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TECHNICAL ARTICLE

Predicting the Height of the Hydraulic Fracture Zone Using a Convolutional Neural Network

Peihe Zhai[1] · Nianzheng Li[1]

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Abstract
After analyzing a large amount of related data, five indicators, such as mining thickness and mining depth, were selected as the main factors influencing the height of the hydraulic fissure zone. On this basis, first the convolutional neural network was trained and tested based on the measured hydraulic fracture zone development height in 40 mining areas to obtain the best convolutional neural network model. Next, the trained network model was used to predict the height of the hydraulic fracture zone of the 1301N working face in the Longgu coal mine. The predicted results were compared with the measured results and the value calculated using the gauge formula and the absolute and relative errors of the model-predicted results were less than the regulatory values. Finally, the convolutional neural network prediction results of the five test cases were compared with back-propagation (BP) neural network and multiple linear regression predicted results, and the absolute error and relative error of the convolutional neural network model prediction results were better than those of the other two predictive models. Thus, the convolutional neural network prediction model is suitable for predicting the height of the hydraulic fracture zone and can predict the developed height of the hydraulic fracture zone more accurately than other predictive methods.

Keywords Coal mine · BP neural network · Multiple linear regression · Regression prediction

Introduction

Following coal seam mining, the roof rock at the working face undergoes significant movement under the influence of mine pressure, resulting in fracturing and the formation of a water-conductive fissure zone (Shi et al. 2012). This zone is capable of transferring water from the aquifer to the working face, creating considerable risk to the safety of coal mining operations. As such, predicting the height of the water-conducting fissure zone has significant benefits in ensuring the safe mining of coal mines and mitigating water hazards in mines.

At present, there are many methods to determine the height of the hydraulic fracture zone, (Bharti et al. 2019; Kumar et al. 2021; Singh et al. 2019) such as field measurement, empirical formula prediction, similar material simulation, and numerical analysis (Shi et al. 2019), but each method has its limitations and drawbacks. Li et al. (2015) analyzed and summarized the main factors affecting the height of the hydraulic fracture zone and used a BP neural network model to predict the height of the hydraulic fracture zone. Shi et al. (2019) used gray correlation analysis to find out the major and minor factors affecting the height of the hydraulic fracture zone, and then used principal component analysis to downscale the data and established a principal components analysis and back propagation (PCA-BP) neural network model to predict the height of the hydraulic fracture zone. Qiao et al. (2022) used regression analysis to determine a predictive formula for the developed height of the hydraulic fracture zone under the conditions of different main control factors. Zhang et al. (2013) used a support vector machine (SVM) to establish a model to predict the height of the hydraulic conductivity rift zone. Lou and Tan (2021) used a particle swarm optimization (PSO) algorithm to optimize the weights and thresholds of the BP neural network to establish a prediction model of hydraulic conductivity rift zone height based on PSO-BP neural network. However, the BP neural network methods have problems such as slow convergence speed and easy falling into local minima, while the predictive performance of the SVM model is closely

✉ Nianzheng Li
1822525558@qq.com

[1] College of Earth Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China

related to parameter selection and the parameter optimization process has not been well solved yet. Therefore, we thoroughly analyzed the factors influencing the height of the water-conducting fissure zone and established a convolutional neural network prediction model using a convolutional neural network, which has rarely been done before (Xie et al. 2017).

Study Area Overview

The Longgu well field is located in the middle of the Juye coalfield, and a tectonic pattern bounded by the Wensi fault, the Yishan fault, the Liaocao fault, and the Shanxian fault has been formed in the regional tectonic range, as shown in Fig. 1 (Yu 2020). The eastern boundary of the Longgu well field is the Tianqiao fault, the western boundary is the top outcrop of the Ordovician system, the southern boundary is the Liuzhuang and Xingzhuang faults, and the northern boundary is the Chenmiao fault and the I exploration line. The bottom of the wellfield is oriented roughly north–south and eastward and is generally a monoclinic structure, with sub-level wide and gentle folds and a certain number of faults, and magmatic rocks intruding into the coal strata in local sections, with a medium degree of structural complexity (Han et al. 2018).

There are two production levels in the mine, − 810 m and − 950 m, and the entire mine area is divided into 16 mining areas, as shown in Fig. 2 (Yu 2020). At present, the main production areas of the mine are the first mining area, the second mining area south, the second mining area north, and the third mining area.

The next level of broad and gentle folds in the well field are mostly near north–south in the axial direction and longer in extension, running through the whole area, with dorsal and oblique intervals. The dip angle of the strata is mostly 5–10°. The local section of the Tianqiao fault has a steeper dip angle, generally 10–30°, while the local section of the Ma Zhuang fault can reach 30°. Throughout the whole well field, the dip angle of the stratum is gentle in the middle and west and steep in the east.

The fracture structure in the well field is controlled by regional tectonics and is mainly divided into two groups: north–south and northeast. Among them, there are more near north–south faults, and the main faults are mostly developed in the axis of the main back slope, followed by northeast faults, while the faults in other directions are not very developed. Generally, the near north–south fault drop is

