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A Deep Learning-based General Defect Detection Framework for Automated Optical Inspection

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***Abstract*—Artificial intelligence (AI) is applied in automated optical inspection (AOI) to help inspect defects and reduce the false discovery rate of AOI in manufacturing industries. In current studies, the training data of AI models are sufficient, and the source data are from the specific production line. However, defect samples are insufficient, and the data source is variant. The current models need more generalization to all machines and take a long training time to build a new model for other appliances. This paper proposes a Deep Learning-based General Defect Detection Framework (DLG-DD) solves the insufficient data issue and the generalization issue of models. We implement a color preprocessing module, a data augmentation module, a data generation module, and four classification models to detect defects and generalize the utilization of DLG-DD. In experiments, we evaluate DLG-DD based on the NEU-CLS and AIdea datasets. The accuracy of DLG-DD is 90%, and the false omission rate and false discovery rate are less than 1%. DLG-DD is a general framework that tackles insufficient data and decreases the false discovery rate of AOI.**

***Index Terms*—Automated optical inspection, defect detection, data augmentation, classification models**

I. Introduction

Artificial intelligence for defect inspection is essential in the manufacturing process. Machine and manual inspection are set at the end of the process to find abnormalities. Machine inspection is fast, but accuracy is low. On the other hand, manual inspection is highly accurate but takes much time. Therefore, factories first adopt AOI to conduct high threshold screening and then manually re-inspection to reduce false alarms and ensure no leaks [1]. However, the high false discovery rate results in high human re-inspection costs.

Many studies implement AI to help detect and classify anomalies. [2] designed an efficient CNN-based approach to detect the defects of copper-clad laminate (CCL) images acquired from an industrial CCL production line. [3] proposed a convolutional neural network (CNN) structure and refinement mechanism to recognize the characters on the printed circuit boards. [4] trained K-Nearest neighbor (KNN), artificial neural network (ANN), and random forest (RF) based on the data of the AOI machine. [5] collected data generated by AOI and built a new lightweight deep ensemble learning method to improve the overall performance. The above researchers trained models with sufficient data and quickly achieved high accuracy.

In reality, defect samples are usually insufficient due to the high yield rate of production lines. This "data insufficient" problem was dealt with in [6] by proposing a new convolutional variational autoencoder (CVAE) to generate sufficient defect data to train the classification model. Generative adversarial networks (GAN) are adopted in [7] to localize anomalies and generate imitations of anomalous samples. Besides, the source of current training data is collected from specific environments. The well-trained defect detection models can only be applied to the target environments. When data comes from different sources, models cannot be generalized.

This paper proposes a Deep Learning-based General Defect Detection Framework (DLG-DD) solve the insufficient data issue and the generalization issue of models. First, we implement four different color preprocessing methods in the DLG-DD. Second, we add a data augmentation module to solve insufficient defect data to generate adequate data. Moreover, a deep convolutional generative adversarial network (DCGAN) model [8] is implemented to increase the variance of generated data. Finally, we build VGG16 [9], ResNet [10], Xception [11], and DenseNet [12] to classify defects and generalize the utilization of the proposed framework. In addition, we utilize the datasets of NEU-CLS [13] and AIdea [14] to evaluate DLG-DD, respectively. From the experiments, the model accuracy is about 90% based on the NEU-CLS dataset. The false omission rate and false discovery rate are about 0.2% based on the AIdea dataset.

II. Related Work

Building an AI model to increase the accuracy of defect detection is the goal in AOI research [15]. In [4], the authors built KNN for the small circuit board dataset. If the dataset was large, KNN might need more computing time. To decrease computing time on a large dataset, ANN and random forest classifiers performed better than KNN. [16] utilized the data of the solder paste inspection (SPI) system for training a deep neural network (DNN) model. The data included area, height, volume, and offsets of solder paste. DNN model predicted the quality of the solder joint. [3] adopted deep learning models to recognize the characters on integrity circuits (IC) and help factories find the print circuit board with faulty IC components. If images are without characters or blurry characters, an image classification system with CNN structure would be adopted to classify images. [17] detected the bubble defects in the glass based on the spherical glass dataset. Using the VGG model, they detected defects smaller than millimeters of detection. The accuracy was about 95%. Although these methods performed well, they were only suitable for their training data. The models

