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Evaluation of Recycled Steel Fiber Effect on Concrete Performance Using Artificial Intelligence Technique

Şevin EKMEN[1*]

[1]*Harran University, Faculty of Engineering, Department of Civil Engineering, Şanlıurfa, Türkiye*
(ORCID:0000-0002-2577-696X)

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Abstract
Reusing waste materials is critical for sustainability and preventing adverse impacts on human life and the environment. Waste vehicle tires have become a big problem due to high consumption. It is possible to separate waste tires into different materials through technological means. Recycled steel fiber is a material obtained from these tires, and various studies have been conducted on its use in concrete. In addition to the geometric properties, such as the length and diameter, the percentage of steel fiber also affects the strength of concrete. In this study, the effect of recycled steel fiber on concrete's compressive and flexural strength values was estimated using artificial intelligence functions with high statistical significance. The relationship between the strength results and the recycled steel fiber properties was determined using literature data. The model's accuracy was demonstrated by comparing the obtained compressive and flexural strengths with the laboratory results. Thanks to the model with a high correlation coefficient created as a result of the study, the effect of recycled steel fiber on concrete performance as an alternative to laborious laboratory tests can be predicted with artificial intelligence-supported functions. With the proposed neural network method, R^2 values of 0.83 for compressive strength measurements and 0.96 for flexural strength measurements were obtained. Based on the findings, it is concluded that the recycled steel fiber-reinforced concrete parameters can be well represented by artificial neural networks, and the presented model can be used as a good alternative to laboratory studies for further research.

1. Introduction

Worldwide, there is worry over the detrimental effects of overconsumption of various materials. Thus, waste management plays a significant role in many nations' management systems. For this reason, creating various usage areas to reuse waste materials is the subject of much research. Tires of vehicles, which provide great convenience in people's daily lives, are also included in this list of waste materials as they complete their lives [1]. Approximately 1.5 thousand tires are produced yearly, and most are left as garbage after use [2]-[5]. Researchers aim to reduce resource consumption and carbon footprint by reusing waste materials. In addition, environmental pollution is also prevented by clearing various large areas of waste [6-7]. In addition, waste vehicle tires must be kept under control due to their flammability. When the chemical composition of vehicle tires is examined, it is seen that 14% by weight is natural rubber, 27% is a synthetic rubber, 28% is carbon black, 14-15% is steel, and 16-17% is filler, etc. [8-9|.

Concrete is a brittle material that can crack or fracture due to loads acting on it above its maximum bearing capacity. The disadvantages caused by this low ductility and limited tensile strength properties of concrete are tried to be reduced by using various fibers [11]-[16]. Many comprehensive laboratory studies are carried out to determine the effect of fibers with different types, proportions, and properties on the engineering properties of concrete [17]-[22]. The most common fiber types examined in the studies are propylene, steel, glass, and carbon fiber. In the studies where the use of fibers in concrete mix design was

*Corresponding author: *ekmensevin@harran.edu.tr* *Received: 07.06.2024, Accepted: 28.10.2024*

carried out, it is seen that the use of steel fiber shows superior performance compared to other fiber types in improving some properties of concrete. Thanks to the use of steel fiber, the energy absorption capacity of concrete is increased, and the deficiencies caused by this fragile structure can be reduced [23]. In addition to the advantages provided by the use of steel fiber, it is also a fact that it creates an extra cost. Since the improvement in the performance of concrete caused by steel fiber cannot be ignored, the use of recycled steel fiber has gained importance in terms of cost reduction and sustainability [24]. Steel fibers obtained from waste vehicle tires by various methods in recycling facilities have different usage areas. Studies on the use of recycled steel fiber in concrete and the evaluation of its effect on the performance of concrete continue to be the focus of interest. Doğruyol et al. [25] examined how the use of waste steel fiber affected the behavior of concrete at high temperatures. Waste tyre steel was substituted for fine aggregate in one experimental group's concrete at a volume of 0.4%, while it was added at 0.8% in the other. Specifically, 400, 600, and 800 °C were the study's target temperatures. The overall findings indicated that fiber-added concrete significantly improved the performance of the concrete at high temperatures. Abed et al. [26] studied the effects of adding crumb rubber and recycled steel fibers to roller compacted concrete. They found that adding recycled steel fibers increased RCC toughness by 909% compared to reference specimens. The study also showed that roller compacted concrete mixtures with these additions are more durable against harmful liquids and more ductile. Ayhan et al. [27] conducted a study on the effect of waste vehicle tire steel fiber on concrete behavior. They used steel fibers at 0.4% and 0.8% by volume in place of fine aggregate in concrete. The results of the compression, flexural, and ultrasonic pulse velocity experiments were analyzed and discussed. The experimental studies revealed that the addition of 0.4% and 0.8% waste tire steel fibers decreased the compressive strength of concrete by 23% and 15%, respectively. On the other hand, the 0.4% and 0.8% waste tire steel fiber additives increased the flexural strength by 5% and 16%, respectively.

Two methods are used to extract recycled steel fiber from waste vehicle tires. These are mechanical recycling and thermo-chemical decomposition [28]. Studies have found that using recycled steel fibers has similar effects on improving the engineering properties of concrete compared to industrial steel fibers. It is believed that recycled fibers can be used as an alternative to industrial fibers in concrete production if the recycling method and source are appropriate. Liew and Akbar [29] conducted studies to examine how recycled fiber affects the engineering properties of concrete. The improving impact of recycled fiber on compressive strength, flexural toughness, shrinkage behavior, and impact resistance was revealed. Leona et al. [30] compared recycled and industrial fibers used in concrete. Using recycled fiber resulted in satisfactory shear deformation and crack behavior. Golpasand et al. [31] determined that the damage seen in concrete under repeated and biaxial loads was reduced due to the addition of recycled fiber. Frančić Smrkić et al. [32] showed that combining recycled and industrial fiber in concrete can achieve the desired mechanical properties and fatigue behavior.

