Weld X-ray image defect recognition based on deep learning

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ABSTRACT

This paper discusses the key link in weld quality assessment —— weld defect feature extraction and defect identification based on BP neural network model. Firstly, the main defect classification of welds and the technical method of feature extraction are introduced in detail, and six feature parameters are proposed and experimental simulation is performed. In terms of image preprocessing, the noise reduction technology based on domain averaging method and segment linear transformation are adopted to enhance the contrast and details of the image, and the weld path area is accurately extracted and segmented by line grayscale curve method and iterative threshold segmentation method based on subtraction technology. Then, the principle and key parameters of BP neural network model are introduced in detail, the optimal model parameters are selected through tuning and training, and the performance of the model is evaluated. Finally, the classification results of the test set are analyzed, demonstrating the performance of the model in identifying cracks and stomata. The experimental results showed that for the test set, the crack defect recognition rate was 100% and 73.3%. A quality and defect identification program, which provides important theoretical support and practical guidance in the field of welding engineering.

Key words: Weld Defect Identification; Bp Neural Network; X-Ray Detection; Threshold Segmentation

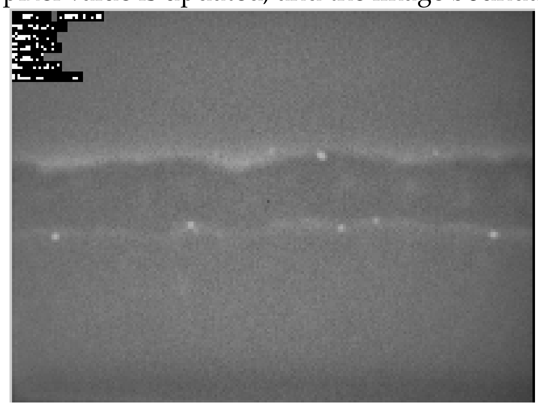
1 INTRODUCTION

Welding is crucial in the manufacturing industry, widely used in aerospace, automotive manufacturing, ship construction and pipeline engineering and other fields, and its weld quality directly affects the overall performance and safety of the structure. As an important non-destructive testing method, X-ray image technology can provide detailed information inside the weld, but traditional artificial visual inspection is inefficient when processing large amounts of data and complex defect patterns. In recent years, deep learning has made breakthroughs in computer vision, especially in image classification and object detection tasks. Applied deep learning to weld X-ray image defect identification can significantly improve the degree of automation and accuracy of detection, automatically extract features, and realize defect detection, classification and evaluation [1]. However, the application of deep learning in this field still faces challenges in data acquisition and annotation, insufficient model generalization ability, and high demand for computational resources. Through further research and technical optimization, it is expected to improve the intelligent and automatic level of weld quality testing. Scholars at home and abroad have some research results in this respect, such as Yao Yuan (2023) through the convolution neural network and batch normalization technology to improve the accuracy of ultrasonic detection weld defect identification, xin-lei zhao (2023) using sliding window and improved Mask RCNN model to enhance the accuracy of weld image defect recognition, lei (2022) using Gaussian hybrid model of oil and gas pipeline weld leakage magnetic detection image automation defect identification. In terms of foreign research, the Faster R-CNN architecture improved by Ajmi Chiraz (2023) is used to detect small pore defects in X-ray welding images. Bansal Abhi (2023) verifies its superiority in weld defect identification by comparing various parameters and hyperparameter combinations of deep learning network [2]. Based on the above studies, this paper will preprocess the X-ray weld image, select the appropriate features and construct the training data set, use the training data set to train the classification model, and use the trained model for defect identification and classification. To verify the model effect, 16 training samples and 24 predicted samples were selected for testing.

