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# Research on Weld Defect Detection and Evaluation Technology based on Deep Learning

Hanlin Geng[1,*], Zhaohui Li, Yuanyuan Zhou

1 Shanghai Spaceflight Precision Machinery Institute, Shanghai, China.

*genghanlin@mail.nwpu.edu.cn

## Abstract

*Aiming at the problems of low efficiency and strong subjectivity in the current detection of weld defects by radiographic imaging technology, an object detection method of weld defects based on multi-channel fusion convolutional neural network is proposed. In this method, the images of weld defects are encoded and input into multiple feature extraction channels formed by parallel fusion of CNN. After that, the extracted features are fused with full connection layer and the feature vectors are output. Finally, the final output is obtained by Softmax for classification. The proposed method is verified by weld defect images in actual production. The experimental results indicate that the mAP of the multi-channel fusion convolutional neural network reaches 76.37%, and the detection accuracy of weld defects is higher than that of other network such as ResNet-50 and VGG-16. The proposed method can be applied to X-ray intelligent detection of weld defects and other scenarios.*

## Keywords

*X-Ray Image; Weld Defect; Object Detection; Multi-Channel Fusion.*

## 1. Introduction

With the rapid development of industrial technology, welding forming technology is widely used in aerospace, equipment, shipbuilding and automobile industries. Due to the influence of environment, personnel operation, welding process and other factors in the welding process, there are many types of defects in the weld seam. According to the national standard for classification and description of weld defects [1], weld defects are divided into six types: weld tumor, porosity, lack of penetration, lack of fusion, slag inclusion and crack. The existence of defects will affect the performance of products, and even cause production safety accidents in serious cases. In actual production, X-ray flaw detection is often used as the detection method of weld internal defects, but a large batch of images will be generated in the inspection process. Furthermore, the manual evaluation method is inefficient and depends on the experience of inspectors. Therefore, the detection standards and accuracy will be restricted by the subjectivity of personnel [2,3].

With the rapid growth of artificial intelligence, many scholars have engaged in-depth research on the intelligent detection of weld defects. The proposal of Convolutional Neural Network (CNN) in deep learning has promoted the development of object detection. Chen Yanfei et al. [4] introduced the residual block into MobileNet, and used ELU activation function to replace ReLU to solve the network degradation problem in MobileNet training. Compared with other networks, it has higher accuracy and less computational complexity. Jiang Hongquan et al. [5] constructed an improved CNN model (IPFCNN) to solve the problem of low feature selection ability of traditional CNN and applied it to weld defect identification. The results indicated that the recognition accuracy was higher than that of traditional ones. Fan Ding et al. [6] used the superpixel segmentation algorithm to construct a new CNN model, which solved the problem of the proportion of RoI in weld defect images and improved the feature extraction ability of the network, achieving an overall recognition rate of 97.8% in the experiment. Zhi Zelin et al. [7] established a deep learning fusion network model for comprehensive analysis of waveform features and image features based on CNN and TCN, which solved the problem of lack of feature integration analysis in existing models and achieved high recognition accuracy.

To sum up, although existing deep learning detection methods can achieve a certain accuracy in the identification task of weld defects, they cannot make detailed classification of different defects with similar morphological characteristics. For example, porosity and slag inclusion with the same circular characteristics. Therefore, based on the Faster-RCNN, this paper optimizes and improves ResNet, connects multiple feature extraction networks in parallel, and fuses them with the full connection layer. During training, the defects of the same type are encoded and input into the channel to extract the specific features of the weld defects. Finally, radiographic images of welding seams in actual production are used for verification, and the results indicate that the proposed network model achieves higher recognition accuracy than the generic model.

## 2. Multi-Channel Fusion Convolutional Neural Network

### 2.1. ResNet Network Structure Analysis

Compared with the common network, ResNet constructs Residual units between every two layers by shortcut and uses Residual Block to stack the network. The deep network established with Residual Block can solve the network degradation problem well [8]. Identity Mappings in Deep Residual Networks [9] further analyzed ResNet back propagation theory and adjusted the structure of Residual Block. The new structure is shown in Fig 1.

