Deep learning model of concrete dam deformation prediction based on CNN

Wen Xi¹,², Jie Yang¹, Jintao Song¹, and Xudong Qu¹

¹ Institute of Water Resources and hydro-electric Engineering, Xi’an University of Technology, Xi’an 710048, China.
² Shaanxi Province Institute of Water Resources and Electric Power Investigation and Design, Xi’an 710001, China.

Correspondence should be addressed to Xudong Qu; qxd@stu.xaut.edu.cn

Abstract: The concrete dam deformation prediction model is a key measure to predict the evolution of structural behavior and evaluate the safe service status. This paper uses open-source deep learning framework TensorFlow as the platform and uses the mature convolutional neural network technology in deep learning theory to establish the concrete dam deformation safety prediction model based on a deep learning. The application of engineering examples shows that the residual map, mean square error, and average percentage error are used as the model fitting and prediction accuracy evaluation standards. Compared with the shallow neural network model and the traditional Statistical model, the concrete dam deformation prediction model based on deep learning has higher prediction accuracy and more stable performance, providing a new method for concrete dam deformation monitoring.

1. Introduction

According to the latest data, China has the largest number of reservoir dams in the world. As of the end of 2018, 98,822 reservoir dams have been built across the country. Concrete dams have always been one of the recommended dam types for dam construction in China due to their safe and reliable performance. Located in high mountains and valleys, it often faces the problem of manual operation and maintenance. The external environment of the concrete dam is complicated during the service process, which further aggravates the difficulty of later monitoring and feedback control. As a direct and accurate reflection of the safety behavior of the concrete dam, data analysis of dam deformation is often used to control the safety of the concrete dam. [ii,iii,iv,v,vi]

There are still certain shortcomings in this regard, and it is impossible to fully transform scientific research results into engineering practice productivity[vii,viii]. Because of the shortcomings of the existing concrete dam deformation prediction theory and the unique advantages of CNN, the CNN network in the deep learning theory is applied to the concrete dam deformation prediction model, which can effectively process, analyze and predict the deformation monitoring data of the concrete dam, and improve the model's performance. The prediction accuracy and generalization are more true to reflect the working behavior of the dam.

2. Statistical prediction model of concrete dam deformation

According to the physical and mechanical characteristics of concrete dams and actual engineering conditions, the statistical prediction model of concrete dam deformation can adopt the following
3. Principles of Convolutional Neural Networks

3.1. CNN STRUCTURE

CNN is mainly composed of the input layer, convolution layer, sampling layer, fully connected layer, and output layer, its basic form is shown in Figure 1.

![Figure 1 Basic structure of the CNN model](image)

3.2. CNN PRINCIPLE

The hidden layer of CNN is mainly composed of a convolutional layer and a sampling layer. Through convolution and pooling operations, the distortion tolerance of the input sample is improved, and the deep structure of the input information is also used to realize the deep mining of the input information features.

The convolutional layer is mainly based on the input two-dimensional form of the data feature matrix, and the convolution kernel is mapped to the hidden layer for deep learning of data features, to realize the deep mining of data features. Assume that the total number of input samples is n, and the k-th input matrix is X_k, its corresponding convolution kernel is W_k, S(i,j) represents the value corresponding to the i-th row and j-th column of the output matrix corresponding to the convolution kernel. The expression of the convolution process is as follows:

$$S(i,j) = \sum_{k=1}^{n} (X_k \otimes W_k)_{(i,j)} + b$$

among them; \(\otimes\) is a convolution operation; \(b\) is the offset value.

The activation function in the network is used to improve the nonlinear ability of CNN, and the commonly used ReLU function is selected. The specific form is as follows:

$$f(x) = \begin{cases} 0, & x \leq 0 \\ x, & x > 0 \end{cases}$$

CNN uses the pooling layer to scale and map the data of its upper layer to reduce the data dimension. The extracted features are scale-invariant and can also prevent over-fitting. Generally, pooling methods such as mean pooling are used.

The output layer of CNN generally adopts the form of fully connected. Considering that the goal of this time is regression analysis, the widely used ReLU function is selected as the activation function of the fully connected layer.
3.3. Parameter training of CNN

The CNN network model is an extension of the neural network model. To prevent overfitting of model parameters, the most commonly used gradient descent method of deep learning is used for parameter training and optimization, and the loss objective function is constructed:

$$L(\theta) = \min \left( \sum_{j=1}^{N} (p_j - o_j)^2 \right)$$ (4)

among them: $$L(\theta)$$ is the objective function; $$p_j$$ is the ideal output value; $$o_j$$ is the actual output value; $$N$$ is the total number of samples.

The parameter update formula is as follows:

$$\theta_i = \theta_{i-1} - \eta \nabla L(\theta_{i-1})$$ (5)

among them: $$L(\theta)$$ is the objective function; $$\nabla L(\theta_{i-1})$$ is the parameter gradient; $$\eta$$ is the learning rate; $$\theta_{i-1}$$ is an un-updated parameter; $$\theta_i$$ is the updated parameter.

4. CNN-based concrete dam deformation prediction model

4.1. Data preprocessing

The statistical method is used to process the gross error of the concrete dam monitoring data, and the water pressure component of the statistical model is selected $$H-H_0$$, $$H-H_0^2$$, $$H-H_0^3$$; The temperature component is taken $$T_s - T$$, $$T_{so} - T$$, $$T_{so} - T$$, $$T_{so} - T$$; The aging component is taken $$\theta$$, $$\ln(1+\theta)$$ . Equal environmental impact factor and displacement monitoring value corresponding to the measuring points. As a model data set, the environmental impact factors are separately standardized, and the model data set is divided into a training set and a test set.