2 IMAGE PREPROCESSING

2.1 Image noise reduction and enhancement processing

The X-ray detection images have high resolution and high contrast, which can clearly show the internal details of the weld and the obvious contrast of the materials with different densities. However, the acquisition process is often accompanied by scattering noise, which affects the image quality and requires noise reduction treatment. This kind of image is usually a gray scale image, relying on the gray scale value to represent the different absorption degree of the material, but the background is complex, which requires accurate treatment technology to separate the weld area and the background [3]. To this end, we used the domain averaging method to reduce noise and reduce the noise in the image by calculating the average of the pixels in the neighborhood around each pixel. First, the image is divided into non-overlapping small areas of size, the local pixel mean is calculated, each pixel value is updated, and the image boundary is specially processed.



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1*Figure 1. Image before noise reduction* **_Figure 2. Image after noise reduction_**

By adjusting the sliding window size, the best balance between smoothing the image and preserving detail. The filtered image noise signal is filtered to a certain extent, and the original weld edge features are well retained, which is conducive to the subsequent feature extraction.

The segmented linear transformation technology is used to enhance the image, and improve the contrast and details of the image are improved by dividing the gray value of the image. The specific method is to segment the range of gray value, and linearly transform the gray value of each segment, to adjust the contrast and brightness of each segment [4].

The processed image gray value is stretched and adjusted in different gray ranges, making the image contrast significantly enhanced and the details clearer, which is helpful for subsequent defect identification and analysis. The gray scale distribution of the original image is concentrated in a narrow range. After the segmented linear transformation, the contrast of the image is enhanced and the details are better displayed.

2.2 Iterated threshold segmentation method based on subtraction technology

The subtraction technique is a method for image preprocessing, one of the methods designed to highlight the target area of interest in the image, eliminate the background interference, and enhance the target features. In the weld image processing, the image of the weld area can be effectively extracted by the subtraction technology to reduce the interference of the background noise [5]. The algorithm is described as:

(1) Initialization

T_0 Set the initial threshold and the upper number of iterations.m

Set the number of iterations.$k = 0$

(2) Iterative segmentation

$k < m$ At that time, perform the following steps:

T_k The images were segmented according to the threshold to obtain two parts: target and background.

The mean gray-value and for the target and background parts were calculated.$Z_0 Z_1$

New thresholds were calculated based on the mean gray values

$$T_{k+1} = \frac{Z_0 + Z_1}{2} \qquad (1)$$

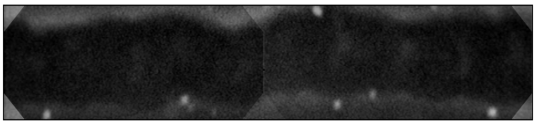
($|T_{k+1} - T_k| < \epsilon\epsilon$ If (is the preset precision), then end the iteration.

Otherwise, update the threshold, and continue with the iteration.$T_k = T_{k+1}$， $k = k + 1$

(3) Results output

T_kThe final threshold is returned as the threshold for the segmented image.

To segment the weld path image based on the above algorithm steps, the results are as follows 3Figure 3 and 4Figure 4:



5Figure 3 Image before subtraction processing

6Figure 4 Post after subtraction processing

3 DEFECTIVE FEATURE IDENTIFICATION

3.1 Classification of main defects of weld joint

Weld defect feature extraction is an important part of weld quality assessment, which is crucial to ensure the integrity and safety of welding structure. First, we need to understand the main defect classification of weld joints: cracks include hot and cold cracks; holes include pores and shrinkage holes; solid inclusion includes slag and tungsten; unfused and unwelded; shape defects include bite, welding tumor, lower collapse, root shrinkage and wrong edge; and other defects with substandard chemical composition and mechanical properties [5]. For these defects, weld feature extraction usually involves image processing, machine vision and deep learning technology, through the weld image or video data, using algorithm for preprocessing, edge detection, area segmentation steps, so as to extract various defects, including defect position, size, shape and quantity, to provide important basis for weld quality assessment and fault diagnosis. In addition, according to the specific welding process and application scenarios, the corresponding weld defect feature extraction scheme is developed [6]. For example, in the automatic welding production line, through the integration of image acquisition, processing and analysis system, real-time detection and warning of weld defects, improve the welding quality and production efficiency.