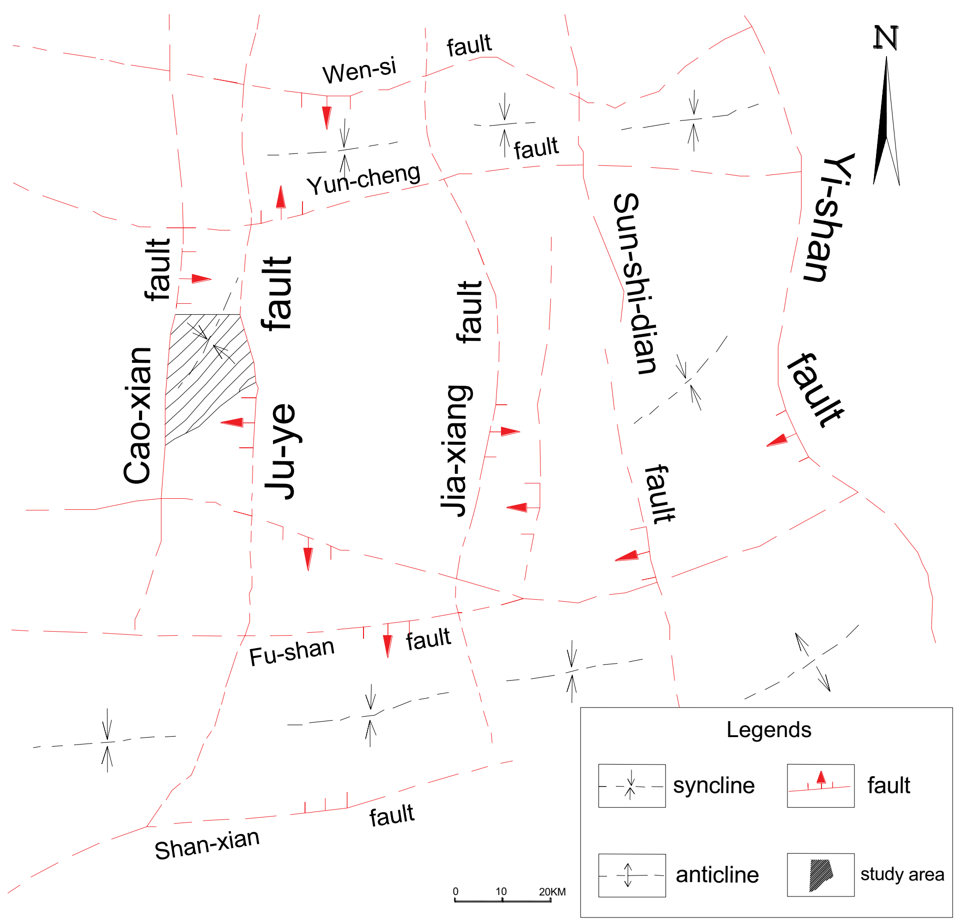


Fig. 1 Regional structure diagram

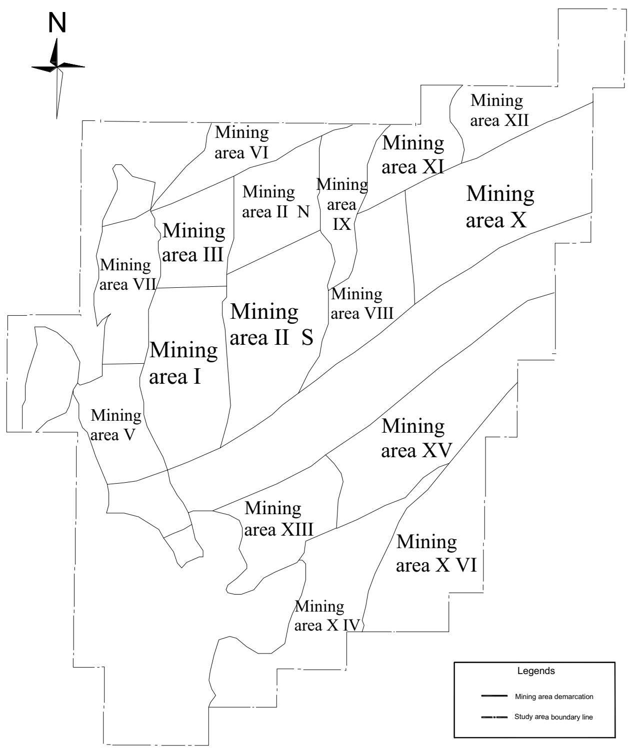


Fig. 2 Schematic diagram of mining area division

small in scale, while the northeast fault drop is large, and the northeast fault cuts the near north–south fault. The Tianqiao, Liuzhuang, Xingzhuang, and Chenmiao faults, which are the boundary faults of the well field, are high-angle positive faults, like most of the faults in the well field, while low-angle reverse faults are less developed (Wu and Peng 2016).

The Longgu coal mine 1301N working face is located in the − 810 m level, one mining area north of the north wing of the track uphill, west of the not yet mined 1302N working face, east of the north zone tape road to protect the coal column, and north of the not-yet explored third mining area. The working face layout is shown in Fig. 3 (Li et al. 2010).

Analysis of Factors Influencing the Evolution of Fractures in Overlying Strata

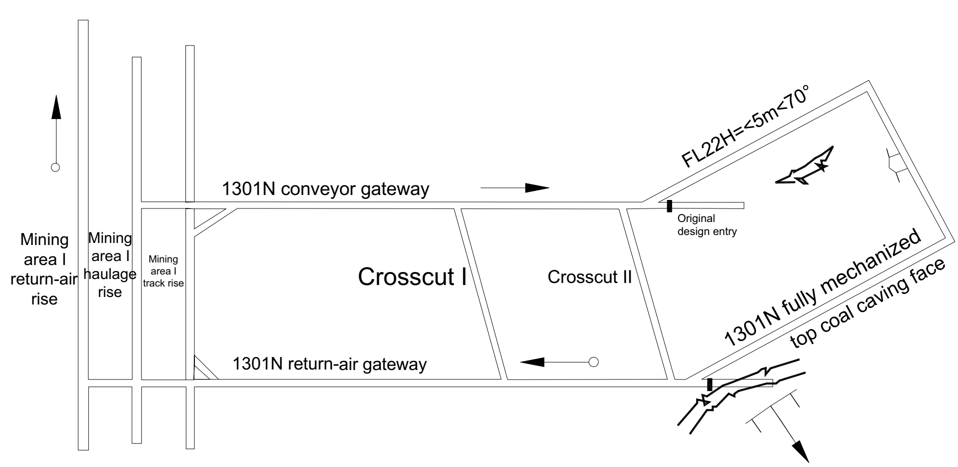
In this paper, five factors, i.e. mining thickness, mining depth, working face slope length, coal seam inclination angle, and overburden structure, were identified as the main factors for predicting the height of hydraulic fissure zone based on various aspects such as the ease of data collection, ease of quantification, and the importance of hydraulic fissure zone development. Secondary factors (e.g. lithology and resistivity) are factors that can be temporarily disregarded or assigned smaller weight values in the predictive model under certain conditions to obtain faster and more accurate predictions (Zhao et al. 2015).

Mining Thickness

The mining thickness is not the thickness of the coal seam, but the thickness of the coal seam being mined, while the thickness of the coal seam refers to the thickness of the objective coal seam in the region. With increased mining thickness, the damage range of the plastic zone of the working face roof becomes larger and the damage degree becomes stronger, resulting in an increase in the height of the caving zone, which affects the development of the water-conducting fracture zone.

When a thin coal seam is mined in a single layer or a medium-thick and thick coal seam are mined in layers for the first time, the height of the hydraulic fissure zone is linearly related to the mining thickness; when thick and extra-thick coal seams are mined in layers, the height of hydraulic fissure zone is a fractional function related to the mining thickness; when the comprehensive mining is released, the relationship between the height of the hydraulic fissure zone and the mining thickness is also a fractional function (Beijing Mining Research Institute, Institute of Coal Science 1981; Li et al. 2015).

