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Compressive strength prediction of recycled concrete based on deep learning

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HIGHLIGHTS

- The deep features of water-cement ratio, recycled coarse aggregate replacement ratio, recycled fine aggregate replacement ratio, fly ash replacement ratio as well as their combinations are learned through neural networks.
- The proposed prediction model is developed using the softmax regression.
- The simulated results show that the prediction model based on deep learning exhibits the advantages including higher precision, higher efficiency and higher generalization ability compared with the traditional neural network model.

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ABSTRACT

Considering on the current difficulties of predicting the compressive strength of recycled aggregate concrete, this paper proposes a prediction model based on deep learning theory. First, the deep features of water-cement ratio, recycled coarse aggregate replacement ratio, recycled fine aggregate replacement ratio, fly ash replacement ratio as well as their combinations are learned through a convolutional neural networks. Then, the prediction model is developed using the softmax regression. 74 sets of concrete block masonry with different mix ratios are used in the experiments and the results show that the prediction model based on deep learning exhibits the advantages including higher precision, higher efficiency and higher generalization ability compared with the traditional neural network model, and could be considered as a new method for calculating the strength of recycled concrete.

1. Introduction

Along with the rapid urban development and economic activities, the generation of construction and demolition (C&D) waste has increased substantially in many parts of the world. At the same time, large quantities of natural aggregates are extracted for construction every year [1]. The utilization of recycled aggregates (RAs) in concrete production can potentially conserve the non-renewable natural resource of natural aggregates, eliminate unnecessary consumption of limited landfill areas and reduce energy consumption. Due to its benefits on preventing the shortage of natural aggregate and the deterioration of ecological environment caused by concrete waste, Recycled Aggregate Concrete (RAC) technology is considered as one of the main candidates for ecological concrete development [2].

However, the variability in the characteristics of RA and RAC prevents the use of RA further. For example, the use of RCA can lead to reduction of up to 40% in compressive strength [1,3]. Low density and high water absorption and porosity, mainly caused by the heterogeneous nature of RA, can influence the properties of fresh concrete and then reduce its workability [4–6].

Over the last two decades, many investigators have made use of various methods to predict the properties of concrete with different components. The compressive strength of recycled concrete is closely related to these factors such as sand rate, water-cement ratio, aggregate grade, aggregate type and substitution rate, mineral fine admixture variety and dosage [7,8]. However, the relationship between those factors and compressive strength shows a complex non-linear relationship, and there is still no definite theoretical formula which can accurately reflect their

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relationships [9,10]. In practice, substantial experiments have to be carried out to ensure the compressive strength of recycled concrete to meet the requirements.

Nowadays various artificial intelligence algorithms, such as neural networks (NN) and support vector machines (SVM), are widely used in concrete strength prediction. In [11–13], the artificial neural network serves as to predict the relationship between the different influencing factors and compressive strength of recycled concrete. The nonlinear mapping ability of BP (Back Propagation) neural network is adopted to establish the non-linear model between input variables and output variables. Thus accurate intensity prediction could be realized through a certain training and iteration. A 7-20-3 BP neural network model is employed in [14] to predict the recycled concrete slump. In [15], the neural network model and ultrasonic pulse velocity test are proposed to predict the concrete compressive strength. Although BP neural network shows good abilities on solving non-linear problems, it also exhibits some disadvantages including slow convergence, over learning and local optimization which will affect the accuracy and efficiency of prediction. In [16] the neural networks and the adaptive neuro-fuzzy inference system are combined to improve the capability of prediction model. In [17], artificial neural networks and regression techniques are used to analyses the relations between concrete components and concrete properties. Furthermore, M5' model tree algorithm is also used in concrete strength prediction [18]. Literature [19] employed multivariable regression to adjust the coefficients and proposed genetic programming to optimized the predict processing. In [20] and [21], a support vector machine (SVM) is employed to establish the prediction model of compressive strength of recycled concrete. This algorithm adopts the principle of structural risk minimization, which has the excellent abilities of global optimal and generalization, and is suitable for solving small samples as well as non-linear prediction problem. In [22] the firefly algorithm is used for parameters optimal of a LSSVR (Least-Squared Support Vector Regression) based prediction model. A self-adaptive fuzzy inference based SVM model is employed in [23] to predict compressive strength of rubberized concrete. In [24], a LSSVR model, based on coupled simulated annealing method, is proposed to find the nonlinear relationship between the concrete compressive strength and eight parameters. Literature [25] investigates and compares the performance of nine data mining models in predicting the compressive strength of a new type of concrete. However, the prediction accuracies of these methods above are largely dependent on the selection of parameters.

