A Lightweight FCNN-Driven Approach to Concrete Composition Extraction in a Distributed Environment

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Abstract. It is of great significance to study the positive characteristics of concrete bearing cracks, fire and other adverse environment for the safety of human life and property and the protection of environmental resources. However, there are still some challenges in traditional concrete composition evaluation methods. On the one hand, the traditional method needs a lot of experimental work, which is time-consuming and laborious; On the other hand, the cost of new technology is high, and its applicability needs further study. Therefore, this paper proposes an improved lightweight model based on fully connected neural network (FCNN) to discover the relationship between the performance of different concrete mixtures and the visual (image) performance of the final synthesis process, so as to realize the prediction of concrete composition. The model is built in a distributed environment, and it can achieve lightweight and convenient effect through remote call learning model. The experimental results show that the method greatly improves the accuracy of concrete composition prediction.

Keywords: Concrete · Lightweight FCNN · Distributed

1 Introduction

Concrete materials are widely used as building materials. In order to accurately analyze the composition of concrete and obtain the positive characteristics of concrete under adverse environment such as cracks and fire, it is necessary to improve the performance of concrete according to different needs [1]. Therefore, the researchers developed a machine learning model, combined with non-destructive testing method to analyze the composition of concrete. For example, combining Particle Swarm Optimization (PSO)

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with Artificial Neural Network (ANN) to analyze the composition and mechanical properties of concrete can effectively solve the problem of multi-variable, multi-output, but the number of research samples for optimal mix design is limited [2, 3]. K-Nearest Neighbor algorithm (KNN) and Finite State Machine (FSM) are also effectively applied to the composition analysis of fresh concrete [4, 5].

For a special type of concrete mix proportion, in the case of small sample size, it is difficult to optimize the parameters of machine learning model to achieve the optimal analysis results. Therefore, the main contribution of this paper is to design three fully connected neural network models, quantify and visually analyze the prediction results, and obtain a best network model for concrete composition prediction. We design a lightweight and efficient Fully Connected Neural Network (FCNN) [6, 7], which is called Three Layer Model with L2 Regularization ($\lambda = 0.001$) (hereinafter referred to as Three Layer Model-L2R ($\lambda = 0.001$)), retaining the characteristics of all data, analyzing the similarity and difference of concrete members, giving accurate prediction results. Finally, the algorithm is deployed on the distributed platform, so that the server hardware does not affect the operation of the algorithm, ensuring the reliability and flexibility of the algorithm [8, 9].

2 Methods

2.1 Three Layer Model-L2R ($\lambda = 0.001$) Overall Network Architecture

The improved fully connected neural network proposed in this paper is a three-layer neural network. The model was designed with two hidden layers (19 units + 38 units), and made use of L2 Regularization (L2R) in the first hidden layer with a λ value of 0.001. The architecture of the model is presented in Fig. 1.

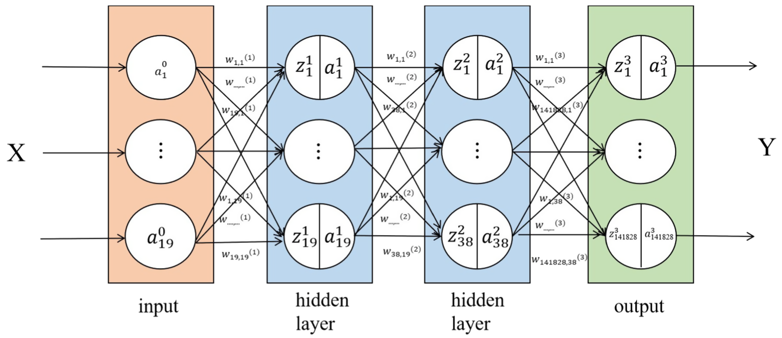

Fig. 1. Three Layer Model with L2 Regularization ($\lambda = 0.001$) model architecture

The network structure is shown in the Fig. 1. The input data is a 19 properties vector of concrete, and the hidden layer has two layers, corresponding to 19 units and 38 units respectively, which means that the 19 dimensional vector is mapped to a 38 dimensional vector through linear mapping, and finally it becomes a 141828 dimensional output. The algorithm idea is that the fully connected neural network is divided into forward propagation and back propagation. Forward propagation gives a predicted value and calculates the error between the predicted value and the real value and the inverse operation optimizes the weights of each link from the gradient direction of error reduction until the training times or the error is within the set range.

