Research on Tailings Dam Displacement Prediction Model Based on CNN

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Abstract: Tailings dam displacement prediction is one of the important elements of safety management in mining enterprises, and accurate prediction and timely maintenance measures are essential to prevent dam failure accidents. However, the existing prediction methods only consider the influence of single factor on tailings dam displacement, resulting in poor accuracy in predicting tailings dam displacements. Improving tailings dam displacement prediction accuracy, an intelligent prediction model based on CNN for tailings dam displacement prediction was established. The results show that the established CNN prediction model, MAE 0.07113, MSE 0.00733, RMSE 0.08565; the prediction results have prediction accuracy and stronger robustness compared with RF, NB and Xgboost prediction models. The research results in this paper are important to support safety and stability of tailing dam operation.

1 INTRODUCTION

In the beneficiation process, the residue remaining after screening and extraction of useful minerals from the ore by physical and chemical action is called tailings. Typically, a tailings dam is a dam built to form a field reservoir for the storage of various ore tailings. Structural instability of tailings dams can cause dam failures, and the quality of their operation has a direct impact on the safety of life and property of mining companies as well as downstream people (He W, 2023).

Machine learning algorithms are widely used in the field of tailings dams and slope deformation, and many mining companies are gradually establishing artificial intelligence tailings dam monitoring systems to dynamically monitor the operation of tailings dams (Liu JX, 2022). Machine learning algorithms are widely used in the field of tailings dams and slope deformation. Hua Guowei et al. (Hua GW, 2022) In order to accurately predict the deformation trend of tailings dam, a PCA-BBO-SVM tailings dam deformation prediction model was established, using Yangjiawan tailings dam data as training data, and demonstrated that the model has higher prediction accuracy and prediction ability for localized fluctuations than the BP model. Si-Cheng Yi et al.(Qin S, 2002) proposed an anomaly data diagnosis model based on multi-point correlation and improved isolated forest algorithm, which can effectively distinguish noise from real anomalous values in tailings dam displacement monitoring sequences and improve the accuracy of the monitoring system. However, the slope deformation is influenced by many factors and the mechanism of influence is complicated, because the statistical model is less flexible, it cannot deeply extract the internal characteristics of the data and achieve better prediction.

Intelligent algorithms mainly refer to the use of a data-driven approach to establish suitable machine learning algorithms for prediction and monitoring of slope deformation. The commonly used intelligent prediction methods are nonlinear model, neural network (BP) (Du J, 2013), support vector regression (SVR) (Cao Y, 2016), Extreme Learning Machine (ELM) (Zhang Lyr, 2022) Numerous machine learning algorithms, such as the displacement and deep learning, have been introduced into the slope deformation prediction model with displacement as the core prediction variable (Kavzoglu T, 2019). Pham et al.(Pham V D, 2020) used the Moth Flame Optimizer (MFO) to optimally search the hyperparameters (values of filters) of the CNN and compared the model with traditional classification algorithms, such as random forest, random subspace, and CNN refined for adaptive slope descent, as well as the analysis demonstrated that the benchmark approach was exceeded in all comparative metrics

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when the suggested algorithm is suitable to be a replacement for monitoring landslide deformation. Wu et al. (Wu L, 2022) used a time series approach to decompose cumulative landslide deformation into periodic and trend deformation, and cubic polynomials were used to predict the trend deformation. Considering the periodic variation of rainfall and reservoir level, the proposed model could better capture the characteristics of the provided data and improve prediction accuracy compared to GRU, and C-GRU attains a lower mean error in squares and represents an important increase in landslide accuracy in forecasting.

In summary, domestic and international research trends show that slope deformation is more displacement-oriented, and slope displacement is influenced by both internal and environmental factors, and intelligent algorithms of machine learning and deep learning among intelligent algorithms are widely applied in the prediction of slope displacement and obtain good development results. However, many factors affect dam deformation, and dam deformation prediction needs to consider more comprehensive factors. Therefore, in this paper, CNN is combined and optimized, and traditional indicators such as infiltration line, reservoir level and other related factors are considered, and weather factors such as wind speed and temperature are incorporated.

2 CNN MODEL CONSTRUCTION

2.1 Tailings Dam Displacement Influencing Factors

Tailings dam displacement is driven by its own geological structure, topography, external human activities, climate, runoff and other conditions, so that the originally stable slope can suddenly and strongly deform. The factors affecting tailings dam deformation can be divided into three categories: first, internal factors, including infiltration line, reservoir water level, dam settlement and other factors; second, environmental factors, including weathering, rainfall, temperature, etc.; third, human factors, including mining operations.

