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Defect Detection of Welding Spots on Steel Plate Surface Based on Improved Resnet Feature Extraction

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Abstract: In order to deal with the problem of defect detection of welding spot on steel plate surface, an improved ResNet feature extraction method is proposed by embedding Squeeze and Excitation (SE) module, then the XGBoost classifier is combined to achieve reliable welding spot defect detection. The experimental results show that the proposed algorithm has achieved remarkable improvement in main indexes such as accuracy, precision and F1 score, the recall rate reaches 97%, which is of great significance for further industrial applications.

1. Introduction

In addition to meeting the standard performance, the industry products also need good surface quality[1,2]. As for the welding spots on the surface of steel plates, in the production process, when the welding machines on the assembly line weld different parts, there will be surface defects such as too little or much solder, wire drawing, welding position deviation, etc.

The quantitative measurement standard adopted by traditional machine vision will be difficult to extract suitable features for detection, which eventually leads to unsatisfactory detection rate. The neural network algorithm related to deep learning can solve this problem well, so it is widely used in the industry[3,4]. Convolutional neural networks (CNN) are suitable for many fields related to images, such as style transfer[5], target detection[6], target tracking[7] and so on. Compared with traditional methods, the advantage of neural network is that the extracted features do not need to be set manually. For some complex scenes, neural network algorithm solves the problem of poor effect of extracting features by setting manually.

In this paper, we pay attention to the quality defects of surface welding spots in steel plate production and processing, and propose an improved algorithm, which effectively combines deep learning algorithm with traditional machine learning algorithm. The whole model is divided into two steps for training. Firstly, the feature extraction ability of neural network is trained, and secondly, the classification ability of traditional machine learning classifier is trained. In the process of model iterative training, the accuracy of the whole model is continuously optimized. The experimental results show that the improved algorithm has achieved remarkable improvement in all indexes, and the recall rate reaches ninety-seven percent, which is of great significance for further industrial application research.

2. Methodology

2.1. Feature Extraction Based on Improved Resnet

ResNet[8] residual network is a convolutional neural network proposed in recent years. The characteristic of residual network is that it is easy to optimize. Compared with other deep neural networks, the network depth will bring more benefits to ResNet, and it tends not to produce the problem of gradient disappearance.

Suppose the input is x, the parameterized network layer is set to H, the output of this layer with x as input is $H(x)$. CNN can learn the mapping relationship between them by iterating and optimizing the loss function, that is, $x \rightarrow H(x)$. Residual learning uses multiple parameterized network layers to fit input and output, learning $x \rightarrow [H(x) - x] + x$, where x is the direct identity mapping, $H(x) - x$ is the residual error between the input and output that need to be learned in the parametric network layer.

In order to consider the actual calculation, ResNet proposes a Bottleneck structure to replace the traditional residual block. It uses 1x1 convolution to reduce or expand the dimension of the feature graph, just like the initial network. Therefore, the number of filters of 3x3 convolution is not affected by the upper input from outside. This design has no effect on the accuracy, but can reduce the network convergence time. Considering the low computational power of industrial scene, ResNet-18, which is lighter in ResNet series, is used in this experiment.

In order to further improve the network performance, the first two BasicBlocks in the original ResNet-18 will be improved to squeeze and exception (SE) modules [9]. The improved network we called SENet-v2 structure is shown in Figure. 1.

