Prediction of Mechanical Properties of Steel Fiber-reinforced Concrete Using CNN

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ABSTRACT

The performance of Steel Fiber-reinforced Concrete (SFRC) is superior to that of conventional concrete. Due to its intricacy and limited available data, the development of a strength prediction model for SFRC is very difficult. To prevail over this constraint, research was carried out to build a deep-learning algorithm for the prediction of flexural, split tensile and compressive strengths of SFRC. To accomplish this, a dataset was created by accumulating SFRC strengths through an extensive literature survey. Initially, the deep features of fine aggregate-cement ratio, coarse aggregate-cement ratio, water-cement ratio, fly ash-cement ratio, super plasticizer-cement ratio, length, diameter and dosage of fiber are learned through a convolutional neural network. Then, softmax regression was used to develop a prediction model. The prediction model is trained and tested using 89 datasets with various mix ratios. From the results, we can conclude that the deep-learning-based prediction model exhibits greater accuracy, greater efficiency and greater generalization capacity compared to those of the conventional neural network model.

KEYWORDS: Steel fiber-reinforced concrete, Deep learning, Convolutional neural network, Strength prediction.

INTRODUCTION

Concrete is considered as a very essential component in the construction industry. Strength and durability are the crucial criteria in the construction of reinforced concrete structures. Nowadays, it is essential to develop well-designed concrete as a reliable construction material. Rapid progress in new technology, as well as the surge in the production of synthetic materials, enable us to produce and use various types of concrete, depending on the required structure, probable external dynamic and static pressures and surrounding environment. Growing demands for greater and stronger buildings, as well as more intricate architectural designs, necessitate the use of high-quality concrete mixtures, which are normally obtained by adding appropriate amounts of suitable additives. Depending on the quality that has to be enhanced, concrete is generally blended with various types of fibers, like steel fiber, glass fiber, basalt fiber, synthetic fiber, natural fiber… etc.

The outcomes of numerous research programs have recently confirmed that discrete and randomly distributed steel fibers can enhance the mechanical properties of concrete, such as durability, toughness, tensile strength, flexural strength, impact resistance and fatigue life. The resulting compound material, usually referred to as Steel fiber-reinforced Concrete (SFRC), has many applications in the areas of tunnelling,

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shotcrete, precast, bridges and stabilization of rock slopes. Due to its superior tensile strength and compression stiffness, SFRC has an enormous potential for use in structural members. Using several different mixtures with variable mix-design and fiber length, Olivito and Zuccarello (Olivito and Zuccarello, 2010) investigated the uniaxial compressive strength and tensile strength of SFRC. Rizzuti and Bencardino (Rizzuti and Bencardino, 2014) analyzed the effects of fiber volume fraction on the mechanical properties of SFRC. They evaluated and compared experimental behaviour in terms of peak load, post-peak behaviour and residual strength. Iqbal et al. (Iqbal et al., 2015) examined the effect of steel fiber content on the properties of steel fiber-reinforced high-strength lightweight self-compacting concrete. Li et al. (Li et al., 2020) conducted the dynamic splitting tensile tests of high-performance steel fiber-reinforced concrete with different fiber contents. Jalil and Sultan (Jalil and Sultan, 2021) investigated the potential improvement in the flexural strength of reinforced concrete beams when plain concrete is partially replaced by Hooked-Steel Fiber Concrete. An earlier study on the compressive performance of SFRC has shown that the toughness of the material increases as the volume fraction and aspect ratio of the fiber increase.

The process of selecting proper ingredients and their relative amounts with the intention of producing concrete of the desired strength, durability and workability is termed as mix design. Mix design is a primary aspect of SFRC performance. As the dosage and properties of the components decide the physical and mechanical properties of the composite, the exact ratio between different constitutive materials has to be designed properly. To get a good resulting SFRC, selecting the right mix of components and their right dosages is very essential. The effect of adding steel fibers of different lengths and diameters on the mechanical properties of concrete was studied by Abbass et al. (Abbass et al., 2018). Zhang et al. (Zhang et al., 2020) investigated the effect of three shapes of steel fibers with four contents on the mechanical properties of concrete.