In recent years, the deep learning theory with autonomous learning ability arouse great interests and has already achieved significant progresses in the fields such as large data analysis, face recognition, sound analysis, fault diagnosis and defect detection [26–29]. As for in the field of concrete strength prediction, the application of deep learning is relatively new. This paper presents a prediction model of compressive strength of recycled concrete based on Convolutional Neural Network (CNN). By using deep learning theory, the deep features of water-cement ratios, recycled coarse aggregate substitution rate, replacement rate of recycled fine aggregate, fly ash content as well as their combinations are learned. Then, these deep features are employed to train a softmax regression model for prediction of recycled concrete compressive strength. The experimental results show that this algorithm avoids not only the preprocessing process but the dependence on the engineering experience of a large number of different dimensions and orders of magnitude. The algorithm extracts the feature matrix directly from the matching data to establish a highly accurate and efficient forecasting model, which provides another new idea for the prediction of compressive strength of recycled concrete.

2. Artificial neural networks and deep learning theory

Artificial neural networks (ANN) is a mathematical or computational model which tries to simulate the structure or functional aspects of biological neural networks [30]. ANN is a parallel and distributed system, which composed of simple processing units. These units, similar to the structure of the human brain, are known as the artificial neurons. The artificial neurons can achieve better performances than the conventional models through calculating specific mathematical functions.

2.1. Artificial neuron and artificial neural network

The artificial neuron is the basic unit of a neural network which consists of weights, bias and the activation function. The structure of an artificial neuron is shown in Fig. 1(a) and the mathematical model is shown as following:

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

where X_m is the input vector, Y is the output, W_m is the weight matrix, b is bias vector and f is activation function.

The artificial neuron can be regard as a linear map function with adjustable weight matrix. By training the value of $\mathrm{W_m}$ to reduce

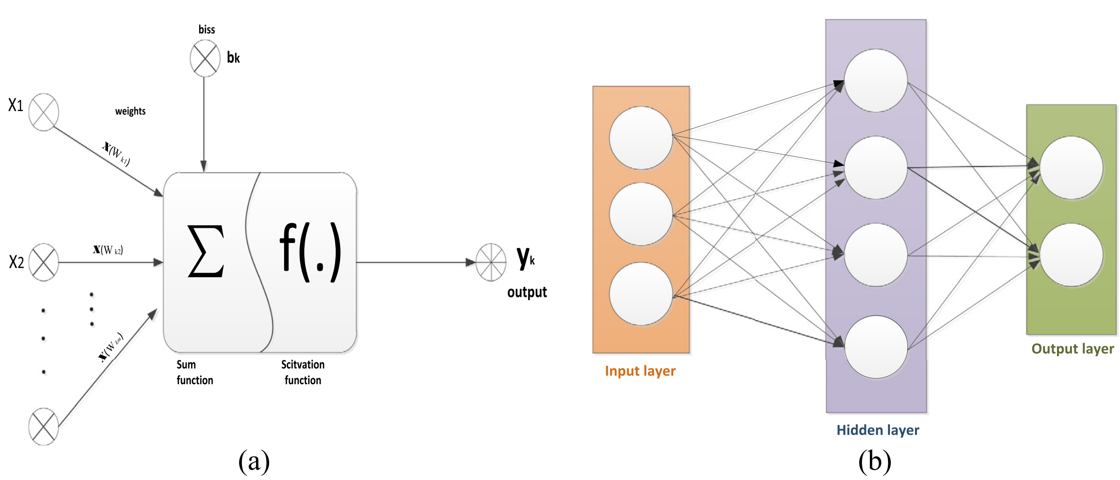

Fig. 1. Structure of artificial neuron and ANN: (a) Artificial neuron; (b) ANN.

