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An Artificial Neural Network-Based Approach to Predict Compressive Strength in Rubberized Concrete Using Experimental Datasets

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Abstract

The incorporation of recycled rubber as a partial replacement for fine aggregate in concrete has emerged as a promising approach for enhancing sustainability in construction. By diverting rubber waste from landfills and reusing it in construction materials, the preservation of ecosystems is promoted, and the demand for extracting and processing natural resources is reduced. However, accurately predicting the compressive strength of such rubberized concrete presents a significant challenge due to the complex relationship between different factors involved. Lately, artificial neural networks (ANNs), a type of artificial intelligence technique, have gained significant popularity for their effectiveness in predicting complex problems. ANNs have been commonly employed in recent years owing to their exceptional ability to recognizing patterns, adaptability, and learning capability. This paper proposes a novel approach to address this issue by utilizing the power of ANNs for compressive strength of rubberized concrete prediction. A thorough dataset from the laboratory is employed to train, test, and validate ANNs. By engaging in a process of training, the ANNs effectively capture the complex interrelationships within the data. This enables ANNs to make accurate predictions of the compressive strength of rubberized concrete. The proposed approach offers flexibility to accommodate different rubber substitution levels and provides a reliable tool for optimizing the mix design parameters to achieve desired strength requirements. The results demonstrate the efficiency of ANNs in precisely predicting the compressive strength of concrete with waste rubber, facilitating sustainable and efficient construction practices. In summary, this research contributes to the utilization of recycled rubber in concrete production and provides valuable insights for predicting the compressive strength of rubberized concrete.

1. Introduction

The disposal of wasted tires in landfills contributes to significant environmental concern, as it allows hazardous and toxic materials to leak into the surrounding environment. On the other hand, disposed tires need a large amount of landfill space, becoming an escalating problem due to the inadequate availability of unoccupied land. Moreover, their impermeable nature allows water to accumulate within tire waste for prolonged periods, creating a breeding environment for mosquitoes [1-2]. Retreading tires offers an economic solution to delay the matter of disposal, allowing them to be used several times. However, as tires approach the end of their usable life, they are often stockpiled. Unfortunately, burning discarded tires in open environments becomes the easiest and most cost-effective disposal method, but it releases harmful gases and toxic substances such as arsenic, mercury, hydrocarbons, and chromium into the atmosphere. This poses significant risks to both fire safety and public health [3-5].

On the other hand, concrete is known for its remarkable compressive strength. However, its tensile strength is relatively lower, which can lead to cracking and reduced structural integrity under certain conditions. In recent years, researchers have been investigating innovative approaches to improve the mechanical properties of concrete to ensure more durable and environmentally sustainable structures [6-8]. One promising method to improve the mechanical characteristics of concrete involves the integration of crumb rubber, derived from recycled tires, as a partial substitution for fine aggregate. The concept of utilizing waste materials in construction not only promotes sustainable practices but also effectively deals with the long-standing environmental concern of tire disposal.

Incorporating crumb rubber into concrete offers various benefits. The rubber particles act as fillers, reducing the volume of fine aggregate and, consequently, decreasing the overall weight of the concrete. Additionally, the rubber particles exhibit unique mechanical properties, such as flexibility and energy absorption, which enhance the concrete's capacity to withstand tensile forces and improve its ductility. Furthermore, the inclusion of crumb rubber can mitigate the concrete's susceptibility to cracking, a common consequence of shrinkage and thermal stress [9-10].

In recent years, numerous studies have been undertaken to explore the application of recycled tires in concrete [11-14]. For example, Hossain et al. [15] assessed the impacts of substituting recycled crumb rubber as a partial replacement of fine aggregate. Different mix designs, with 5% and 10% crumb rubber, were considered to assess the compressive and flexural strength of concrete. In line with this research, higher crumb rubber content resulted in a reduction in both compressive strength and flexural strength. Moving on, Arunkumar [16] studied the utilization of waste rubber as a fiber in different proportions: 0.5%, 1%, 1.5%, and 2% of volume fractions. Adding fiber up to 1% enhanced the setting properties and mechanical performance during all stages of curing. After 90 days, the low calcium geopolymer mix exhibited increased compressive strength, split tensile strength, and flexural strength when 1% wasted fiber was added. However, incorporating more than 1% waste rubber fiber led to a decline in all strength parameters.