In the last few decades, the development of techniques to get the optimal mix design has been an area of research interest. Huang et al. (Huang et al., 2020) proposed an artificial intelligence-based multi-objective optimization model to enable an efficient method of finding the optimum mix design for SFRC. The main intention of all mix design procedures is to decide on a sufficient and cost-effective material to produce a concrete that can fulfil the desired properties as closely as possible. The characteristics of special concrete deeply rely on numerous features, including the nonhomogeneous behaviour of its constituents. Thus, an apparent perceptive of such intricate behaviour is required for the successful use of these materials in various designed structures. Over the last few years, several researchers have been working on developing prediction models with great precision using deep-learning techniques to determine the concrete strengths. A study was carried out by Bilim et al. (Bilim et al., 2009) to predict the compressive strength of ground granulated blast furnace slag concrete using ANN. Kostić and Vasović (Kostić and Vasović, 2015) proposed a prediction model for concrete compressive strength using ANN. They also conducted an experiment to find the concrete compressive strength with various water cement ratios for different ages of concrete. Nikoo et al. (Nikoo et al., 2015) constructed sample models of cylindrical concrete parts with different characteristics to predict the compressive strength. Larbi et al. (Larbi et al., 2019) studied the influence of database size on a considered architecture of multilayer feed forward ANN results for predicting the compressive strength of concretes containing reclaimed asphalt pavement. Alabi and Mahachi (Alabi and Mahachi, 2020) proposed a statistical model for the evaluation of the compressive and split tensile strengths of the recycled aggregate concrete comprising Lathe Waste Steel Fiber by utilizing Artificial Neural Network.

When compared to ordinary concrete, the development of strength prediction techniques for SFRC is still in its early stages due to its complex nature and limited available data. Altun et al. (Altun et al., 2008) investigated the usability of ANN to estimate the compressive strength of steel fiber-added lightweight concrete. They designed ANN and MLR models, based on their experimental results. Açikgenç et al. (Açikgenç et al., 2015) developed an ANN model using the data collected from literature with the goal of determining the concrete mix composition based on volume fraction, length and diameter of steel fiber and compressive strength of SFRC. Here, the authors restricted their model to predict only the compressive strength. Kang et al. (Kang et al., 2021) devolved machine learning-based prediction models for compressive and flexural strengths of SFRC. They established eleven machine-learning algorithms based on the collected dataset. Only boosting and tree-based models had optimal performance, whereas the remaining models exhibited poor performance. To overcome these constraints, research was carried out to develop an optimal deep-learning model to predict the compressive, split tensile and flexural strengths of SFRC. To achieve this, a dataset was created through an extensive literature review on SFRC.

In the past few years, deep-learning methods with independent learning capacity have stimulated great interest and have already achieved considerable progress in the areas of big data analysis, face and voice recognition, error identification and visual perception. But, the application of deep-learning methods in the field of concrete strength prediction is comparatively new. Cha et al. (Cha et al., 2017) proposed a vision-based method using a deep architecture of CNN for detecting concrete cracks without calculating the defect features, which showed quite better performances and found concrete cracks in realistic situations. Deng et al. (Deng et al., 2018) proposed a prediction model based on deep-learning theory to predict the compressive strength of recycled aggregate concrete. Abuodeh et al. (Abuodeh et al., 2020) employed two deep machine-learning techniques; namely, Sequential Feature Selection and Neural Interpretation Diagram, to identify the critical material constituents of Ultra High-performance Concrete that affect the ANN.

In this paper, we developed a prediction model to determine the compressive, split tensile and flexural strengths of SFRC based on Convolution Neural Network (CNN). It is a renowned deep-learning architecture motivated by the instinctive visual perception process of living creatures. By using CNN, the deep features of fine aggregate-cement ratio, coarse aggregate-cement ratio, water-cement ratio, fly ash-cement ratio, super plasticizer-cement ratio, length, diameter and dosage of fiber along with their compositions are learned. The softmax regression model uses deep features of the input parameters to predict SFRC concrete strengths. The process extracts the feature matrix directly from the corresponding data, resulting in a highly accurate and efficient computational model that offers a novel approach to predict specific SFRC strengths.