Fig. 3 Working face roadway location diagram



Mining Depth

In actual coal mining, the original rock stress to which the rock seam is subjected to increases with the mining depth. Mining of the rock seam induces a new stress equilibrium state. In addition, the damage range of the surrounding rock after excavation shows a strong positive correlation with the burial depth of the coal seam; that is, under normal mining conditions, the greater the mining depth, the more the coal body is affected by the mine pressure, and the more serious the damage is, which eventually leads to greater development of the water-conducting fissure zone (Li et al. 2022; Xun et al. 2021).

Slope Length of the Working Face

According to material mechanics, the bending degree of a rocking beam fixed at both ends is proportional to the span of the rocking beam. So, the larger the span of the mining face, the greater the downward bending of the top rock beam, the higher the probability of rock beam fracture, and the greater the height of fissure zone development. Therefore, the slanting length of the working face is an important factor indispensable for predicting the height of the hydraulic fracture zone.

Coal Seam Dip Angle

For horizontal and gently inclined coal seams, the inclination angle of the seam is small, and the top slab will not slide along the inclination after the coal seam collapses during mining. When the inclination angle is relatively large, the top slab will slide along the inclination when it collapses. When we mine upward inclined, the developed height of the fissure zone is limited. And with inclined mining, the fissure zone height is increased. Therefore, the size of the coal seam inclination angle also has an important influence on the development height of the hydraulic fissure zone.

Overlying Rock Structure

The stronger the overlying rocks and the less the coal seam hardness, the greater the possibility of coal seam drawdown. The increase of coal seam drawdown area also affects the height of the water-conducting fissure zone development. Therefore, we take the overburden rock structure as a reference factor affecting the development of the hydraulic fissure zone, and we usually classify the overburden rock structure according to the uniaxial compressive strength of the overburden rock, including hard-hard type, soft-hard type, hard-soft type, and soft–soft type. Among them, the hard-hard type of hydraulic fracture zone has the greatest height, and the soft-weak type hydraulic fracture zone has the smallest. In the order of development height from largest to smallest, we designated these four types as 1, 0.75, 0.50, and 0.25, respectively (Li et al. 2015).

Secondary Factors

To simplify the hydraulic fracture zone height predictive model, some minor factors can be left out for the time being, and after the prediction model is established, it can be decided whether the minor factors need to be considered according to the accuracy requirement. Undeniably, secondary factors (such as lithology and resistivity) can influence the height of the hydraulic fracture zone to some extent, but in engineering practice and to simplify the predictive process, the secondary factors can be ignored as long as accuracy is retained.

Convolutional Neural Network Model

An Overview of Convolutional Neural Networks

The proposal of convolutional neural networks was inspired by the receptive field mechanism in biology. The receptive field mechanism refers to the property of some neurons in the auditory and visual nervous systems that receive signals only from the stimulus area they innervate. The size of the receptive field can be calculated recursively by the following equation.

$$R_e^i = min\left(R_e^{i-1} + \left(K_e^i - 1\right)\prod_{j=0}^{i-1} s_e^j, L_e\right), \tag{1}$$

where: $e \in \{\omega, h\}$,ω is the width of the input image, h is the height of the input image.L_e is the size of the original input data, R_e^i is the size of the perceptual field in the layer i, K_e^i is the size of the convolution kernel in the layer i, and s_e^j is the sliding step of the convolution kernel in layer j. In particular, for the original input data layer, R_e^i as well as s_e^j are 1; for the activation layer and batch normalization (BN) layer, R_e^i and R_e^{i-1} are equal and the value of s_e^j is 1 for the fully connected layer,$R_e^i = L_e$.

The convolutional neural network is a deep feed-forward neural network with local connectivity and weight sharing, which uses multilayer algorithms for supervised learning of binary classifiers to analyze data. Convolutional neural networks mainly consist of an input layer, a convolutional layer, an activation layer, a pooling layer, and a fully connected layer. As shown in Fig. 4, unlike fully connected methods, convolutional neural networks are locally connected, which requires each node to be connected to only some of the nodes in the lower layer. Moreover, convolutional neural networks also have a feature of weight sharing, i.e. the weight

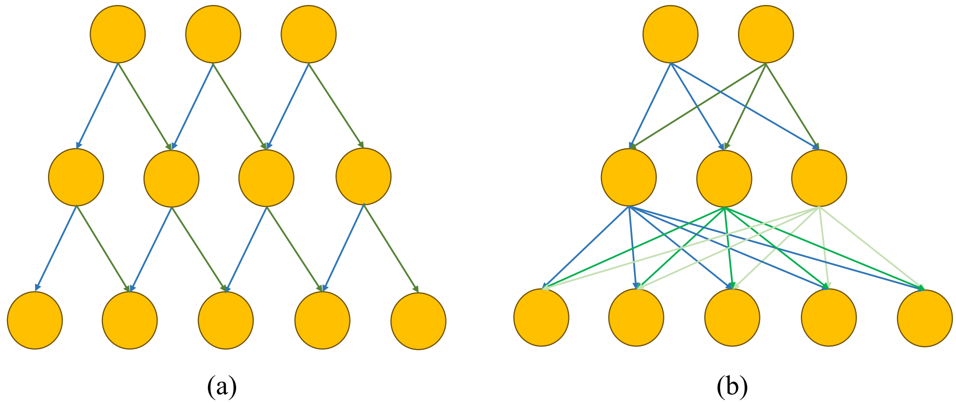


Fig. 4 Convolutional neural network connection method (**a**) and full connection (**b**)

coefficients of nodes at different locations in the same convolutional layer are shared. These two features allow convolutional neural networks to have obviously fewer coefficients and greatly improved operational efficiency compared with other fully connected neural networks.