Artificial Neural Networks (ANNs) have a working system that mimics the functioning of the human brain [33]. ANNs create a model based on the biological processes of the brain, such as learning, thinking, remembering, reasoning, and problem-solving [34]. In addition to solving complex relationships, ANNs can obtain accurate or near-accurate results by creating the appropriate input-output model in case of missing data. ANNs can also produce generalized responses for low-quality, noisy data, and new scenarios [35]. There have been many studies showings how effective ANN models are in problem-solving and how consistent results are obtained [36]-[42]. Awolusiki et al. [43] used an artificial neural network technique to evaluate the performance of steel and coconut fibers used in discontinuous reinforcement in concrete. It is consequently advised to use ANN for the prediction and assessment of fiber-reinforced concrete that contains steel and coconut fibers, since this strongly shows that ANN can comprehend the current link between the input variables and the output. Golafshani and Behnood [44] conducted a study using an artificial neural network assisted by multi-objective multi-verse optimizer algorithm to predict the mechanical properties of concrete containing waste foundry sand. The study achieved several optimal ANN models for compressive strength, splitting tensile strength, modulus of elasticity, and flexural strength, showing the potential for accurately estimating these properties. Jay et al. [45] investigated the suitability of response surface methodology and artificial neural network in predicting the mechanical strength of concrete with fine glass aggregate and condensed milk can fibers. Both techniques closely predicted the experimental values for compressive and splitting tensile strength. Statistical parameters indicated the effectiveness of both modeling approaches for concrete strength prediction. Almasaeid et al. [46] developed an artificial neural network model to assess concrete strength after exposure to high temperatures without further destructive testing. They used destructive and non-destructive testing methods to investigate the effect of high temperatures (200–800 °C) on concrete compressive strength. The artificial neural network analysis showed that concrete compressive strength and the level of exposure temperature can be predicted accurately using non-destructive test results, with a coefficient of determination of 0.944.

The properties of the steel fiber used in concrete are highly influential on the change in the performance of concrete. It is crucial to accurately determine the concrete's length, diameter, length-to-diameter ratio, and fiber content to ensure compliance with desired specifications. Many laboratory studies are needed to determine the full effect of these properties. Experimental studies bring disadvantages such as time and energy loss, cost increase, and resource consumption. Considering these situations, artificial intelligence studies are of great importance. Thanks to the studies on this subject, these negative situations are minimized, and the studies to be carried out are accelerated. Recently, many artificial intelligence studies, including design criteria for various types of concrete, have been carried out [47]-[50]. As a result of the research, it was seen that there is almost no artificially assisted study that considers the use of recycled steel fiber obtained from tires in concrete. However, it is imperative to know the change in concrete performance depending on the properties of the recycled steel fiber. Thanks to the artificial intelligence model based on the function exhibiting the relationship between input and output parameters, highly correlated results for different data sets can be obtained, offering an alternative to arduous laboratory studies.

In this study, the compressive strength and flexural strength values of concrete corresponding to the length, diameter, and ratio of recycled fibers were predicted by artificial neural networks. Artificial neural networks were employed to simulate networks by utilizing experimental data from literature. Prediction functions were created to determine the correlations between the properties of recycled fiber and the mechanical properties of concrete. These correlations were then evaluated for their accuracy.

2. Material and Method

End-of-life waste vehicle tires go through sorting stages in various recycling facilities. Thanks to shredding machines, the tires, which are divided into rubber, steel fiber, and other wastes, can be used as raw materials in different fields of activity. Rubber tires are first cut into pieces of 5 cm in size for ease of transportation and storage. In the following stages, they are classified into different sizes: coarsely shredded, crumbled, granulated, and powdered [51]. After the tire pieces are brought to various sizes and passed through sieves, they are used in sections such as walking trails, playground floors, and sports fields.

In this study, the use of steel fibers obtained from waste vehicle tires by various recycling methods in concrete was examined. The geometric properties of the recycled steel fibers vary depending on the type of waste tire used and the steel fiber's separation process. Upon review of various studies, it is evident that the use of recycled steel fibers varies in percentage, length, and diameter. The studies also revealed the effect of these parameters on concrete's mechanical properties. In this study, artificial neural network functions with excellent correlation coefficients were used to predict concrete's mechanical properties corresponding to recycled steel fiber's properties. Many studies in the literature were reviewed, and data sets from various studies [52]-[62] were used to be simulated in artificial neural networks. The compressive and flexural strength values corresponding to the length, diameter, and percentage of recycled steel fiber were obtained through artificial neural networks.

In experimental studies, fibers extracted from waste vehicle tires are used in concrete mixtures to examine their impact on concrete performance through various laboratory tests. The aim of using this waste as recycled steel fiber is to determine the effect of its use on concrete performance. After processing the data from the laboratory tests into a computer, prediction values were calculated using an appropriate model created with ANN in this study. Figure 1 provides a representative diagram of the entire process. Waste steel fibers can be extracted from tires using various methods, resulting in diverse geometric properties. To evaluate their effectiveness, concrete samples are produced in a laboratory using varying proportions of waste steel fibers with different length and diameter ratios. Subsequently, the samples are subjected to relevant tests. The ANN's desired data stock is achieved by meeting compressive and bending strength values, the two most crucial concrete-use criteria. It is essential to consider how the input parameters affect the output data. The criterion of whether the laboratory results obtained are only within certain limits may be insufficient. Processing the laboratory data to create an appropriate model in artificial neural networks is necessary. This model will allow for a detailed and comprehensive statistical evaluation of strength values. After the program's essential categorization process, these processed data become suitable for model creation. The precision of the model is crucial for obtaining results that closely align with actual values. For this reason, the correlation coefficient of the resulting model is aimed to be close to 1. Thus, depending on the model created by artificial neural networks, prediction values reflecting the performance criteria of concrete are reached.