ARTIFICIAL NEURAL NETWORK

Artificial neural network is a computational model which consists of (Priddy and Keller, 2009) neurons, activation function, connection weights and bias. The mathematical representation of the basic artificial neuron is as follows:

$$Y = f\left(\sum WX + b\right) \tag{1}$$

where Y is the output, f is an activation function, W is the weight vector, X is the input vector and b is the bias. The neuron may be viewed as a linear feature map with an adjustable weight matrix. The artificial neural network model comprises numerous interconnected groups of artificial neurons, as displayed in Fig. 1. All artificial neurons of each layer are completely linked to each neuron of the immediately preceding and following layers over associated weights. Every neuron in the model receives an input signal from all the neurons of the preceding layer. The weights are utilized to show the influence of input values in the preceding layer on the process elements and they may be adjusted to get the desired output. In the ANN model, data is transferred from the input layer to the output layer in a single direction. The learning procedure is carried out to reduce the difference between the actual and output values. Throughout the learning stage, ANN can alter its model based on the significant information passing through the network. We can use artificial neural networks to model almost all the complex connections between the input and output data.

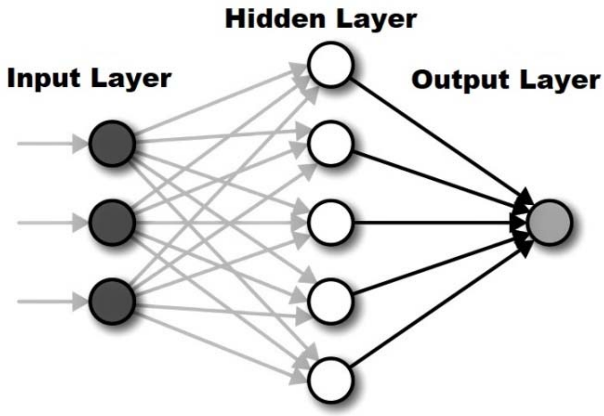


Figure (1): Structure of artificial neural network

CONVOLUTIONAL NEURAL NETWORK

Motivated by the inherent visual perception process of the living organism, the Canadian psychologist and computer scientist G.E. Hinton suggested a theory of deep learning. This theory gave a fresh path to conventional machine-learning methods. Its fundamental configuration is a multilayer deep neural network (DNN) which can form an abstract high-level representation of the underlying features. In deep-learning, one of the most important classes of DNN is the Convolutional Neural Network (CNN) which is the regularized interpretation of multilayer perceptron and has an exceptional capacity for sequent data analysis. To extract the deep features of the data, the algorithm of CNN adopts sequential convolutional and pooling layers. The connectivity sequence between neurons is analogous to the neural system of the animal perception cortex, which avoids the pre-processing of the primary data.

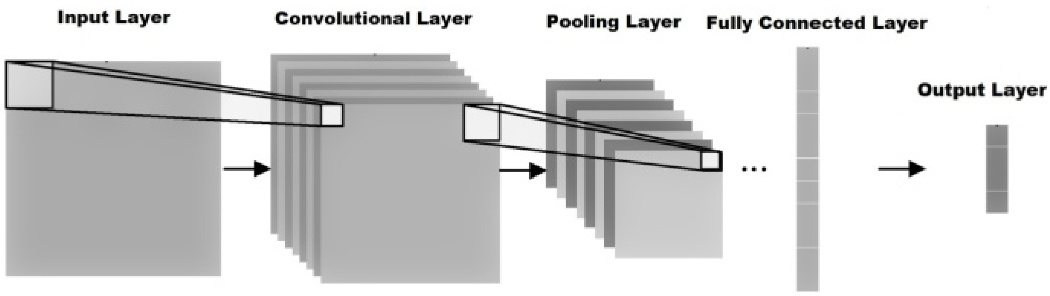


Figure (2): Basic structure of convolutional neural network

The fundamental architecture of CNN comprises a sequence of hierarchical levels, which includes a convolutional layer, a pooling layer, a fully connected layer and a conventional classification model. The convolutional layer creates a feature matrix of the input data from the preceding layer using a set of weights. Neurons in each filter of the convolutional layer are directly associated with the input data and multiply it by the weights, which leads to the reduction of time and complexity of the convolutional neural network. The CNN has a greater error tolerance for the input data, so it can detect the hierarchical representation with more precision. The deep features of the input data are extracted in the form of a matrix by the convolutional layer. Every feature matrix can be considered as a plane with parallel computation capacity, which significantly reduces the number of free parameters. The computation procedure of the convolution layer is shown in Fig. 3. The output of the convolutional process is computed by convolving an input X with n number of filters as follows:

$$X_i = f(X * W_i + b_i) \tag{2}$$

where X_i is the output corresponding to the i^th^ convolution filter, W_i is the weight of the i^th^ filter, b_i is the i^th^ bias, $*$is the convolution operator and f is the activation function.

