Research on CNN-based intelligent recognition method for negative images of weld defects

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Abstract: The existing technology of automatic classification and recognition of welding negative images by computer is difficult to achieve a multiple classification defect recognition while maintaining a high recognition accuracy, and the developed automatic recognition model of negative image defect cannot meet the actual needs of the field. Therefore, the convolutional neural network (CNN)-based intelligent recognition algorithm for negative image of weld defects is proposed, and a B/S (Browser/Server) architecture of weld defect feature image database combined with CNN is established subsequently, which converted from the existing CNN by the migration learning method. It makes full use of the negative big data and simplifies the algorithm development process, so that the recognition algorithm has a better generalization ability and the training algorithm accuracy of 97.18% achieved after training. The results of the comparison experiments with traditional recognition algorithms show that the CNN-based intelligent recognition algorithm for defective weld negatives has an accuracy of 92.31% for dichotomous defects, which is significantly better than the traditional recognition algorithm, the established recognition algorithm effectively improving the recognition accuracy and achieving multi-category defect recognition. At the same time, the CNN-based defect recognition method was established by combining the image segmentation algorithm and the defect intelligent recognition algorithm, which was applied to the actual negative images in the field with good results, further verifying the feasibility of CNN-based intelligent recognition algorithm in the field of defect recognition of welding negative images.

1. Introduction
The quality of welds will directly affect the normal operation of oil and gas pipelines [1]. The traditional assessment method is to evaluate the weld by hand, which is not only a heavy workload for the evaluator and easy to fatigue, but also a low efficiency. In order to reduce the work intensity of the evaluator and improve the accuracy of the evaluation, it is significant to achieve automatic detection and identification of weld defect images through the use of computers [2].

Nowadays, domestic and foreign scholars have proposed many computer-aided defect detection algorithms, which can be mainly divided into methods based on edge detection algorithms for defect feature extraction, machine learning methods that design shallow network structures with artificially defined defect feature parameters, neural networks trained by a large number of images that have been labeled with defects, and deep learning methods that allow machines to learn autonomously and achieve classification of defects.
Mengxi Liu, Ding Fan, Zhongyu Yang, Hongquan Jiang, Longfei Zhang, Ferguson Max K et al. further validated the feasibility of CNNs in the field of weld defect recognition by improving the classical CNN structure, but lacked practical engineering application examples [3-8]. Zhifen Zhang et al. investigated the deep learning based on weld image robot online defect detection technology, but a lot of research is still needed before industrial application [9].

Duanfei Liu, Yanfei Sun, Jian Li, Lusong Que, Kaixuan Wu, and Hao Niu studied the feasibility of edge detection algorithms in the field of weld defect recognition [10-15], but due to the varying quality of negative images of weld and complex backgrounds, edge detection algorithms applicable to all negative images are difficult to obtain, further causing the defect recognition models based on edge detection algorithms to be less accurate and difficult to apply to many types of defect recognition.

P. Baniukiewicz, Xin Hu, Luiyao Wang, and Ye Huang, et al. implemented automatic recognition model of weld defects by designing artificial neural networks [16-19], but they performed poorly in terms of recognition accuracy due to the great subjectivity of the defect feature parameters defined by hand and the simple network structure. In order to solve these problems, automatic recognition model and classification of weld defect features is considered by using a combination of migration learning techniques and deep learning, with the aim of increasing the recognition classification while ensuring a high accuracy rate.

2. CNN-based weld defect identification method

2.1 Introduction to CNN and migration learning methods

Deep learning is a new research direction in the field of machine learning, with the ultimate goal of enabling machines to have the same analytical learning capabilities as humans, capable of recognizing data such as text, images and sounds. Deep learning is a complex machine learning algorithm that has achieved results in speech and image recognition that far surpass previous related techniques [20]. But performing deep learning often requires large amounts of data, expensive hardware, and even more expensive elite engineering talent. Typical deep learning models are convolutional neural networks (CNNs) and deep confidence networks (DCNs).

CNN is a multilayer supervised learning neural network, and the convolutional and pool sampling layers of the implicit layer are the core modules to realize the feature extraction function of the CNN. The network model improves the accuracy of the network through frequent iterative training by employing gradient descent to minimize the loss function to adjust the weight parameters in the network layer by layer in the reverse direction. CNN has a very outstanding performance on image classification datasets.

