validation, 15% testing, and 70% training data split. By examining different hidden layer configurations, this research illustrates how ANNs can effectively enhance traditional modeling methods, demonstrating their potential to optimize structural analysis and improve design methodologies in civil engineering. Thus, the application of ANNs not only supports the accurate prediction of structural behavior but also aligns with the broader goal of advancing engineering practices through innovative computational techniques. [8]
Compression strength plays a significant role in evaluating materials' performance and structural design. Traditional analytical models often rely on empirical correlations and simplifications, leading to limitations in accurately capturing complex nonlinear relationships. An ANN is like a black box. After training the ANN, one can input several numerical values, and the ANN will prompt another numerical value that represents the predicted compressive strength of the concrete [9]. Factors Influencing ANN-Based Compression Strength Prediction Input parameters, such as material composition, curing conditions, manufacturing process parameters, and environmental factors, play a vital role in ANN-based compression strength prediction.

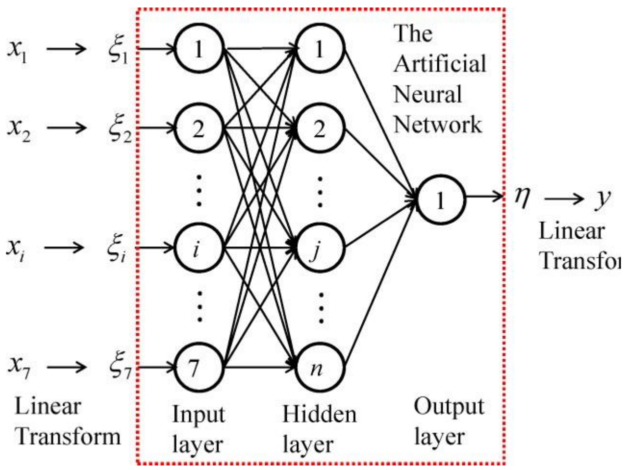

Fig. 2. Typical Neural Network Architecture [9]

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of biological neural networks. The fundamental building blocks are units (‘nodes’) comparable to neurons, with weighted connections that resemble synapses in biological systems. ANNs learn from data through a training process using algorithms such as backpropagation, excelling in capturing nonlinear relationships and adaptively adjusting internal parameters. They are widely used in applications like image recognition, natural language processing, and predictive analytics due to their ability to model complex patterns. Their performance improves with larger datasets and increased computational power, making them ideal for tasks requiring high accuracy and adaptability [10]. ANNs also have the capability to generalize from training data, allowing them to make predictions or classifications on unseen data, further enhancing their utility in real-world applications.

E. Innovative Material Optimization

The composition, mineralogy, and chemical properties of primary materials greatly influence the strength and durability of a brick. Aggregates, Portland cement, additional cementitious materials, and chemical admixtures comprise these materials. To ensure the long-term functionality of infrastructures, an accurate assessment of their effects on brick's overall strength and durability is crucial. However, no comprehensive geological and chemical evaluation of the raw materials of brick utilized in Philippine infrastructures exists. Established local practices have primarily concentrated on physically evaluating concrete mixtures and mortars. However, this method fails to specify the nature of harmful components, such as reactive silica in aggregates, which are common in tectonically active geologic regions such as the Philippines. Furthermore, multiple aggregate resources are being produced to satisfy the Philippines' infrastructure development-driven high demand [11].

RHA is locally available, comparatively affordable, and more environmentally conscious than present industrial materials. RHA consists mainly of silicate and other oxides such as iron, aluminum, calcium, and magnesium oxides, among others. Table 1 demonstrates the chemical evaluation of the rice husk. Several studies show that RHA includes 90-95% amorphous silica, which may enhance the workability, strength, and flexibility of the mixed concrete. The incorporation of RHA reduces initial surface absorption, permeability, and absorbing qualities, and increases concrete resistance [12].

