A New Confidence Propagation Algorithm for Regional Image Based on Deep Learning

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Abstract. In order to improve the accuracy of regional image confidence propagation calculation, a regional image confidence propagation algorithm based on deep learning is designed. Firstly, the relevant information is collected, and then the data similarity is calculated. Finally, the regional image confidence propagation algorithm based on deep learning is calculated. The experimental results show that the regional image confidence propagation algorithm based on deep learning improves the calculation accuracy and reduces the calculation time.

Keywords: Deep learning · Regional image · Confidence · Communication

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1 Introduction

At present, the research on the confidence of regional image is particularly important. Confidence, also known as reliability, or confidence level and confidence coefficient, means that when sampling to estimate population parameters, due to the randomness of the sample, the conclusion is always uncertain [1]. The span of confidence interval is a positive function of confidence level, that is, the greater the degree of assurance required, a wider confidence interval is bound to be obtained, which correspondingly reduces the accuracy of estimation [2].

Document [3] proposed a deep learning algorithm based on convolution neural network for automatic classification of lung nodules, and realized the division and extraction of regional features. [4] has applied deep learning algorithm to image segmentation and achieved some results. [5] pointed out that the traditional method of line fault detection in floatation mainly focuses on extracting specific foam features for segmentation, such as color and shape. Because the same segmentation algorithm can not be applied to all cases, it often leads to low accuracy and efficiency. An automatic flotation condition recognition method based on convolution neural network (CNN), transfer learning and support vector machine (SVM) is proposed. More specifically, CNN acts as a trainable feature extractor to handle bubble images, and SVM acts as an identifier to detect faults.

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Compared with the existing identification methods, the CNN-SVM model can automatically extract the characteristics of bubble images and perform high-precision fault detection.

In order to improve the accuracy of region image confidence propagation analysis, a region image confidence propagation algorithm based on deep learning is designed. Deep learning is a new branch of machine learning. Its purpose is to simulate the human brain to establish a neural network. It can use multiple information processing layers to process image, text, sound and other information, such as human brain [6]. By simulating the nervous system of the human brain, we use a hierarchical model to extract more abstract features from data layer by layer. Such multi-layer nonlinear information processing can be applied to image recognition, pattern recognition and feature extraction. Low level features can form high-level features. We turn such hierarchical structure into deep structure, which shows that deep learning is applied to confidence propagation. It is of great significance in multicast algorithm.

2 Regional Image Information Collection

Before calculating the confidence propagation of regional image, collecting regional image information and mining data, we first use the hybrid structure of deep learning algorithm to pre train the abnormal data, clean and dimensionless the relevant data sources, and get a standardized data matrix and standardized dimension vector [7, 8]. The processing formula is as follows:

$$x_e = \frac{v - s_g}{\sqrt{s_j D(k)}} \tag{1}$$

In formula (1), x_e represents the inherent modal function in the state space of the data source, s_j represents the weight vector of the data, $D(k)$ is the steady-state probability of the overall data, v is the multivariable time series of the data, and s_g is the cleaned data source.

On this basis, the query function [9] is used for further mining, and the process is as follows:

The initial population was constructed by using the cluster centers.

Step 1: randomly extract g network data from complex network data to form sample set $g_m = \{m_1, m_2, \ldots, m_3\}$;
Step 2: randomly select a network data v from the sample set as the first cluster center, and select the network data o with the largest distance from v as the second cluster center;
Step 3: use deep learning algorithm to calculate the distance between the remaining data in the network, and set the nearest value as $D_j = \min\{d_v, d_{v2}\}$;
Step 4: obtain the abnormal network data information corresponding to the nearest distance above;
Step 5: repeat the above steps until all network abnormal data clustering is finished;
Step 6: according to the above process, V cluster center is regarded as the suitable population, and the calculation is repeated until the initial population with B individuals is generated.

