A Deep Learning-based Generic Solder Defect Detection System

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***Abstract*—Automated optical inspection (AOI) is essential in the electronic manufacturing production line. Strict screening rules lead to a high false alarm rate of AOI. Many industries use AI models to classify defects. The lack of flawed data and the uneven distribution of categories is a big challenge for model training. Furthermore, the AI model must be retrained when adding new production line data, and the time cost is high. In order to reduce the false alarm rate and improve the generalization of the AI model, we build a deep learning-based generic solder defect detection system (GSDD) to classify defects into seven types. In GSDD, the color gradation adjustment module solves the problem of color difference, and the data augmentation module solves the problem of variable data. In the experiment, we use the data set provided by the enterprise to evaluate the accuracy of the model to 96%, and the model can be applied to different machines. Thus, GSDD is a general model and can efficiently detect defects.**

I. Introduction

Defect detection is an essential process on an electronic manufacturing line. There are two methods for detecting PCBA today, one is to judge defects through an AOI machine, and the second is manual detection. AOI detection speed is fast, but the accuracy rate is low; while manual labor has a high accuracy rate, the labor cost is high. In addition, the number of defect data of new products is few. The uneven amount of defect data in each category will lead to the overfitting of the model. The difference in image color gradation will lead to a poor model training effect. It is a big challenge to build a high-accuracy defect detection model using "small and diverse" data.

In this paper, we build a deep learning-based generic solder defect detection system. This system only uses a small number of images to build a model to classify normal and seven kinds of defects in solder joints. In GSDD, there are an image size modification module, a data augmentation module, a color gradation adjustment module,and three classification models to detect defects. The "data augmentation module" is used to solve the problem that the amount of defect data is insufficient, and the quantity is uneven. The "color gradation adjustment module" is used to solve the problem that defect data generated by different machines will have different color levels, resulting in model incompatibility.We use VGG16, ResNet, EfficientNet models for training; our final experimental results can achieve an accuracy rate of 96%. Therefore, the proposed system can be adapted to different production lines without retraining model and significantly increase the utilization of the models.

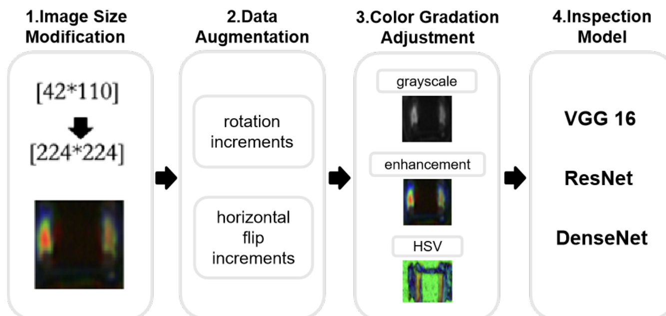

Fig. 1. GSDD architecture.

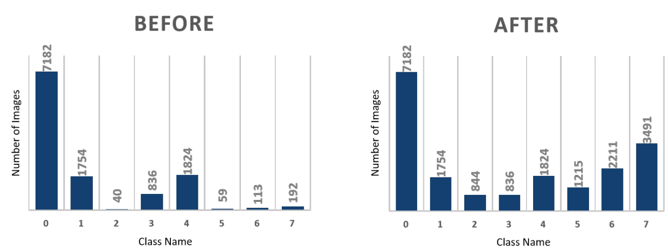

Fig. 2. Data comparison chart before and after the augmentation.

II. Generalized solder defect detection system

The generalized solder defect detection system has four parts, namely the image size modification module, data augmentation module, color gradation adjustment module, and solder defect detection model. The system architecture is shown in Fig 1.

A. Image size modification module

The pre-trained models we get are all 224*224 pixels as input. So, we changed the picture is significantly improved from 42*110 to 224*224 pixels.