2.2 Back Propagation (BP) Algorithm

BP is an optimization process. BP is the most commonly used optimization algorithm in neural networks [10]. This direction is opposite to the forward propagation direction, so it is called back propagation. There are three main equations:

$$W^l = W^l - a\frac{\partial J\left(\alpha^l\right)}{\partial W^l} \tag{1}$$

$$b^l = b^l - a\frac{\partial J\left(\alpha^l\right)}{\partial b^l} \tag{2}$$

$$J\left(a^l\right) = \mathrm{J}\left(\sigma\left(Z^l\right)\right) = \mathrm{J}(\sigma(W^l a^{l-1} + b^l)) \tag{3}$$

The output value a^l of each neuron was calculated forward; The error term of each neuron is calculated in reverse δ^l; The random gradient descent algorithm iteratively updates the weights w and b, and the loss function J of the output layer l.

2.3 Baseline Model

A baseline model was designed in order to provide a minimum benchmark of performance and allow for meaningful comparison with various model improvements. The baseline model is a multi-layer perceptron with multiple inputs (19 properties), a single hidden layer (19 units), and multiple outputs (141828 scaled pixel values for the mixture image).

3 Deep Learning Distributed System

In this paper, we proposed an improved lightweight fully connected neural network model based on the distributed environment to predict the composition of concrete. The structure of the distributed system is shown in Fig. 2. Users can use any programming language supporting network programming, through the specified IP address or domain name address, according to the interface documentation provided by the system, they can access all kinds of deep learning computing resources provided on the host computer of the system [11–15].

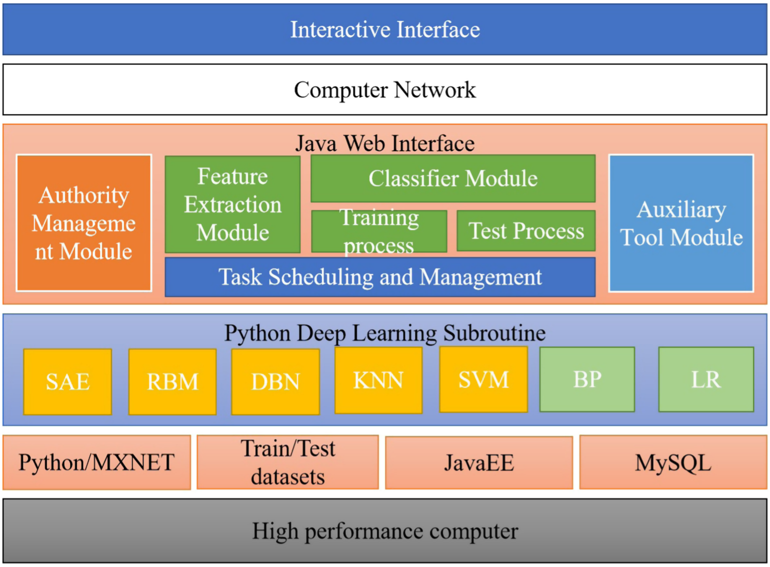

Fig. 2. Architecture of deep learning distributed system

4 Experiment and Analysis

4.1 Datasets

There are three sets of data that are used to build the model, a set of the concrete properties and a set of visual representations of the mixtures. The data sets are comprised of 3523 samples of the concrete properties and their corresponding mixtures.

4.2 Evaluation Metrics

The evaluation criteria used to determine model performance included Mean Squared Error (MSE) that means the expectation of the square of the difference between the estimated value of the parameter and the real value of the parameter. Root Mean Squared Error (RMSE) is the arithmetic square root of the mean square error, and Mean Absolute Error (MAE) is the average of absolute error, which can better reflect the actual situation of predicted value error. Model performance was determined using Structural Similarity Index (SSIM) which is a metric used to measure image quality on a scale of zero (no similarity) to one (perfect similarity).

4.3 Model Performance

To evaluate the effectiveness of improved FCNN Model proposed in this paper, three sets of comparative experiments were carried out on the given dataset.

The experiments so far indicate that we can derive meaningful results using simple model architectures. The MSE, MAE, RMSE, SSIM metrics for the cross-validation and

Table 1. Results of model evaluation on training, testing, and validation sets

Model name	10-fold cross-validation		Validation set			
	MSE	RMSE	MSE	RMSE	MAE	SSIM
Baseline model	0.013 (±0.003)	0.114 (±0.055)	0.987	0.990	0.937	0.968
Baseline model-L2R (λ = 0.001)	0.018 (±0.003)	0.134 (±0.055)	0.987	0.988	0.950	0.984
Three Layer Model-L2R (λ = 0.001)	0.012 (±0.002)	0.110 (±0.043)	0.995	0.992	0.985	0.995

the evaluation using the validation set are presented in Table 1. The metrics show that the next best performing models are Baseline Model with Three Layer Model with L2-Regularization (λ = 0.001).