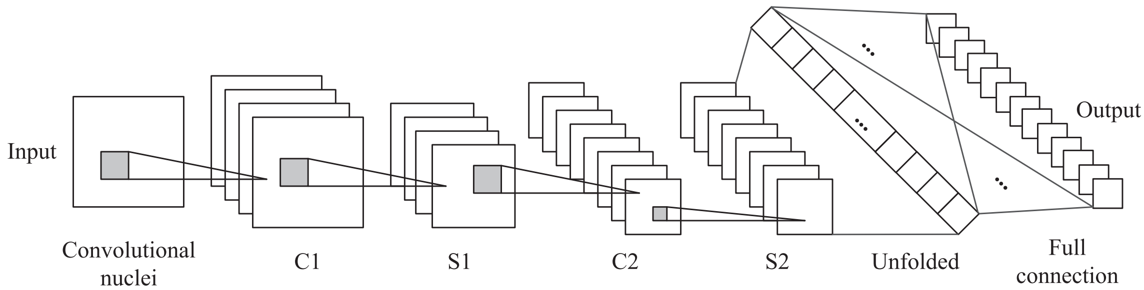

Fig. 2. Basic structure of CNN.

the distance between the target and the output, a perceptron is obtained. However, the perceptron is a binary linear classifier which is unsuitable to solving nonlinear problems such as the XOR problem. Therefore, ANN model has been carried out.

An ANN model, which is shown in Fig. 1(b), consists of a number of interconnected group of artificial neurons. Each artificial neuron is fully connected to each other through connection weights and receives an input signal from the linked one. These weights are used to present the effect of an input parameter in the previous layer on the process elements and it can be adjusted to produce an output needed. In an ANN model, the information is transmitted to the output layer from the input layer in one direction. Then, the learning process is conducted to minimize the deviation between the actual values and output values. In most cases the ANN is an adaptive system that can change its model according to the relevant information flowing through the network during the learning phase. ANN can be used to model almost any complex relationships between the inputs and outputs of the data.

2.2. Multi-layer neural networks

Inspired by the mechanism of mammalian brain recognition, Hinton proposed a deep learning theory [29]. This theory is a new direction of traditional machine learning technology, and its basic structure is a multi-layer artificial neural network, named deep neural network (DNN). Through the multi-layer nonlinear transformation, the combination of the underlying features can form a more abstract high-level representation. Moreover, the learning system is no longer dependent on artificial feature selection, and the distributed features of the data representation can be found autonomously and the complex expression function also can be learned through it. CNN is a typical deep learning neural network which has been developed in recent years. The CNN algorithm adopts the serial convolution layer and the pooling layer to arrange the data feature layer by layer. Its spatial structure and algorithm are very similar to the neural model of the animal visual perception system which does not need to pre-process or reconstruct the original data. Furthermore the CNN avoids extracting data characteristics manually as the traditional machine learning algorithms and the weight sharing network structure of CNN is more similar to the biological neural network, resulting in greatly reducing the complexity of the network model. Therefore, the CNN has rapidly aroused researcher's great interests since it appears [31].

As shown in Fig. 2, the basic structure of the CNN consists of series of stages. The first few stages are composed of two combinations: convolutional layers and pooling layers, while the last stage consists of a fully connected layer and a traditional classification model. The convolutional layers contain a number of filters, which convolute the input from the previous layer through a set of weights and compose a feature output, generally called as feature map. Within each filter, neurons are directly connected to the input data points and multiply the data points by the weights. All the neurons in the same filter share their weights, leading to the reductions the optimization time and complexity of the CNN.

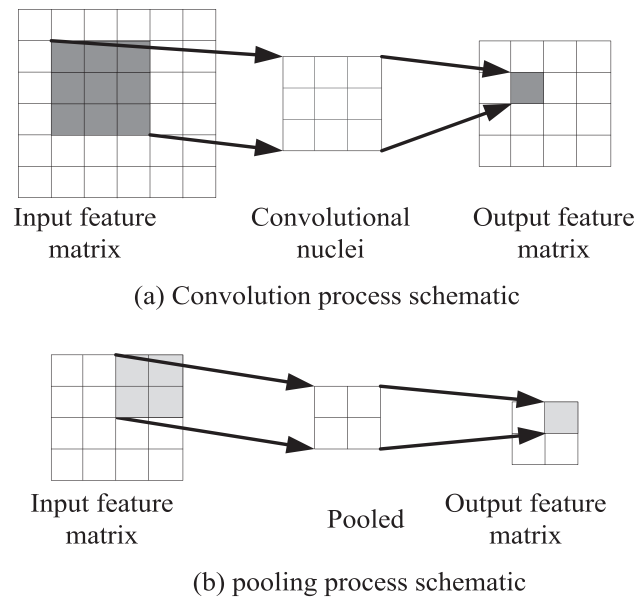

Fig. 3. Schematic diagram of convolution and pooling process.