Table 1. Chemical evaluation of the rice husk [12]

Constituent	% Composition
Fe2O3	1.28-1.38
SiO2	22.12-90.20
Al2O3	0.85-1.23
CaO	1.21-1.24
MgO	0.21-1.21
Loss on ignition	3.95

As the primary component of concrete, Portland cement is not an environmentally friendly material, as its production releases a substantial quantity of carbon dioxide (CO2) into the atmosphere. Each ton of cement clinker production is estimated to generate approximately one ton of CO2 along with other greenhouse gases (GHG). In addition, the constant construction of infrastructures increases the quantity of minerals (lime) extracted from quarries, resulting in the devastation of mountains and river basins. [13].

Supplementary Cementitious Materials (SCM) such as RHA have been used effectively as an alternative to standard Portland cement in the concrete industry, yielding various environmental, technical, and economic benefits. When utilizing RHA concrete in real-life situations, its mechanical qualities, especially compressive strength (CS), should be investigated. The laboratory-based experimental processes and analyses used to figure out the CS are tedious and expensive. To address these issues, dependable artificial intelligence (AI)-based algorithms for accurate CS estimates can be deployed [14].

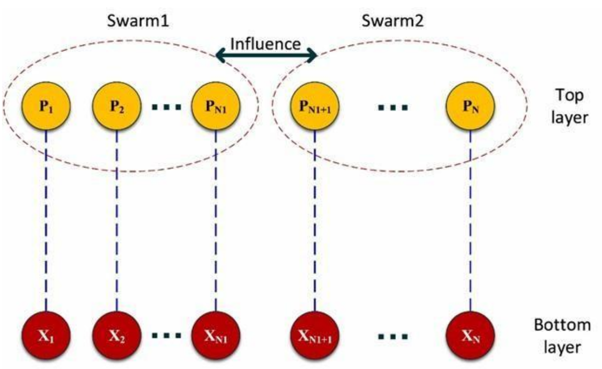

Fig. 3. The structure of PSOTD [14]

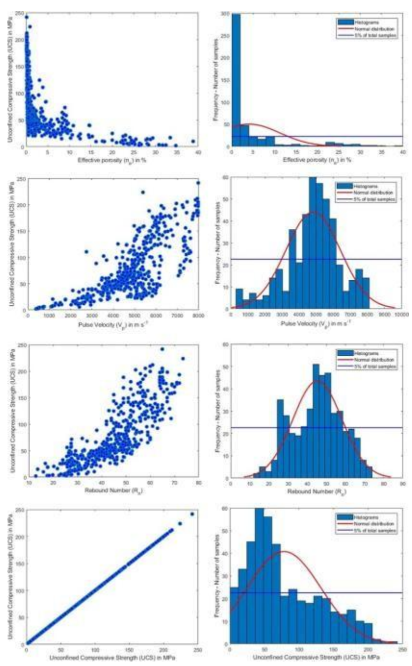

Fig. 4. Scatters and distributions of the database's input and output parameters [14]

According to Asteris et al. (2024), the validity of the constructed ANN-based model, similar to other mathematical simulators, is limited to the parameter ranges encompassed by the training datasets, as illustrated in Table [2]. The model demonstrates high reliability within these ranges, particularly where there is a significant density of data. This is evidenced by the histograms in Figure [5], which showcase the model's enhanced predictive consistency for compressive strength across parameters such as low porosity (<5%), medium pulse velocity (4500-6500 m/s), rebound values (45-55), and UCS values below 100 MPa.

Table 2. Statistics of the database's input and output parameters [15]

Variable	Symbol	Units	Category	Data used in NN Models				
				Min	Average	Max	STD	CV
Effective porosity	n_e	%	Input	0.06	4.04	38.82	7.18	1.78
Pulse Velocity	V_p	m/s	Input	375.00	4815.25	7981.00	1593.42	0.33
Rebound Number	$R_{n,L-type}$	-	Input	12.88	45.34	75.34	12.82	0.28
Unconfined Compressive Strength	UCS	Mpa	Output	2.03	78.23	241.56	53.39	0.68

Chen et al. (2023) comprehensively analyzed the error percentages associated with the ANN model's predictions across two distinct datasets: training and testing. Their results indicate that the absolute error percentage for the training dataset is exceptionally low, with exceptions limited to a small fraction of the data. In contrast, while the absolute error percentage for the testing dataset is slightly elevated, it remains below 15% across all instances. This observation underscores the model's robustness and generalizability, affirming its capacity to maintain accuracy and reliability across diverse conditions and data variations.