Liu and Zhang [17] investigated the effect of rubber granules on the mechanical properties of concrete. The experimental results demonstrated a decrease of 15% in both the flexural and compressive strength of the concrete. This decrement was attributed to the soft nature of rubber powder within the concrete structures. In another study, Mehrani et al. [18] explored the influence of waste rubber powder on the mechanical properties of lightweight concrete. The research findings indicated a notable improvement in the mechanical characteristics of the concrete when 5% of waste rubber powder was included in the mixture. Al-Tayeb et al. [19] conducted a study to examine the impact of the cement replacement by waste rubber powder on the concrete compressive strength. Concrete specimens were fabricated, incorporating 2.5%, 5%, and 10% of the rubber as substitutes for cement. The results demonstrated that the compressive strength decreased by 19%, 32%, and 53% when 2.5%, 5%, and 10% of cement were replaced with waste rubber powder, respectively.

Precise predictions of the concrete's compressive strength after incorporating crumb rubber are essential to fully leverage the advantages of this addition. Conventional experimental approaches used to determine concrete strength can be time-consuming, expensive, and often constrained by the availability of suitable testing facilities. In contrast, ANNs offer a robust and efficient alternative for predicting concrete strength characteristics. ANNs are computational models inspired by the human brain and have the remarkable capability to learn from large datasets and establish intricate relationships between input and output parameters [20-22]. Training an ANN with a significant amount of data on concrete mixtures incorporating crumb rubber allows establishing reliable prediction models for the compressive and tensile strength of the resulting concrete.

Gupta et al. [23] pioneered the development of an ANN model to predict the compressive strength of rubberized concrete under different durations of elevated temperatures. The model considered input parameters like the amount of rubber in the mixture, the water-to-cement ratio, the length of time subjected to the strength conditions, and elevated temperature. The experimental study covered three water-to-cement ratios (0.35, 0.45, and 0.55), varying rubber content (0%, 5%, 10%, 15%, 20%, and 25%), elevated temperatures ranging from 150 to 750 degrees Celsius with increments of 150, and exposure durations of 30 minutes, 60 minutes, and 120 minutes. The results demonstrated that elevated temperature had the most significant influence on the compressive strength of rubberized concrete, followed by rubber content.

Moving on, Zhang et al. [24] proposed a regression model and a neural network based on a genetic algorithm to predict the compressive strength of rubberized concrete with ultrasonic pulse velocity (UPV). The study utilized a database comprising 158 data pairs. The findings demonstrated that the genetic algorithm-based neural network effectively predicted the compressive strength of rubberized concrete. Compared to conventional regression models, this method exhibited excellent accuracy and proved to be a viable option for achieving more precise predictions.

In a different investigation, Hatami et al. [25] evaluated the influence of integrating waste rubber powder on the compressive and tensile strengths of concrete. In this study, an ANN is developed to predict mechanical characteristics of rubberized concrete based on the reference sample's properties. The outcomes indicated a decrease in the mechanical characteristics of concrete with increasing proportions of waste rubber powder in all replacement ratios. Based on previous studies, predicting the material characteristics of rubberized concrete is a complex process influenced by various factors. Currently, there is insufficient research on a computational approach for swiftly predicting the mechanical properties of rubberized concrete, and there is a need for further research by employing ANNs as a computational tool. ANNs rely on data-driven learning rather than explicit mathematical models, setting them apart from conventional analytical methods. This study seeks to assess the feasibility of substituting crumb rubber for fine aggregate in concrete and aims to develop precise prediction models using ANNs for its compressive strength. The outcomes of this research could offer valuable insights, fostering the progress of eco-friendly construction techniques and the creation of durable infrastructure.

2. Materials and Methods

2.1 Experimental Procedure

In this research, crumb rubber ranging in size from 2 to 4 mm is employed as a partial substitute for fine aggregates at different weight percentages in the concrete, varying from 0% to 15% in increments of 5%. Type 1 Ordinary Portland Cement (OPC) was used as the cement in this investigation because of its adhesive properties essential for maintaining the cohesion of different components in the concrete mix, resulting in a durable and sturdy structure. The compressive strength of the concrete is substantially impacted by the granularity of the aggregate. Larger aggregates, such as gravels, enhance the strength of the concrete, providing it with mass and volume that upgrade its capacity to bear loads and endure compressive strength. In this research, the coarse materials were crushed and selected to attain a nominal size of 20 mm. Also, fine aggregates play a crucial role by filling the gaps between larger particles owing to their smaller size and smooth texture, thereby lubricating the mix and increasing its cohesion.