The structure has higher fault tolerance to the input samples, and can realize the hierarchical expression of data more accurately. The convolution layer is used to extract the local features of input data and consists of multiple feature matrices. Each characteristic matrix can be regarded as a plane (the same convolution kernel on the same plane), so it shows the ability of parallel computation, resulting in greatly reducing the number of free parameters. Different planes correspond to different convolution kernels so that the extracted features are more fully demonstrated [32].

The calculation process of the convolution layer is shown in Fig. 3(a). Suppose the convolutional layer input is $X \in R^{A \times B}$, where A and B are the dimensions of the input data. Then the output of the convolutional layer can be calculated as follows:

$$C^l = f(X \otimes W^l + b^l) \tag{2}$$

where C is the l-th feature map of the convolutional layer, X represents the input data matrix, W is the weight matrix of l-th filter of the current layer, f is the activation function, K is the convolution kernel, b is the bias, $\otimes$ is an operater of convolution.

A pooling layer usually follows a convolution layer to obtain a lower resolution representation of the convolution layer activations through sub-sampling. Neighbor pooling units take input from the patches that are shifted by more than one row or column, thereby reducing the dimension of the representation and creating invariance to small shifts and distortions. The pooling function, including max pooling, mean pooling and weighted pooling, computes statistics of the activations. In the CNN method, the max pooling function is the most commonly used one. The process of pooling function is shown in Fig. 3(b), and the calculation is as following:

$$P = \max C \tag{3}$$

where P is the output of pooling layer and C is the output of convolution layer.

After several combinations of convolutional layers and pooling layers, there will be a fully-connected layer. The fully-connected layer is similar to the traditional multilayer neural network and can be applied through different classification models. The softmax regression, which can achieve a fast computation and an accurate result, is the most popular output layer. The output of the softmax regression can be calculated as follows:

$$O = \frac{1}{\sum_{j=1}^{n} \exp(X \times K_j + B_j)} \begin{bmatrix} \exp(X \times K_1 + B_1) \\ \exp(X \times K_2 + B_2) \\ \ldots \\ \exp(X \times K_n + B_n) \end{bmatrix} \tag{4}$$

In the learning process, the back-propagation algorithm is adopted, that is, the weight matrix is adjusted by reducing the mean square error of the ideal output and the actual output. The Mean Square Error (MSE) is calculated as follows:

$$\mathrm{MSE} = \frac{1}{2}\sum_{j}(y_j - o_j)^2 \tag{5}$$

where y_j is the actual output and o_j is the ideal output.

The essence of the convolution neural network is to learn a number of filters that can extract the characteristics of the input data, extract the topological features hidden in the data through layer-by-layer convolution and pooling, and finally get the input data with translation, rotation and scaling, the characteristics of the nature of change. This method can learn the features implicitly from the data, avoid explicit feature extraction, and exhibits higher accuracy and efficiency than traditional neural networks.

3. Materials

3.1. Cementitious materials

The test employed 42.5 ordinary Portland cement produced by Anhui Conch Cement Co, its oxide composition and main physical properties are shown in Tables 1 and 2. The fly ash used in the test was II grade fly ash produced by Huaneng thermal power plant. The main chemical composition and physical properties of fly ash are shown in Table 3. The water for concrete mixing and maintenance was the ordinary tap water.

3.2. Aggregate

The recycled coarse aggregate used in this test was obtained from the pier of an abandoned highway bridge. The average value of compressive strength of the recycled coarse aggregate was measured by sampling the core of the pier, which is 37.8Mpa. First, manual crushing was used to crush the abandoned concrete, then magnetic sorting and debris sorting were employed to remove debris from concrete fragments. Next, the jaw crusher was used to break the concrete blocks to meet the requirements of small size concrete particles. Finally, these small concrete particles were selected manually to satisfy the requirements of 5–30 mm continuous gradation. The main physical properties are shown in Table 4.

The recycled fine aggregate used in this test consist of sand particles with no cement slurry on the surface, sand with cement slurry on the surface, cement stone particles and a small amount of crushed stone. The particle size range of recycled fine aggregate is 0.08–5 mm and the recycled fine aggregate fineness modulus was 2.8, the screening results are shown in Table 5.

Table 1
Chemical analysis of cement (wt%).

SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO_3	Na_2Oeq	f-CaO
22.64	4.62	3.62	64.68	2.80	0.46	0.578	0.92

Table 2
Conch cement clinker performance analysis results.