Three Layer Model-L2R (λ = 0.001). This section provides a summary of the modeling process and includes details on the performance of Three Layer Model-L2R (λ = 0.001). Figure 3 shows the Three Layer Model-L2R (λ = 0.001) change results of MSE and MAE in each iteration during model training. It is obvious from the Fig. 3 that the training and test curves gradually approach the x-axis with the increase of the number of iterations, that is, they gradually approach the coincidence, that is, the MAE and MSE of the training set and the test set always decrease and approach 0, indicating that the model training effect is good. Besides, the training history shows that there are some minor fluctuations of the testing MSE, with more fluctuation with the MAE. In this paper, in order to show the visual prediction effect, the best and worst outputs generated using the verification set are shown in Fig. 4 and Fig. 5 respectively, in which different colors represent the distribution of different component attributes of concrete. Through the comparison with the original map, it can be seen that the predicted attribute components are basically consistent with the original map, and a good prediction effect

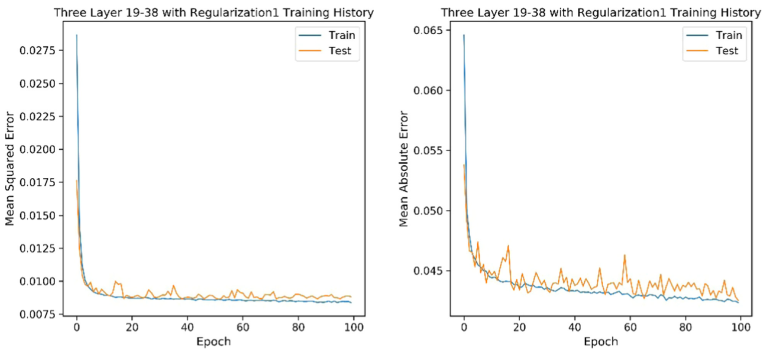

Fig. 3. Three Layer Model-L2R (λ = 0.001) model training history

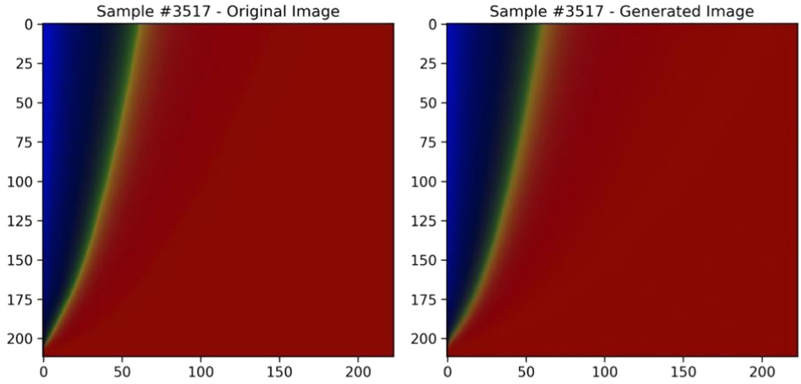

Fig. 4. Best output generated by Three Layer Model-L2R ($\lambda = 0.001$) model for sample

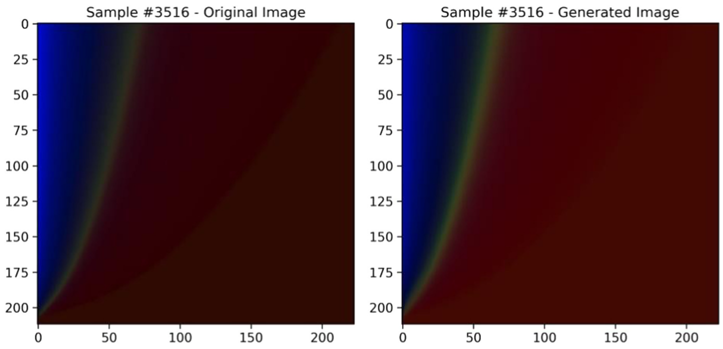

Fig. 5. Worst output generated by Three Layer Model-L2R ($\lambda = 0.001$) model for sample

is achieved. The worst output as shown in Fig. 5 for this model is exceeds the baseline model with which indicates that this model is closer to the best performance.

5 Conclusion

In this paper, we propose a deep learning distributed system, and propose an improved fully connected neural network on this system to discover the correlation between samples of nineteen concrete properties and the resulting mixtures that comprise them. The results of experimentation indicate that a three-layer architecture with 19 units and 38 units in the hidden layers, and L2 regularization ($\lambda = 0.001$) in the first hidden layer has the best performance overall, especially when given challenging unseen data. The recommendation is therefore to make use of this model for future work.

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