In this study, all ingredients have been mixed thoroughly using a concrete mixer to ensure homogeneity. Standard concrete mixing practices were followed while preparing both conventional and rubberized concrete samples. After that, the mixed concrete was poured into molds of standard dimensions for testing. Each sample is properly labeled to identify the mixed proportions. At the next step, the cast samples were cured in a water tank to maintain proper moisture levels for optimal concrete strength development. Following the designated 28-day curing duration, tests of compressive strength were carried out on the samples utilizing a Universal Testing Machine (UTM), and the maximum load at the point of failure was recorded for each sample.

Collecting data on compressive strength values for both rubberized and conventional concrete samples has been completed. In this stage, accuracy and consistency in testing procedures are crucial to obtain reliable results. The water-to-cement (w/c) ratio was maintained at 0.48, while the percentages of crumb rubber used ranged from 0% to 15%. Following this, the compressive strength results of rubberized concrete were compared with those of conventional concrete at various curing ages. The data was subjected to statistical analysis to identify any significant differences between the two concrete types. In the subsequent phase, the rubber content in concrete mixtures was optimized to achieve desired compressive strength while maximizing the use of recycled rubber materials. In this study, 550 datasets of concrete mix design were gathered from the research laboratory of concrete technology to verify the feasibility and reliability of the ANNs developed in this study to predict the compressive strength of rubberized concrete.

2.2 Artificial Neural Networks

This section focuses on another part of the methodology of this research, which involves the utilization of ANNs for predicting the compressive strength of rubberized concrete. Figure 1 shows the methodological flowchart employed in this study. This flowchart outlines the step-by-step procedure for predicting the compressive strength of rubberized concrete using ANN. As illustrated in Figure 1, the methodology involves stages including data collection and preprocessing of data, data partitioning, model design, training implementation, and evaluation of the ANN technique. The final step involves a comparison between the results obtained from the ANN and experimental datasets. In this section, the theory, foundation, and architecture of ANNs are explained.

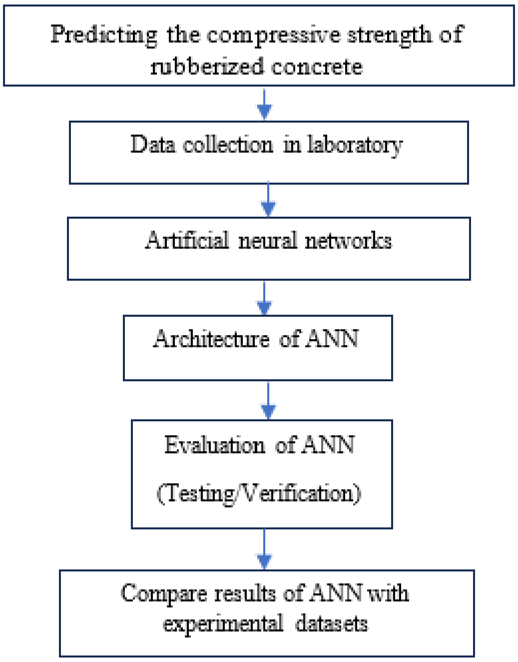

Fig. 1 *Flowchart of the methodology*

ANNs represent a method of data processing that imitates the operations of biological nervous systems, such as the human brain. They comprise numerous interconnected processing units known as neurons, which utilize a form of human-like learning through examples to tackle problems [26-28]. The learning mechanism in neural networks involves adjusting the connections between neurons. There are several types of ANNs, each differing in how their neurons are linked, the computations they execute, the transmission of patterns of activity, and the learning process they employ. ANNs have gained popularity for addressing real-world challenges, particularly those with no clearly defined algorithmic solution or problems deemed too complex to define using conventional technologies.

