Research on Semiconductor Chip Grade Classification and Real-Time Evaluation Method Based on Hybrid Artificial Intelligence Technology

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Abstract: Semiconductor chips are widely used in various industries, making the classification of their quality grades and real-time evaluation crucial for ensuring optimal performance and reliability. This paper presents a semiconductor chip grade classification and real-time evaluation method based on hybrid artificial intelligence techniques, effectively improving the accuracy and efficiency of the classification process. Through extensive experiments on real-world data sets, the method demonstrated superior performance in terms of classification accuracy, real-time evaluation, and generalization capabilities compared to traditional methods.
Keywords: Semiconductor Chip; Grade Classification; Real-Time Evaluation

1. Convolutional Neural network model design

1.1 System Overview

The CNN network structure in this paper is mainly modified based on AlexNet. The main process of the experiment is divided into four parts: acquisition of varistor images, aiming at the appearance defects of varistor, 6 classification design of CNN model, training and testing.

(1) Preprocess the acquired varistor image data set, add classification labels, and then randomly divide the tagged data into training set, verification set and test set according to a ratio of 7:1:2; Finally, the data set is amplified to balance the samples of each category.

(2) Based on AlexNet network model, a convolutional neural network model suitable for the recognition of varistor appearance features is designed;

(3) Using the prepared training set and verification set to train the network, the training process is the process of feature learning and classification. In this process, the network is fine-tuned, mainly to adjust the network structure, adjust the super parameters;

(4) If the model is not optimized, proceed with (3); if the model is optimized, proceed with (5);

(5) The trained CNN model is used to test the test images in the data set and the test results are obtained.

The hardware configuration of the computing platform used in this document is as follows: the GPU is NVIDIA GTX 1070Ti, the DDR2 memory is 6GB, and the SSD is 120GB.

1.2 Alexnet Network model

The Alexnet network model has many advantages compared to previous deep learning network models.Firstly, because the ReLU function is used instead of T function and S function, which are often used before, as the activation function, the convergence speed of network model training is improved, and the problem of gradient disappearance is avoided. In the first two convolution layers of Alexnet, a LRN(local response normalization) layer is added to the ReLU activation function. The activated neurons inhibit adjacent neurons to achieve local inhibition, so that the value with large response in the feature graph becomes larger, so as to improve the generalization ability of the model. Finally, Alexnet uses overlap pooling and

Dropout technology to effectively prevent overfitting.

1.3 Improved convolutional neural network model based on Alexnet

The CNN model proposed in this paper is based on the classical CNN network junction Alexnet. Based on Alexnet, a convolution layer and a global average pooling layer are used to replace the last three fully connected layers in Alexnet. Using global averaging pooling layer instead of full connection layer can make the conversion between feature map and final classification easier and more natural. Second, a large number of training and tuning parameters of the full connection layer are no longer required. Reducing the spatial parameters will make the model more robust and better anti-overfitting effect. Finally, the speed and accuracy of the model are improved.

1.4 Evaluation Index

Since you want to predict whether and where each object appears in the image, you need to evaluate the object classification and positioning performance of the model.

Calculate the number of correct detections TP and the number of false detections FP for each category in a picture. We can calculate the precision of each category.

$$precision = \frac{TP}{TP + FP}$$

After the correct predicted quantity TP is obtained, similarly, the missed sample number FN is calculated. Recall(the total number of actual labels can also be used as the denominator):

$$recall = \frac{TP}{TP + FN}$$

However, under the conventional threshold value of IoU, the confidence level of mAP will be very different in different models.For this reason, the researchers came up with a way to solve this problem, which is to use an evaluation index that can be used for any model - precision - recall curve. For a given task and class, the precision - 1 recall curve is calculated from the output sorting of the algorithm. Recall rate is defined as the percentage of all positive examples that rank above a given grade. Accuracy is the percentage of positive samples among all samples above that level. AP is defined as the average accuracy of the 11 recall rates. In fact, this AP is the area under the entire accuracy-recall curve.