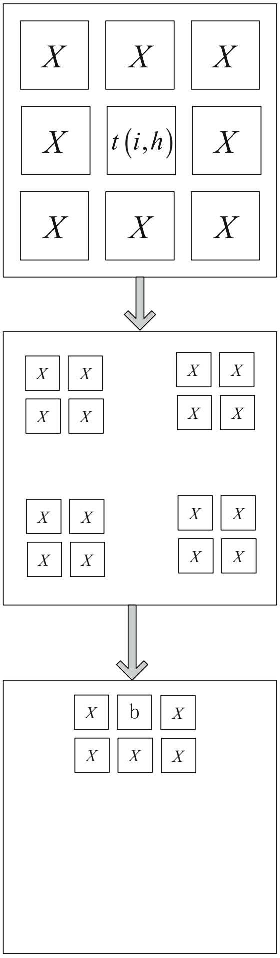

Fig. 1. Correction matrix

Step 7: the query function is the key to active learning. Therefore, the maximum uncertainty equation is a simple application of the query function to query the initial population. The information entropy is used to calculate the uncertainty of the classifier, that is, the greater the information content, the greater the uncertainty. The formula is as follows:

$$H(x) = -\sum_{y \in Y} P\left(\frac{y}{x}\right) \lg P\left(\frac{y}{x}\right) \tag{2}$$

In formula (2), x is an example, y is a classifier sample, P is a classifier prior probability, and H is an uncertain function, namely information entropy function [10–12]. Examples of the most uncertain and optimal amount of information are selected as follows:

$$u = \arg\max_{x \in U} H(x) \tag{3}$$

In formula (3), u is the most uncertain equation and U is the sample set where x is located. Outliers are subject independent samples, which will reduce the accuracy of classifier and bring noise to training [13–16]. Therefore, outliers should be removed from the training set. Therefore, the following correction matrix is proposed (Fig. 1):
The above figure shows the schematic diagram of correction matrix. If data point $q(i, h) = 0$ takes four diagonals of points as correction matrix, and then uses the matrix to correct it. If the number of non-zero points in the four points in the matrix is greater than 2, then judge $q(i, h) = 1$, and determine the corresponding another 0, the top point value of 1 matrix is 0, otherwise, the opposite is true.
Step 8: after preprocessing the correction matrix, two complementary data are obtained, and then the two images are superimposed. Since outliers will appear after stacking, k-nearest neighbor (KNN) density is used to remove outliers. The density measurement formula is as follows:

$$A(x) = \frac{1}{k} \sum_{s_i \in s(x)} similarity(x, S_i) \tag{4}$$

In formula (4), k is the number of samples with the greatest similarity to x. To sum up, the selected most informative examples are manually labeled and added to the training for iterative training model [17].
Through the above process, the regional image information mining and collection is completed.

3 Regional Image Similarity Calculation

In order to calculate the regional image similarity and analyze the data similarity information, the decision tree model is used to decompose the data similarity. The standardized dimension vector [15, 18, 19] of standard data is calculated to provide the basis for data analysis in the next step. The calculation formula is as follows:

$$y_0 = y_i \times \begin{bmatrix} y_1 \\ y_2 \\ y_m \end{bmatrix} \tag{5}$$

In formula (5), y_1, y_2 and y_m represent the main elements contained in y_0, and y_i is the main element of data.

According to the above-mentioned standardized data information, the prediction variables and determinants of abnormal data are defined, and the principal component is extracted. The following formula is used to extract the principal component of data. The calculation formula is as follows:

$$F_I = \frac{p \otimes x_0 y}{Y_i} \tag{6}$$

In formula (6), p represents the frequently occurring data, $x_0 y$ represents the frequently occurring data eigenvalue vector, and Y represents the time complexity of decomposition.

After extracting the principal components, the regression equation of the data is established, and the expression is as follows:

$$(x_b, x_n) = X_u \times \frac{a_1 + a_2 + a_3 + a_n}{t} \tag{7}$$

In formula (7), (x_b, x_n) is the linear regression coefficient of data, a_1, a_2, a_3 and a_n represent frequently occurring data, and X_u and t represent the correlation between data variables.

According to the above definition, the establishment of linear regression equation of data is completed [20]. On this basis, using depth learning algorithm, the mixed feature recognition and data classification of data are analyzed according to the classification attributes of network data. Assume that the attribute set of the data is X, singular value decomposed into:

$$X = ND * \frac{t}{v_i} \tag{8}$$

In formula (8), X represents the verification information of the data ontology mapping, ND represents the feature vector of the data, and $\frac{t}{v_i}$ represents the weighted value of the distributed feature quantity of the data.

The feature value of the data is extracted as the training subset, and the deep learning algorithm is used to analyze the similarity of the information [21–23]. The network data information is reconstructed. The average information feature expression after spatial data reconstruction is as follows:

$$I(Q, H) = \sum_d a(z)(l, h) \tag{9}$$

In formula (9), $I(Q, H)$ is the ontology concept set of data, $\sum_d a$ is the redundant data set, z is the joint distribution probability of data, and (l, h) is the abnormal data information.