The Convolutional Layer

The height prediction of the hydraulic fracture zone is a textual data regression prediction problem, so it needs to use a one-dimensional convolution. In general, a one-dimensional convolution is often used in signal processing to calculate the delay accumulation of a signal. Suppose a signal generator generates a signal x_t at each moment t, and the decay rate of its information is ω_k, i.e. after $k-1$ time steps, the information is ω_k times of the original one. Suppose $\omega_1 = 1$, $\omega_2 = \frac{1}{2}$, $\omega_3 = \frac{1}{4}$; then, the signal "y_t" received at moment "t" is the superposition of the information generated at the current moment and the delayed information of the previous moments.

$$\begin{aligned} y_t &= 1 \times x_t + \frac{1}{2} \times x_{t-1} + \frac{1}{4} \times x_{t-2} \\ &= \omega_1 \times x_t + \omega_2 \times x_{t-1} + \omega_3 \times x_{t-2} \\ &= \sum_{k=1}^{3} \omega_k x_{t-k+1} \end{aligned} \tag{2}$$

We call $\omega_1, \omega_2, \omega_3 \ldots$ the convolution kernel. Suppose the length of the convolution kernel is K; then its convolution is a sequence of signals, x_1,x_2,$x_3\ldots$:

$$y_t = \sum_{k=1}^{K} \omega_k x_{t-k+1} \tag{3}$$

The convolution of the signal sequence x and the convolution kernel ω is defined as. $y = \omega * x$,where * denotes the convolution operation.

In general, the length K of the convolution kernel is much smaller than the length N of the signal sequence. A

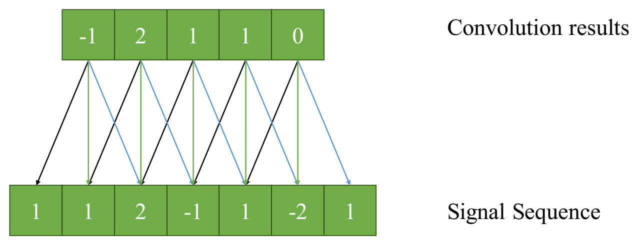


Fig. 5 One-dimensional convolution example

one-dimensional convolution example is given in Fig. 5, where the convolution kernel is [− 1, 0, 1] and the numbers on the connected edges are the weights in the convolution kernel.

The Pooling Layer

The pooling operation is a special operation in convolutional neural networks, the main purpose of which is to prevent overfitting. In most cases, we use average pooling and maximum pooling. As shown in Fig. 6, the first averages the pooled template, which preserves the overall characteristics of the data within the template, while the second retains the maximum value of the information within the template (Ma 2022).

The Fully Connected Layer

The so-called fully connected layer, as the name implies, means that every node in each layer is connected to every node in the previous layer and acts as a classifier for the whole convolutional neural network, as shown in Fig. 7.

Convolutional Neural Network Construction

Sample Selection

By browsing a large number of literature materials, 40 measured samples of hydraulic fracture zones with similar

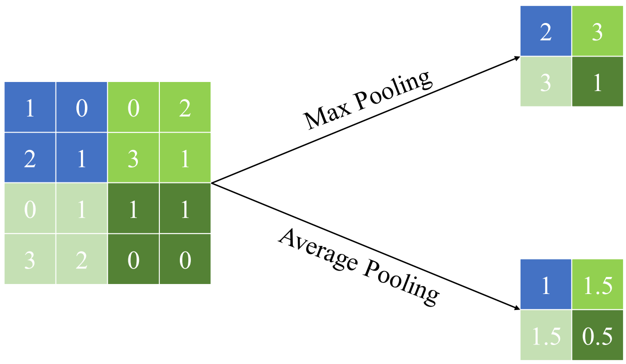


Fig. 6 Maximum and average pooling

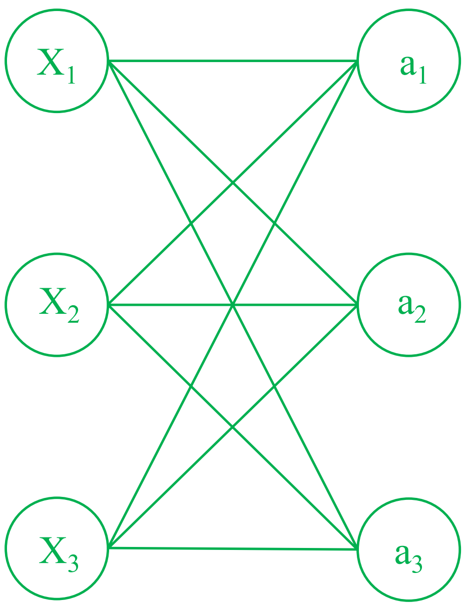


Fig. 7 Fully connected layer

geological conditions were obtained (Ma et al. 2020, 2022a, b; Zhao 2022). These 40 samples were divided into 35 training samples and five test samples, according to the need for convolutional neural network prediction work. The collated sample data are shown in Table 1 (Yao et al. 2022; Xie et al. 2017).

Model Evaluation and Parameter Settings

Evaluation of Validation Metrics

After the training of the model is completed using the sample data, indicators are needed to evaluate the training results. Since this paper explores the regression prediction problem, the root means square error (RMSE) and the loss function were used to evaluate this prediction model. The RMSE is used to describe the deviation of the measured value from the predicted value. When the RMSE is larger, it means that the predictive accuracy is poor; when the RMSE is smaller, it means that the predictive accuracy is better. The value of the root means the square error is calculated by dividing the sum of squares of the differences between the predicted and measured values by the number of samples, using the formula shown below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(r_i - p_i\right)^2}{n}}, \tag{4}$$

where r_i denotes the measured value of the ith sample, p_i denotes the predicted value of the convolutional neural network model for the ith sample, and n denotes the overall number of samples.

The role of the loss function is to describe the size of the gap between the predicted and true values of the model, and to guide the model toward convergence during the training process. When a model is perfect (although not present), its error is 0. When the model has problems, the error, whether negative or positive, deviates from 0. The closer the error is to 0, the better the model is.

The convolutional neural network training process is shown in Fig. 8. The convolutional neural network model performs supervised learning training, and the training process is divided into two stages: forward propagation and backward propagation. Before starting the training, the convolutional neural network structure is determined, the initial parameters are set, and the sample data are fed into the model to propagate the data forward. The model learns the predicted values of the hydraulic conductivity fracture zone height in the training samples and compares them with the true values to obtain the root mean square error, and then back-propagates. An optimization algorithm is used to update the weight matrix, thus reducing the error of the model. The number of training sessions needs to be determined based on the actual training of the model.

This experiment was performed in Matlab 2019b using its neural network toolbox for iterative training. The neural network toolbox enables users to calculate the output of the selected network and call the activation function directly (Cong 2003). This experimental program was written as well as optimized using Matlab 9.7. Before starting the experiment, the model parameters were debugged. ReLU was selected as the convolutional layer activation function and SGDM was selected as the optimization algorithm. The parameters that affect the model prediction loss (Loss) and root mean square error (RMSE), along with Learning rate, MaxEpochs, MiniBatchsize, and Dropout were determined; the specific parameter values are shown in Table 2.