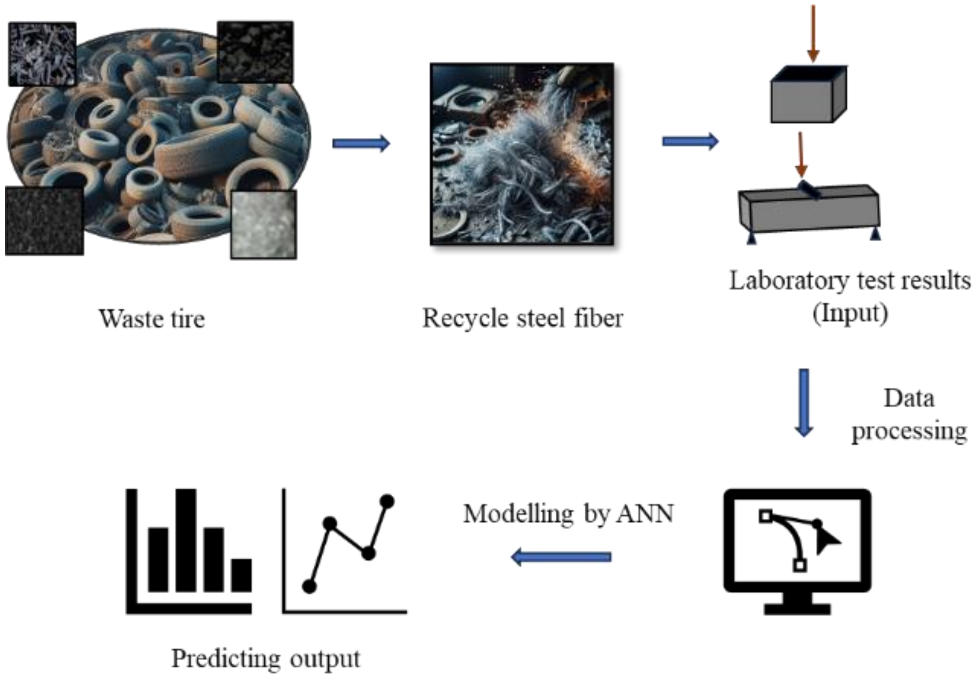

Figure 1. Flowchart for extraction of recycled steel fiber and modeling by ANN.

Some studies have been conducted on the usability of steel fibers obtained from waste tires in concrete production. Within the scope of these studies, along with the changing geometric properties of the recycled steel fiber, there has been a change in the rate of recycled steel fiber incorporation into concrete. While the amount of use was determined by mass in some studies, most studies calculated the incorporation rates by volume. The selection criterion for this study was the literature research conducted using recycled steel fiber by volume. Studies in the literature have shown that varying the length, diameter, and percentage of recycled steel fibers affects the performance of concrete. The 2D graph containing all the experimental data used in generating the function with artificial neural networks is given in Figure 2. Three different representations of the compressive and flexural strength values obtained are presented depending on each input parameter. Figure 2 (a) shows the compressive and flexural strength values corresponding to different recycled steel fiber lengths. In the literature studies evaluated within the scope of this search, the lengths of recycled steel fibers used in concrete ranged from 12 mm to 60 mm.

Figure 2 (b) displays the varying diameter ratios of the recycled steel fibers used in these studies and the compressive and flexural strength values obtained accordingly. The diameters of the steel fibers incorporated into the concrete varied between 0.22 mm and 1 mm. When the mix designs of the studies were examined, it was seen that different percentages of recycled steel fibers were used by volume. These steel fiber addition percentages and the corresponding compressive and flexural strength values are presented in Figure 2 (c). The recycled steel fiber percentages varied between 0.11% and 3.16%.

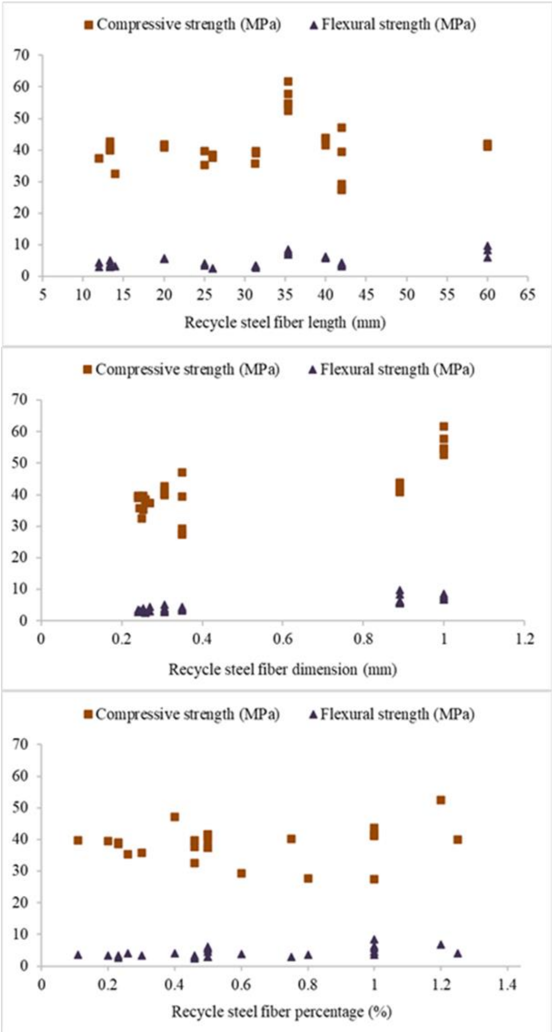

Figure 2. Compressive and flexural strength values in the literature studies depending on a) the length of recycled steel fiber (mm), b) the diameter of steel fiber (mm), and c) the percentage of steel fiber used (%).

The literature data graph to be used in the artificial neural network model is shown in Figure 3, represented in four dimensions. While recycled steel fiber length, diameter, and utilization rate constitute the input parameters, the output parameter obtained from the laboratory tests was the compressive strength. Compressive strength values vary depending on the geometric properties of the recycled steel fiber, and the amount of addition is shown in different colors. The compressive strength values increase as the color changes from blue to yellow. Thanks to this 4-dimensional graph, the effect of all the properties of the recycled steel fiber on the compressive strength values can be seen when examined together.