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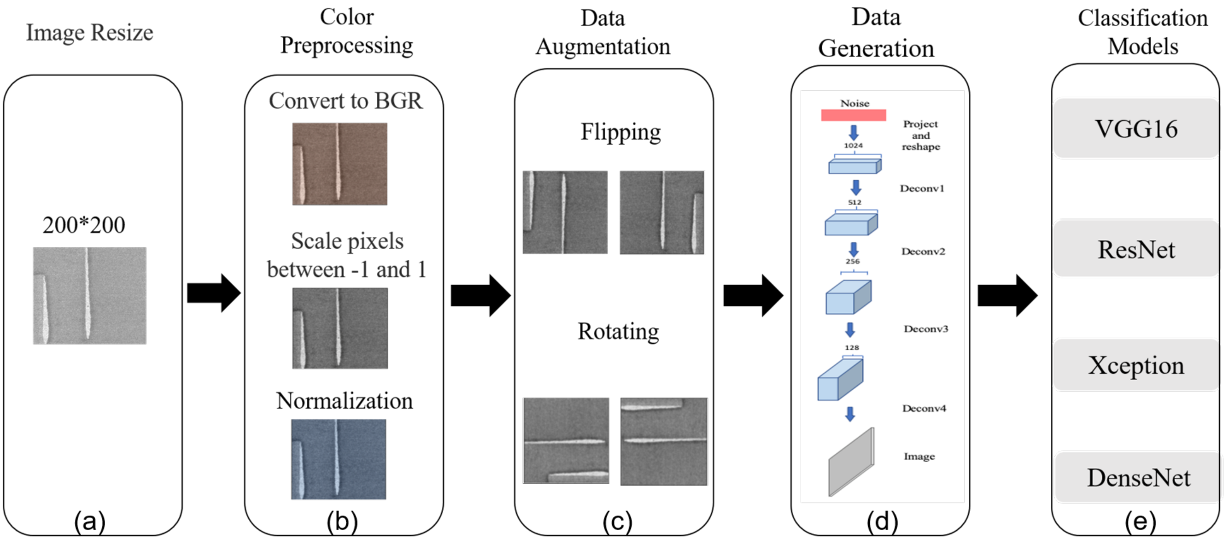

Fig. 1. DLG-DD framework.

could not generalize to other datasets if data came from different sources.

Besides, in reality, the training data was insufficient since the abnormal rate of the products was very low. Some researchers designed GAN to solve this issue. [18] proposed a data augmentation method based on GAN and Gaussian mixture models. This method effectively increased the number of training samples, reduced distribution differences between training and test sets, and controlled the features of the generated images to a certain extent. It significantly increased accuracy, improving from around 75% to nearly 90% across various classification networks in almost all experiments. [19] devised a dual auto-encoder-based anomaly detection neural network called DAGAN to address the issue of sample imbalance within their study. [20] built a one-class classification model with pre-trained GANs for industrial anomaly detection. The result showed that GAN captured the features of industrial images and generated good industrial images. In [21], authors designed a data augmentation framework for small manufacturing defect datasets. They modeled the training data distribution of the NEU-CLS dataset. They adopted GANs to sample additional synthetic data, which can be used to augment the real data for subsequent training of a CNN classifier. It significantly improved the performance of the CNN for surface defect classification. However, traditional GAN took much work to control the data generation process. Conditional generative adversarial networks (CGAN) added label information in the input to increase the controllability of unsupervised GAN. [22] adopted CGAN to generate the defect images. Higher-resolution image data is necessary while building the AI model for the AOI system. Deep convolutional generative adversarial networks (DCGAN) [8] can increase the clarity of the defect on the generated image. [7] segmented anomalies on pixel-level based on the proposed DCGAN model and generated anomaly samples. The computation resource of the DCGAN model is relatively less. According to the advantages of DCGAN, we would like to adopt DCGAN to increase image generation performance.

III. Deep Learning-based General Defect Detection Framework

We propose a Deep Learning-based General Defect Detection Framework (DLG-DD) for AOI, as shown in Fig. 1. In this framework, we design a color preprocessing module, a data augmentation module, and a DCGAN module to improve the data's quality, quantity, and variety. We also build four convolutional neural networks (VGG16, ResNet, Xception, and DenseNet) to classify AOI images and compare the results of each model.

A. Color Preprocessing

In the color prep-processing module, we resize images to 200*200 pixels and implement three color preprocessing methods to reduce the gap between the input images and the ImageNet dataset used by the pre-trained model.