Performance	Analysis Results	
Fineness 0.08/%	2.9	
Standard consistency %	28.2	
Le Chatelier soundness test	Qualified	
Setting time (min)	Early condensate	187
	Final condensate	2236
Flexural strength (Mpa)	3d	4.5
	28d	9.6
Compressive strength (Mpa)	3d	23.7
	28d	46.9

Table 3
The main chemical composition of fly ash (wt%).

MgO	Al_2O_3	SiO_2	Na_2O	SO_3	K_2O	CaO	Fe_2O_3	Loss of ignition
1.23	28.98	54.70	0.45	0.58	1.65	4.48	5.24	2.24

Table 4
Main physical properties of recycled coarse aggregate.

Performance	Test Results
Moisture content %	3.7
Water absorption %	2.0
Apparent density kg/m^3	2580
Loose bulk density kg/m^3	1440
Close bulk density kg/m^3	1560
Mud content %	1.71
Crushing index %	12

Table 5
Recycled fine aggregate screening results.

Sieve size/mm	Retention/%
5	0.4
2.5	24.7
1.25	30.6
0.63	23.5
0.315	18.4
0.16	1.5
<0.16	0.9

Fig. 4. Test device.

3.3. Concrete mixing design and compressive strength

In this experiment, the concrete was stirred and formed by ASTM C192-C192M method, and the mixed ratio of recycled concrete was calculated. This test adopted concrete modes of 100 mm cube, and loaded the concrete mixture at one time. After 3 min vibration on the vibration table, excess concrete was scraped and the modes were then smoothed by a spatula. The formed concrete was conserved in the conservation room where the temperature was 20 ± 2 °C and the humidity was 90%. After 24 h conservation, the molds were demolished and the modes were numbered. Finally, the modes were placed in the water of 20 ± 3 °C till the prescribed age.

The servo press machine is adopted for the compressive strength test. The testing modes are hold in the machine and the strain gauge is connected with the pressure sensor to monitor the compressive strength. The servo press machine and the strain gauge shown in Fig. 4. In this test, 4 sets of strength data were prepared on different mixed parameters, the specific mixing ratio and strength test results are shown in Tables 6-1 to 6-4.

Table 6-1
Strength of RAC on different water-cement ratio.

W/C	7d	28d	W/C	7d	28d	Other
0.34	42.9	52.4	0.5	31.9	42.4	C: 340
0.36	41.4	51.3	0.52	30.7	41	FA: 0
0.38	39.9	50.2	0.54	29.6	39.5	FAR: 0
0.4	38.4	49.1	0.56	27.6	37.1	S: 656
0.42	36.9	47.9	0.58	25.6	34.9	RS: 0
0.44	35.4	46.8	0.6	23.6	32.5	RS/S: 0
0.46	34.2	45.4	0.62	21.6	30.2	G: 610
0.48	33.1	43.9	0.64	19.6	27.9	RG: 610
						RG/G: 50

Table 6-2
Strength of RAC on different fly ash replacement ratio.

C	FA	FAR	7d	28d	C	FA	FAR	7d	28d	Other
340	0	0	29.4	39.8	285.6	54.4	16	24.3	37.8	S: 656
333.2	6.8	2	28.9	39.7	278.8	61.2	18	23.6	37.3	RS: 0
326.4	13.6	4	28.2	39.5	272	68	20	22.9	36.9	RS/S: 0
319.6	20.4	6	27.6	39.4	265.2	74.8	22	22.1	36.7	G: 610
312.8	27.2	8	26.9	39.2	258.4	81.6	24	21.3	35.6	RG: 610
306	34	10	26.3	39.1	251.6	88.4	26	20.5	35	RG/G: 50
299.2	40.8	12	25.6	38.7	244.8	95.2	28	19.7	34.3	W: 184
292.4	47.6	14	24.9	38.2	238	102	30	18.9	33.7	W/C: 0.54