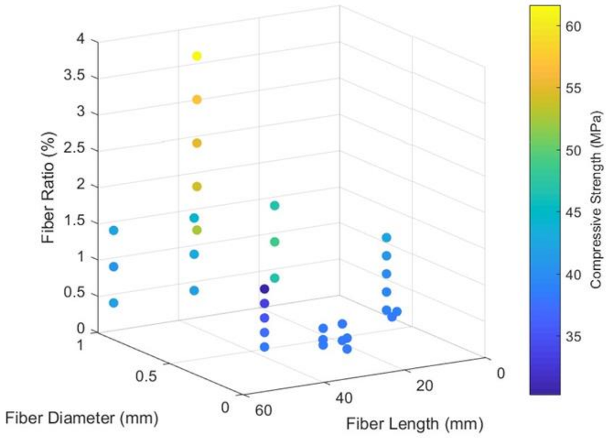

Figure 3. Compressive strength values depending on the recycled steel fiber properties in the literature studies.

The 4-dimensional graph showing the relationship between the recycled steel fiber properties and the flexural strength values of concrete is given in Figure 4. Functions with artificial neural networks were generated using the input parameters, including the properties of the recycled steel fiber, and the output parameter, including flexural strength. The flexural strength values vary depending on the recycled steel fiber's length, diameter, and usage rate, shown in different colors. The flexural strength values increase as the color changes from blue to yellow. Thanks to this 4-dimensional graph, the effect of all recycled steel fiber properties on the flexural strength values can be seen when examined together.

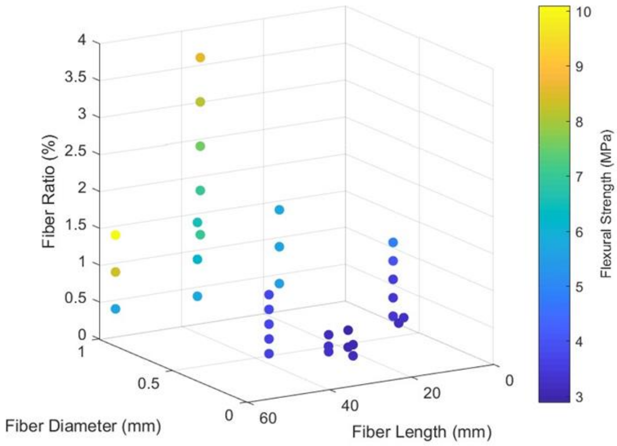

Figure 4. Flexural strength values depending on the recycled steel fiber properties in the literature studies.

3. Results and Discussion

Neural networks are a method of artificial intelligence inspired by the human brain. They can be used for many functions, such as solving complex problems, building models, grouping, and making predictions. Neural networks use a structure in which nerve cells called neurons are connected. These connections are expressed as weights and boundaries. The data is passed through the network, and each neuron produces inputs, processes, and results. Artificial neural networks progress through a learning process. Initially, weights and bounds are chosen randomly. Then, the significance increases as they are trained on the data. It is stated in various studies in the literature that working with a sufficient number of data points is one of the most critical factors for training a network [63]-[64].

In this study, prediction functions were created using artificial neural networks between recycled steel fiber properties, ratios, and compressive and flexural strength values. Network training was performed using the Matlab program [65]. Table 1 presents this study's options when using artificial neural networks.

Figure 5 shows the network diagram representing the model created with artificial neural networks. This network model consists of 3 layers: input, hidden, and output. The number of neurons in the hidden layer depends on the number of values and data used to create the model. In this study, as seen in Figure 5, this number is 10. The number of neurons in the hidden layer varies depending on the model's suitability created with artificial neural networks.

Table 1. Options used in ANN

Method	Levenberg-Marquardt
Neuron Number	10
Number of Hidden Layers	1
Data Distribution	Random
Training, Testing, and Validation Data Distribution	70%, 15%, 15%
Performance Checker Function	Mean Square Error (MSE)

In other words, it is designed to allow the creation of the output closest to the target values for the networks to be created. The input parameters that formed the input layer in the artificial neural network model were steel fiber length (mm), steel fiber diameter (mm), and steel fiber ratio (%). These input parameters are connected to the hidden layer with network connections established at different weights. After the learning and training stages in the artificial neural network model, the data of the output layer are predicted. In this study, concrete's compressive strength and flexural strength values constitute the output parameters.

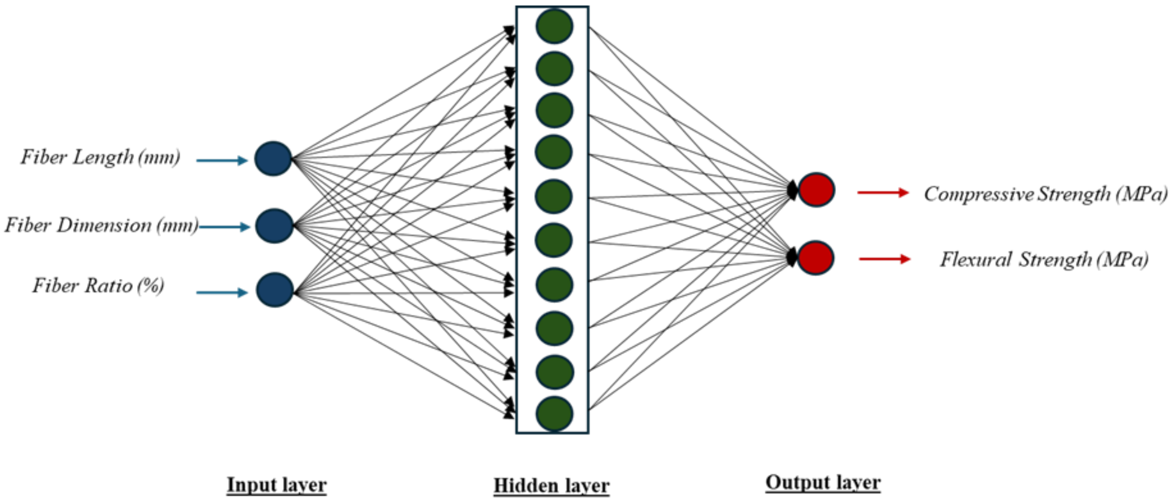

Figure 5. ANN working mechanism showing the output parameters obtained depending on the input parameters included in the study.