Table 1 Learning and training samples for the height of the hydraulic conductivity fracture zone

No	Test location	X1[1] (m)	X2[2] (m)	X3[3] (m)	X4[4] (°)	X5[5]	Y[6] (m)
1	Mine 01	3.6	359	150	2.3	0.25	30
2	Mine 02	6.3	480	170	4	0.75	68.6
3	Mine 03	3	484	143	17	0.5	40
4	Mine 04	3.7	360	70	23	0.5	56.8
5	Mine 05	4	232	71	8	0.5	33
6	Mine 06	8.7	435	153	8	1	71
7	Mine 07	8.6	357	169	6.5	0.5	65.5
8	Mine 08	5.8	368	125	6	1	70.7
9	Mine 09	8	450	170	8	0.5	86.8
10	Mine 10	6.4	414	193	9	0.5	72.9
11	Mine 11	7.8	329	134	8	0.75	83.9
12	Mine 12	6.4	270	120	11.5	0.5	62
13	Mine 13	9.6	302	120	7	0.25	112
14	Mine 14	4.1	330	150	7	0.25	38
15	Mine 15	9.9	332	93	2	0.75	125.8
16	Mine 16	5.8	553	180	8	0.25	65.3
17	Mine 17	3	168	137	5.5	0.25	27.8
18	Mine 18	5.3	542	175	15	1	67.5
19	Mine 19	5.9	296	148	4.5	1	114.7
20	Mine 20	4	350	136	9	0.25	35
21	Mine 21	1.7	320	65	6	0.5	27
22	Mine 22	6.5	263	180	4	1	83.9
23	Mine 23	7.1	412	160	9.5	0.5	74.4
24	Mine 24	8.7	409	198	6	0.5	83
25	Mine 25	3.7	420	70	23	0.5	56.8
26	Mine 26	2.4	550	180	15	0.5	55.3
27	Mine 27	1.9	173	70	20	1	25.3
28	Mine 28	2.03	89	69	7	1	45.9
29	Mine 29	2	230	85	37	0.25	52.5
30	Mine 30	4.3	56	55	0	1	42.5
31	Mine 31	2.5	350	135	5	0.75	20
32	Mine 32	3.4	117	200	2	0.75	72
33	Mine 33	1.7	320	65	6	0.5	27.5
34	Mine 34	2	150	174	23	0.25	58.4
35	Mine 35	3	125	150	5	0.25	22
36	Mine 36	4	282	71	8	0.5	33
37	Mine 37	2.2	101	158	1	0.25	63
38	Mine 38	4	49	135	5	0.25	45
39	Mine 39	3.8	446	143	17	0.5	40
40	Mine 40	1.9	173	70	20	0.75	26.7

[1]Mining thickness

[2]Mining depth

[3]Working face slope length

[4]Coal seam inclination

[5]Overburden structure

[6]Height of water-conducting fissure zone

The main role of the learning rating is to control the rate of the gradient descent. If the learning rate is too small, it will slow down the convergence speed; if the learning rate is too large, it will hinder the convergence and lead to oscillation near the extreme value point. Thus, a suitable learning rate can converge quickly and accurately.

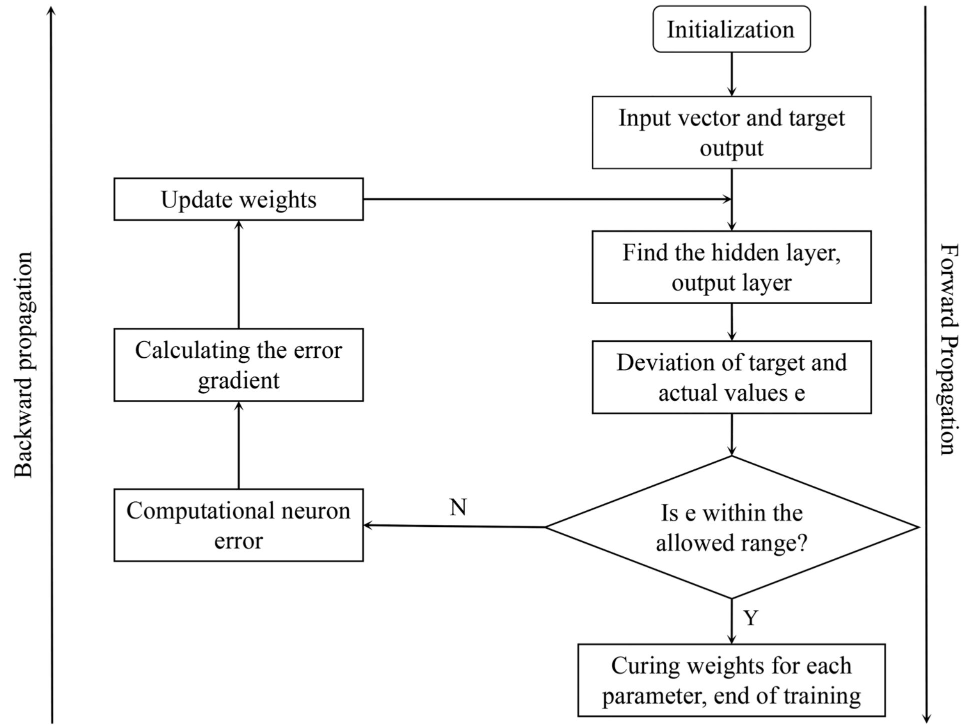


Fig. 8 Convolutional neural network training process

Table 2 Specific values of experimental parameters

Experimental parameters	Value
Learning rate	0.0005
MaxEpochs	8000
Batchsize	35
Dropout	0.2

Therefore, in this paper, the SGDM optimization algorithm was chosen to adjust the learning rate; the initial learning rate was set to 0.0005.

MaxEpochs indicates the maximum number of training times of the model. After a lot of experiments, we found that the loss value starts to stabilize at about 2000 iterations, and the RMSE value starts to stabilize at about 5000 iterations. Therefore, to avoid chance, the maximum number of training was set at 8000.

Batch size indicates the number of samples used for one parameter learning, and its size affects the degree of optimization of the model. In general, we chose the number of samples (35) as the batch size value.

Dropout indicates that each neuron has a certain probability of being discarded, i.e. its output is set to zero, and thus the weights are not updated. Its function is to prevent overfitting. The Dropout value was determined to be 0.2 based on the experience of the study, i.e. 20% of the nodes were randomly selected not to work for each training.