The pooling layers, generally coming after a convolutional layer, are used to decrease the size of the feature maps. As the number of parameters decreases, the amount of computation performed on the network will also reduce. The pooling layer summarizes the features contained in a region, produced by the convolutional layer. As a result, the model is much more robust to deviation in the position of the features. The important non-linear functions to execute pooling in CNN are weighted pooling, max pooling and average pooling, where max pooling is more familiar. Fig. 4 shows the procedure for the pooling function. After a sequence of convolutional and pooling operations, we get a fully connected layer which is analogous to the conventional multi-layer neural network.

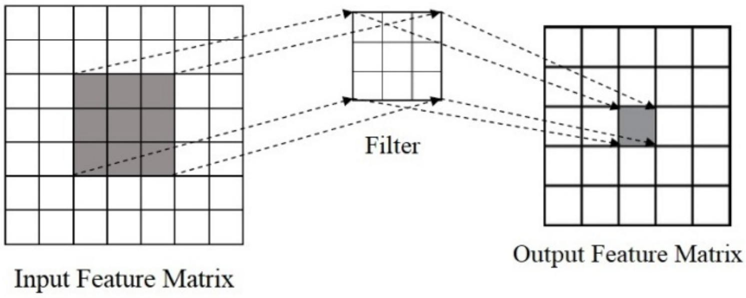


Figure (3): Convolution process

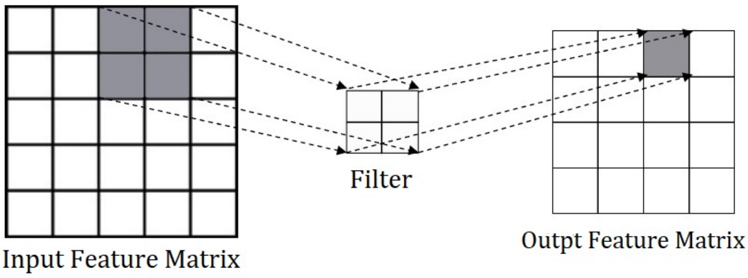


Figure (4): Pooling process

The softmax regression, which can accomplish both a fast computation and a precise result, is the most accepted activation function to normalize the output layer of a neural network. The softmax regression is defined by the formula:

$$o = \frac{1}{\sum_{j=1}^{n} \exp(X \times K_j + B_j)} \begin{bmatrix} \exp(X \times K_1 + B_1) \\ \vdots \\ \exp(X \times K_n + B_n) \end{bmatrix} \quad (3)$$

In the learning procedure, the back propagation method is used to adjust the connection weights to reduce the mean square error (MSE) of the predicted outputs and the actual outputs. The MSE is computed as follows:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2 \quad (4)$$

where a_i is the actual value and p_i is the predicated value. The CNN can learn the features implicitly from the data, which avoids explicit feature extraction and exhibits greater precision and efficiency than conventional neural networks.

DATABASE

The success of the deep-learning model in predicting the behaviour of SFRC mixtures depends on the comprehensiveness of the training data. A good training dataset should contain ample information about the material behaviour to qualify the trained neural network as a material model. To build a relationship between the mixture variables of SFRC and their measured strengths, we need a variety of experimental data. The basic parameters considered in this study were fine aggregate-cement ratio, coarse aggregate-cement ratio, water-cement ratio, fly ash-cement ratio, super plasticizer-cement ratio, length, diameter and dosage of fiber. A dataset of 89 mixtures from the literature was retrieved and the CNN model was designed for strength prediction. The training of CNN was carried out using a pair of input and output vectors consisting of mixture variables and concrete strengths, respectively. The data used in this study was collected from 11 references: (Faisal Fouad Wafa, 1990), (Köksal et al., 2008), (Song and Hwang, 2004), (Thomas and Ramaswamy, 2007), (Söylev and Özturan, 2014), (Yazici et al., 2007), (Afroughsabet and Ozbakkaloglu, 2015), (Nili and Afroughsabet, 2010), (Ibrahim and Che Bakar, 2011), (Bazgir and Fu, 2016) and (Yu et al., 2013).