4. Prediction model of recycled concrete strength based on deep learning

4.1. Convolution neural network prediction model establishment

This paper chose the water cement ratio, recycled coarse aggregate replacement ratio, recycled fine aggregate replacement ratio and fly ash replacement ratio as the input variables and the sample strength as output variables. Since these ratio parameters are different from the general image, text and other data, it is not easy to express by deep learning method. A 2×2 matrix which consists of 4 concrete mixed parameters was used as the input of CNN. Since the input parameters were fewer, the single layer convolutional neural network structure was selected. The model was composed of the input layer, the convolutional feature layer and the traditional neural network output layer. The input layer is a 2×2 pixel composed of four kinds of matching parameters. The convolution kernel k and the bias b were set in the convolution characteristic layer. The activation function was chosen to be the sigmoid function. Through the convolution between the pixels, the influence of the 4 input parameters on the compressive strength of the sample can be extracted, and it can be expressed by 4 convolution kernels. The traditional neural network layer employs the four features obtained by the feature layer as input value, set the weight and bias, and get the final output value. The prediction model structure is shown in Fig. 5.

4.2. Predictive model training

In this experiment, the prediction model of convolution neural network was established by the Matlab platform. According to the mixing design above, there were 74×10 sets of different RAC mixing ratio. The training data was composed of the front 10 sets of Tables 6-1 and 6-2 as well as the front 15 sets of Tables 6-3 and 6-4. Thus, there were 50 sets of samples used to train the CNN predictive model and the rest 24 samples were used as test data.

Table 6-3
Strength of RAC on different recycled coarse aggregate replacement ratio.

G	RG	RG/G	7d	28d	G	RG	RG/G	7d	28d	Other
1220	0	0	26.9	35.7	549	671	55	30.4	39.2	C: 340
1159	61	5	27.1	36.1	488	732	60	31.2	38.9	FA: 0
1098	122	10	27.3	36.4	427	793	65	32.2	38.7	FAR: 0
1037	183	15	27.5	36.8	366	854	70	32.8	38.4	S: 656
976	244	20	27.7	37.1	305	915	75	32.6	38.5	RS: 0
915	305	25	27.9	37.5	244	976	80	32.3	38.6	RS/S: 0
854	366	30	28.1	37.8	183	1037	85	32.1	38.8	W: 184
793	427	35	28.5	38.2	122	1098	90	31.8	38.9	W/C: 0.54
732	488	40	28.9	38.7	61	1159	95	31.5	39	
671	549	45	29.2	39.1	0	1220	100	31.3	39.1	
610	610	50	29.6	39.5						

Table 6-4
Strength of RAC on different recycled fine aggregate replacement ratio.

S	RS	RS/S	7d	28d	S	RS	RS/S	7d	28d	Other
656	0	0	26.9	35.7	295.2	360.8	55	18.3	26.5	C: 340
623.2	32.8	5	25.4	34.4	262.4	393.6	60	18	26.6	FA: 0
590.4	65.6	10	23.8	33.1	229.6	426.4	65	17.6	26.6	FAR: 0
557.6	98.4	15	22.3	31.8	196.8	459.2	70	17.3	26.7	G: 610
524.8	131.2	20	20.8	30.5	164	492	75	17.2	26.6	RG: 610
492	164	25	19.3	29.2	131.2	524.8	80	17.1	26.4	RG/G: 50
459.2	196.8	30	17.8	27.9	98.4	557.6	85	17	26.3	W: 184
426.4	229.6	35	18	27.5	65.6	590.4	90	16.9	26.1	W/C: 0.54
393.6	262.4	40	18.2	27.1	32.8	623.2	95	16.9	26	
360.8	295.2	45	18.4	26.8	0	656	100	16.8	25.8	
328	328	50	18.6	26.4						

Notice: C-cement; FA-fly ash; FAR-fly ash substitution rate; S-natural sand; RS-recycled fine aggregate; RS/S-fine aggregate substitution rate, G-aggregate; RG-recycled coarse aggregate; RG/G-coarse aggregate substitution rate; W-water; W/C-water-cement ratio.