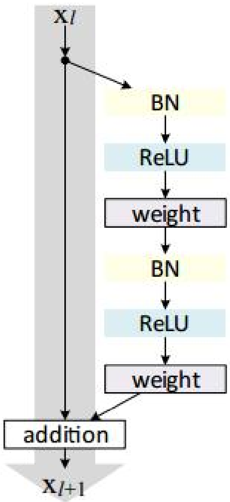


**Figure 1:** Residual Block

The new structure uses shortcut as the trunk path and residual path as bypass. The trunk path maintains the "purity" of shortcut so that the information flow can be transmitted intact in both forward and backward propagation. Thus the network blocks at either end of shortcut are not affected by the weighted parameters of the intermediate layer when transmitting information. Batch Normlizition and ReLU are uniformly placed in front of the weight layer on the residual path as pre-activation, so that the network is easier to optimize and has stronger generalization ability to avoid network degradation.

ResNet can efficiently extract image features for most images. However, the shape of weld defects is changeable, and some defects (porosity and slag inclusion) have the similar morphological characteristics. Therefore, ResNet cannot extract defect features effectively in this case, which leads to the decline of network training effect and limits the further improvement of detection accuracy.

## 2.2. Multi-Channel Fusion ResNet

Hi Z has pointed out in the paper [7], the weld defect data have two characteristics: graph and waveform. In this paper, parallel CNN and TCN are built to extract the graphic features and waveform features from the weld defect data respectively. Then the full connection layer is used to fuse two extracted features, and Softmax is used to classify the fusion features. Finally, good results are obtained. Inspired by that work, this paper attempts to use multi-channel convolutional neural network for feature extraction of various types of weld defects. Based on ResNet, a multi-channel fusion convolutional neural network (MC-ResNet) is proposed. The MC-ResNet structure is shown in Fig 2.

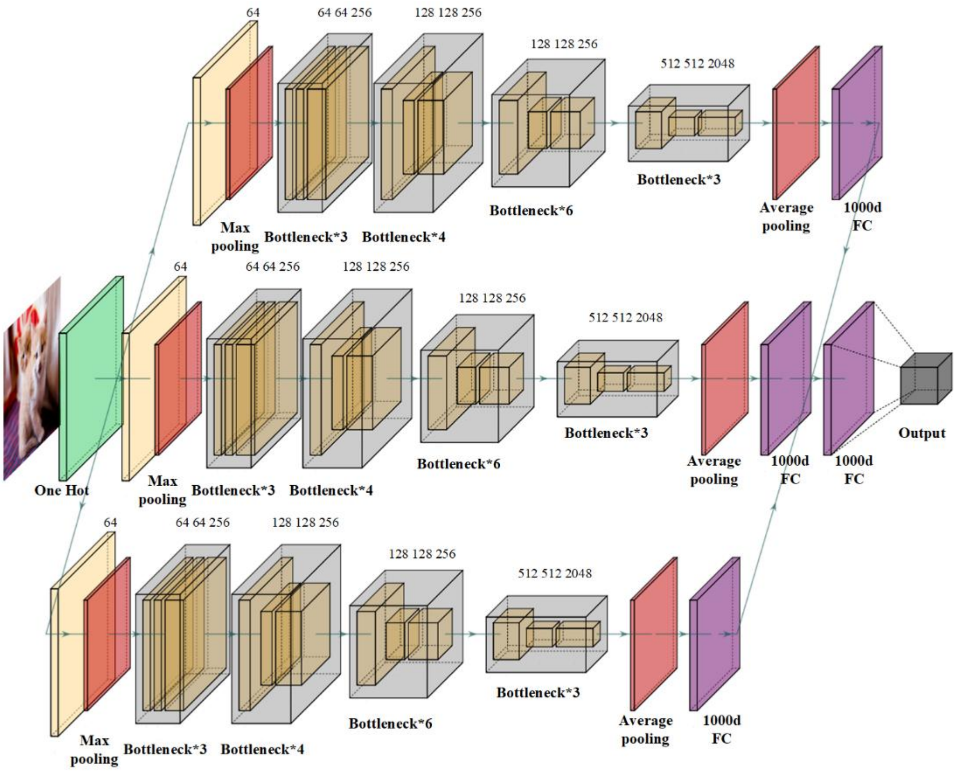


**Figure 2:** Structural of multi-channel fusion convolutional neural network

MC-ResNet establishes three channels for three kinds of weld defects. Each CNN channel contains 1 Max Pooling layer, 4 Bottleneck convolution blocks, 1 Average Pooling layer and 1 full connection layer. Each Bottleneck block consists of 3 convolutional layers, and the Bottleneck blocks are stacked in series. A single channel has 54 convolution layers.