The multilayer perceptron is the most widely utilized type of neural network among the various alternatives. Typically, it includes an input layer with a neuron count equivalent to the number of parameters relevant to the given problem. Additionally, there is an output layer with a neuron count matching the desired number of quantities derived from the inputs. The intervening layers are known as hidden layers. The architecture of an ANN comprises three layers: the initial input layer, the intermediary hidden layer, and finally, the output layer. Figure 2 provides an example of an ANN structure, featuring five neurons in the input layer, three neurons in the intermediate hidden layer, and four neurons in the output layer. Information or signals enter through the input layer, traverse the hidden layer, and ultimately progress to the output layer [29-30].

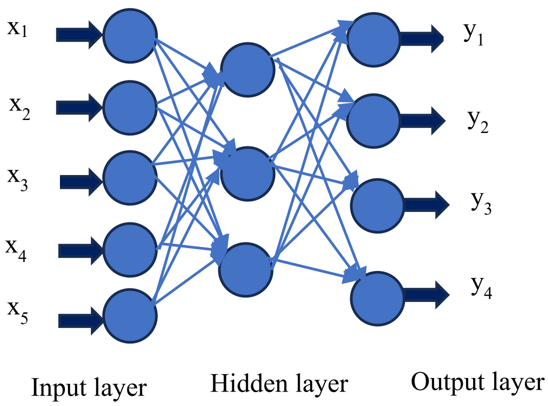

Fig. 2 *An example of an artificial neural network architecture [31]*

In layers beyond the input layer, each neuron undertakes a computation by combining the outputs from the preceding layer's neurons, along with an additional bias term. The weights assigned to these linear combinations, along with the biases, play a crucial role in determining the coefficients used in this process. Before reaching the summing node, each input undergoes multiplication with its corresponding weight. Following this, neurons in the hidden layer conduct computations using a non-linear function applied to their input. Usually, the sigmoid function is selected for this purpose, displaying a range between 0 and 1. To align with the requirements of the sigmoid function, it is essential to appropriately scale the datasets to fall within the range of 0 to 1 [32-33]. In summary, the input layer acts as the first recipient of data from the external environment. This data is then transmitted to the hidden layer, where it undergoes summation and processing. The resulting sum is subsequently input into an activation function, which captures the non-linear aspects of the problem and improves the accuracy of the output.

The Backpropagation (BP) algorithm is commonly employed in ANNs owing to its capability to mathematically model complex nonlinear relationships [34-35]. Its evaluation is based on a performance index that aims to minimize the Mean Square Error (MSE). The process involves reducing the error between the predicted output of the network and the actual output until a point is reached where satisfactory agreement is achieved with the training datasets [36-37]. The MSE algorithm quantifies the error by comparing the target output with the output generated by the network. This algorithm falls under the category of supervised training, where a learning rule is presented with a set of examples illustrating the desired behavior of the network. The algorithm modifies the weights and biases of the ANN to reduce the magnitude of the average error between predicted and actual values. This fine-tuning process continues until the error is minimized to an acceptable level. Once the networks are considered trained, they are exposed to testing data, and the outcomes are compared with the actual results for validation. In this research, the backpropagation learning algorithm is utilized, with the main emphasis of the learning process being the determination of the connection weights in the neural network.

In this study, ANN was trained using MATLAB 2023a, and various architectures using input datasets were trained to obtain the output with high precision. In this research, an algorithm called feedforward backpropagation (BP) was employed to train an ANN. Throughout the training process, the network was exposed to a series of examples used for training purposes, and the weights and biases underwent iterative adjustments through optimization techniques such as gradient descent or its variations. The primary goal of training was to minimize the discrepancy between the real datasets and the predictions made by the ANN, thereby enhancing the network's accuracy in making predictions. The study employed seven input parameters for the ANN model, consisting of cement (C), water (W), fine aggregate (FA), coarse aggregate (CA), waste crumb rubber (WCR), superplasticizer (SP), and fly ash (FA). These parameters play significant roles in predicting the compressive strength of rubberized concrete. Cement contributes to strength by acting as the primary binder, while water influences the water-cement ratio, which is critical to achieving optimal strength. Fine and coarse aggregates provide bulk, reduce voids, and enhance load-bearing capacity.