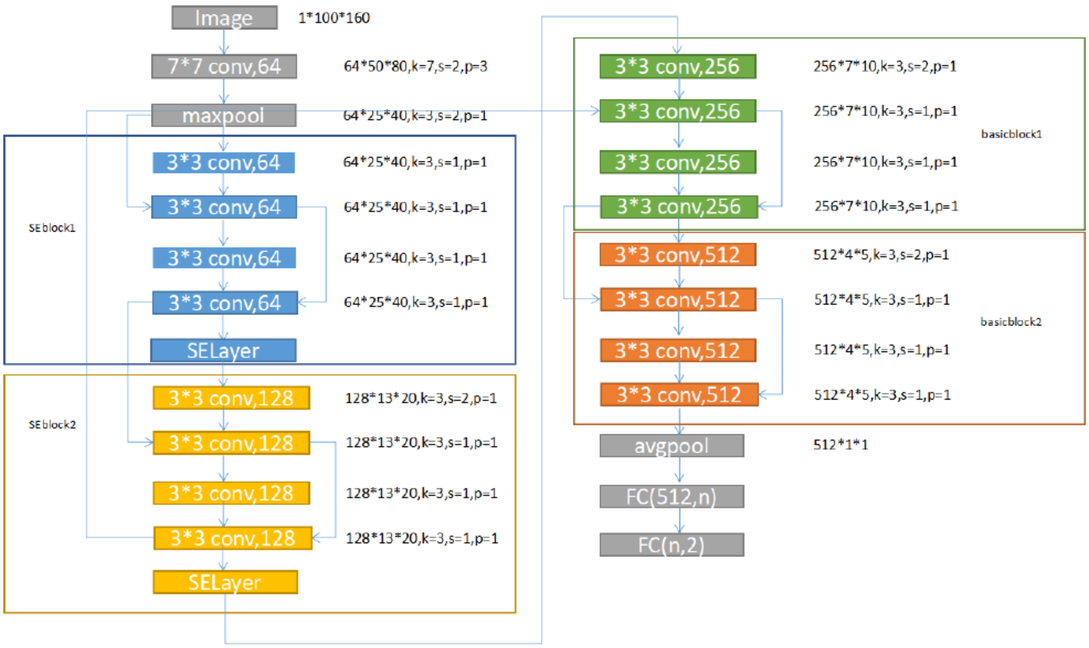

Figure 1: Improved SENet-v2 network structure

2.2. Welding Spot Defect Identification Based on Xgboost

In the traditional machine learning algorithm, the feature extraction process is set and guided manually, and the feature extraction structure is simple and the feature types are relatively single. Deep learning generates high-dimensional feature map feature maps from input images through multiple network layers, so more abundant image feature information can be obtained. Taking the features extracted from SENet-v2 network as input and using XGBoost classifier [10] to identify, the structure of the defect detection system for steel plate welding spot is shown in Figure. 2.

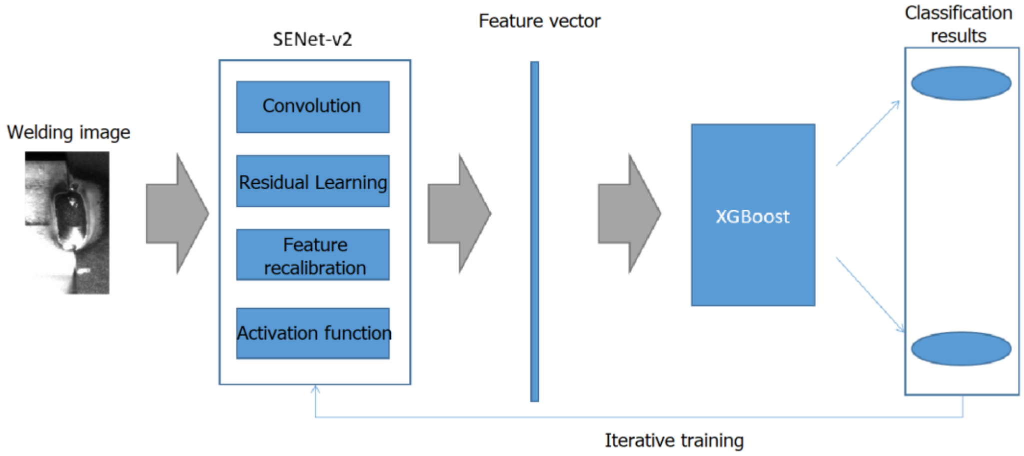

Figure 2: Schematic diagram of defect detection algorithm for steel plate welding spots

First, the welding spots image is input into SENet-v2 as input x. After a series of convolution calculation, residual learning, feature recalibration and activation function, a one-dimensional 1×n feature vector is obtained from the input of the last full connection layer of SENet-v2, where n is a manually set superparameter, which is the target parameter of iterative training. Secondly, the feature vector is input into XGBoost model for classification judgment, and the classification result is obtained. According to the quality of the classification result, that is, whether the model is over-fitted or not, the size of n is dynamically adjusted, so that the SENet-v2 model and XGBoost model are iteratively trained, and the feature extraction performance and classification performance of the model are dynamically adjusted, and finally the overall performance of the model is optimized.