The stability of the model across various datasets and parameter ranges underscores its robustness with negligible accuracy degradation. The observed low error rates within the training dataset indicate the model's proficiency in encapsulating underlying data relationships. Furthermore, its performance on the testing dataset, albeit with a slight increase in error, corroborates its generalization capability. This consistent predictive performance renders the model particularly suitable for applications in real-world engineering and material science, where data variability is prevalent.

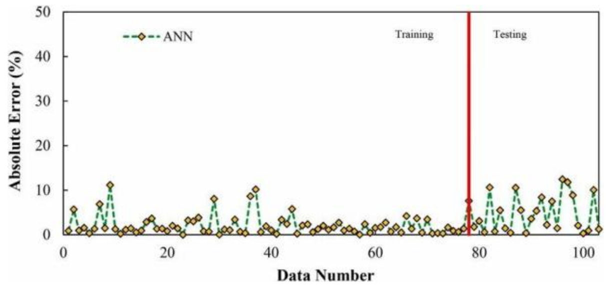

Fig. 5. ANN model Error percentage diagram in the network training and testing process. [7]

Hossain et al. (2023b) demonstrated the comparison of the expected and real values for different curing conditions CS of UHSFRC with Sf by various hidden neurons (used 2, 4, 6, 8, 10, 12, and 14), and anticipated results based on the regression model is given in Figure 6. As can be seen, the ANN model accurately anticipated the actual outcomes, which is useful in many applications. Figure 6 depicts the dispersion of real and anticipated CS values with errors for the ANN model. In this model, the maximum and lowest training values were reported to be 226.36 and 66.78 MPa, respectively.

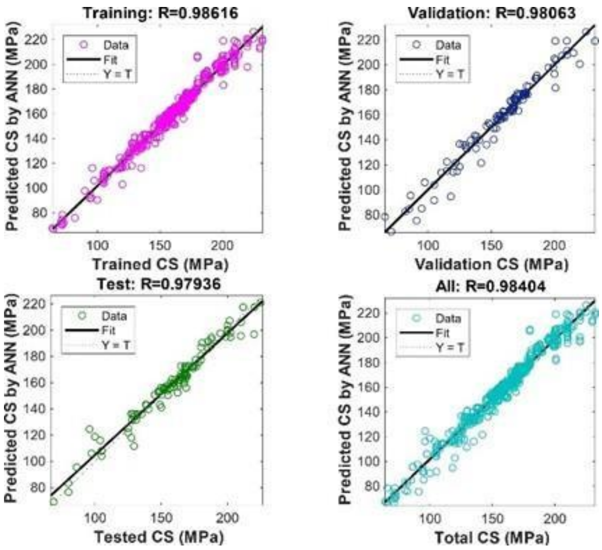

Fig. 6 ANNs module of regression for ten hidden layers. [16]

The model execution process starts by dividing the dataset into three key segments: training, validation, and testing, after the network setup is finalized. Throughout the three stages of model development, the selection process emphasizes topologies that exhibit the highest correlation values while maintaining low error rates. Table 3 outlines the neural network parameters employed during the training, validation, and testing phases [17].