The inclusion of crumb rubber generally reduces compressive strength due to its low stiffness and weak bonding but improves ductility. Superplasticizers enhance workability and allow for lower water content, indirectly increasing strength. Fly ash, as a supplementary cementitious material, improves long-term strength and durability by participating in pozzolanic reactions. Together, these parameters affect the concrete's mechanical performance in complex ways that can be effectively modelled using an artificial neural network [38-40].

Within the BP algorithm, a set of seven specified parameters is initially introduced as an input dataset. These inputs produce a set of corresponding outputs. Following this, the error, calculated as the difference between the generated output and the intended output, spreads backward via the network. The mean square error (MSE) diminishes via this process, causing the output of the ANN to converge towards the intended target. A well-trained ANN can yield beneficial outcomes when presented with a new sample as input. In order to achieve this, the datasets were scaled to a range of 0 to 1 and subsequently introduced into the input neurons. The training procedure continues, constantly refining and adapting the weights until the ANN can produce outputs that are considered acceptable in comparison to the desired values.

3. Results and Discussions

Predicting the compressive strength of concrete, which has undergone partial replacement with waste crumb rubber using ANNs, involves the careful selection of relevant input parameters that can impact the concrete's strength. In this investigation, factors such as cement content, water content, the quantity of sand and coarse aggregate in the mix, the percentage of waste crumb rubber in the concrete mix, superplasticizer, and fly ash have been considered. Waste crumb rubber is a crucial parameter since it represents the extent of rubber replacement, which has a significant impact on strength.

Rubberized concrete mixes frequently encounter workability issues due to the inclusion of rubber particles, which can raise viscosity and weaken the flowability of the mixture. The introduction of superplasticizers can enhance workability by decreasing the necessary water content to uphold the desired consistency. This can be advantageous for achieving increased compressive strength and durability in the concrete. It is essential to consider the compatibility of superplasticizers with the rubber utilized in the mixture. Some superplasticizers may not be suitable for use with rubber particles, underscoring the importance of evaluating their compatibility through testing within the specific mix.

Moreover, the incorporation of fly ash into rubberized concrete aims to improve workability, mitigate heat of hydration, support strength, and contribute to sustainability. Nonetheless, achieving the desired performance and durability necessitates accurate mixed design and compatibility testing. The interaction between fly ash and rubber particles is taken into account, as certain rubberized concrete blends might encounter challenges in this interaction. Hence, it is advisable to conduct compatibility testing to ensure optimal performance.

The training of the ANN begins with a dataset of 550 concrete mix designs collected from the concrete laboratory at University Tun Hussein Onn Malaysia (UTHM) [41-42]. These datasets included information on cement and water content, the amounts of sand and coarse aggregate, the percentage of waste crumb rubber in the concrete mix, superplasticizer, and fly ash. In this study, the strength of concrete was from 12 to 42 MPa. Among the 550 datasets, 390 (70%) were utilized as training sets, while 85 were allocated for testing, and an additional 85 were designated for validation purposes. The dividing of the datasets was performed randomly between the training, testing, and validation sets, and each dataset has been statistically checked to make sure that it covers the range of input variables.

This research utilized various structures of ANN, each distinguished by specific parameters such as the number of hidden layers, the neurons situated in each individual layer, and the type of transfer functions. These architectures experienced training using existing datasets to accomplish the study objectives effectively. The results indicated that a network with just one hidden layer exhibited acceptable convergence throughout the ANN training process. Consequently, the chosen architecture was configured as 7-20-5-1, comprising three layers. The input layer comprises seven neurons, each corresponding to one of the primary parameters influencing the compressive strength of rubberized concrete namely cement (C), water (W), fine aggregate (FA), coarse aggregate (CA), waste crumb rubber (WCR), superplasticizer (SP), and fly ash (FA), as detailed in the previous section. The hidden layer of the ANN includes 20 neurons, and the output layer presents only one neuron, which represents the compressive strength of rubberized concrete (CS). It's important to mention that adding more neurons to the ANN increases the complexity of calculations and time demands. In summary, the choice of the 7-20-5-1 architecture for the ANN was made to strike a balance between compatibility cost and accuracy, ensuring an optimal trade-off between efficiency and performance. The optimal architecture chosen for this study is illustrated in Figure 3.