Transfer learning is a machine learning approach that migrates knowledge from one task to another. Migration learning is a training method by migrating the network structure and weights originally used for solving one task to another task and getting better results in the other task as well. In case of insufficient samples, migration learning can be used to migrate these generic feature learning from other already trained networks, thus saving training time and getting better recognition results. Transfer learning can transfer knowledge from a relevant problem rather than developing a fully customized solution to the problem and can solve a specific problem more easily.

Due to the difficulty of obtaining the actual weld film on site, the transfer learning method is used to transform the trained CNN, which further reduces the training data, computing power and engineering required to build a deep learning model suitable for weld recognition. The number of talents makes the CNN-based weld recognition model easier to develop and has better generalization capabilities.

2.2 Open source defects Feature database

2.2.1 Image pre-processing

Using MATLAB to adjust the grayscale of the original negative image, through a large number of experiments to obtain a suitable gray value threshold, the original negative image gray value range of
0-255, adjusted gray value is divided into three ranges: 0, 25.5-102, 255. through the adjustment process to compensate for the lack of light transmission due to the shooting, weakening the impact of the image too bright or too dark, increasing the negative image Contrast, so that the defects are more prominent.

![Image](image1.png)

(a)Original negative images  
(b)Grayscale adjustment of images

Figure 1 Image pre-processing comparison chart

2.2.2 Defective feature image extraction

The extracted defect features are divided into three categories: circular defects, strip defects, and other defects (containing normal images as well as other kinds of defects). By adding the other category, the trained recognition model can be initially applied to the recognition of defects in actual weld negatives.

![Image](image2.png)

(a) strip defects  
(b) circular defects  
(c) other defects

Figure 2 Three kinds of defects sample diagram

By manual extraction, 385 original defect images were extracted from 500 actual weld negatives in the field, including 153 circular defect images, 60 strip defect images and 172 other defect images.

2.2.3 Defect feature database

A relational database was created to store defect images and further developed into a B/S architecture database. The designed page visualizes the defect feature image database and has a specific defect type filtering function. The design of the defect feature database also considers the problem of adding new data and provides a function to upload new data to the database, which is of great significance for the
later integration and sharing of the database and further improvement of the established defect image recognition algorithm.

2.3 Intelligent identification method for weld image defects

2.3.1 Alex Net Introduction
After extensive research and comparison, Alex Net was finally selected as the pre-trained network.

Alex Net is one of the CNNs \([5-6]\), which has 8 layers, including 5 convolutional layers and 3 fully connected layers.

Alex Net uses ReLU instead of Sigmoid, which has a certain improvement in the training speed. At the same time, Alex Net uses the maximum pooling layer to avoid the blurring effect of the average pooling layer, while there is an overlap between the outputs of the pooling layers, further enriching the image features. Alex Net also introduces the Dropout function, which solves the problem of model overfitting and makes the network more generalizable, and also improves the computing speed due to the reduced network complexity.

Another innovation of Alex Net is the LRN local response normalization \([7-8]\), the LRN local response normalization is designed to improve the generalization ability of the model by mimicking the function...
of side suppression, which makes the relatively larger values of response comparisons. The specific formula is as follows:

\[ b_{x,y} = a_{x,y} / (k + \alpha \sum_{j=\max(0,l-n/2)}^{\min(N-l+1+l \cdot n/2)} (a_{x,y})^2) \]  

(1)

where \( a \) represents the output of the \( i \)th convolutional kernel \((x,y)\) coordinate in the feature map that has undergone the ReLU activation function, \( n \) denotes several adjacent convolutional kernels, and \( N \) denotes the total number of convolutional kernels in this layer. The constants \( k \), \( n \), \( \alpha \) and \( \beta \) are hyperparameters and their values are to be determined by the validation set.

2.3.2 Establish weld image defect intelligent recognition algorithm

The images in the defect database are transformed by writing functions in MATLAB to enable them to be input into Alex Net, and then migration learning is performed. To further ensure the reliability of the recognition algorithm, the data volume was further expanded by using vertical flip, horizontal flip, and image rotation \((15^\circ, 30^\circ)\) on these defect images, and the amount of image data used for training and testing was expanded from 320 to 5120, which ensured that the intelligent recognition algorithm could be trained with sufficient data volume. The 5120 defective images were randomly assigned as training and test sets in the ratio of 75% and 25%. The remaining 65 defective images out of 385 original defective images were used as a test set to verify the accuracy of the model.