Table 3: Neural Network Parameters [17]

Function	Network Type
Network	Feed-Forward Backpropagation
Training Algorithm	Levenberg-Marquardt Algorithm
Learning	Gradient Descent with Momentum
Performance Indicator	Mean Squared Error
Transfer Function	Hyperbolic Tangent Sigmoid

Advances in computational technology and the availability of online simulation software have significantly enhanced the application of neural network models, underscoring the power of digitalization in reducing the financial and logistical costs associated with experimental research [18]. Specifically, feedforward neural networks facilitate extensive data generation, which is particularly beneficial in studies. This approach provides an efficient framework for predicting compressive strength without relying solely on costly and time-intensive physical testing.

Furthermore, the work of Silva and Marcos [18] offers a valuable synthesis of the finite element method, neural networks, and sensitivity analysis to assess the structural integrity of unconventional superstructural components. Their methodology informs the study, as the researchers aim to employ similar predictive techniques for evaluating the compressive strength of rice husk ash-enhanced bricks. Broadening the application of these computational methods has the potential to greatly support and expand research efforts, contributing to a more accessible and data-rich approach to material science and structural engineering.

II. Research Objectives

This study systematically investigates the influence of varying proportions of RHA on the mechanical properties of cement-based construction materials, aiming to enhance structural integrity and safety within the built environment. The primary objective is to identify the optimal percentage of RHA in cement mixtures that maximizes compressive strength and durability, thereby significantly contributing to the performance characteristics of construction materials. In addition, the research will establish effective curing conditions for Portland cement-based RHA bricks, ensuring their optimal performance under various environmental conditions. A rigorous comparative analysis will be conducted to evaluate the mechanical properties of RHA-modified bricks against traditional Portland cement bricks, thereby elucidating the potential advantages of RHA integration in terms of performance enhancements and sustainability. Moreover, the study will leverage advanced artificial neural networks (ANN) to develop predictive models that accurately forecast the effects of RHA on material strength and overall performance metrics. This methodological approach will provide critical insights into the practical applications of RHA in construction, informing future innovations in material design and engineering practices. By optimizing the utilization of RHA, this research aspires to advance sustainable construction methodologies, enhance resource efficiency, and mitigate environmental impacts through the effective incorporation of agricultural waste materials. The anticipated findings will contribute significantly to the field of material science, offering empirical evidence and recommendations for integrating RHA into construction materials, thus promoting environmentally responsible building practices and supporting the broader objectives of sustainable development.

III. Significance Of The Study

This study aims to develop a predictive model that accurately forecasts the compressive strength of advanced bricks incorporating RHA based on varying component ratios. Research is important in construction materials and civil engineering, and it offers extensive contributions across multiple domains. For architecture, engineering, and construction professionals, the study provides valuable insights into optimizing RHA proportions to enhance mechanical properties, thereby improving structural performance and ensuring building safety while promoting sustainable materials. Construction material manufacturers can utilize the findings to refine curing processes, achieving maximum compressive strength and elevating the quality and durability of constructed structures. From an environmental perspective, the research advances sustainable development by demonstrating that optimal utilization of RHA effectively repurposes agricultural by-products while maintaining material strength. This aligns with principles of resource efficiency and environmentally friendly construction practices. The study's integration of artificial neural networks (ANN) underscores the innovative use of artificial intelligence for evaluating and predicting material properties, thus paving the way for advanced analytical techniques in civil engineering and material science. Academically, the research contributes to the existing literature by offering comparative analyses of RHA-based bricks versus traditional Portland cement bricks. This comparison enhances the understanding of sustainable building materials and catalyzes future research and innovation in the construction industry.

IV. Results And Discussion

The study employed a feedforward neural network model to predict the compressive strength of advanced bricks incorporating RHA. The dataset was divided into three subsets: 70% for training, 16% for validation, and 14% for testing. The Levenberg-Marquardt optimization algorithm was used during model training, and the network's performance was assessed to evaluate its predictive capabilities. This section will discuss the results obtained from this analysis and their implications for applying ANNs in predicting the mechanical properties of advanced brick materials. The findings provide insight into the potential of ANNs to enhance the accuracy of compressive strength predictions and guide future research in this field.