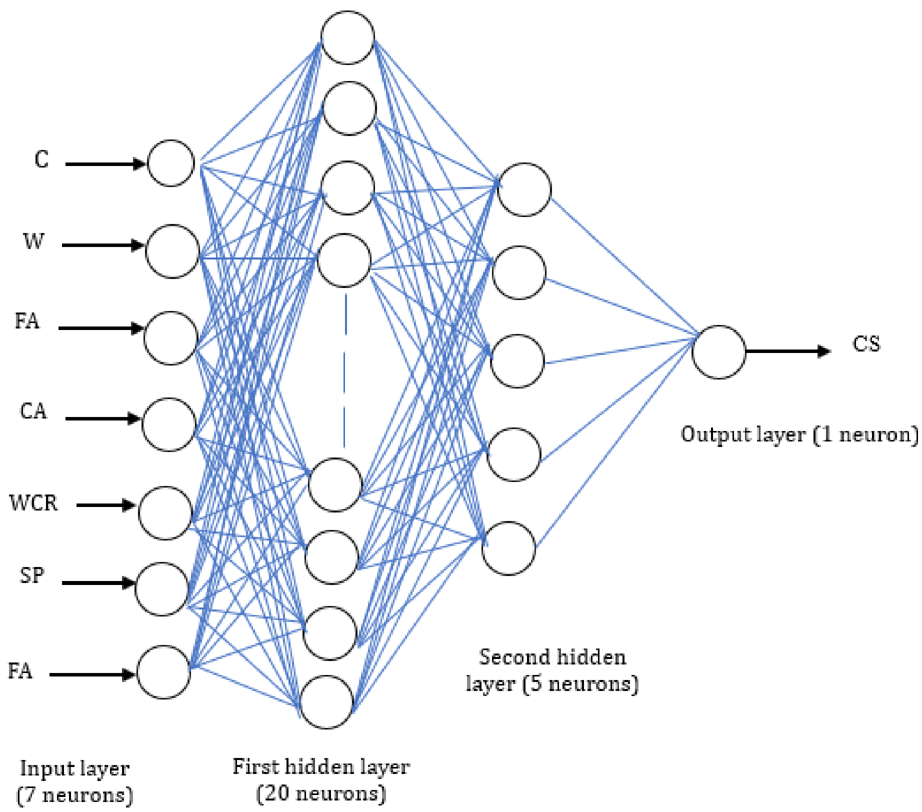

Fig. 3 *Optimal ANN structure for predicting the compressive strength of rubberized concrete*

Following that, the network went through iterative training until the mean square error reached its minimum, ensuring stability in the network. According to the results, the training datasets exhibited a correlation coefficient of 0.995. Following the completion of training, the ANN learned information from the samples, allowing it to predict the compressive strength of rubberized concrete with a mean squared error (MSE) of 0.0004248. Figure 4 depicts a visual contrast between the ANN-predicted compressive strength of concrete and the actual values obtained from experiments during the training phase.

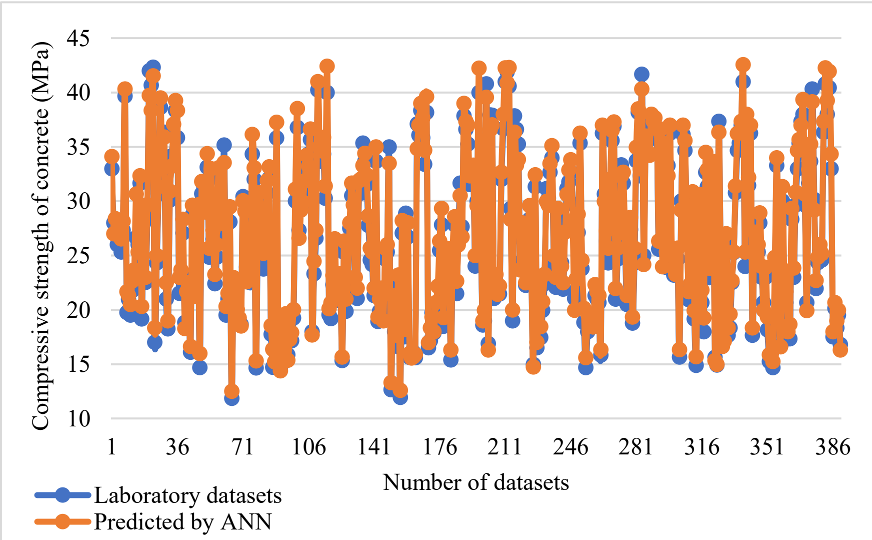

Fig. 4 *Comparison of ANN-predicted vs. actual compressive strength of rubberized concrete (training data)*