$$AP = \frac{1}{11} \sum_{r \in \{0, 0.1, \ldots, 1\}} P\,\text{int}\,erp(r)$$

In addition, the variation of precision - recall curve is caused by the slight variation of sampling order. Therefore, an interpolation method can be adopted in the calculation of accuracy: the accuracy of each recall level r can be interpolated by using the maximum accuracy measured by the method whose recall rate exceeds r:

$$P\,\text{int}\,erp(r) = \max_{r^{'}: r^{'} \geq r} p\left(r^{'}\right)$$

So after 2010, the method of calculating AP was changed to use all data points.Firstly, aps are calculated separately according to the above method, and then the average value of all kinds of aps is taken to obtain mAP. This is how the mAP is computed in the object detection problem. Since this paper is to classify the appearance defects of varistor, in order to ensure the effectiveness and practical value of the proposed method, average precision mean (mAP), the most important index in multi-classification target detection, is used to evaluate the model. The larger the mAP value, the better the classification effect of the model is defined as:

$$mAP = \frac{\sum_{k=0}^{5} AP_k}{6}$$

Where , $k \in [0,5]$ is the label of the 6 categories of the classification, AP_k representing the average precision of category k, mAP is the average of the average precision of all categories.

Particle swarm optimization is a swarm intelligence algorithm derived from bird behavior. The particle swarm optimization algorithm has fast convergence speed and few parameters, but is prone to falling into local optimization. Therefore, set the number of iterations of the PSO algorithm to a smaller value, perform global optimization under the initial conditions, and then use the grid method for traversal optimization.

2. Experiment and analysis

2.1 Data Set

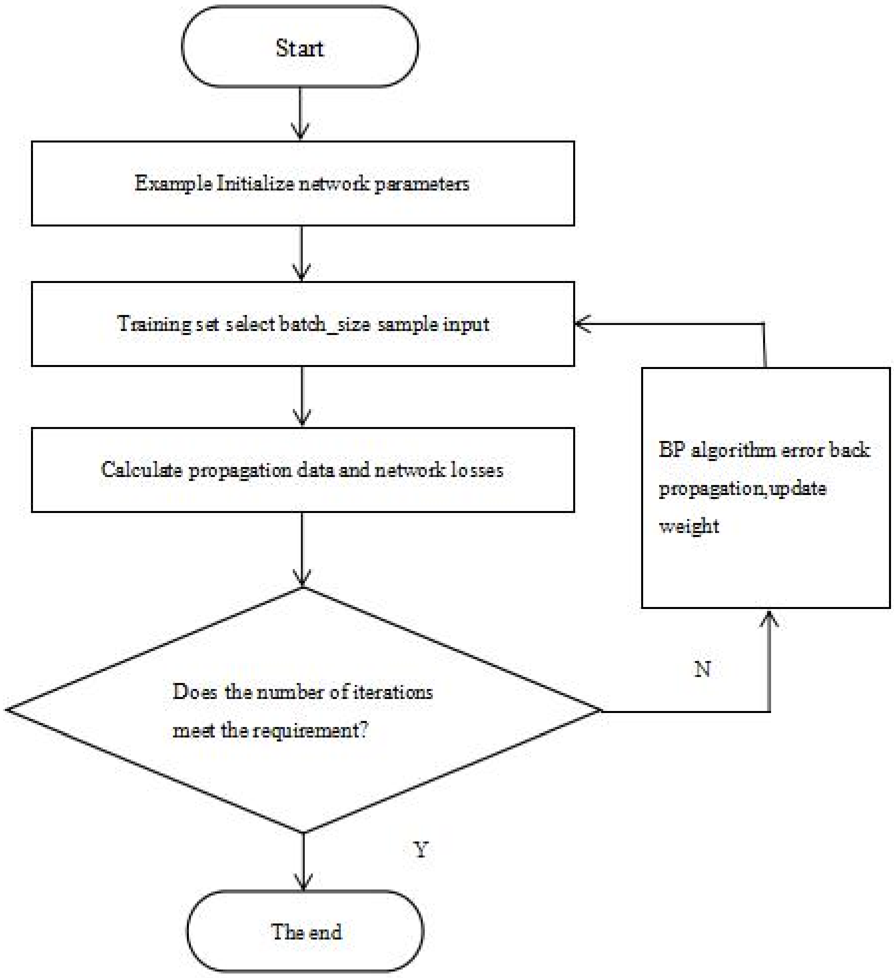
The method used in this paper divides all image data into three parts: training set, verification set and test set. The segmled image data is allocated to train, val and test data sets in a scientific ratio of 7:1:2 to obtain the original data set. In this paper, all kinds of image samples are rotated 45, 90 and 135 degrees, and the original image and the rotated image are flipped horizontally. Then, 15, 75, 105, 165 degrees of rotation and horizontal mirror were added to the image data with large quantity gap, and the six categories of experimental data set required by the experiment were finally enhanced. The distribution is shown in Table 1.