The inputted weld defect images are firstly processed by One-Hot encoding. Before this, it should be ensured that each sample in the weld defect image data only contains the same type of defect. Then the images with the same coding are packaged into a batch. All samples in one batch generated at this time have the same defect type. Then, the batch is inputted into the corresponding channel according to the encoding, which only extracts the characteristics of the corresponding defect type. After that, the extracted features are inputted into the full connection layer of the channel. After the above operations, the corresponding defect features were extracted from the three channels respectively. A full connection layer is used to fuse the features extracted from the three channels and output the feature vectors. Finally, the final eigenvetors is classified by Softmax classifier. The multi-channel feature fusion process of weld defect images is shown in Fig 3.

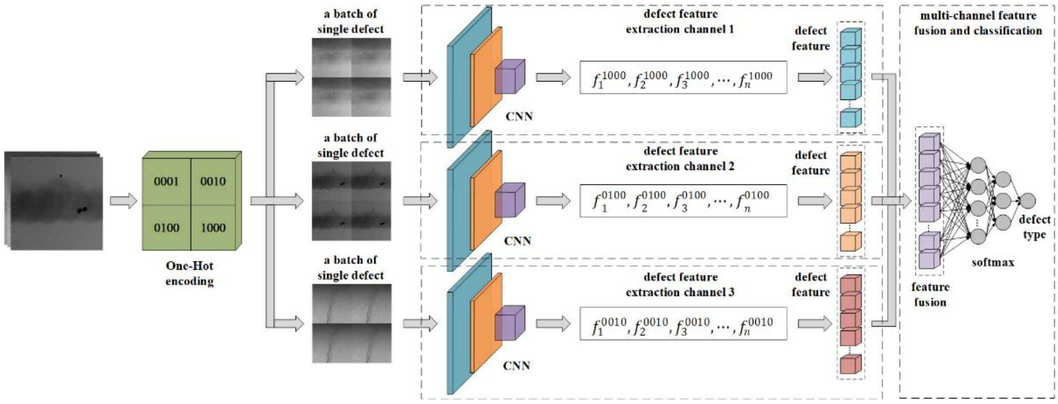


**Figure 3:** Multi-channel feature fusion process of MC-ResNet

In MC-ResNet, the CNN with feature extraction function is combined in parallel, and the number of feature extraction channels is set according to the type of weld defects. The weld defect data used in this paper have three types: porosity, slag inclusion and crack. Correspondingly, three feature extraction channels are set up in MC-ResNet. And the number of channels can be extended according to the number of types of objects detected in the dataset. Compared with ResNet, the proposed network sets feature extraction channels according to the number of detected object types. The "purity" of training samples in a single channel is guaranteed, which is equivalent to simplifying the detection task into a binary classification problem of "defective" and "non-defective". Thus, the feature extraction ability is improved. The network proposed in this paper simplifies the problem of multi-object detection by using specific channels to extract features of specific objects, which makes the network pay more attention to the local difference information of images. It is beneficial to extract details and improve the detection accuracy of weld defects.

## 3. Experiment and Analysis

### 3.1. Weld Defect Dataset

In this paper, the network training is carried out by using the radiographic images of welding seam produced by an aerospace research institute during 2016-2021. There are 1,540 pictures in the original data, including four types: porosity, slag inclusion, crack and no defect. Each sample is accompanied by a test report issued by professional inspectors.

In actual production, different workpiece detection process is different. Therefore, the radiographic image quality of welding seam is not consistent, and some images have problems such as over-exposure, noise and image blur. In order to improve the image quality of the dataset, data cleaning is performed on the original samples to filter out unqualified images. Then, Gaussian filter is used to remove the noise in images. Meanwhile, image sharpness is improved by gamma correction and other image enhancement methods. After obtaining qualified dataset, "Labelme" is used to annotate the samples. And the annotated dataset is sorted into "PascalVOC" format. The images after annotation are shown in Fig 4.