- Converting images to BGR channel: We convert the input images to the BGR channel and subtract the average BGR of the ImageNet dataset, as shown in Fig. 1(b).
- Scaling pixels between -1 and 1: We divide each image pixel value by 127.5 and subtract 1 to scale the value between -1 and 1.
- Normalization: We normalize the images based on the average color of the ImageNet dataset.

We will choose the color preprocessing methods in each model according to the accuracy.

B. Data Augmentation

In this module, we develop data augmentation methods [23] to increase the number of training data and improve the model's performance. Since there are many directional defects in the manufacturing process, such as scratches and cracks, we implement horizontal flipping and vertical flipping to augment data in DLG-DD, as shown in Fig. 1(c).

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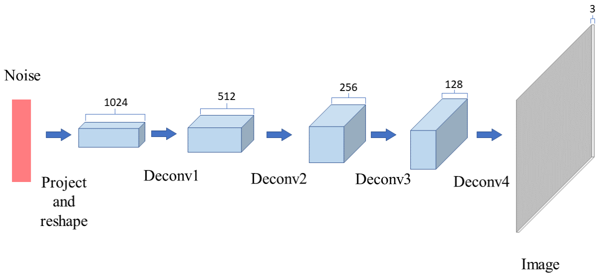

Fig. 2. Generator of DCGAN.

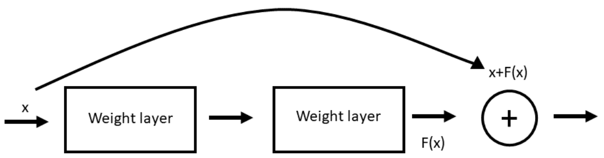

Fig. 3. Residual block of ResNet.

C. Data Generation

To increase the variety of data, we adopt DCGAN [8] to generate more data. In DCGAN, the discriminator adopts stridden convolutions instead of pooling layers, and the generator chooses fractional-stridden convolutions instead of pooling layers, as shown in Fig. 2. The generator and the discriminator both used batch normalization. Fully connected hidden layers are removed for deeper architectures. ReLU is adopted in all generator layers except for Tanh in output. In the discriminator for all layers, the activation function is LeakyReLU.

D. Classification Model

To generalize DLG-DD and fit different data, we develop VGG16, ResNet, Xception, and DenseNet as pre-trained models. After building four pre-training models, we modify the fully connected layers of the four models.

1) VGG16: VGG16 [9] consists of two modules. The first module is used for feature extraction and comprises 16 convolutional layers with a $3x3$ kernel. Each convolutional layer uses ReLU as the activation function and is followed by a maximum pooling layer with a size of a $2x2$ kernel. Finally, the second module has three fully connected layers as the classifier.

2) ResNet: ResNet [10] proposed an "identity shortcut connection" concept to skip one or more layers to overcome the vanishing gradient problem in deep networks. In the deep network, there are some redundant layers. A jump connection is added in every two layers as a residual block to make the input and the output the same, as shown in Fig. 3.

3) Xception: Xception [11] is an inception module from the Inception-v3 network. There are about 20 million hyperparameters in the Xception network. It contains 36 convolutional layers. Depthwise separable convolutions are designed to perform convolutions on each channel to learn the correlation between channels.

4) DenseNet: DenseNet [12] is also proposed for solving the vanishing gradient issue. Suppose the convolutional neural network contains a short connection between the layer close to the input and the layer close to the output. In that case, the convolutional neural network can be trained more deeply, accurately, and effectively. Therefore, DenseNet connects each layer to every other layer in a feed-forward method. There are L connections in the traditional convolutional neural network with L layers, but $L*(L+1)/2$ direct connections between each layer and the next layer. The feature maps will be the input to the next layer and subsequent layers, as shown in Fig. 4.

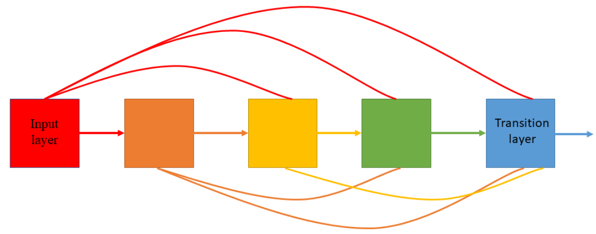

Fig. 4. DenseNet.