As shown in Table 1, the Levenberg-Marquardt method was preferred to generate the prediction function with artificial neural networks by this data set. A single hidden layer and ten neurons were used. Training, testing, and validation data distribution is random at 70%, 15%, and 15%. Mean Square Error (MSE) was considered to check and improve the performance. Fiber length, diameter, and ratio were independent variables, while compressive and flexural strength were chosen as separate dependent variables. For this reason, two different analyses were performed, and two other functions were obtained for compressive and flexural strength. Figure 6 shows the correlation coefficient values of the function for compressive strength. The closeness of this correlation coefficient (R) to 1 gives information about the model's accuracy. Figure 1 shows how the data used in creating a function relates to prediction values for training, testing, validation, and all data. The graph also displays how closely the function aligns with the ideal curve. The obtained correlation coefficients were within the range of 0.76 to 0.95. The highest correlation coefficient was obtained in the test phase, while the lowest was obtained in the validation phase. However, the correlation coefficient obtained in validation is high enough to show that the model is usable. The high correlation coefficients indicate that the function is a good indicator of the data model and has a high prediction success.

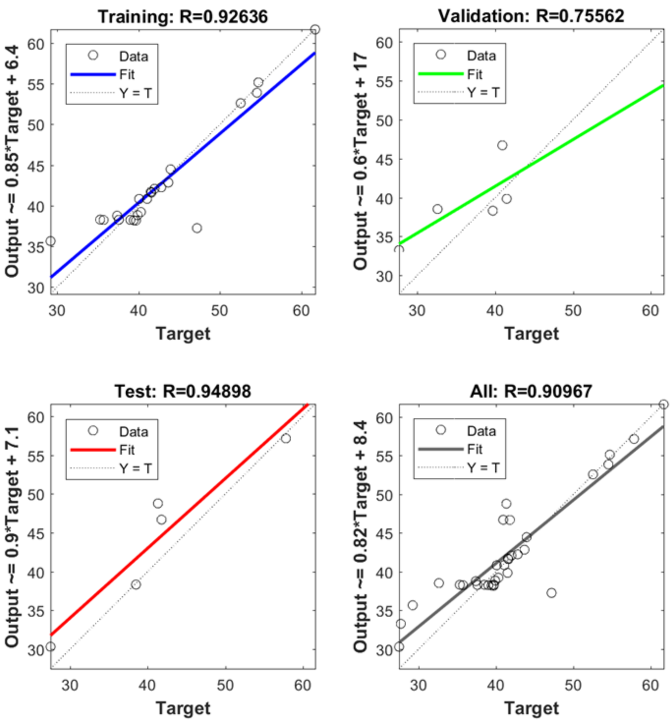

Figure 6. Correlation coefficient values of the function created for compressive strength (R).

Determining the relationship between the strength values obtained based on the model created with ANN and the actual values is essential. High determination (R^2) values representing this relationship indicate the suitability of the model function. Yıldizel et al. [24] obtained the coefficient of determination between actual and predicted values as 0.98 for compressive strength and 0.97 for flexural strength using artificial neural networks in their study on foam concrete samples containing waste car tires.

Table 2 details the relationship between the predicted compressive strength values and the target output values depending on different input parameters with artificial neural networks. Trial learning test stages were carried out to create the most appropriate model with artificial neural networks. For each of these stages, different data were used in various numbers. Finally, a connection covering all data was revealed due to the networks created and the information obtained. A relationship equation is given for each of these stages in the process of reaching the target values. These equations show the connection between actual values and predicted values. The expression y represents the compressive strength value predicted by ANN, while x represents the compressive strength values obtained from laboratory tests. Table 2 also shows the correlation and determination results, representing the closeness of the data obtained by the model to the laboratory results. The closeness of these numbers to 1 allows us to have information about the model's suitability. The coefficients of determination obtained for training, validation, and testing are 0.86, 0.57, and 0.9, respectively. The correlation coefficient of the model equation for all data was 0.91.

A model was also created to predict flexural strength values with artificial neural networks. The correlation coefficients (R) of the function reflecting this model are presented in Figure 7. Correlation coefficients for estimating flexural strength values were determined for training, validation, testing, and all data, similar to the function created for compressive strength.

Table 2. Equations and relationship coefficients of the ANN model for output values representing compressive strength.

	Output-target correlation	R	R^2
Training	y:0.85x+6.4	0.93	0.86
Validation	y:0.6x+17	0.76	0.57
Test	y:0.9x+7.1	0.95	0.90
All	y:0.82x+8.4	0.91	0.83

The correlation coefficients of the function created for flexural strength were higher than those obtained with compressive strength. When the relationships created for all stages were examined, the highest correlation coefficient was 0.99, and the lowest value was 0.98. It was seen that it had high correlation coefficients. The relationships of the prediction results obtained for flexural strength with the target values were also obtained around the ideal curve. These high correlation coefficients showed the accuracy of the function reflecting the model. Gupta et al. [66] investigated the mechanical properties of concrete samples containing waste tyres exposed to high temperatures and obtained the correlation coefficient as 0.98 using artificial neural networks.