3. Experiment and Results Analysis

3.1. Experimental Setup

The image acquisition system of steel plate welding spot consists of Hikvision MV-CE060-10UM industrial camera, Hikvision MVL-HF0628M-6MPE industrial FA lens, focusing light source and PC. The acquisition method is manual acquisition by MVS software, and the experimental object is elevator door bed steel plate. Figure. 3 shows the image acquisition system of steel plate welding spot in this paper.

The production of data sets will indirectly affect the final performance of the model. Firstly, the enhanced image data are put into different folders according to the number of welding spots, and the folders are named according to the sequence of numbers 1-7. Secondly, the image data is named in the format of date-steel plate number-camera number -label. At the same time, a form file in csv data format is generated for each welding spot, and the file contains the address and label of the image data file needed for training, so as to prepare for the subsequent dataset reading of neural network.

Divide the data set of welding spot images, and divide the images of seven welding spots into training set, test set and verification set according to the ratio of 6:3:1. After data enhancement, the training set is 8086 images, the test set is 4039 images, and the verification set is 1347 images. System data annotation is mainly based on welding spot offset defects, as shown in Figure 4.

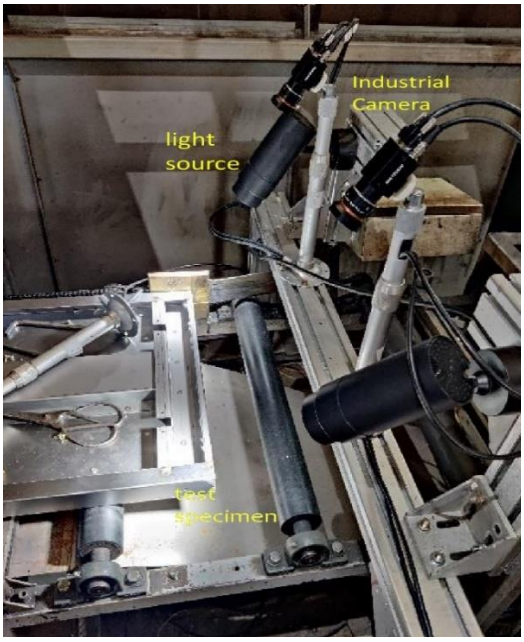

Figure 3: Welding spots defect image acquisition system

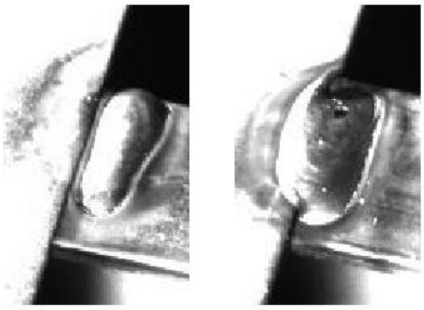

Figure 4: Offset defect image of welding spot

3.2. Analysis of Results

Firstly, the network part is trained, and the performance of the model is verified after the training is completed. The traditional machine learning indicators are used for the model performance indicators, namely, the precision rate (P), the recall rate (R), the Accuracy rate (Acc) and the F1-Score. The details are shown in Table 1:

Table 1: Comparison of experimental results of SENet-V2

Index	Precision	Recall	Accuracy	F1-Score
HOG-SVM	95.59%	95.75%	93.49%	95.67%
HOG-XGBoost	94.94%	96.68%	93.74%	95.80%
BPNet	94.61%	95.08%	92.25%	94.84%
ResNet	94.77%	96.36%	93.36%	95.56%
SENet-v2	**95.26%**	**96.05%**	**93.49%**	**95.66%**

Through the analysis results, it can be found that the overall performance of SENet-V2 model is improved compared with ResNet, and some indexes are better than those based on traditional machine learning.