2.2 CNN Model

Fundamental structure of CNN consists of input layer, convolutional layer, pooling layer, fully connected layer and output layer. Generally, multiple convolutional layers and pooling layers are adopted, and the convolutional layers and pooling layers are set up alternately, which means that one convolutional layer attaches to one pooling layer, and the pooling layer attaches to another convolutional layer following the pooling layer. The output feature surface of the convolutional layer of each neuron is locally connected to its input, and the corresponding connection loadings are weighted and added to the local input plus bias to obtain the input value of the neuron.

2.3 Convolutional Layers

The convolutional layers of a CNN extract different features of the input through convolution operations. The first convolutional layer extracts low-level features for edges, lines, and corners, while the high-level convolutional layer extracts the high-level features. Each convolutional layer in a CNN satisfies the following relationship with respect to the size of each output feature surface (namely, the number of neurons):

$$\mathrm{o}MapN = \left(\frac{iMapN - CWindow}{CInterval} + 1 \right) \quad (1)$$

where iMapN is dimension of each input feature surface; CWindow is dimension of the convolutional kernel; CInterval is the length of the sliding step of the convolutional kernel in the layer preceding it, and in general, there is a need to make sure that Equation (1) is integrable or the CNN network structure requires additional processing. Amount of trainable parameters within each convolutional layer CParams satisfy equation (2)

$$CParams = (iMap \times CWindow + 1) \times oMap \quad (2)$$

Where oMap is one of the number of output eigenfaces of each convolutional layer; ioMap is one of the number of input eigenfaces.1 denotes the deviation, which is shared among the same output eigenfaces.

Among the CNN structures, more depth and more number of feature facets, the greater the feature space that the network can represent, the stronger the network learning ability, but at the same time, it will also make the network computation more complex as well as prone to overfitting. Thus, in practical applications, the depth of the network, the number of feature facets, the size of the convolution kernel and convolution's sliding step should be appropriately selected in order to obtain a good model while shortening the time of training.

2.4 Pooling Layer

The pooling layer is immediately followed by the convolutional layer, which also consisting of multiple eigenfaces, each uniquely corresponding to one of the eigenfaces of its previous layer, without changing the number of eigenfaces. Let the output value of the lth neuron of the nth output eigenface in the pooling layer be t_{nl}^{out} , then we have

$$t_{nl}^{out} = f_{sub}(t_{nq}^{in}, t_{n(q+1)}^{in}) \quad (3)$$

where t_{nq}^{in} denotes the output value of the qth neuron on the nth input eigenface of the pooling layer; $f_{sub}(\bullet)$ can be the take maximum function, take mean function, etc. The size (number of neurons) of each output eigenface of each pooling layer in the CNN $DoMapN$ is

$$DoMapN = (\frac{oMapN}{DWindow}) \quad (4)$$

Where the pooling kernel is of size $DWindow$, the pooling layer decreases the computational effort in the network model by reducing the number of connections between convolutional layers, i.e., reducing the number of neurons through the pooling operation.

2.5 Fully Connected Layer

Within a CNN structure, multiple convolutional and pooling layers are followed by the connection of one or more fully connected layers. Similar to MLP, the neurons in a fully connected layer are fully connected to all neurons in the previous layers. While fully connected layers enable the integration of local information from convolutional or pooling layers with category distinctions.

3 RESULTS

In order to study the tailing dam displacement variation data as well as to better train the neural network, this paper adopts the monitoring data of a tailing pond as the test data for training the model. The input data include factors such as infiltration line, reservoir water level, dam settlement and rainfall. The sample size is 8261, of which the training set is 80% and the validation set is 20%.

3.1 CNN Prediction Results

The results of training and simulation of CNN convolutional neural network as shown in Fig. 1. The chart shows that CNN has a better prediction effect, and the predicted value is close to the real value. the RMSE of CNN is 0.08565, MAE is 0.07113, and MSE is 0.00733, which basically matches the real value in the first period of data, and some deviations appear in the middle of June, but the overall trend is consistent with the real value The overall trend is basically consistent with the true value. The reason for the deviation may be due to the existence of partial rainfall, the rainfall season should be in July-August, and less rainfall in January-May, resulting in a small change in the data of rainfall, and it is difficult for the model to learn the effect of rainfall on displacement, so it leads to a certain deviation in the middle of June.