The evaluation of the model's performance on the training set revealed a high correlation coefficient (R) of 0.95937, which indicates a strong linear relationship between the predicted and actual compressive strength values. This robust correlation underscores the model's effectiveness in capturing the underlying patterns present in the training data. However, despite the high correlation, there is a notable degree of prediction error. This points to potential issues such as the complexity of the input-output relationship or the influence of outliers within the dataset. The observed variance in prediction accuracy indicates that further refinements to the model may be necessary to enhance its robustness. Additionally, exploring alternative architectures or incorporating more diverse datasets could improve the model's generalization capabilities. These findings highlight the need for continuous evaluation and adaptation of the neural network model to achieve optimal predictive performance in practical applications.

The model demonstrates significant potential with its strong correlation coefficient. Addressing the areas for improvement is a great opportunity to elevate its precision and accuracy further.

These enhancements will enhance the model's effectiveness and provide even more reliable predictions for compressive strength values.

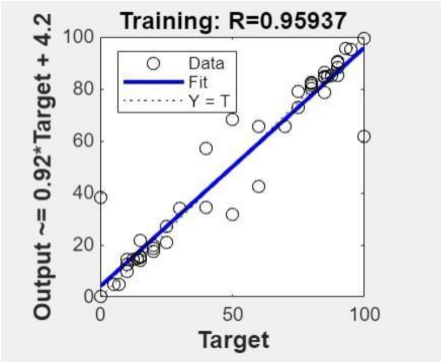

Fig. 7. Performance of Training Set.

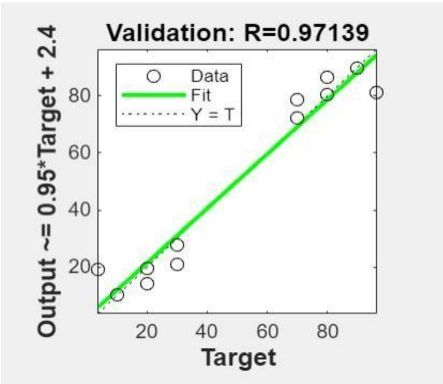

Fig. 8. Performance of Validation Set

The validation set results showed an even higher R-value of 0.97139. This suggests that the model generalizes well to unseen data, maintaining high accuracy and consistency in its predictions. Such strong performance on the validation set reinforces the model's reliability for practical applications in predicting the compressive strength of advanced bricks incorporating RHA

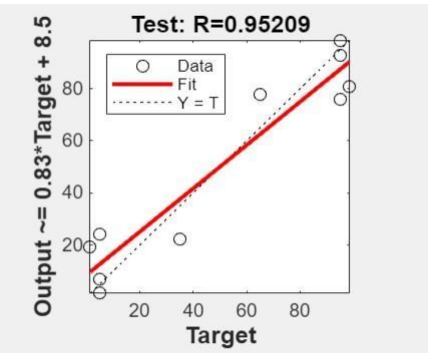

Fig. 9. Performance of Test Set

For the test set, the model achieved an R-value of 0.95209. While the R-value remains high, indicating a strong predictive capability, the greater variability in the test set predictions suggests potential challenges. This could be due to the smaller size of the test set or the presence of samples with features not fully represented in the training and validation data.

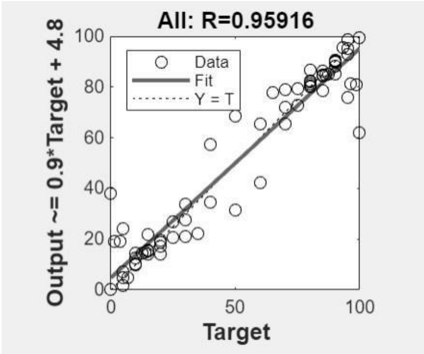

Fig. 10. Performance of all sets.