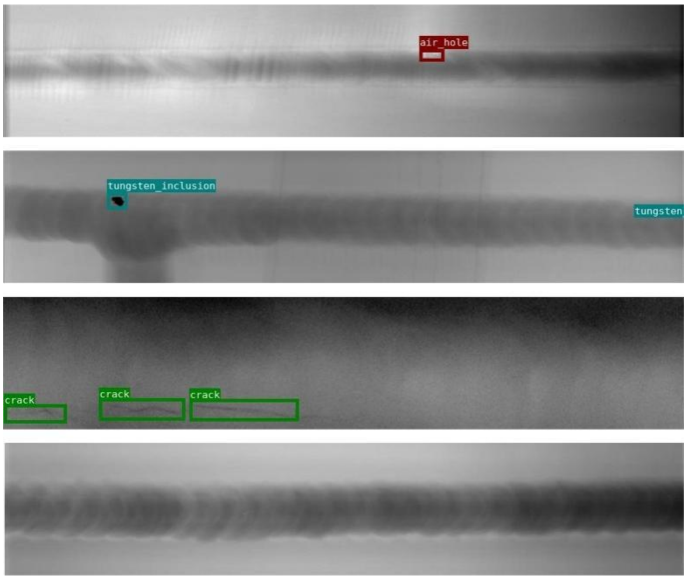


**Figure 4:** Radiographic images of porosity, slag inclusion, crack, no defect

Finally, in order to avoid the problem of over-fitting in network training due to the little sample size of dataset, the number of images in dataset is extended to 2844 by data enhancement. And the dataset is divided into training set and validation set, of which 1422 are training set and 1422 are validation set. Dataset division is shown in Table 1.

**Table 1:** Division of Weld Defect Dataset

| Dataset | Porosity | Slag inclusion | Crack | Total |
|---|---|---|---|---|
| Training set | 657 | 470 | 295 | 1422 |
| Validation set | 657 | 471 | 294 | 1422 |

## 3.2. Evaluation Index

To verify the effectiveness of MC-ResNet, mean average precision (mAP) is used to measure the performance of the network. The samples are divided into four types, true positive (TP), false positive (FP), true negative (TN) and false negative (FN), according to the combination of the real defect category and the predicted defect category.

The basis for determining the predicted defect of network as TP is that the intersection over union (IoU) of the predicted defect is greater than the threshold value. In this paper, IoU=0.5 is set as the threshold to determine that the predicted defect is TP. Those greater than this value are regarded as positive samples, while those less than this value are regarded as negative samples. According to the above description, calculate the precision rate and recall rate. The P-R curve is drawn according to the value of precision and recall, and the avreage precision (AP) is the area under the P-R curve. mAP is calculated by averaging the AP values of each category, which is used as an evaluation index to verify the predictive ability of the network. The formula of precision and recall rate is shown in Table 2.

**Table 2:** Calculation Formula of Evaluation Index

| Evaluation index | Formula |
|---|---|
| Precision | $precision = \frac{TP}{TP+FP}$ |
| Recall | $recall = \frac{TP}{TP+FN}$ |

## 3.3. Experimental Running Environment

The experiment is run under Ubuntu Server 20.04, using PyTorch 1.10.0 deep learning framework and Python 3.8 environment. The CPU used in the experiment is Intel Xeon Gold 6330 with 48GB memory. The GPU model is Nvidia RTX 3090 24GB. CUDA 11.2 is used for GPU computing framework, and Cudnn 8.3 is used for deep neural network acceleration computing.

## 3.4. Results

To verify the effectiveness of MC-ResNet, MC-ResNet, ResNet-50 and VGG-16 are used as backbone of Faster-RCNN for horizontal comparative analysis. At the same time, one-stage methods represented by YOLO and SSD are used for longitudinal comparative analysis.

The above methods use the dataset described in Table III for training and validation, and the number of epochs is 15. To avoid the randomness in the experiment affecting the results, the experiment is repeated for 5 times, and the average value of the 5 results is taken as the final result. The results are shown in Table 3.