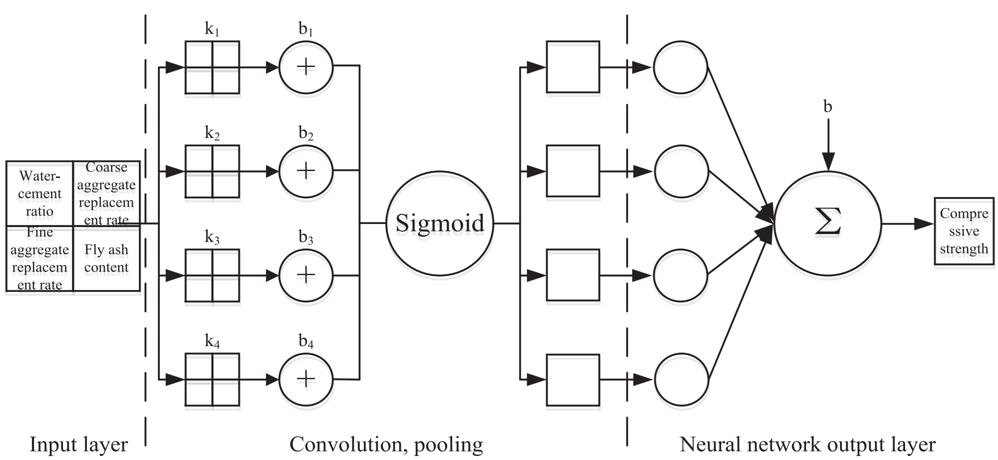

Fig. 5. Convolution neural network prediction model structure.

4.3. Prediction results and analysis

After 33 epochs of learning, the training of CNN was completed and the test data was used to test the prediction model. The network output value of the training data and the network prediction value of the test data could be obtained, which is shown in Fig. 6.

As shown in Fig. 6, the values obtained through the training and testing of CNN model are very close for experimental results, indicating a strong correlation between the input and output parameters of the CNN model. The relative error can be calculated from the testing data by using the following equation:

$$RE = \frac{|P_i - A_i|}{A_i} \times 100\% \tag{6}$$

where A_i is the actual value and P_i is the predictive value.

Fig. 7 shows the histogram of the relative error percentage rate of testing set samples predicted by the CNN model. The max and min relative errors found are 18.93% and 0.01%, respectively. Approximately 85% of the data shows the error less than 10% and all the data achieves the error less than 20%. This is another indication of the high correlation between the results obtained by CNN and the experimental results. All statistical values prove that the proposed CNN model is suitable to predict the compressive strength values.

In order to compare the performances with the deep learning method, a 4-9-1 BP neural network and a support vector machine (SVM) model were used to establish the prediction model respectively. The relative error of these three neural networks, which is