Secondly, in the part of training the classifier, the performance of the model is verified after the training is completed. The traditional machine learning indicators are used for the model performance indicators, namely, the precision rate (P), the recall rate (R), the Accuracy rate and the F1-Score. The details are shown in Figure 5:

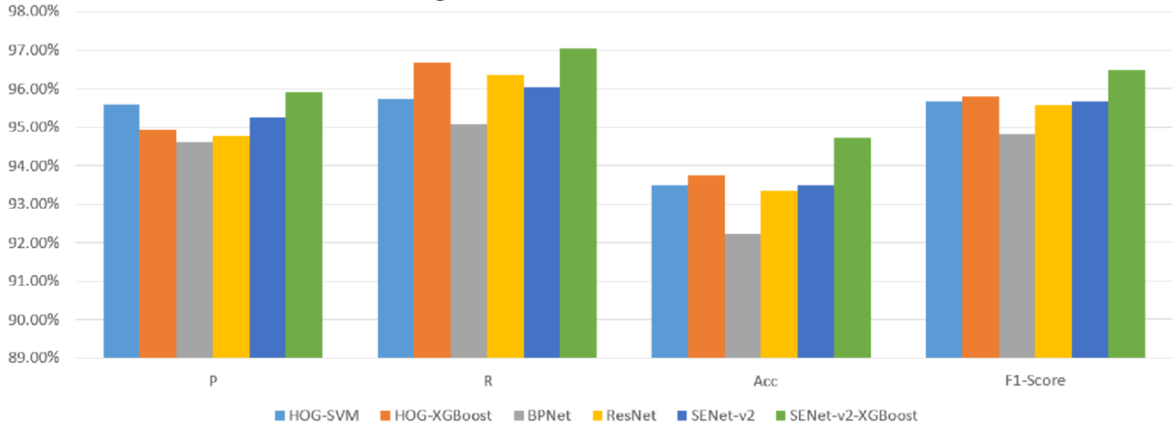

Figure 5: Comparison of experimental results of various models

Through the analysis results, it can be found that the effect of SENet-v2-XGBoost model is improved compared with all other models in the experiment, among which the accuracy and recall rate are the most obvious, indicating that the model has a higher detection efficiency for negative samples. The overall performance of HOG-SVM model is impressive, with all indexes exceeding 90%. Using the same feature extraction method, that is, HOG feature description operator, SVM model has a higher accuracy rate than XGBoost, which indicates that SVM has a higher detection rate for positive samples, but the effect of SVM model is slightly inferior to XGBoost model in other indexes.

When the parameters are similar, the overall performance of ResNet model is improved compared with BPNet, but the detection effect is still not as good as the two methods based on traditional machine learning. Compared with ResNet, the overall performance of SENet-v2 model has been improved, and some indexes have surpassed those of traditional machine learning methods. Compared with the traditional machine learning method, the improved algorithm introduces SENet-v2 as a feature extractor, which shows that the features extracted by the network model are more diverse and more obvious than those extracted by HOG, which is more conducive to XGBoost model to make decisions. Compared with the deep learning method, the improved algorithm uses XGBoost as the classifier, which shows that the traditional machine learning model is more powerful in classifying feature vectors than the last full connection layer of the network model, and the detection rate is higher.

4. Conclusion

In this paper, an improved algorithm for defect detection of welding spot on steel plate surface is proposed, which effectively combines deep learning algorithm with traditional machine learning algorithm. The whole model is divided into two steps for training. Firstly, the feature extraction ability of neural network is trained, and secondly, the classification ability of traditional machine learning classifier is trained. In the process of model iterative training, the accuracy of the whole model is continuously optimized. The experimental results show that the improved algorithm has achieved remarkable improvement in all indexes, and the recall rate reaches ninety-seven percent, which is of great significance for further industrial application research.

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