CNN MODEL TO PREDICT SFRC STRENGTHS

In this paper, we consider fine aggregate-cement ratio, coarse aggregate-cement ratio, water-cement ratio, fly ash-cement ratio, super plasticizer-cement ratio, length, diameter and dosage of fiber as the input variables and Compressive Strength, Split Tensile Strength and Flexural Strength as output variables. It is difficult to represent these input parameters in a deep-learning approach, as they are distinct from the typical video, audio, text, image, …etc. Therefore, we consider a 3X3 matrix containing 8 significant SFRC parameters as the input for a convolutional neural network. As the input parameters are much less, we choose a single-layer CNN model. Here, the CNN structure consists of the input layer, the convolutional feature layer and the output layer. In the convolutional feature layer, the kernel k and the bias b were adjusted. The sigmoid function was adopted as the activation function. The impact of the 8 input parameters on the sample strengths may be retrieved through convolution of matrices and can be represented by convolution kernels. The features extracted from the convolutional and pooling layers are used as input values for the traditional neural network layer, which then sets the weight and bias to calculate the final output value. The organization of the CNN prediction model is shown in Fig. 2.

TRAINING OF PREDICTIVE MODEL

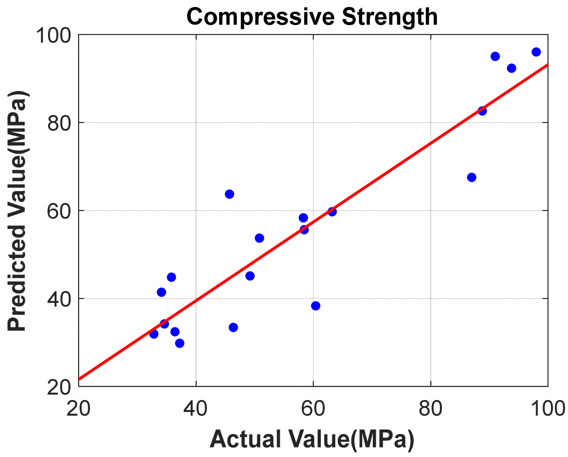
In this study, the MATLAB platform was used to create the CNN prediction model. A set of 70 samples were used to train the predictive model based on CNN. The training of CNN was completed after 280 epochs of learning with 99% precision. Then, the prediction model was tested by using the remaining 19 samples. The strength values of the test samples, predicted by the CNN model are compared with the actual experimental values. The predicted strength values collected from the CNN model, are almost near to experimental results, as shown in Fig. 5, which indicates a strong correlation between the output and input parameters. The Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) are used to calculate the relative error of the testing data.

$$MEA = \frac{1}{n}\sum_{i=1}^{n} |y_i - y_i'| \tag{5}$$

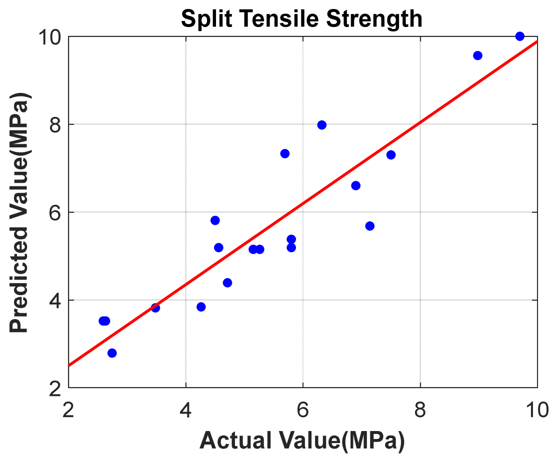
$$MAPE(\%) = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - y_i'}{y_i}\right| \times 100 \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - y_i')^2} \tag{7}$$

where y_i' is the predicted value and y_i is the actual value. Fig. 6 illustrates the histogram of the relative error percentage of predicted strengths from testing samples by the CNN model. The maximum and minimum relative errors for compressive, split tensile and flexural strengths are respectively 36% and 0%, 26.2% and 0% and 24.8% and 2.3%. Approximately 70% of the samples exhibit less than 10% error, which illustrates a good correlation between the results obtained by the CNN model and the experimental outcomes. The above statistical data confirms that the proposed CNN model is appropriate to predict the compressive, split tensile and flexural strengths of SFRC.