3.2 Extraction of weld defect characteristics

1. Edge smoothness (FLT)

Characteristic description: Edge flatness is used to quantify the smoothness of the edges of the weld defects.

computational formula:

$$FLT = \frac{IP^2}{S^2} \tag{2}$$

$$IP = \int\int r^2 f(x, y)dxdy \tag{3}$$

2. Tip Sharp (USP)

Characteristic Description: Tip sharpness is used to quantify the sharpness of both ends of the weld defect.

computational formula:

$$USP = \frac{S_1 + S_2}{S} \tag{4}$$

Specifically, S1 and S2 are the area of 1 / 4 of the long diameter of the defect, and S is the total area of the defect [7].

3. Perimeter to area ratio

Characteristic description: Perimeter to area ratio is used to describe the complexity of the defect shape.

computational formula:

$$T = \frac{C}{S} \tag{5}$$

4. Filling degree index is (ε)

Characteristic description: The fill degree index is used to describe the shape direction of a defect in a specific direction (e. g., horizontal and vertical).

computational formula:

$$\varepsilon = \frac{S}{L_x \times L_y} \tag{6}$$

Where S is the defect area, and Lx and Ly are the lengths of the defect in the horizontal and vertical directions, respectively [8].

5. Symmetry (SYM)

Characteristic description: Symmetry is used to quantify the degree of symmetry of the weld defects.

computational formula:

$$SYM = \frac{S_1}{S_2} \tag{7}$$

Where the definitions of S1 and S2 are dependent on the specific symmetry measure (e. g., it can be the defect about the center line or the symmetrical area of a straight line).

6. Relative gray scale (REG)

Characteristic description: the relative gray scale is used to quantify the gray scale difference between the weld defect and the surrounding area, that is, the blackness of the defect.

computational formula:

$$REG = \frac{A}{B} \tag{8}$$

Where A is the average of the defect area and B is the average of the area around the defect (e. g., the area of 5 pixels) [9].

3.3 Experimental simulation

In this paper, the above algorithm is simulated for 24 sets of picture defects, as shown as follows:

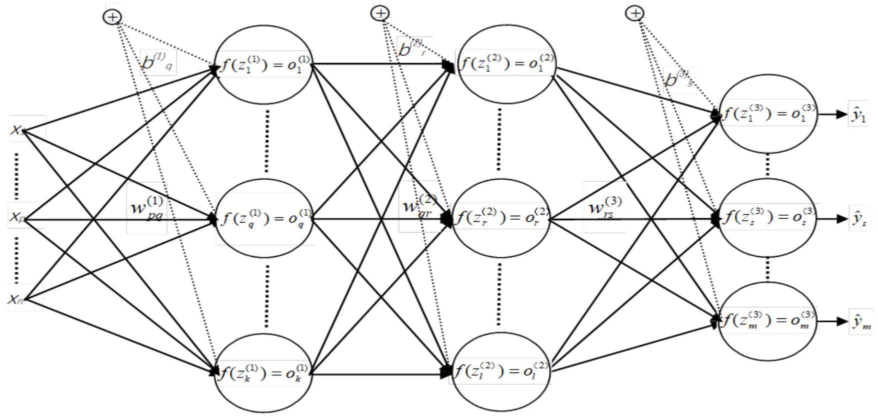
1Table 1 Bp neural network training set

Defect type	Edge straightness	Sharpn ess	The perimeter area ratio	Filling index	Symm etry	Relative gray
blowhol e	0.1175	0.3313	0.1365	0.3498	0.6813	0.5873
blowhol e	0.1175	0.3293	0.1360	0.3497	0.6841	0.5873
			...			
flaw	0.1069	0.3233	0.1653	0.4066	0.6671	0.5344
flaw	0.1069	0.3223	0.1657	0.4066	0.6704	0.5344

The above data is input as the data set into the subsequent prediction model as the training set.