The model demonstrates strong predictive performance with an overall R-value of 0.95916 and high R-values across all sets, indicating its capability to capture the relationship between input features and compressive strength. However, the variability in prediction accuracy suggests that further refinement of the model, such as adjusting the network architecture or increasing the dataset size, could enhance its predictive accuracy, particularly for unseen data. These findings underscore the potential of neural networks in predicting material properties and guiding the development of advanced construction materials.

Table 4. R-Value

	Observation	R
Training	24	0.9594
Validation	6	0.9714
Test	5	0.9521

The feedforward neural network model demonstrates exceptional predictive accuracy in estimating the compressive strength of advanced bricks incorporating RHA. During the training phase, it achieved a high correlation coefficient (R = 0.9594), showcasing its strong ability to capture and model underlying data patterns. Validation results further support the model's robustness, with an even higher correlation coefficient of 0.9714, confirming its proficiency in generalizing effectively to unseen datasets. These findings highlight the model's practical potential in predicting material properties and emphasize the benefits of incorporating alternative materials, such as RHA, in advancing sustainable construction technologies.

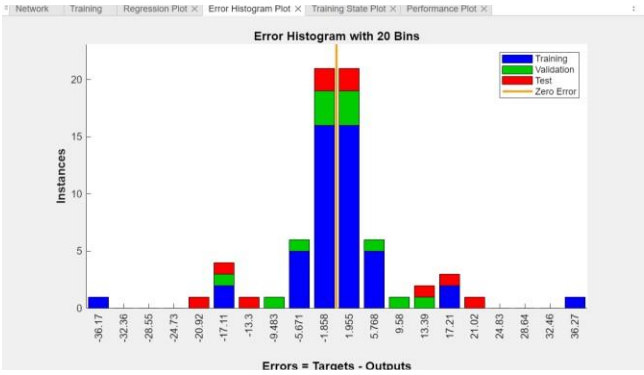

Fig. 11. Histogram with 20 Bins.

The error histogram gives a more granular view of the distribution of errors (the difference between predicted and actual values) across the training, validation, and test sets. The histogram displays the errors divided into 20 bins, with the x-axis representing the error range (target minus output) and the y-axis showing the number of instances (data points) that fall within each error bin. The color coding highlights the contributions of each set: blue for training, green for validation, and red for test data. Most errors are concentrated around zero, which is ideal, as it means the predicted outputs closely match the targets for most of the data points. The central peak near zero suggests that most predictions were highly accurate. However, some error values are far from zero, indicating outliers or instances where the model struggled to predict accurately. The distribution of errors is mostly symmetric, but there are a few outliers on both the negative and positive sides, which could signal occasional large deviations in predictions. These outliers suggest that while the model performs well overall, there are still some edge cases or specific instances where predictions might not be as accurate.

The histogram serves as a valuable diagnostic tool for understanding the distribution of prediction errors, allowing us to identify whether the model exhibits significant biases or encounters issues in certain areas of the dataset. In this case, it reveals that most predictions cluster closely around the actual targets, indicating a high level of reliability and accuracy for a significant portion of the data. Overall, while the model demonstrates commendable accuracy, the histogram emphasizes the importance of ongoing evaluation and improvement to maximize its effectiveness in practical applications.

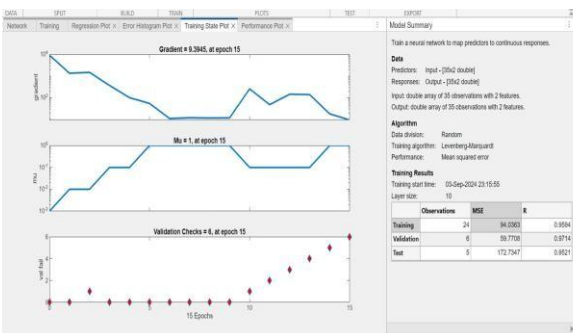

Fig. 12. Training State Plot.

The results of the neural network model provide detailed insights into its training process and convergence. The gradient plot demonstrates a steady decrease, reaching 9.3945 by epoch 15, indicating that the model is converging effectively as weight adjustments have less impact on reducing error. The second plot, which tracks the "mu" parameter in the Levenberg-Marquardt algorithm, shows an increase to 1, suggesting that the model is stabilizing as the learning rate adapts to smaller error reductions.