(a)



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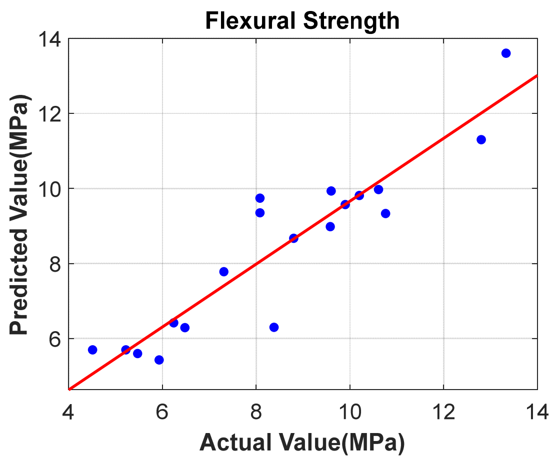
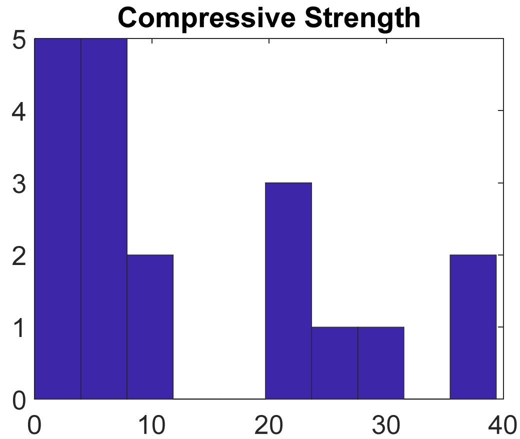


(c)

Figure (5): Prediction results of CNN on compressive, split tensile and flexural strengths

Table 1. Relative errors

	Max. Relative Error (%)	Min. Relative Error (%)	MAPE (%)	RMSE	MAE
Compressive Strength	36.0	0.0	13	9.38	6.76
Split Tensile Strength	26.2	0.0	13	0.82	0.64
Flexural Strength	24.8	2.3	9	0.92	0.72



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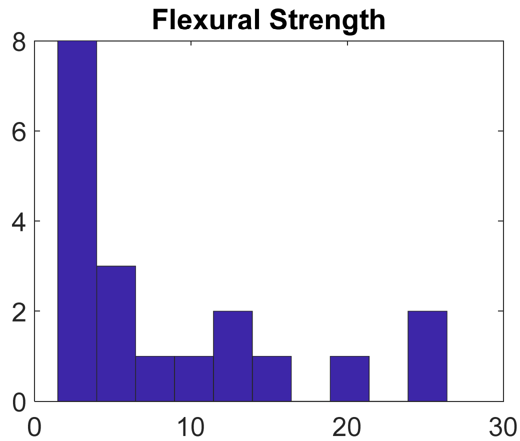

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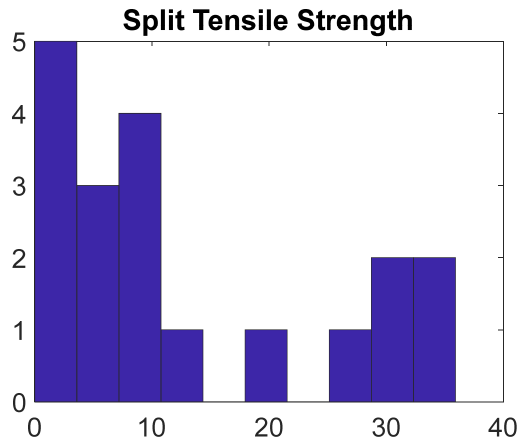

(c)

Figure (6): Histogram of the relative error percentage

CONCLUSION

As the characteristics of SFRC are irregular in nature, the relationship between the concrete strengths of SFRC and its mixing proportion is nonlinear. Thus, in this research work, we proposed a predictive model based on CNN. The model predicts the strengths by learning the deep features of the variables of the SFRC mixture and their combinations. To demonstrate the potential of the proposed model, 89 samples with diverse mixing proportions were used in the study. The obtained outcomes confirm that the prediction model formulated on CNN has the advantages of greater accuracy, greater efficiency and greater generalization capacity when compared to a conventional neural network model. From this study, we can also conclude that, in the future, if we get more experimental data on SFRC, we can achieve less relative error with the same CNN model developed in this research work. Also, one can use this proposed model with some modification for the prediction of concrete characteristics by collecting the dataset of special concrete with different attributes. Furthermore, this research could be extended to explore other deep-learning models with the hybridization approach, when it is desirable to explore modeling of special concrete mixtures and ingredients.

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