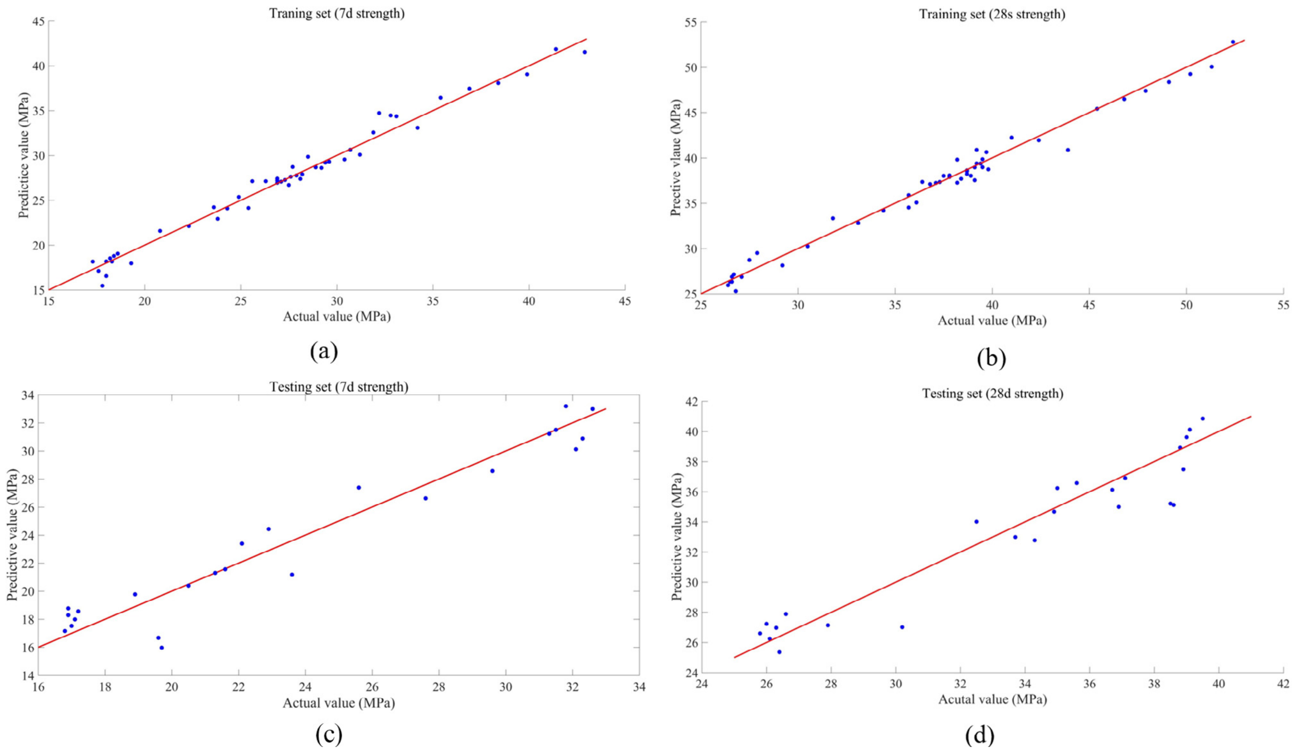

Fig. 6. Prediction results of CNN on 7d and 28d compressive strength (a) Training set of 7d strength; (b) Training set of 28d strength; (c) Testing set of 7d strength; (d) Testing set of 28d strength.

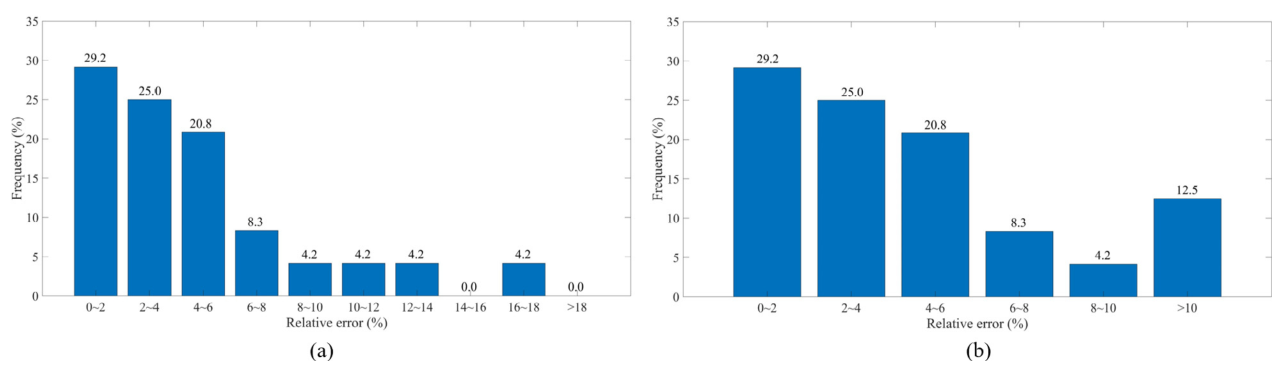

Fig. 7. Histogram of the relative errors achieved with actual and predictive values: (a) Testing set of 7d strength; (b) Testing set of 28d strength.

Table 7
Error comparison of three prediction models.

Relative error (%)	BPNN		SVM		CNN	
	7d	28d	7d	28d	7d	28d
Max	39.25	17.63	21.37	14.21	18.93	10.55
Min	7.63	5.76	3.25	1.76	0.31	0.01
Average	10.89	6.63	7.48	4.35	5.42	3.65

calculated by using Eq. (6) are shown in Table 7. It can be seen from this table that the CNN exhibits higher accuracy and stronger generalization ability compared with the BP neural network and the SVM, resulting it is more suitable for prediction of the compressive strength of recycled concrete. In addition, compared with the 7d prediction results, the 28d prediction results are more accurate. It is mainly due to the characteristics of recycled aggregate, especially the strength showing fluctuations in the early time. Thus, the prediction of early strength is relatively difficult. As the later strength is relatively stable, the prediction results are more accurate.

5. Conclusion

Due to the variability in the characteristics of RAC, it is a nonlinear relationship between the compressive strength of RAC and its mixing ratio. Therefore, a predictive model based on CNN is proposed in this paper. The CNN model can predict the strength by learning the deep features of the water-cement ratio, the recycled coarse aggregate replacement ratio, the recycled fine aggregate replacement ratio, the fly ash replacement ratio as well as their combinations. In order to prove the capability of the proposed method, 74 sets of concrete block masonry with different mixing ratios are used in the experiments. The results show that the prediction model based on deep learning exhibits the advantages including higher precision, higher efficiency and higher generalization ability compared with the traditional neural network model.

Conflicts of interest

The authors declare no conflict of interest.

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