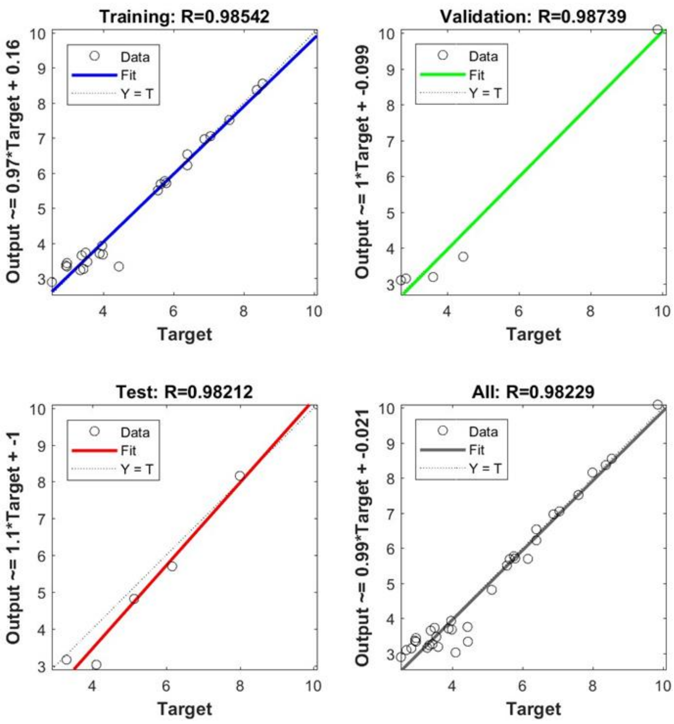

Figure 7. Correlation coefficient values of the function created for flexural strength (R).

Table 3 details the relationship between the predicted flexural strength values and the target output values depending on different input parameters with artificial neural networks. Trial learning test stages were carried out to create the most appropriate model with artificial neural networks. Various data were used in multiple numbers for each of these stages. Finally, a connection covering all data was revealed due to the networks created and the information obtained. A relationship equation is given for each of these stages in the process of reaching the target values. These equations show the connection between actual values and predicted values. The expression y represents the flexural strength value predicted by ANN, while the x represents the values obtained from laboratory tests. Table 3 also shows the correlation and determination results, representing the closeness of the data obtained by the model to the laboratory results. The closeness of these numbers to 1 allows us to have information about the model's suitability. The coefficients of determination obtained for training, validation, and testing are 0.97, 0.97, and 0.96, respectively. The correlation coefficient of the model equation for all data was 0.98.

The coefficient of determination (R^2) for compressive strength was 0.83, while for flexural strength it was 0.96. The coefficient of determination of the function for flexural strength is higher than the value obtained for compressive strength, and the coefficients of determination representing the data relationships for both compressive and flexural strength are at acceptable levels as they are very close to 1.

Table 3. Equations and relationship coefficients of the ANN model for output values representing flexural strength.

	Output-target correlation	R	R^2
Training	y:0.97x+0.16	0.98	0.97
Validation	y:1x+0.099	0.99	0.97
Test	y:1.1x+1	0.98	0.96
All	y:0.99x+0.021	0.98	0.96

MSE explains the error relationship between the prediction values obtained with artificial neural networks and the actual values. In artificial neural networks, different numbers of iterations are performed for the model to predict the data. Thanks to the software used, it can be determined in which iteration the lowest MSE value is reached. Figure 8 shows the Mean Square Error values depending on iterations for compressive and flexural strengths. Figure 8 (a) shows that the best performance for compressive strength is obtained at the 10th iteration. It is seen that the prediction function selects the optimum point where the error is minimized among 16 iterations.

Figure 8 (b) shows that the flexural strength prediction function underwent 19 iterations, with the optimum value obtained at the 13th iteration.

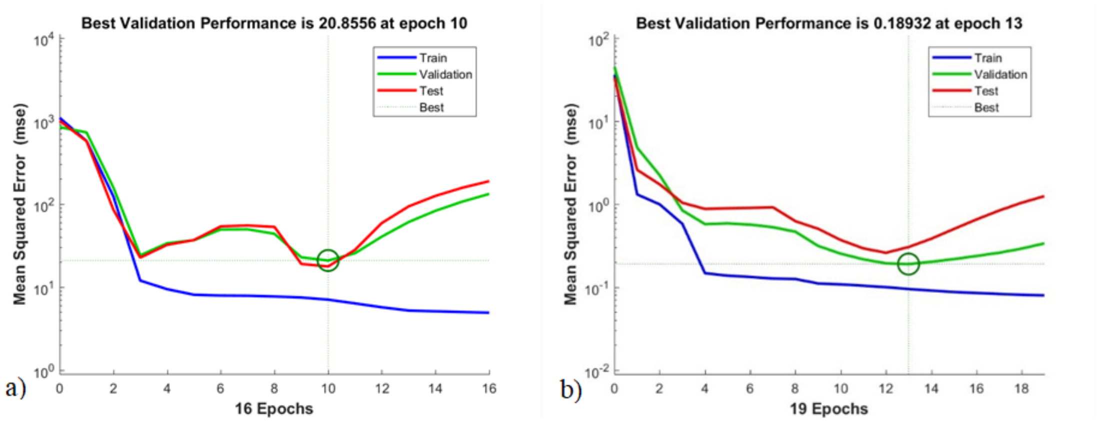

Figure 8. Mean Square Error values depending on iterations for a) compressive strength, b) flexural strength.

Figure 9 (a) illustrates the error conditions for Training, Testing, and Validation for compressive strength separately, thus presenting the error histogram for the whole dataset. Error values are obtained by numerically subtracting the output values from the target values representing the experimental results. Thanks to the program, the difference between the predicted and actual laboratory values was determined for different numbers of data. It can be seen from the figure that the error rates are low.

Figure 9 (b) shows the error histogram for flexural strength values. The error histogram includes the error rates for Training, Testing, and Validation separately. In addition, the value showing the lowest error rate is indicated as zero error. While the zero value for compressive strength values was 0.07, this result was obtained as 0.028 for flexural strength.