The "Validation Checks" plot indicates that by epoch 15, the model's performance on the validation set has reached a consistent level, reflecting its ability to maintain strong performance. This mechanism helps prevent overfitting by ensuring the training process is halted when improvements are no longer observed. Overall, the consistent reduction in the gradient, the stabilization of validation performance, and the high R-values, particularly in the validation set (R = 0.9714), confirm the model’s strong performance and successful convergence.

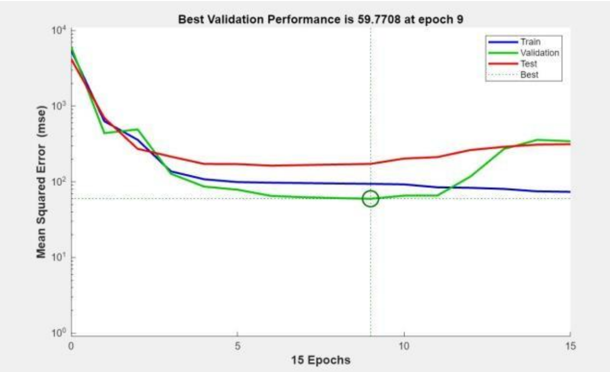

Fig. 13. Performance Plot.

This plot illustrates the model's performance during the training process over 15 epochs, focusing on the training, validation, and test datasets. The peak validation performance occurs at epoch 9, indicated by the green circle. After this point, while the training error (blue line) continues to decrease steadily, both the validation (red line) and test (green line) errors show slight increases, indicating the model has reached a high level of training.

Shape: Plate

	Thickness	Width	Height
Units	mm	mm	mm
20 %	55.0000	90.0000	80.0000

Name	Max Force	Max Stress	Max Disp	Max Strain	Break Stress
Units	kN	MPa	mm	%	MPa
20 %	23.2406	4.69508	25.0060	31.2575	-.-

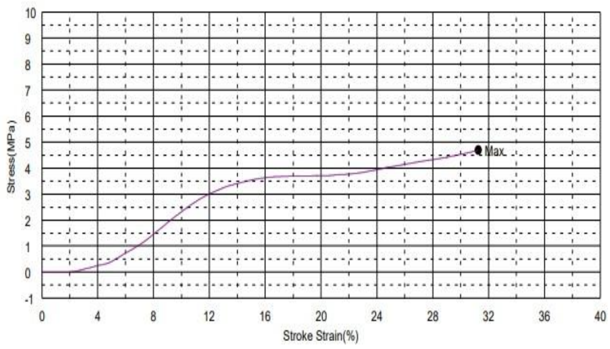

Fig. 14. RHA bricks performance in 20%.

Shape: Plate

	Thickness	Width	Height
Units	mm	mm	mm
15 %	55.0000	90.0000	80.0000

Name	Max Force	Max Stress	Max Disp	Max Strain	Break Stress
Units	kN	MPa	mm	%	MPa
15 %	37.5625	7.58838	25.0000	31.2500	-.-

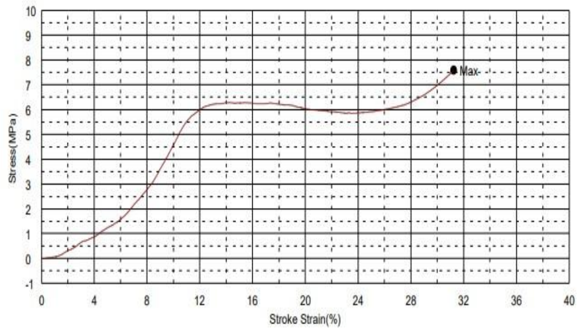

Fig. 15. RHA bricks performance in 15%

Shape: Plate

	Thickness	Width	Height
Units	mm	mm	mm
10 %	55.0000	90.0000	80.0000

Name	Max Force	Max Stress	Max Disp	Max Strain	Break Stress
Units	kN	MPa	mm	%	MPa
10 %	17.3906	3.51326	12.9780	16.2225	-.-