Overall Structure Determination

The overall structure of the CNN model is shown in Fig. 9. The model is divided into 10 layers, from top to bottom: the first layer is the input layer, which is responsible for passing the sample data into the model, and the size of the input layer is $5 \times 1 \times 1$, based on the size of the model. The second and fifth layers are convolutional layers with depths of 16 and 32, respectively. The convolutional kernel size is 3×1 and the move step size is 1. A BN layer is connected after each convolutional layer to perform the batch normalization work. The BN layer is followed by the ReLU activation layer. The ReLU activation function is simple to derive compared to the sigmoid and tanh activation functions. When using functions such as sigmoid, the computation is large, and when back-propagating the error gradient, the derivation involves division, and the computation is relatively large. The eighth layer is the Dropout layer, which sets the dropout to 0.2 to prevent overfitting. The ninth layer is the Fully Connected layer, which acts as a classifier. The 10th layer is the regression layer because this is a regression problem.

Results

Training Model Prediction Results

After several debugging sessions, the convolutional neural network model was highly developed and the RMSE value

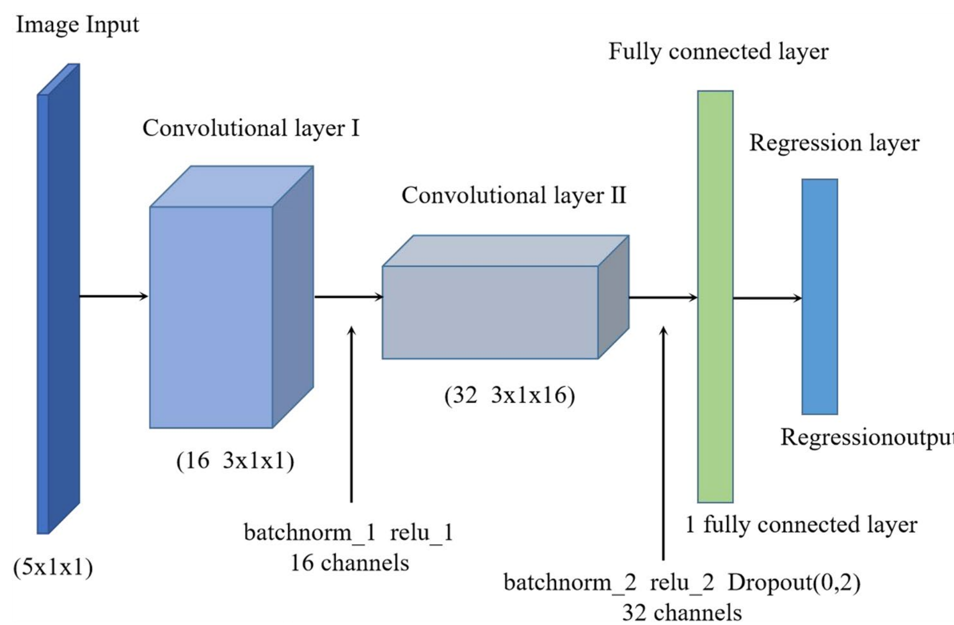


Fig. 9 CNN overall structure

of its training set was reduced to 1.44. From Fig. 10, it can be seen that the RMSE and Loss values of the convolutional neural network model decrease and stabilize as the number of training sessions becomes larger. After several times of debugging, the Loss value began to converge to 0 when the number of training sessions reached about 2000, and the RMSE value began to stabilize when the number of training sessions reached about 5000. The training ends when the number of training sessions reaches 8000. As can be seen from Fig. 11, the predicted values of the convolutional