4.2. Model training and prediction

The preprocessed standardized data set training samples are converted into a 3×3 matrix as the model input, and the error backpropagation is solved by the gradient descent algorithm to make the model loss function meet the set error requirements, and the optimal solution of the network model parameters is obtained. Input the independent variable factor data of the test set into the trained optimal parameter prediction model to obtain the corresponding deformation prediction results.

4.3. Model performance evaluation

According to the concrete dam deformation prediction model evaluation system, the results of the concrete dam deformation prediction model based on CNN and the deformation prediction model results based on the classic least square method OLS and support vector machine SVM were compared and analyzed.

5. Engineering example application

5.1. Project introduction

A project is located in Fujian Province, with a total installed capacity of 250MW and a total reservoir capacity of 47 million m³. The power station pivot barrage is a roller-compacted concrete gravity dam, and the deformation monitoring includes items such as horizontal and vertical displacement of the dam. A total of 11 dams are arranged. Measurement points, including 9 working measurement points, are located at the top of each dam section; 2 check base points are located at the left and right ends of the tension line. The horizontal displacement of the dam is monitored by the tension line method, and the tension line is fixed the end is arranged at 01+107.025 on the right side of the dam, and the leading end is arranged at 0+93.50 on the left side of the dam. Figure 2 is the plan layout of the monitoring...
points of the tension line of the concrete dam.

![Figure 2 Plane layout of monitoring points for extension line of the concrete dam crest](image)

5.2. Predictive model impact factors and data set selection
The horizontal displacement of the ex1 measuring point from June 2, 2016 to October 22, 2018 was selected as the model-dependent variable sample, and the water depth, temperature and derived variable data in front of the dam in the reservoir area were selected as the model-independent variable sample, a total of 864 samples. The original sample data is subjected to gross error elimination and standardization. The number of test samples is 164. Based on this, the application research of the concrete dam deformation safety prediction model based on OLS, SVM, and CNN is carried out.

5.3. Predictive model training and prediction

5.3.1. Model parameter setting
According to the experiment of the relationship between the target loss function and the model parameters, the SVM kernel is determined to be a radial basis function, that is, a Gaussian kernel, and the kernel parameter C=0.72. First, the initial weights and paranoid parameters of the CNN model are randomly generated through the built-in random function of TensorFlow. The learning rate selected by experience is 0.11, and the activation functions of the convolutional layer, the pooling layer and the fully connected layer are all selected as the ReLU function. The objective loss functions of the OLS, SVM and CNN models are all square loss functions, and the model solving methods are all gradient descent algorithms.

5.3.2. Model prediction analysis
Based on the preprocessed standardized monitoring data, a concrete dam deformation prediction model based on OLS, SVM and CNN was established. Figure 3 shows the actual measured value and predicted value process line of each model concrete dam deformation prediction model.

![Figure 3 Process line of predicted and measured value of concrete dam deformation of each model](image)
Through the analysis of Figure 3, it can be seen that the deep learning-based CNN concrete dam deformation prediction model curve has the highest agreement, the target loss function is the smallest, the model training results are better, and its prediction performance is also significantly better than the statistics-based OLS and SVM concrete dams. Deformation prediction model. It also proves that traditional statistical methods and shallow machine learning methods still have certain defects in the establishment of concrete dam deformation prediction models, and deep learning can better mine the internal characteristics of monitoring information to reflect the structure the authenticity of it has good practical reference value.

5.3.3. Model evaluation
In order to verify the performance of the CNN-based concrete dam deformation prediction model, the commonly used prediction value and the measured value residual map, the mean square error and the average percentage error evaluation index are selected to measure the accuracy of the prediction model, and the accuracy of the prediction model is measured based on OLS, SVM and CNN. The accuracy calculation results of the concrete dam deformation prediction model of the concrete dam are compared and analyzed. The smaller the calculation result, the higher the accuracy of the model. The horizontal displacement residuals of each model are shown in Figure 4. The calculation results of RMSE and MAPE of each model are shown in Table 1.

![Figure 4 Model horizontal displacement residual diagram](image)

Table 1 Accuracy indexes of prediction models

| Predictive model | RMSE  | MAPE  |
|------------------|-------|-------|
| OLS              | 0.328 | 29.708|
| SVM              | 0.247 | 24.779|
| CNN              | 0.032 | 3.164 |

Analyzing Figure 4 and Table 1, it can be seen that compared to the traditional statistical method OLS, the shallow machine learning algorithm SVM effectively improves the accuracy of the model, but the CNN prediction effect based on deep learning is the best and has high accuracy. Compared with the indicators of the OLS and SVM concrete dam deformation prediction models, the CNN-based concrete dam deformation prediction model has the smallest horizontal displacement residual, with RMSE lower than 0.1 and MAPE lower than 10, which are all in a lower interval. Therefore, based on CNN's concrete dam deformation prediction model has better accuracy performance, and the prediction results are closer to real data.

6. Conclusion
(1) Compared with the traditional concrete dam deformation prediction model, the successful application of shallow machine learning theory has further improved the fitting and prediction accuracy of the model, but most intelligent prediction models still have certain defects in terms of prediction performance. Cause practical application difficulties.

(2) The concrete dam deformation prediction model based on CNN effectively improves the
prediction accuracy, robustness, and generalization capabilities of the model, and enhances the adaptability of the model to monitoring data. These good properties further strengthen the deformation of the concrete dam. The sensitivity of safety warnings.

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