4 DEFECT RECOGNITION MODEL BASED ON THE BP NEURAL NETWORK MODEL

In this study, BP (back propagation) neural network model is used to realize the effective classification of defect types based on multiple characteristic parameters of the weld. The BP neural network is a multi-layer feedforward network that adjusts the weights and bias terms in the network through a backpropagation algorithm to minimize the error between the predicted output and the actual output. Its network structure includes the input layer, hidden layer and output layer. The input layer contains six neurons, corresponding to six characteristic parameters: edge smoothness, sharpness, circumference area ratio, fill index, symmetry, and relative gray; The output layer contains two neurons to predict the probability of stomata and crack [10]. The activation function is used to introduce non-linear factors, commonly used as sigmoid and ReLU. During forward propagation, the input data undergo a nonlinear transformation of the hidden layer, reaches the output layer and is converted into a probability distribution via the softmax function. By calculating the loss function value (e. g., cross-entropy loss), the back-propagation algorithm calculates the gradient layer by layer, and updates the weight and bias terms using the gradient descent algorithm. After several iterations of training, the network parameters are optimized until the preset stop condition is met (such as the maximum number of iterations or the loss function value converges). During the training process, the early stop strategy and the regularization technique can be used to prevent overfitting.



7Figure 5 Schematic of the Bp neural network model

Its main parameters include:

Input layer activation function, hidden layer activation function, output layer activation function, and number of hidden layer neurons.

After multiple parameter adjustment, the training accuracy of the test set was taken as the evaluation index, and the optimal model parameters were selected as:

2Table 2. Selected Bp neural network model parameters

Parameter name	Parameter values
Data cut	0.4
Data shuffle	Yes
Activation function	Output layer logsig Hidden layer Tasing
Solver	Trainlm
Learning rate	0.05
L2 regular term	1
Iterations	1000
Number of hidden layer 1 neurons	10

Test result:

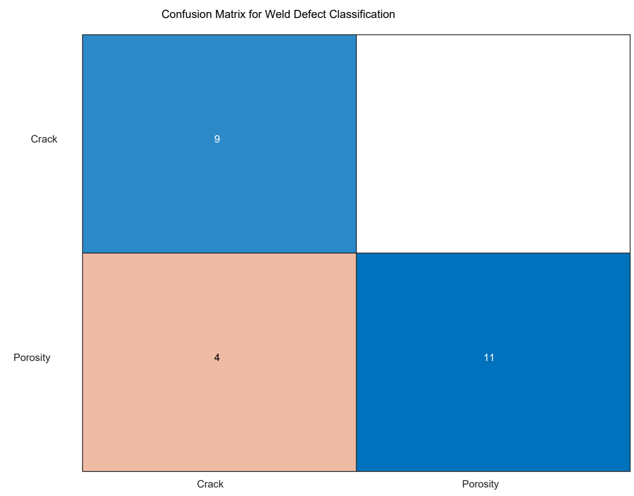


Figure 6 Confusion matrix results

Based on the prediction results of the test set, the model achieved a 100% recognition rate in identifying cracks, showing excellent performance. However, when identifying stomata, the model showed a slightly lower recognition rate of 73.3%, meaning that some of the stomatal samples were incorrectly identified as cracked. This discrepancy may arise from the similarity of stomata and cracks in some features, or because of the relatively small number of stomatal samples in the training dataset. To improve the model's recognition rate of stomata, consider increasing the number of stomata samples, adjusting the model parameters or structure, and introducing methods such as ensemble learning or transfer learning. Through further optimization and improvement, the overall classification performance of the model will be expected.

5 CONCLUTION

This paper presents a weld defect identification scheme based on feature extraction and BP neural network model. By analyzing the main defects of weld, six characteristic parameters, including gray value, shape and texture. According to the characteristics of X-ray weld detection image, the field average method and segment linear transformation enhancement technology are adopted to significantly improve the image quality. Combining line grayscale curve method and iterative threshold segmentation method based on subtraction technique to realize accurate extraction of weld path area. The BP neural network model demonstrated high accuracy and robustness in crack and stomatal recognition. The experimental results show that the model has good performance in the different types of defect recognition, especially in maintaining high recognition accuracy in the complex background, which verifies its effectiveness and practicability in weld defect identification. Future studies can further optimize the model to improve the identification accuracy and apply it to more practical scenarios to verify its wide applicability.

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