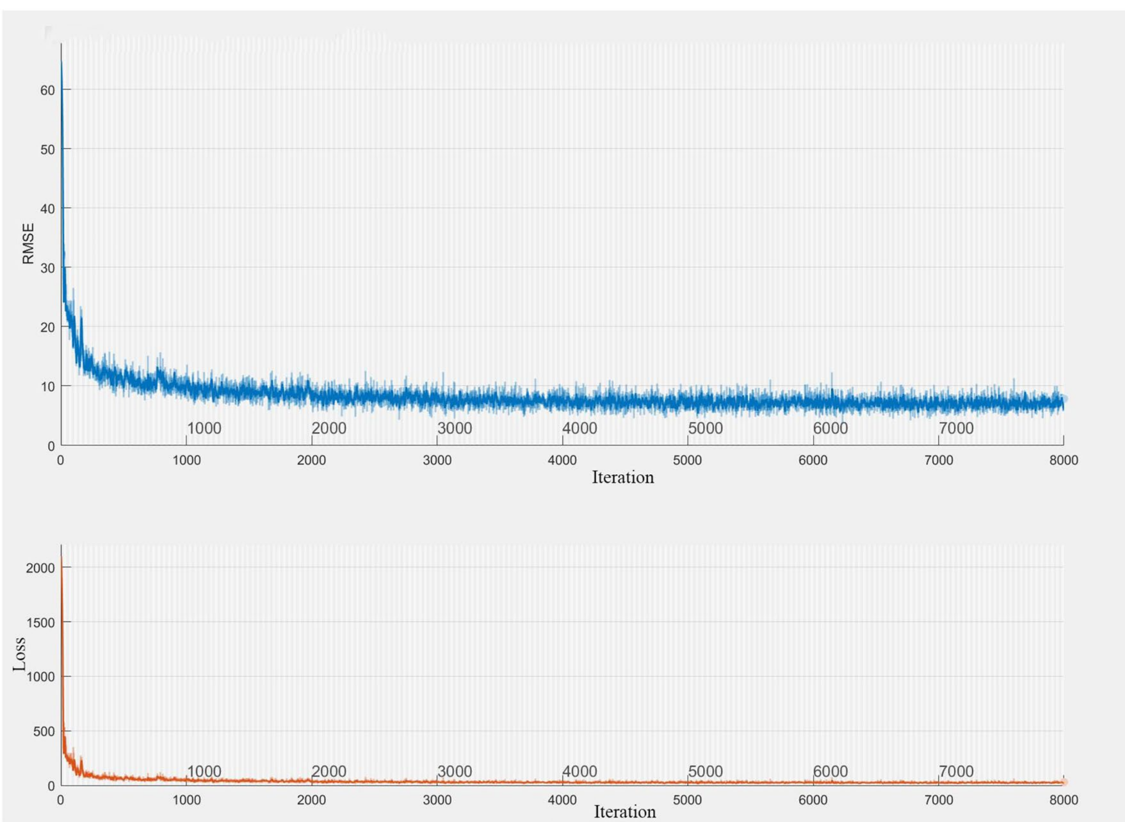


Fig. 10 Training progress chart

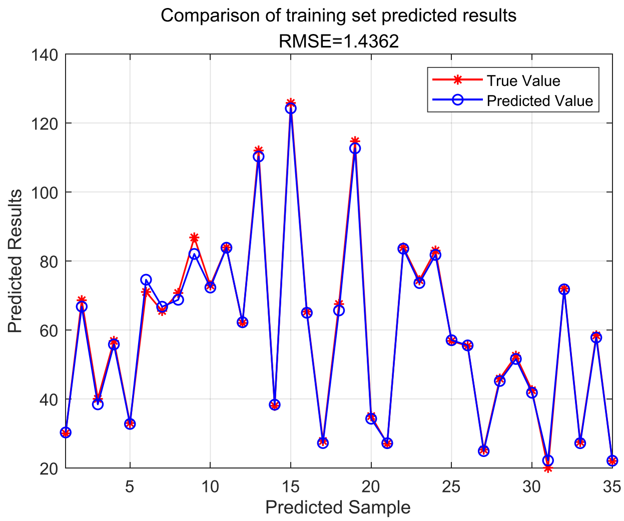


Fig. 11 Training set prediction curve

neural network model on the training set match highly with the trend of the actual value curve, and there is only a slight difference between the specific values. Therefore, the model has no obvious overfitting phenomenon and has a more accurate prediction ability, which can be applied to predicting the height of the hydraulic fracture zone.

Model Testing

The last five samples in Table 1 were loaded into the trained convolutional neural network model as test samples, and the prediction results of the convolutional neural network model were compared with the calculation results of the formulas given in the literature and the measured results (State Bureau of Coal Industry 2000). The equation of the statute was:

$$H_{li} = 20\sqrt{\sum M} + 10, \quad (5)$$

where $\sum M$ denotes the accumulated mining thickness. The results of the collated comparison are shown in Table 3.

The maximum absolute error calculated by the convolutional neural network model was 2.3 m, and the maximum relative error was 6.9%. The maximum absolute error calculated using the empirical formula in the protocol was -37.7 m and the maximum relative error was 59.8%. This indicates that the results of the convolutional neural network model training are closer to the actual situation than the results calculated by the empirical formula. The relative error was kept below 10%, while the maximum absolute error of the results calculated by the protocol formula can reach nearly 60%. The reason for the big difference is because the convolutional neural network model considers the influence factors of the hydraulic fracture zone more comprehensively than the regulation, and the calculation formula in the regulation only utilizes the mining thickness and rock properties.

Discussion

Field Measurement Discussion

This convolutional neural network model achieved good results in both the training and test sets. To verify its practicality, the 1301N working face of the Longgu coal mine was selected for the field test. The method used for the field test was the downhole segmental water injection observation technique, and the instrument used was the “double-end plugging leak detection device for a borehole" shown in Fig. 12.

In the process of mining a working face, according to the regulation, the top coal and bottom coal are detected once every 30 m and 30 m of inclination and 55 lines and 440 points are detected. The coal thickness of the block north of the second joint lane is 8.0–9.7 m, and the gangue exposed in the working face 400–450 m north of the second joint lane

Table 3 Comparison of the test sample convolution prediction results with the measured values and the calculated values of the protocol

No	Test location	Height of water-conducting fracture zone			R compared to M		C compared to M	
		M[1]	R[2]	C[3]	AE[4] (m)	RE[5] (%)	AE (m)	RE (%)
36	Mine 36	33	34.4	35.3	1.4	4.2	2.3	6.9
37	Mine 37	63	25.3	62.7	− 37.7	59.8	− 0.3	0.5
38	Mine 38	45	34.4	42.4	− 10.6	23.6	− 2.6	5.8
39	Mine 39	40	33.7	38.6	− 6.3	15.9	− 1.4	3.6
40	Mine 40	26.7	23.0	25.0	− 3.7	13.8	− 1.7	6.5