According to the difference of different data attributes in clustering, the accurate probability density function is obtained as follows:

$$G = P_A^K(1 - F) \tag{10}$$

In formula (10), G is the similarity coefficient of data at sampling time, P_A^K is the information distribution density, and $1 - F$ is the calculation parameter of similarity between data and data.

According to the above formula, complete the calculation of data similarity. On this basis, deep learning common models are used to classify the relevant data. Automatic encoder is used to learn the representation (encoding) of a group of data, which is usually used to reduce the dimension. The simple description of automatic encoder is to encode first and then decode. The automatic encoding assumes that the output data are the same as the input data, and adjusts the parameters of the encoding automatically in the learning process to obtain the weight of each layer. Recently, automatic encoder has been widely

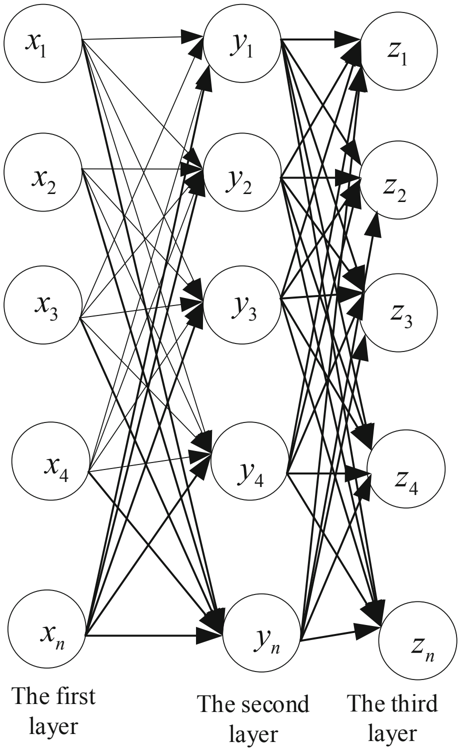

Fig. 2. Automatic encoder structure

used in learning data generation model. As shown in the figure is a simple automatic encoder (Fig. 2):

Among them, there are n cells in the first layer, m cells in the second hidden layer. The input X is the binary vector of n dimension, and the G-dimensional hidden layer represents h through the hidden layer. In general, nonlinear sigmoid functions are used to map in the coding stage [24]:

$$Y = S(WX + b) \tag{11}$$

In formula (11), S represents a non-linear function. Similarly, in decoding, the vector needs to be reconstructed by a similar function.

$$X' = S\left(W^T Y + b'\right) \tag{12}$$

In formula (12), X' represents the output of reconstruction, which can also be called the re representation of X. The symbol T is the matrix transposition, W is the weight, and b' is the bias. During the training process, the parameters can be adjusted by minimizing the error. The formula of error should be based on the assumption of reconstruction data distribution:

$$L\left(X', X\right) = X' - X^2 \tag{13}$$

At this time, when the hidden layer is linear, the effect of the first layer to the hidden layer in the automatic encoder is the same as that of PCA. When the hidden layer is nonlinear, the results of the hidden layer can be stacked into many layers, and the input distribution of the automatic encoder becomes multimodal [19, 20, 25]. When input X is a probability vector or a binary vector, the error function is defined as:

$$L(X', X) = -\sum_{n}^{i=1} [x_i \log x_i' + (1 - x_i) \log(1 - x_i')] \tag{14}$$

The training process of automatic encoder is as follows:

Firstly, the unsupervised learning method is used to learn the features of unlabeled sample data. Because when training labeled data, the parameters can be adjusted according to the error between the output and the real value, which is different from automatic encoder. Therefore, in the training process of the automatic encoder, the difference between the output data and the input data is adjusted to minimize the error through encoding and decoding two stages.

Second, layer by layer training, through the encoder to learn features, and then to the next layer of training. According to the minimum reconstruction error in the first step, we think that the output is basically consistent with the original input. When the parameters of the first layer are fixed, we also start to train the second layer to get the parameters of the second layer.

Third, the automatic encoder is supervised to fine tune. Through the above two steps of training, we can get the final automatic encoder. At this time, we need to connect a classifier to classify the data. We can connect the SVM classifier, input the results of the second step into SVM, and then use the labeled data for supervised fine tuning. After the fine-tuning is completed, it can be applied to the real scene for classification.