After building four pre-training models, we modify the final fully connected layers. We adopt two sets of fully connected layers with ReLU activation, a normalization, and a dropout layer. Finally, a fully connected layer with a softmax function is developed as a classifier. We use categorical cross-entropy as the loss function and Adam as the optimizer. The learning rate is set to 0.001 during the initialization process and will be dynamically adjusted during the training process. If the loss does not decrease after ten epochs, the learning rate is zoomed out ten times to get the best training results.

IV. Experiments

This section will conduct experiments on the NEU-CLS dataset [13] and AIdea dataset [14]. We only know those images are optical, but we need to know the source of data and manufacturing process. Therefore, the generalization ability of our framework can be tested by these two datasets.

We select the color preprocessing methods in the following experiments and then use data augmentation and DCGAN to increase the data variability. Finally, we compare four classification models based on accuracy, false omission rate, and false discovery rate.

A. Evaluation Metrics

We use accuracy, false omission, and false discovery rates to evaluate DLG-DD. False Positive (FP) represents pseudo defects. False Negative (FN) means actual defects. True Positive (TP) and True Negative (TN) represent the images that are correctly classified. In industrial production lines, false omission, and false discovery rates are two important indicators. The false omission rate represents the proportion of instances where no defects are present among all incorrect judgments. The false discovery rate represents the proportion of instances where no defects are present among all instances classified as having defects. The low false omission rate and false discovery rate mean the model can accurately classify defective and normal products.

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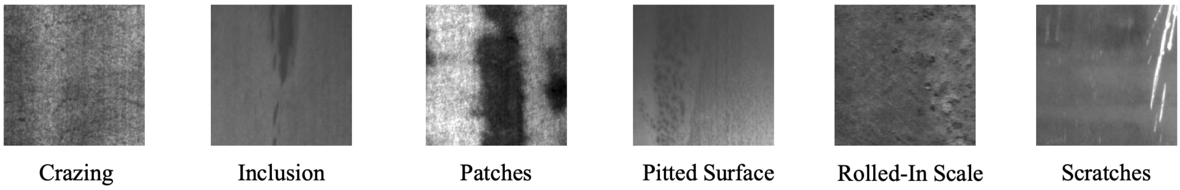

Fig. 5. NEU-CLS dataset [13].

TABLE I
NUMBER OF HYPERPARAMETERS OF FOUR MODELS

	VGG16	ResNet	Xception	DenseNet
Original	14,714,688	58,370,944	20,861,480	18,321,984
Total	15,247,174	59,689,862	22,180,398	19,575,366
Trainable	15,245,126	59,536,390	22,123,822	19,344,262

TABLE II
COMPARISON OF COLOR PREPROCESSING METHODS BASED ON THE NEU-CLS DATASET

Method / Accuracy(%)	VGG16	ResNet	Xception	DenseNet
Converting images to BGR channel	82.22	84.4	83.33	83.33
Scaling pixels between -1 and 1	81.94	83.05	85.50	84.72
Normalization	80.55	82.22	83.88	85.55

$$Accuracy = \frac{TP+TN}{TP+FN+TN++FP} \quad (1)$$

$$False\ Omission\ Rate = \frac{FN}{FN+TN} \quad (2)$$

$$False\ Discovery\ Rate = \frac{FP}{FP+TP} \quad (3)$$

B. Model setting

The number of trainable hyperparameters for each model is shown in Table I. After constructing four models, we obtain the number of original hyperparameters for each model. After adding a fully connected layer, a dropout layer, and a normalization layer, we get the number of total hyperparameters for each model. In the normalization layer, we can only modify α weight and β weight in Keras module. Therefore, after deducting non-trainable hyperparameters in the normalization layer, we obtain the number of trainable hyperparameters for each model.

C. Experiments of NEU-CLS Dataset

In this experiment, we evaluate DLG-DD by the NEU-CLS dataset. There are 1800 defect images with six classes in NEU-CLS dataset [13]: crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches. The size of each image is $200 * 200$ pixels, as shown in Fig. 5. We divide 80% of the dataset into the training set and 20% into the testing set.

First, we use the testing set to select the color preprocessing method of four models according to the accuracy, as shown in Table II. Converting images to the BGR channel is the most accurate color preprocessing method in VGG16 and ResNet, respectively. Scaling the pixel between -1 and 1 is the most accurate color preprocessing method in Xception. Normalization is the most accurate color preprocessing method in DenseNet.