[1]Measured value

[2]The calculated value of the protocol

[3]The predicted value of the convolutional neural network

[4]Absolute error

[5]Relative error

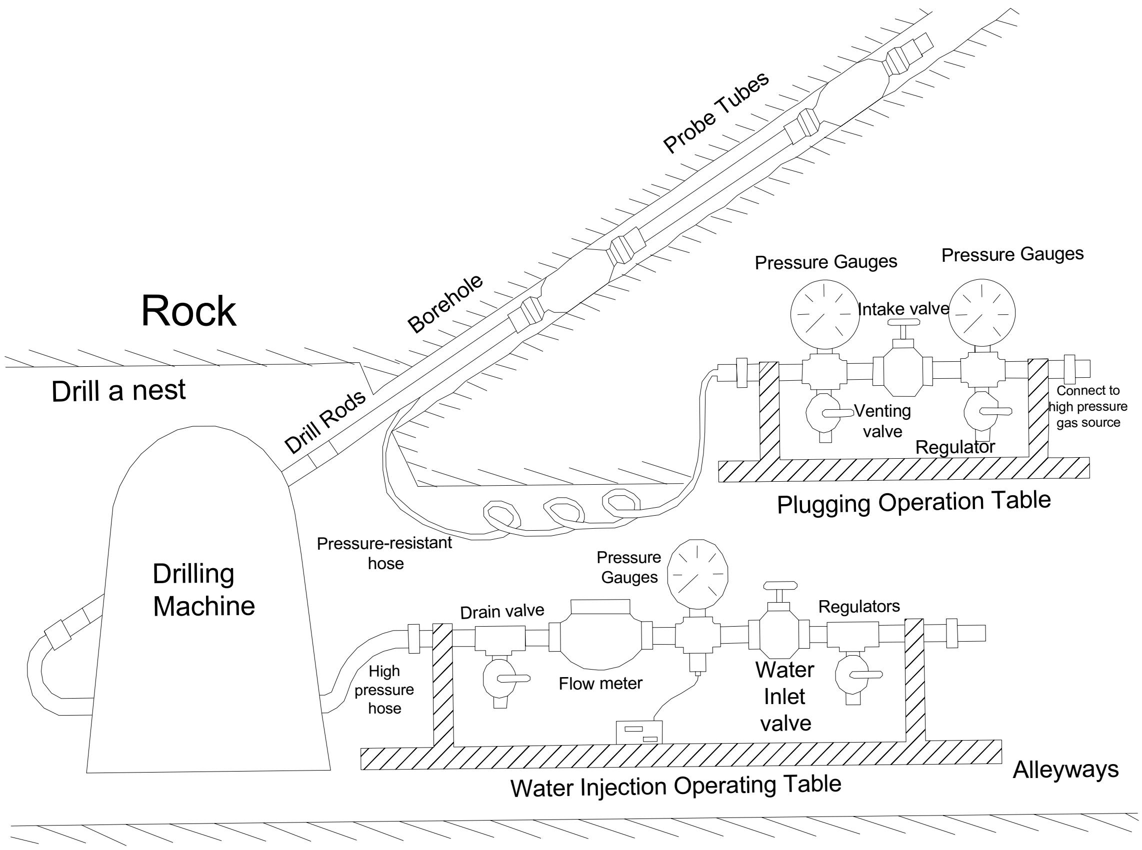


Fig. 12 Drill hole double end blocking leak detection device

is 0.2–2.0 m thick; the area is about 5120 m^2. The coal thickness between the first and second joint lane is 7.6–9.7 m, the coal thickness of the upper part of the working face south of the first joint lane is 3.6–7.3 m, and the coal thickness of the lower part of the working face is about 5.0–8.1 m in the middle of the working face The coal thickness is 7.0–7.3 m. The height of the water-conducting fracture zone in the 1301N working face of the Longgu coal mine was measured to be 74.6 m.

Then the convolutional neural network model was used to predict the height of the water-conducting fissure zone at the 1301N working face of the Longgu coal mine. First, the influencing factors were processed to the data. The mining thickness of 1301N working face is 8.5 m, the mining depth is 600 m, the working face slope length is 220 m, the coal seam inclination angle is 3°, and the overburden structure is hard-soft type (the value was taken as 0.5). Combining the above data into the convolutional neural network model, the predicted height of the water-conducting fissure zone in the 1301N working face of the Longgu coal mine after iterative training was 76.08 m. The absolute error and relative error of the calculated and predicted results of the protocol formula were respectively calculated, and the predicted results of the convolutional neural network model and the calculated results of the protocol formula were compared with the measured values (see Table 4).

Synthetic Comparison Discussion

There are many methods for regression prediction of the development height of the water-conducting fracture zone. As discussed earlier, most researchers choose the BP neural network prediction and multiple linear regression prediction methods given the perspective of accuracy and complexity. The BP neural network is a multilayer feedforward network trained by an error back propagation algorithm and is one of the most widely used neural network models. A BP neural network with a single hidden layer can be implemented to approximate the discontinuous function with arbitrary accuracy, and the BP neural network includes two processes: forward propagation of data and backward propagation of errors. When the output layer result differs from the desired result, back propagation of the error signal is performed, and the output of the network is made close to the desired output by repeated iterations of the two processes.

Univariate linear regression is often used to explain changes in the dependent variable. In real-world studies, changes in the dependent variable are often influenced by

Table4 Comparison of predicted values with actual measured values and calculated values in the regulation for 1301N working face in Longgu coal mine

Working surface	Height of water-conducting fracture zone			R compared to M		C compared to M	
	M[1]	R[2]	C[3]	AE[4] (m)	RE[5] (%)	AE (m)	RE (%)
Longgu coal mine 1301N	74.6	68.3	76.1	−6.3	8.4	1.5	2.0

[1]The measured value

[2]The calculated value of the protocol

[3]The predicted value of the convolutional neural network

[4]The absolute error

[5]The relative error

several important factors, so two or more influences are used as independent variables to explain the changes in the dependent variable, which is known as multiple regression. When multiple independent variables are linearly related to the dependent variable, the regression analysis performed is multiple linear regression.

When y is the dependent variable, $x_1, x_2, ...x_k$ is the independent variable, and the relationship between the independent variable and the dependent variable is linear, the multiple linear regression model is:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k + \varepsilon, \tag{6}$$

where b_0 is the constant term, $b_1, b_2, ..., b_k$ is the regression coefficient, and ε is the error term.

To show the accuracy of the model prediction, the convolutional neural network model established in this paper was tested against the BP neural network and the multiple linear regression models (Qiao et al. 2022). The debugged and optimized BP neural network model and the multiple linear regression model constructed by SPSS were used to predict the height of the hydraulic conductivity fracture zone under the uniform influence factors. Then the sample data in Table 1 were selected for training, and the absolute and relative errors of the last five sets of sample data under the three prediction models were calculated and compared.

The experimental results are shown in Table 5. The maximum absolute error of the BP neural network prediction was − 5.6 m, and the maximum relative error was 12.4%. The maximum absolute error of the multiple linear regression prediction was -5.1 m, and the maximum relative error was 13.2%. The maximum absolute error of the convolutional neural network prediction was 2.3 m, and the maximum relative error was 6.9%. Thus, the convolutional neural network model proved to be more accurate than the BP neural network model and the multiple linear regression model.

Conclusions

There are many factors that affect the height of the hydraulic fissure zone. In this paper, a hydraulic fissure zone height prediction model based on a convolutional neural network was established based on five factors: mining thickness, mining depth, working face slope length, coal seam dip angle,

Table 5 Comparison of convolutional neural network prediction results with BP neural network prediction results and multiple linear regression prediction results

Height of water-conducting fracture zone				C compared to M		L compared to M		B compared to M	
M[1]	C[2]	L[3]	B[4]	AE[5] (m)	RE[6] (%)	AE (m)	RE (%)	AE (m)	RE (%)
33	35.3	37.4	31.3	2.3	6.9	4.4	13.2	− 1.7	5.2
63	62.7	57.9	57.4	− 0.3	0.5	− 5.1	8.1	− 5.6	8.9
45	42.4	49.3	46.7	− 2.6	5.8	4.3	9.6	1.7	3.8
40	38.6	44.9	45.0	− 1.4	3.6	4.9	12.2	5.0	12.4
26.7	25.0	28.9	29.0	− 1.7	6.5	2.2	8.2	2.1	7.9

[1]Measured value

[2]Convolutional neural network prediction value

[3]Multiple linear regression prediction values

[4]BP neural network prediction value

[5]Absolute error

[6]Relative error

and overburden structure. 40 mine samples from previous studies were selected for training and testing.

The convolutional neural network prediction model established in this paper was compared with the BP neural network prediction model and the multiple linear regression prediction methods used by previous authors, and the results showed that the error of the convolutional neural network prediction model was much less than these two methods. Thus, using the convolutional neural network prediction model improved the predictive accuracy and can be effectively used to predict the height of the hydraulic fissure zone.

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Data availability The data underlying this article can be found in the article and its references.

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