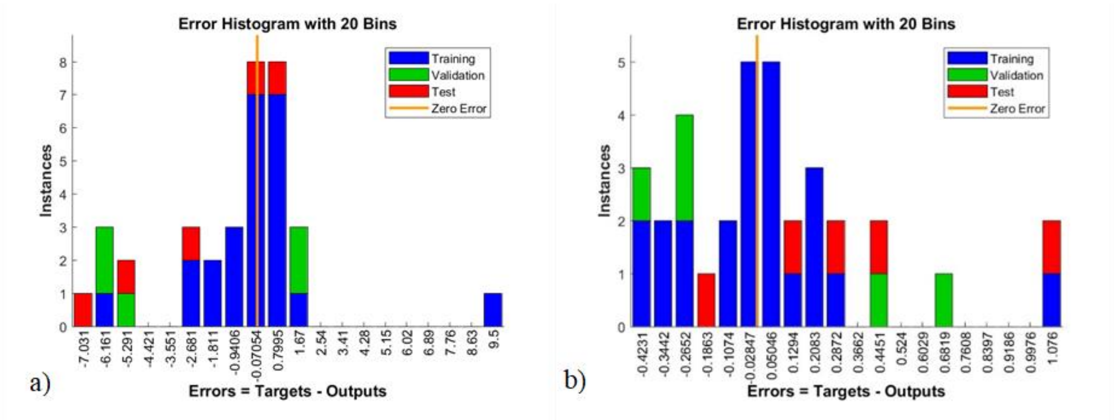

Figure 9. Error Histogram for a) compressive strength, b) flexural strength.

Figure 10 (a) presents the parameters that generate the network to predict the compressive strength results. To avoid erroneous predictions, all values governing the network's control values, convergence, and error functions are shown.

When creating a prediction model, the function that yields the closest results to the available data is generated. The parameters of the network structure used to create the function for flexural strength are presented in Figure 10(b). Since the minimum error rate is targeted during the prediction, the network's control values and all values governing the convergence and error functions are also created.

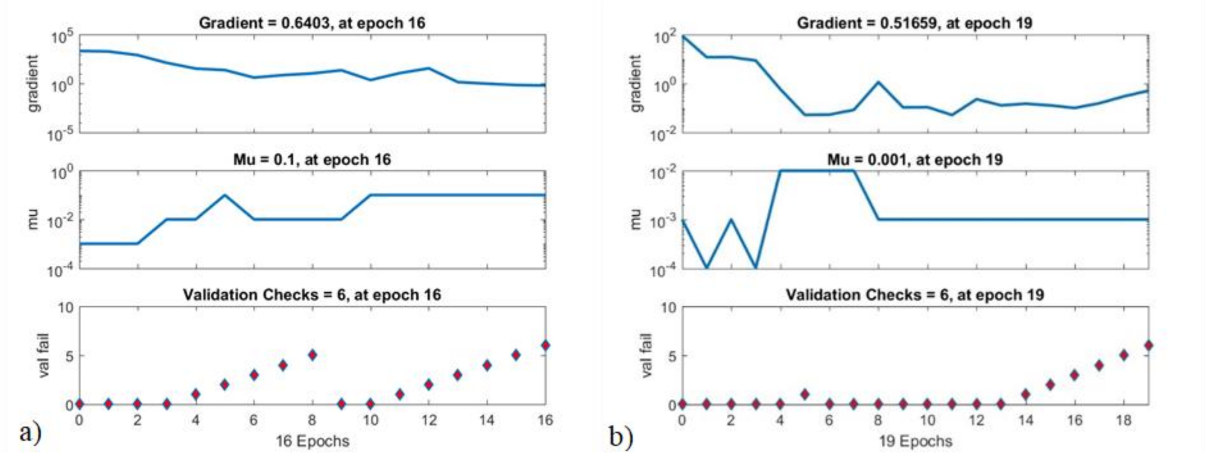

Figure 10. a) Parameters used in mesh generation for a) compressive strength, b) flexural strength.

Figure 11 shows the results obtained with ANN for compressive strength among the output parameters. Compressive strength values are given depending on the input parameters. The figure presents the compressive strength results predicted by ANN, considering the fiber properties, alongside the compressive strength values obtained from laboratory tests in the literature. Thanks to this 5-dimensional graphic design that allows all input and output parameters to be presented together, it was possible to evaluate and analyze the data. The figure shows two scales for the actual and predicted values of compressive strength results. The color change represents the ANN's values, while the round markers' size indicates the accurate laboratory data. The compressive strength values predicted by ANN varied between 30.27 MPa-61.63 MPa and increased from blue to red. The actual compressive strength values obtained from laboratory tests varied between 27.44 MPa-61.69 MPa and increased from a small to a large diameter marker.

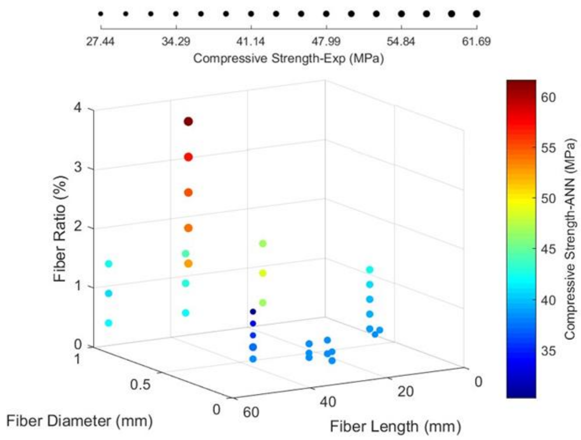

Figure 11. Values of laboratory and ANN results for compressive strength depending on recycled steel fiber properties.

Figure 12 shows Actual flexural strength values and the data obtained from the model created through ANN using inputs determined as steel fiber length, steel fiber diameter, and steel fiber usage percentage. Thanks to this 5-dimensional graphic design that allows all input and output parameters to be presented together, it was possible to evaluate and analyze the data. The color changes on two different scales represent the flexural strength values obtained by ANN. On the other hand, the actual laboratory data are represented by changes in the size of the round markers used in the representation. The flexural strength values predicted by ANN varied between 2.9

MPa-10.09 MPa and increased from blue to red. The actual flexural strength values obtained from laboratory tests varied between 2.54 MPa-9.86 MPa and increased from a small to a large diameter marker.