After training, the ANN can be utilized to predict the compressive strength of rubberized concrete using datasets that were not included in the training process. Upon finishing the training procedure, the testing dataset was employed to assess the accuracy of the selected ANN. Figure 4 illustrates the contrast between the predicted compressive strength of rubberized concrete by the ANN and the actual datasets. This evaluation included 85 recently added datasets employed as testing sets to assess the predictive abilities of the network. The outcomes predicted from the testing datasets have been contrasted with laboratory results, as depicted in Figure 5.

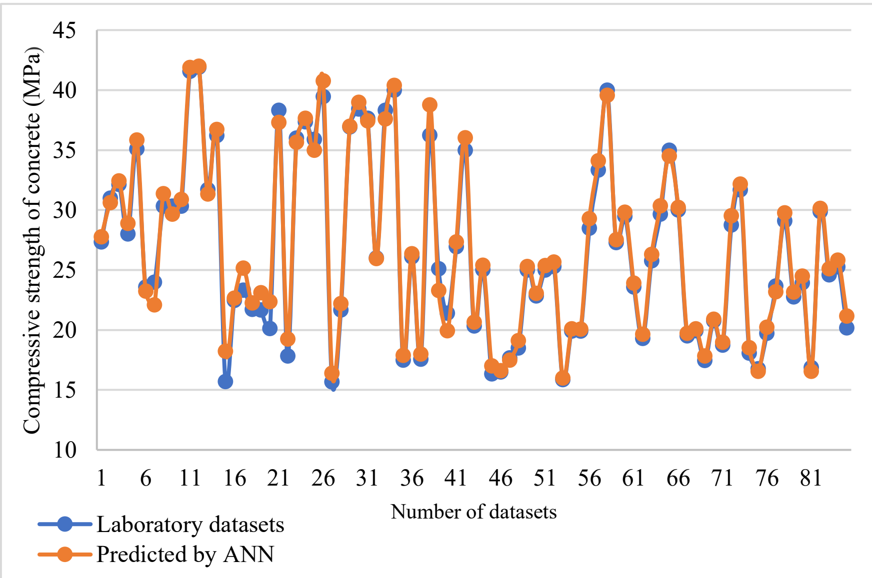

Fig. 5 *Comparison of ANN-predicted vs. actual compressive strength of rubberized concrete (testing sets)*

The ANN exhibited proficiency in predicting the compressive strength of rubberized concrete, as indicated by an MSE of 0.0006518 for the testing sets, showcasing a strong alignment with the actual outputs. The testing datasets revealed a correlation coefficient of 0.989. These findings indicate that the network effectively predicted the compressive strength of rubberized concrete in the majority of instances, as reflected by the combination of minimal error rates and elevated correlation values. It is commonly recognized that training an ANN with extensive datasets can considerably enhance its performance.

Moreover, the validation set was employed as an extra precaution to assess the neural network's capability to generalize and reduce the likelihood of overfitting. This process was conducted to assess the consistency and precision of the trained network's performance. The graph in Figure 6 demonstrates the comparison between the predicted compressive strength of rubberized concrete using ANN and the actual data from the validation sets. The validation outcomes confirmed the ANN's effectiveness in learning the correlation between input and output datasets, as demonstrated by a low MSE of 0.000737 and a high correlation factor of 0.987. Figure 6 demonstrates that the selected network displayed a robust correlation between its inputs and outputs, showcasing its ability to accurately capture and represent the underlying relationship. Additionally, the high correlation coefficient of 0.987 further confirms the model's effectiveness, showing a very strong linear relationship between predicted and actual compressive strength values. Together, these results validate the ANN's reliability and robustness in modeling complex material behavior.