![Figure 5 Schematic diagram of the training process](image)

It can be seen through the training process that the overall accuracy rate of the defect image recognition algorithm is increasing with the increasing number of training samples and training times, and it can be predicted that with the increasing number of samples in the database in the future, the accuracy rate of the image defect recognition algorithm can also be improved more. After the training is completed, the training accuracy rate of the model is verified by the test set and reaches 97.18%, and it can realize the recognition of circular defects, strip defects and other defects.
2.4 Analysis of results

The recognition accuracy of each algorithm is verified using the defect images in the test set. The established intelligent recognition algorithms for weld image defects are compared with classical support vector machine (SVM) and artificial neural network (ANN). The SVM is a 2-layer shallow network structure with a Liblinear classifier for classification [18], and the ANN is a BP algorithm with random initialization of internal parameters [19].

![Figure 6 Example of partial test results](image)

| Recognition algorithm                                      | Accuracy  |
|------------------------------------------------------------|-----------|
| Classical support vector machines                           | 84.62%    |
| Artificial neural networks                                  | 76.92%    |
| CNN-based intelligent recognition algorithm for weld image defects | 92.31%    |

Table 1 Comparison of the accuracy of the second classification

By comparing the accuracy of the recognition algorithms, it can be seen that the established CNN-based image defect intelligent recognition algorithm has a higher accuracy rate of binary defect recognition than other recognition algorithms. It indicates that the established image defect intelligent recognition algorithm is able to perform better feature recognition for the diversity and complexity of defect types in weld negatives images, which also makes the established image defect recognition algorithm have higher accuracy rate and further verifies the feasibility of the CNN-based defect recognition algorithm.
2.5 Image segmentation algorithm and example application

Since different types of weld defects have different sizes and dimensions, the recognition accuracy of the algorithm is further improved by designing different algorithms for segmenting the weld negatives.

For strip defects, the original negative image should be segmented into larger blocks because the defect size is generally larger, and then input into the recognition algorithm for recognition. For circular defects, the defect size is generally smaller, the original negative image should be further subdivided, and then input into the recognition algorithm for recognition.

The CNN-based weld negative image defect recognition method is established by combining the weld negative segmentation algorithm and the weld image defect intelligent recognition algorithm. The effect of the recognition model in engineering practice is further tested by using the complete actual negative images of weld in the field.

![Figure 7 example of bar defect operation](image1)

![Figure 8 example of circular defect operation](image2)
3. Conclusion
By using the transfer learning method to transform the deep learning model, the established negative image of weld defect binary classification intelligent recognition method has higher recognition accuracy than other traditional recognition models under the condition of achieving multi-category defect recognition, which further verifies the feasibility of the CNN-based weld negative image defect intelligent recognition method. At the same time, the CNN-based recognition algorithm has the ability of self-learning, and it can be gradually improved with the continuous improvement of the defect feature database. The use of transfer learning method also makes the established recognition algorithm have better engineering application value, its development cycle is short, low hardware requirements, can establish different defect databases for different engineering backgrounds, by using different defect databases to train the recognition algorithm for specific engineering backgrounds, the combination of big data and deep learning model to establish a targeted and meet the actual application of engineering weld defect intelligent. The recognition model can be established for different engineering backgrounds.

The established intelligent recognition method for the second classification of weld image defects can be initially applied to the detection of actual weld negatives, but there are still many shortcomings and further research is needed. Combined with the big data of weld negatives, the advantages of deep learning methods can be given full play to increase the classification of defect recognition while ensuring a high accuracy rate, further forming an intelligent recognition system that can identify multiple defects such as porosity, cracks, slag, unfused, and unwelded, to meet the actual needs of the field and realize the intelligent recognition of weld negatives images.

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Innovation point name
Intelligent recognition technology of negative image of weld defects, B/S architecture of weld defect feature image database.
Innovation point content
1. The use of migration learning technology combined with deep learning models simplifies the development process of recognition models, with lower hardware requirements and shorter training time.
2. A weld defect feature image database with B/S architecture is established, which is significant for the integration and sharing of weld negative data, and the recognition algorithm is trained with the defect feature database, which fully combines the negative big data and deep learning model.
3. The established welding seam negative image defect intelligent recognition algorithm has self-learning capability, can be continuously improved with the increase of defective samples of the defective feature database, to further improve the recognition accuracy and increase the recognition classification.
4. Different segmentation algorithms are developed for different defect types to further improve the recognition accuracy of the recognition algorithm and to enable the established recognition model to be applied to industrial practice.

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