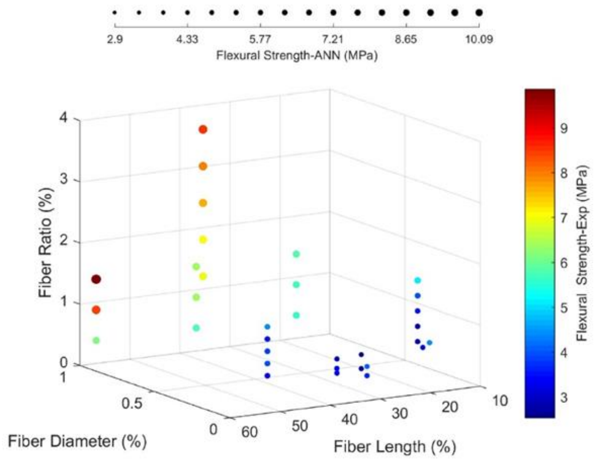

Figure 12. Values of laboratory and ANN results for flexural strength obtained depending on recycled steel fiber properties.

In Figure 13, both the actual compressive and flexural strength values obtained as a result of laboratory tests and the predicted compressive and flexural strength values obtained by the function generated by ANN are presented together. The change in strength values depending on the properties of the recycled steel fibers is shown. Compressive strength values are indicated with a + sign, while flexural strength values are marked with an asterisk. It is also seen in the graph that the strength values obtained by ANN and the laboratory results are compatible with each other.

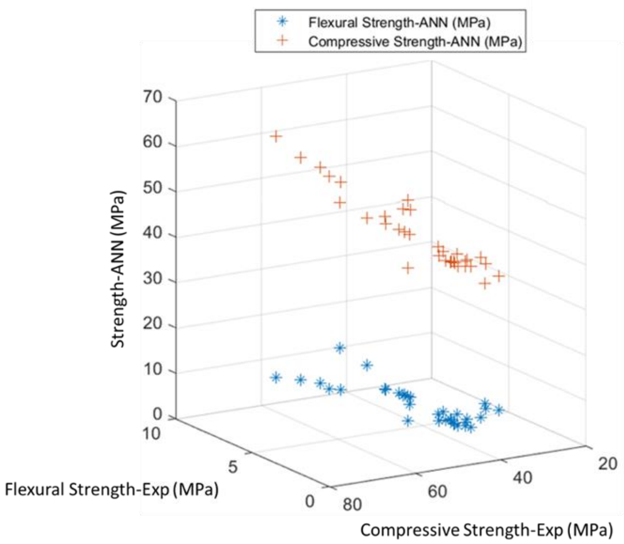

Figure 13. Laboratory and ANN strength values depending on recycled steel fiber properties.

4. Conclusion and Suggestions

In studies where steel fiber obtained from waste tires is used in concrete production, the geometric properties and amount of fiber vary. Depending on the length, diameter, and addition rate of the steel fiber used, there is expected to be a connection between the engineering properties being investigated. For this reason, establishing a good correlation between them will contribute to determining the performance results of applications with different properties. In this study, experimental data on the produced concrete were obtained from the literature to obtain a good correlation between the properties and usage rate of recycled steel fiber and the compressive and flexural strength of the produced concrete. The compressive strength and flexural strength values, two critical parameters reflecting the mechanical properties of the produced concretes, were successfully predicted by artificial neural networks depending on the length, diameter, and percentage of steel fiber used. Graphical analysis of the results obtained by artificial neural networks and the results of the experimental data obtained from the literature were analyzed graphically. Correlation coefficients between laboratory results and prediction values were determined. From the graphs obtained, it is seen that the data predictions made with artificial neural networks within the scope of this study are well approximated to the experimental data. Excellent correlation coefficients and low error rates were obtained for the compressive and flexural strengths of concretes produced depending on the properties of recycled steel fiber. The evaluations of the results of the study are given below.

- Literature research was reviewed, and a -dimensional graph showing the effect of geometrical properties and usage rate of recycled steel fiber on the compressive and flexural strength values of the concretes produced was created.
- Levenberg-Marquardt method was preferred to generate the prediction function with artificial neural networks. A single hidden layer and ten neurons were used. Training, testing, and validation data distribution is random at 70%, 15%, and 15%.
- Equations showing the relationship between the compressive strength predicted by ANN and the actual values are given. The highest correlation coefficient is 0.91. The closeness of this number to 1 indicates the accuracy of the generated function.
- The correlation coefficient of the equation showing the relationship between the target flexural strength values obtained by ANN and the laboratory results is relatively high, and it was received at 0.98.

- The compressive strength values obtained from laboratory tests varied between 27.44 MPa and 61.69 MPa, while the compressive strength values predicted by ANN varied between 30.27 MPa and 61.63 MPa.
- While the target flexural strength values varied between 2.54 MPa and 9.86 MPa, the values obtained with the ANN model varied between 2.89 MPa and 10.09 MPa.
- Depending on the input parameters of length, diameter, and percentage of use, which reflect the properties of recycled steel fiber, a 5-dimensional graph was created in which the compressive and flexural strength values predicted by artificial neural networks and the actual values were presented together. Thus, it was possible to compare the output data with the laboratory results practically.
- Based on the findings, it is concluded that the recycled steel tire-reinforced concrete parameters can be well represented by artificial neural networks, and the presented model can be used as an excellent alternative to laboratory studies for further research.
- Considering the importance of using recycled waste materials in concrete production, waste tyre was used in this study. Thanks to artificial neural networks, time, energy, and cost losses that occur as a result of laboratory experiments can be minimized. In the future, it is aimed to make the effect of using waste tires more known by using various modeling and optimization methods different from this study.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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