4 Implementation of Confidence Spread Calculation of Regional Image

The message of belief propagation algorithm is transmitted between data points, so it has a lot of computation. Therefore, the idea of segmentation is introduced to transmit messages between the segmented regions, and a region based belief propagation algorithm is proposed [26]. The first mock exam can reduce the time complexity of the belief propagation algorithm, and the constraint of the same model in the segmentation area can eliminate the influence of distorted data points on the result. [27, 28] can also improve the ability of the belief propagation algorithm to process data. Since the purpose of belief propagation algorithm is to minimize the global energy function and obtain the optimal data distribution, in order to realize the confidence propagation algorithm based on the segmentation region, this paper first defines the region based global energy function.

Therefore, this paper uses the plane template set to replace the search space, in order to take the optimal distribution of the plane template instead of the optimal distribution. The global energy function based on region is defined as follows:

$$E(f) = \sum_{m} \lambda(s_i, s_j)/g \tag{15}$$

In formula (15), g is the set of adjacent segmentation region pairs, and $\sum_m \lambda(s_i, s_j)$ is the label of the plane template allocated by the segmentation area in the template set.

In order to minimize the global energy function formula and obtain the optimal template distribution, the message and confidence transfer functions are further modified. The modification process is as follows (Fig. 3):

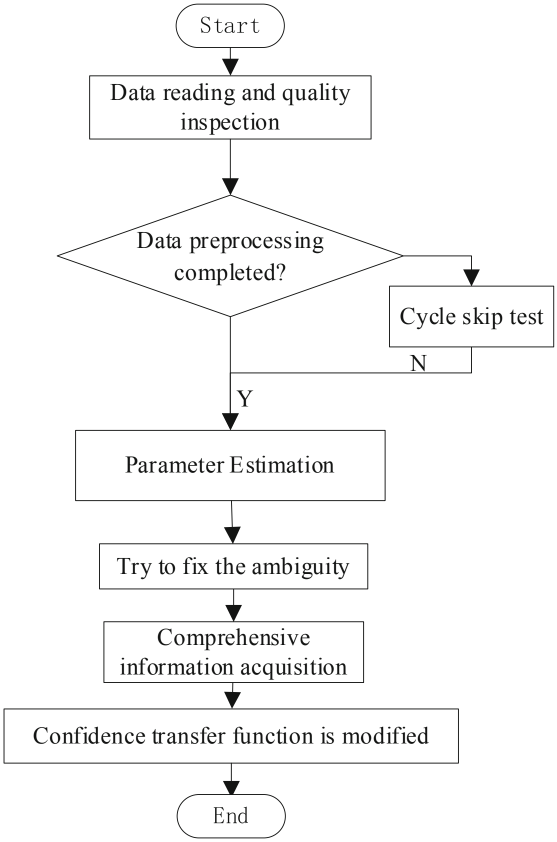

Fig. 3. Modifying process of confidence transfer function

At the same time, the smoothing term in the global energy function is calculated based on the data points in the segmented region, and the data items are calculated based on all the data points in the segmented region, so it is necessary to redefine the inter region smoothing cost and the intra region matching cost.

Message and confidence transmission can be defined as message iterative transmission based on segmented region:

$$k = \min_o /k + o/p \tag{16}$$

In formula (16), p represents the label set corresponding to the template in the parallax plane template set, o represents the adjacent region set of the segmented region,

k represents the set of other adjacent segmentation regions, and $\min_{o}$ represents the label of the plane template assigned by the segmentation area in the template set.

After T iteration, the transmitted message tends to be stable. At this time, the confidence level under different parallax plane templates of each segmentation region tends to be stable, and the iteration stops. Sample and the most representative sample, define a confidence measure function. Using the sample confidence value provided by this function, the most representative examples that need to be labeled manually and the examples with the highest correct rate added to the next round of self-training can be obtained. The confidence formula is as follows:

$$Confidence\ (p_{n1}, p_{nz}) = \left| p_{n_1} - p_{n2} \right| \tag{17}$$

In formula (17), $_{n_1}$ and $_{n2}$ are two nodes of the output layer, p_{n1} and p_{nz} indicate positive and negative polarity respectively, that is, node probability. Therefore, the definition of confidence function is intuitive and reasonable. The higher the value, the greater the confidence value of the classifier, that is, the greater the probability that the output is correct classification.