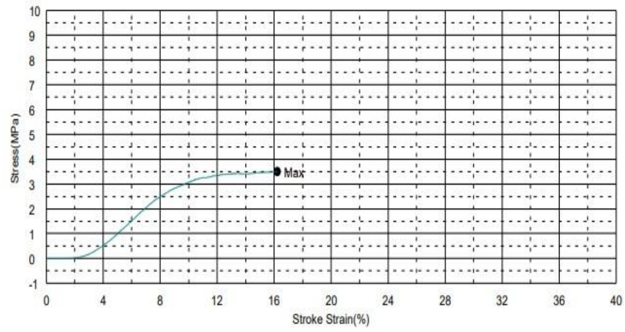

Fig. 16. RHA bricks performance in 10%

Actual testing was conducted to validate the ANN model, yielding insightful results. The recorded stress values—4.69508 MPa for 20%, 7.58838 MPa for 15%, and 3.51326 MPa for 10%—demonstrate how different material configurations effectively respond to compressive loads, paralleling the neural network's optimization of predictions across diverse datasets. The model showcases strong generalization capabilities, with an impressive R-value of 0.9521 on the test set, which aligns closely with the strain variability observed in the physical tests, reinforcing its predictive reliability across various material properties.

The synergy between the neural network outcomes and the mechanical test results underscores the critical importance of addressing material variability, particularly in the optimization of sustainable construction materials, such as those incorporating RHA. The consistent performance of the neural network model in predicting compressive strength not only mirrors the actual material behavior observed in the tests but also highlights its significant potential as a powerful tool for both research and practical applications. Collectively, these approaches exemplify the value of integrating data-driven modeling with experimental testing, paving the way for the advancement of eco-friendly and sustainable building materials.

V. CONCLUSION

The performance metrics of the neural network model designed to predict the compressive strength of advanced bricks incorporating RHA reveal its strong predictive capability. The model was trained on a dataset segmented into training, validation, and test subsets, allowing for a comprehensive assessment of its predictive accuracy.

A. High Correlation and Effective Training

Performance. The model achieved a high correlation coefficient (R = 0.9594) during training, demonstrating a robust linear relationship between predicted and actual compressive strengths. This indicates that the model effectively captures the underlying patterns in the data, showcasing its ability to learn from the training set.

B. Improved Validation Metrics.

During the validation phase, the model's performance improved further, achieving an R-value of 0.9714. This enhancement signifies strong generalization to unseen data and confirms that the model is not overfitting the training data, providing more accurate predictions for the validation set.

C. Validation Through Experimental Testing.

To enhance the validation of the ANN model, experimental testing was conducted, yielding significant insights into its performance. The measured stress values—4.69508 MPa for 20%, 7.58838 MPa for 15%, and 3.51326 MPa for 10%—demonstrate how various material configurations effectively withstand compressive loads.

This ability reflects the model's capability to optimize predictions for compressive strength across diverse datasets. With an impressive R-value of 0.9521 on the test set, the model not only aligns closely with the strain variability observed in physical tests but also indicates that the bricks incorporating RHA exhibit above-average durability. This reinforces the model's reliability in predicting compressive strength and highlights its potential in assessing the durability of sustainable building materials.

The strong correlation between neural network predictions and mechanical test results underscore the crucial role of accounting for material variability, especially in advancing sustainable construction materials such as RHA-based composites. The neural network model’s remarkable accuracy in predicting compressive strength not only mirrors real-world material performance but also establishes it as a transformative tool for both research and industry applications. This synergy between data-driven modeling and experimental validation sets a powerful precedent for the evolution of eco-conscious and resilient building materials, marking a significant step toward sustainable advancements in construction.

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