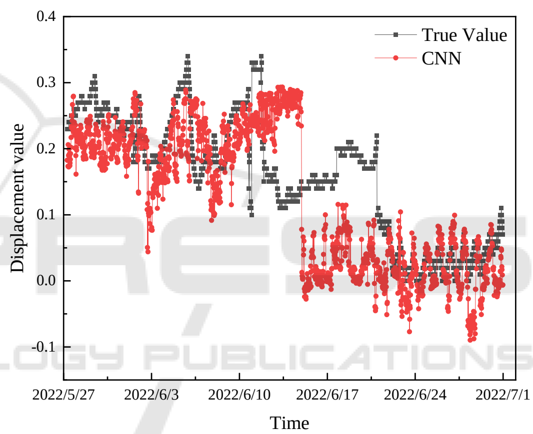

Figure 1. CNN prediction diagram.

3.2 Multi-Model Comparison Test

In order to verify the prediction effect of the CNN model proposed in this paper compared with other models, the RF algorithm, Xgboost model and NB algorithm were used to compare with the CNN model, as shown in Fig. 2. The RMSE value of the Xgboost test set was 0.09322, the MAE value was 0.07836 and the MSE value was 0.00869. The RMSE value of RF test set is 0.09601, MAE value is 0.07532, and MSE value is 0.00921. The RMSE value of NB test set is 0.09444, MAE value is The predicted results of the NB model did not effectively predict the trend of displacement changes, and the predicted results maintained fluctuations in fixed values, which had large deviations from the true values.

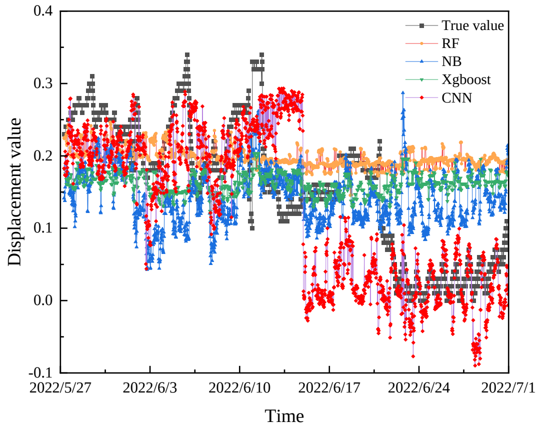

Figure 2. Multi-model prediction comparison diagram.

The comparison graph of prediction errors of the four models is shown in Fig. 3, which indicates that the MAE, MSE and RMSE of the CNN model are smaller, indicating that its model prediction is better and more suitable for tailings dam deformation prediction. The model fully explores the relationship between the time series data of tailings dam deformation and the influencing factors, learns the long-term trend and law of tailings dam deformation over time in depth, and achieves a high level of prediction.

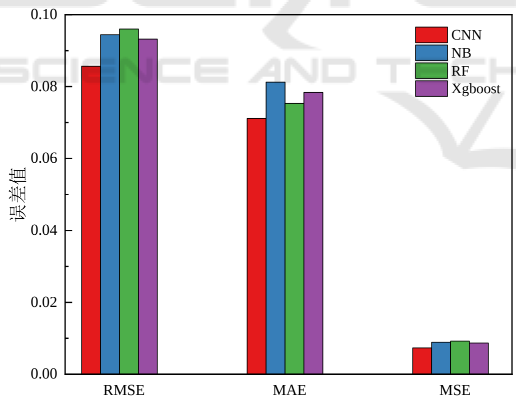

Figure 3. Multi-model error comparison diagram.

4 CONCLUSION

(1) The predicted values of the CNN-based tailings dam displacement prediction model are closer to the real values and have better prediction effects, with RMSE of 0.08565, MAE of 0.071138 and MSE of 0.00733.

(2) By comparing CNN prediction model with many other prediction models outperforms RF, NB and Xgboost prediction models, and the predicted values fit better with the true value curve. The model achieves excellent prediction performance by fully exploiting the relationship between time series data and avoiding problems such as gradient disappearance. After comparison experiments, it is found that this model has excellent prediction ability in the field of tailings dam deformation prediction and can be widely applied.

(3) Although the constructed model has achieved good prediction results, research on the performance of the prediction model still needs to be strengthened. Subsequently, the characteristics of tailings dam deformation data will be explored, the spatial correlation of different monitoring data will be further considered fully, and the implied relationships of different factors affecting monitoring will be analyzed in depth.

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