The simplified diagram of confidence transmission is as follows (Fig. 4):

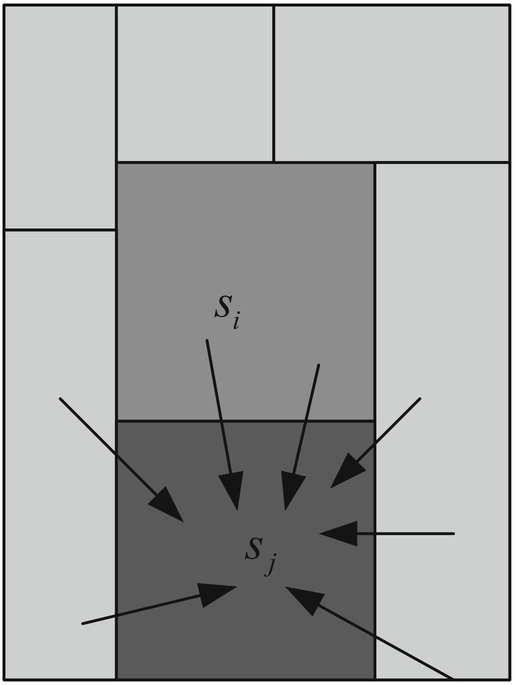

Fig. 4. Simplified graph of confidence transmission

In this case, the confidence degree of segmentation region S_i can be expressed as follows:

$$f^*(s_i) = \arg \min_{f(x_i) \in F} b_{s_i}(f(s_i)) \tag{18}$$

In formula (18), s divides the region, and after obtaining the best plane template label of each segmentation region, the difference value of data points in each region is calculated according to the plane template equation corresponding to the template set.

The most representative examples are selected from the query function (which combines density measurement and information function), and the annotation data is added to the training set to update the classifier performance. At the same time, the confidence measure function selects some of the most credible examples to label automatically, and adds them to the next training cycle. In the next training cycle, the training data can be enriched by adding high confidence samples and expert manually marked samples. The training process is iterative until the iteration criteria are met. In the testing stage, the original test corpus in the target language is translated into the source language by machine translation, and then the classification results are calculated by trained classifiers (Fig. 5).

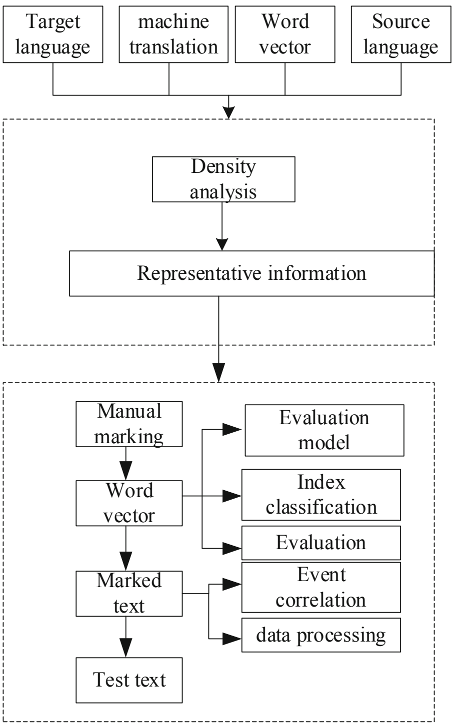

Fig. 5. Regional image information classification process

Through the above process, the confidence propagation calculation of regional image is completed.

5 Experimental Comparison

In order to verify the effectiveness of the regional image confidence propagation algorithm based on deep learning, the experimental comparison is carried out, and in order to ensure the rigor of the experiment, the research method is compared with the convolution neural network based feature map deep learning in literature [3] and the support vector machine based fault detection in flotation process in literature [5], and the accuracy and calculation time of the three methods are compared.

5.1 Comparison of Computational Accuracy

Data set 1 and data set 2 are calculated respectively, and the calculation accuracy of this research method is compared with that of literature [3] and literature [5]. Accuracy is an index to measure the accuracy of data transmission within the specified time. The accuracy formula is as follows

$$\gamma = \frac{\alpha}{\beta} \times 100\% \tag{19}$$

Where, γ is the precision, α is the error code in transmission, and β is the total number of transmitted codes (Figs. 6 and 7):