**Table 3:** Identification Results of Weld Defects by Different Methods

| Method | Precision | | | mAP |
|---|---|---|---|---|
| | Porosity | Slag inclusion | Crack | |
| MC-ResNet | 79.11 | 68.13 | 81.89 | 76.37 |
| ResNet-50 | 78.72 | 46.00 | 84.06 | 69.67 |
| VGG-16 | 80.03 | 45.25 | 75.12 | 66.81 |
| SSD | 77.47 | 52.60 | 77.86 | 69.30 |
| YOLO | 66.23 | 42.11 | 47.34 | 52.00 |

It can be seen from Table 3 that the mAP of MC-ResNet is the highest and achieves the best recognition results. From the analysis of network structure, ResNet-50 and MC-ResNet have the same network depth, so there is a small difference in the precision of porosity and crack. However, the precision of ResNet-50 for slag inclusion is relatively low, only 46.00%. As can be seen from Fig 5, porosity and slag inclusion have the same circular features, mainly on the grey values have certain differences. ResNet-50, which mainly relies on shape features of object for recognition, is difficult to distinguish such differences. In comparison, MC-ResNet sets up multi-channel for feature extraction, which improves the ability to distinguish defects with similar shape features, and increases the precision of slag inclusion to 68.13%. VGG-16 has a shallow network depth, so it is inferior to ResNet-50 and other deep networks in feature extraction performance. Therefore, VGG-16 has low precision and mAP.

One-stage methods such as YOLO and SSD unify object classification and bounding box regression in object detection, and directly generate the classification probability and bounding box coordinates of objects. Therefore, the precision of one-stage algorithm is lower than that of two-stage algorithm from the algorithmic level. The SSD method here uses ResNet-50 as backbone, so its overall performance of defect identification is higher than that of VGG-16. However, compared with the Faster-RCNN method of MC-ResNet and ResNet-50 as backbone, its precision and mAP are still low.

Fig 5 shows the curves of mAP and loss value of several methods in training. As can be seen from Fig 5, after 10 epochs, the losses of ResNet-50, VGG-16, SSD and YOLO methods converge gradually, while mAPs are basically stable. However, the loss of MC-ResNet method is still decreasing at the end of 14 eopchs, and mAP also shows an upward trend. Therefore, it can be predicted that by increasing the epoch of MC-ResNet method, the precision and other comprehensive recognition ability of the method can be further improved.

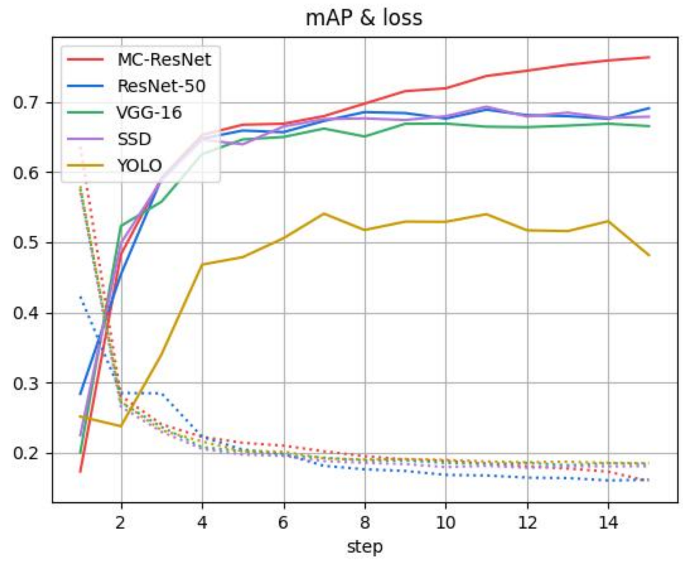


**Figure 5:** Curves of mAP and loss of several methods

## 4. Conclusion

In this paper, a weld defect object detection model based on multi-channel fusion convolutional neural network is proposed, and the effectiveness of proposed model is verified through experiments. The main conclusions are as follows:

1) Based on ResNet-50, a feature extraction strategy of parallel fusion of convolution layers is proposed, which extends the existing deep learning model construction method, enhances the feature extraction ability of similar shape features defects, and improves the precision of deep learning model for weld defect detection.

2) The proposed model is verified by weld defect radiographic images generated in actual production. The results indicate that the MC-ResNet model has higher precision than ResNet-50, VGG-16, SSD and YOLO methods, especially for defects with similar shape features. Compared with ResNet-50, the mAP of MC-ResNet improves 6.70%, and the precision of slag inclusion defect increases 22.12%. Subsequently, this method can be applied to the welding seam radiographic detection of welding products.

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