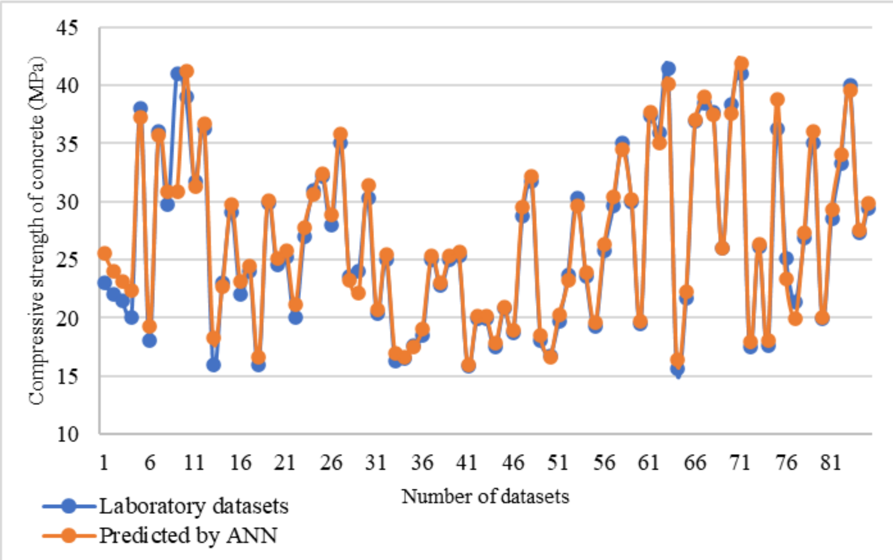

Fig. 6 *Comparison of ANN-predicted vs. actual compressive strength of rubberized concrete (validation sets)*

By comparing the ANN outcomes alongside the real datasets, it enabled the observation of how the input variables affected the compressive strength of rubberized concrete. According to the predicted outcomes, the factor exerting the most important impact on the compressive strength of concrete when partially replaced with waste rubber can differ based on various factors such as the particular mix design, rubber properties, and testing conditions. The findings of this research highlight the importance of the waste rubber percentage in the concrete mixture. Generally, an increase in the rubber replacement ratio tends to lead to a decrease in compressive strength, mainly because rubber lacks the strength and rigidity of conventional concrete components such as aggregate. However, accurate correlation can be influenced by factors like rubber particle size and distribution. The strength of the material can be influenced by the size and arrangement of waste rubber particles. Smaller particles that are evenly distributed may have a lesser negative effect on strength when compared to larger or unevenly distributed particles.

4. Conclusion

The study utilized seven independent variables, including cement, water, fine aggregate, coarse aggregate, waste crumb rubber, superplasticizer, and fly ash, as input parameters for the ANN. The outcomes showed that the ANN, functioning as an intelligent computing approach, exhibited a high level of accuracy in predicting the compressive strength of rubberized concrete, showcasing its promising potential. The research shows that ANN is a reliable and efficient method for predicting the compressive strength of rubberized concrete, especially in situations where conducting extensive experimental configurations is both time-intensive and come with a significant cost.

According to the results of this study, the behavior of this concrete significantly differs from conventional concrete due to the inclusion of waste crumb rubber. The findings indicated that incorporating waste crumb rubber as a substitute for sand can reduce its compressive strength. This reduction happens because rubber particles lack the strength and rigidity inherent in sand particles, weakening the overall concrete structure. Moreover, the uneven shape and poor adhesion properties of rubber particles could result in voids within the concrete mix, making its strength even weaker. By optimizing the rubberized concrete mixture, taking factors such as particle size, suitable bonding agents, and balanced mix proportions into account, the negative impact on compressive strength can be minimized. Furthermore, this approach can enhance other essential properties like flexibility, acoustic properties, energy absorption, and durability that can enhance the concrete's ability to withstand tensile forces and improve its ductility and make the incorporation of waste crumb rubber more effective. Moreover, incorporating crumb rubber can reduce the concrete's vulnerability to cracks, a common issue caused by shrinkage and thermal stress. In conclusion, this research aimed to connect the gap between using sustainable materials and employing advanced prediction methods, moving us toward a future where construction practices are not only more environmentally friendly but also better prepared to tackle the new challenges of the world.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm the contribution to the paper as follows: S.J.S. Hakim: ***study conception and design, analysis and interpretation of results, supervision;*** *M.H.W. Ibrahim:* ***data collection, methodology;*** *A. M. Mhaya:* ***analysis and interpretation of results;*** *S.B.H.S. Mohamad****: conceptualization and draft manuscript preparation.***

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