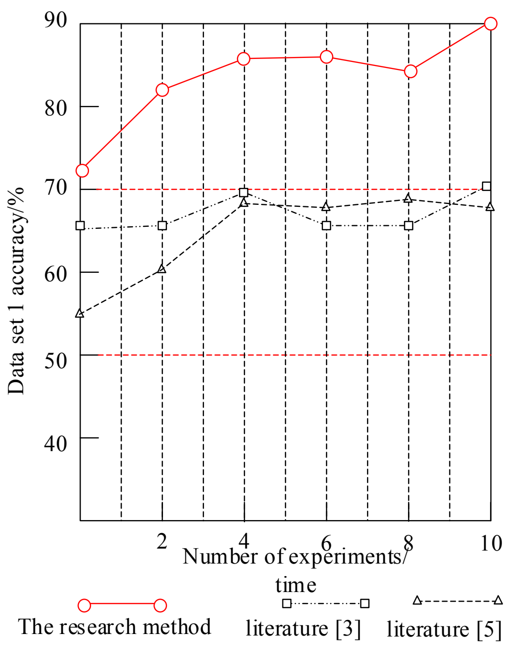

Fig. 6. Comparison of computational accuracy of Data Set 1

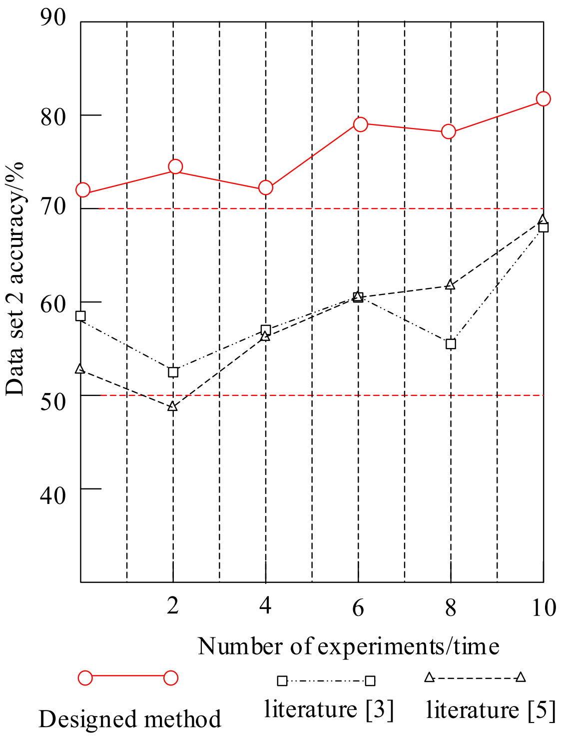

Fig. 7. Comparison of computational accuracy in Data Set 2

It can be seen from the analysis of the above figure that the calculation accuracy of the regional image confidence propagation algorithm based on deep learning is higher, and the data accuracy can be guaranteed at more than 72% in both data sets, which is higher than the methods in literature [3] and literature [5]. This is because this method uses the deep learning algorithm to calculate the similarity of regional information, and improves the calculation accuracy.

5.2 Time Comparison

The results of comparison between the algorithm in this paper and the methods in literature [3] and [5] are shown in the following figure: the calculation time is to test the calculation time of three methods for each group of data with 10 groups of data in dataset 1 as samples.

As shown in Fig. 8, the algorithm of confidence propagation of regional image based on deep learning in this study consumes less time. It is an ideal state within 5 min, and can meet the needs in the actual application process. Compared with the method in literature [3] and [5], it takes more time to calculate. Therefore, the effectiveness of this method is proved.

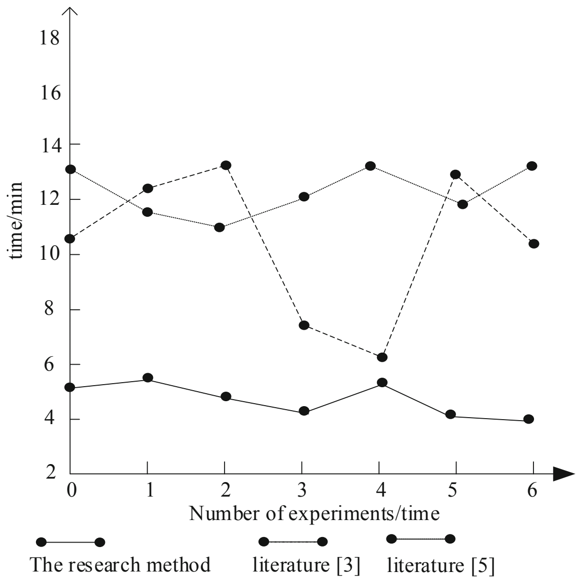

Fig. 8. Comparison of identification time

6 Conclusions

A region image confidence propagation algorithm based on deep learning is designed, and the effectiveness of the method is verified by experiments. However, due to the limitation of research time, there are still some shortcomings in the method of this study. In the follow-up study, we need to further optimize the method of this study.

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