B. Data augmentation module

First, observe the distribution of image data in the eight categories of the training set, such as solder insufficient, wrong component, and tombstone. Then, augment on categories that are a small amount of data. The above method can make the image data evenly distributed during the subsequent training, which is beneficial to the training and optimization of the model. In order to avoid the problem of confusion in identifying defects by the incremental method. For example,

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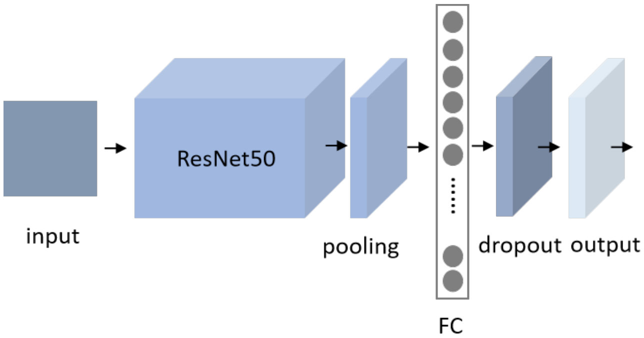

Fig. 3. Model architecture.

If we rotate and increment the data of "component flip," it may cause the system to misjudge that the component is standing sideways. We adopt different data increment methods for distinct defect categories. We made rotation increments for defect categories such as excessive solder, component shifted and did horizontal flip increments for defect categories such as tombstone, solder skip, wrong part, and missing component. The data augmentation result is shown in Fig 2.

C. Color gradation adjustment module

Since the color and brightness of the images collected by different machines are different, we convert the images to unified color space and try the color space conversion of grayscale, color enhancement, and Hue, Saturation, Value(HSV). In order to make the model applicable to different machines.

D. Solder defect detection model

Choosing a suitable preprocessing model can improve the efficiency of subsequent training. This paper uses a series of preprocessing models such as DenseNet [1], ResNet [2], VGG16 [3] and EfficientNet [4] to build a generalized solder detection system. We also add self-designed convolutional layers to the model. After testing and detection, we found that using ResNet to build a solder defect detection model has the best accuracy. When building ResNet, we froze the previous layers, trained the last five layers, and added global average pooling, fully connected layers, and dropout layers to prevent overfitting. The activation functions are Relu and Softmax; we use the Adam optimizer when compiling the model, the learning rate is 0.0001, and the final loss function is Categorical Cross Entropy. The model architecture is shown in Fig 3.

III. Experiment

We have two PCBA datasets with different color scales referred to as A and B datasets. First, use the A dataset to train the model and use the B dataset to test whether the model is general. We used the input of four-color spaces to check which works better. The results are shown in Table I.

Overall, the model has a better classification effect on the image defects of HSV and color enhancement. Therefore, we perform data augmentation on these two datasets and add a 10% B dataset for mixed training to test whether the model is suitable for the new production line. Due to the poor effect of EfficientNet, we use VGG16 for new model training. The results are shown in Table II. Among them, ResNet has the best color enhancement accuracy.

TABLE I
The dataset uses four color spaces.

	DenseNet	***ResNet***	***EfficientNet***
original	34%	41%	5%
gray scale	41%	50%	66%
HSV	53%	23%	65%
color enhancement	71%	46%	5%

TABLE II
HSV and color enhancement with data augmentation.

	DenseNet	***ResNet***	***VGG16***
HSV	59%	85%	37%
color enhancement	75%	96%	76%

IV. Conclusion

In this paper, we proposed a deep learning-based generic solder defect detection system. In this system, we designed a data augmentation module to solve the data imbalance problem with fewer defect data and a color gradation adjustment module to make the model adapt to the image color of different machines. Through these modules, the accuracy rate of defect classification of this system can reach 96%, and it can adapt to different production lines, significantly increasing the model's generality.

Finally, we packaged the system into the form of executing. Users can add the images to be predicted without the python environment to identify defect categories. The operation is quite simple and convenient.

In the future, if new categories of defects data are repeatedly added, the model will be retrained. Then the model will only recognize the new class and forget how to recognize the old class. We hope to introduce incremental learning. When the model is trained with new categories of data, it can retain and integrate the old categories simultaneously to improve the accuracy of defect identification.

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