After selecting color preprocessing methods, we use data augmentation to increase the data quantity and DCGAN to increase the data variability. Since there is no normal class in the NEU-CLS dataset, we only use "accuracy" to evaluate the performance of four models. As shown in Table III, the accuracy of the four models exceeds 85%. The accuracy of DenseNet reaches 90.27%, the highest of the four models. Therefore, DenseNet will be chosen as the classification model for NEU-CLS dataset.

TABLE III
ACCURACY OF THE FOUR MODELS BASED ON THE NEU-CLS DATASET

	VGG16	ResNet	Xception	DenseNet
Accuracy(%)	85.27	86.38	88.88	90.27

TABLE IV
COMPARISON OF COLOR PREPROCESSING METHODS BASED ON THE AIDEA DATASET

Method/ Accuracy(%)	VGG16	ResNet	Xception	DenseNet
Converting images to BGR channel	89.44	95.28	92.85	93.08
Scaling pixels between -1 and 1	88.53	93.87	95.73	95.73
Normalization	88.93	92.88	94.86	96.01

D. Experiments of AIdea Dataset

In the experiment, we evaluate DLG-DD by the AIdea dataset. There are 2528 defect images with six classes in AIdea dataset [14]: normal, void, vertical defect, horizontal defect, edge defect, and particle. The size of each image is $512 * 512$ pixels, as shown in Fig. 6. We divide 80% of the dataset into the training set and 20% into the testing set.

Based on the accuracy obtained by using different color preprocessing methods on the test set, we select the color preprocessing method for four models according to the accuracy. In Table IV, we can see that each model's best color preprocessing method is the same as the result of the NEU-CLS dataset. Therefore, we recommend using VGG16 to convert images to the BGR channel method. The input of ResNet should be processed by subtracting the average BGR of the ImageNet dataset method. Each pixel of Xception network image should be divided by 127.5 and subtracted by 1 to get a better result. Normalizing the images is the best color preprocessing method for DenseNet.

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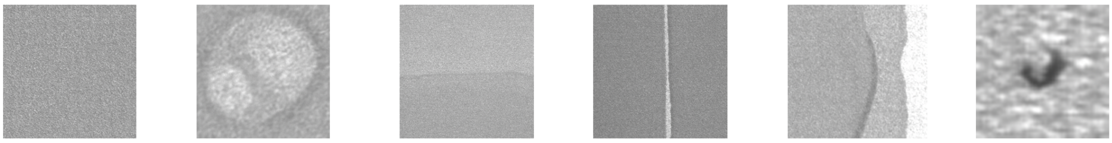

Normal | Void | Vertical Defect | Horizontal Defect | Edge Defect | Particle

Fig. 6. AIdea dataset [14].

TABLE V
ACCURACY OF THE FOUR MODELS BASED ON THE AIDEA DATASET

	VGG16	ResNet	Xception	DenseNet
False Omission Rate	2.56%	0.79%	0.59%	0.19%
False Discovery Rate	1.97%	0.39%	0.39%	0.19%

After selecting color preprocessing methods, we use data augmentation to increase the quantity of training data and use DCGAN to increase the variability of training data. There are normal classes and five defect classes in AIdea dataset. We merge five defect classes into one defect class and use the false omission rate and false discovery rate to evaluate the performance of the four models. As shown in Table V, the false omission and false discovery rate of DenseNet are the lowest. Therefore, DenseNet is the best classification model for the AIdea dataset.

V. CONCLUSION

In this research, we proposed a deep Learning-based general defect detection framework (DLG-DD) for AOI. In DLG-DD, we developed three color preprocessing methods to adjust the color of images. We also implemented vertical and horizontal flipping in the data augmentation module to increase the training data. To increase the data variability, we adopted DCGAN to generate more data. Finally, we built VGG16, ResNet, Xception, and DenseNet to classify AOI images.

Besides, we evaluated DLG-DD based on the NEU-CLS and AIdea datasets. Based on the NEU-CLS dataset, the four models' defect classification accuracy is higher than 85%. Especially in the DenseNet model, the accuracy is more than 90%. In the AIdea dataset, the false omission rate and false discovery rate of ResNet, Xception, and DenseNet are all less than 1%. In conclusion, DLG-DD can solve the insufficient data issue and effectively reduce the false omission and false discovery rate. The goal of applying generalized AI technology in the AOI field is also achieved in this paper.

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