Table 1 six kinds of varistor experimental data sets

	train	Val	test
0(There are printing lossless subjects)	1050	150	300
1(No printing lossless subject)	525	75	150
2(Subject of printing damage)	525	75	150
3(No printing damage subject)	350	50	100
4(Normal stitching)	1050	150	300
5(Damaged stitch)	1050	150	300
Total	4550	650	1300

2.2 Model Training

After designing the CNN network model, the next step is to use the prepared training set for model training. The whole training process is actually a process of CNN feature self-learning, mainly learning convolutional kernel parameters of each convolutional layer and network parameters such as inter-layer connection weights. The specific training process of CNN network is shown in Figure 1:



2.3 Experimental results and analysis

After the training, the CNN4VDR classification model was obtained. Table 2 below shows the test results of appearance defect classification of 1300 test samples.

Table 2 Results of varistor defect classification

Network model	0	1	2	3	4	5	mAP
CNN4VDR	1.0	0.9228	0.9343	0.9985	0.9993	0.9999	0.9758
Alex net	1.0	0.8272	0.8128	0.9368	0.9899	0.9993	0.9277

MAP obtained by testing CNN4VDR model in the above table reaches 0.9758, and AP values of all categories are above 0.92, which verifies the effectiveness of the CNN4VDR model proposed in this paper in classifying the appearance defects of varistor. At the same time, when 1300 test images were tested under the CNN4VDR model, the average detection time of each image was only 17ms, while the mAP obtained by the Alexnet model under the same parameter conditions was 0.9277.

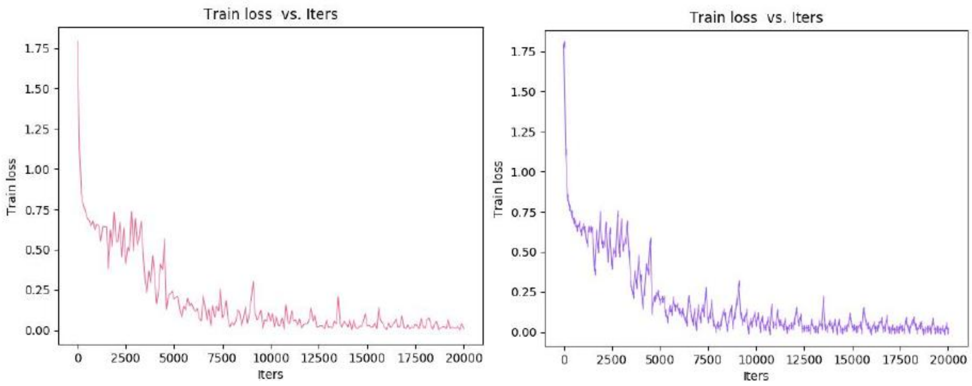


Figure 2 Training loss of CNN4VDR network (left) and Alexnet network (right)

The training loss-iteration curves of the two network models are very similar, It shows that the improved CNN4VDR model in this paper not only achieves better recognition effect, but also the robustness of this model does not decrease compared with Alexnet.

3. Conclusion

In this paper, based on convolutional neural network, the appearance defect classification of varistor is proposed, and a method of appearance defect detection based on convolutional neural network is proposed. In this paper, Mean Average Precision (mAP) was used to evaluate the appearance defect classification performance of the proposed model. Under CNN4VDR model, the mAP of six categories of appearance defects of varistor can reach 97.58%, which is better than AlexNet model, and the average detection time of a sample is about 17ms. Experiments show that the CNN4VDR model can identify various appearance defects of the main body and pins of varistor efficiently and accurately.

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