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Based on Deep Convolutional Neural Network and Machine Vision Applied to the Surface Defect Detection of Hard Disk Metal Gaskets

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***Abstract* – This Study aims at the surface defects of aluminum gaskets as the detection targets. The types of defects are yellow spots, incomplete grinding and bump damages. The detection method will select image processing or deep learning according to the characteristics of the defects. The characteristic of yellow spots has many variables of random shapes and different shades of color, it is difficult to use image processing to detect defects, therefore, this Study selects deep learning as the detection method of yellow spot and the detection network architecture is a modified architecture based on U-Net. It also proposes the preprocess of removing the background of the image before the model training, by removing the outer pixel value out side the gasket area on the image. It was found that the preprocess can improve the Intersection over Union (IoU) by 0.041. The experiment results showes that using the proposed network architecture the evaluation of yellow spot IoU is 0.611 which is better than the original U-Net with a model accuracy of 99.56%.**

Keywords – Deep Convolutional Networks, Automated Optical Inspection, Digital Image Processing, Metal Gaskets, Defect Detection.

I. INTRODUCTION

Nowadays, due to the needs of industrial automation production, products are not only trouble-free in use, but also the standards for appearance defects have also gradually improved. Due to the advancement of industrial technology, metal rings have been mass-produced, but manual detection of product defects and faults is still being used at present, resulting in prolonged production time. The bump damage defect of the product's metal ring at the edge of the ring and the yellow spots defect, which has the problem of color depth and unapparent is easy to cause inconsistency during inspection according to the inspector's standards for defect. This increases the misjudgment rate and inspection time leading to increase in the company's costs, and affecting the standard of product appearance. Aiming at this defect problem, we use Automated Optical Inspection (AOI) to replace manual inspection, which can shorten the inspection time and quantify and fix the defect standard. However, the evaluation criteria of defects still need to be identified manually, and the selected light source will also change the characteristics of defects appeared in the image. If the defect characteristics on the image are judged manually and are far from the actual piece, it will affect the subsequent establishment of defect standards. Therefore, the selection of light sources and lighting methods are very important in the field of Automated Optical Inspection. .

II. RELATED RESULTS IN THE LITERATURE

In recent years, using the deep convolutional networks as a defect detection method has achieved a high recognition rate [1], but the network model will cause the problem of gradient divergence as the number of layers increases. In 2019, Yih-Fan Chen, Chao-Ching Ho, et al. [2] of our laboratory proposed a modification based on the ResNet network model, removing the pooling layer of the first convolutional layer of the network, and adding a fused-layer architecture after the fifth convolutional layer, in order to increase the amount of information for that defect characteristic. If the network model has a larger difference in the input value of the weight that requires different learning rate to be assigned, hence add BN before or after the excitation function can make the learning rate consistent. The network model can avoid spending extra time training the contour characteristics of the front layer by means of transfer learning [3]. In addition to judging whether the image is a defect, in order to further obtain the position of the defect on the image, fully convolutional networks can be used [4]; therefore, this Study will pair up the above method and combined with machine vision as the method of surface defect detection for metal gaskets.

III. RESEARCH METHOD

Based on the inspection situation, the deep learning framework introduces the U-Net [5] network model as the basic architecture for yellow spot defect detection. The network model performs Semantic segmentation, so the defect classification is pixel wise. The input image before feeding to the neural network is preprocessed to remove the background of the image by removing the by removing the outer pixel value out side the gasket area on the image. After this the the complete gasket image is given as input to the Neural network.

The proposed neural network is a modified network architecture based on the U-Net [5] network and in this article it is called RM1024; this improvement is to remove the original fifth layer of 1024 dimension. This removal moderately reduces overfitting caused by the network model at deeper layers. Also, to moderately alleviate the overfitting Dropout (0.5) layer is added in the third and fourth layers. According to the host GPU memory capacity of 11G, the input image size is adjusted from the original 572×572 image size to 512×512 image size to adjust the memory usage within the aavailable range. The training parameters are shown in Table 1. The training is 1st conducted using the original U-Net architecture and than the proposed RM1024 architecture. The study shows that the proposed architecture produces bettter accuracy than the original U-Net.

Table 1. Network Model Parameters.

No. of epochs	20 epochs
Input image size	512 × 512 pixels
Train images	195
Data augmentation	19946
Validation images	56
Steps per epoch	500
epochs	30
Batch Size	$\frac{20141}{40}$ = 500 / epoch
Learning Rate	0.0001

To evaluate the quality of the model metrics such as accuracy and Intersection Over union (IoU) is used. Model accuracy is a metric that characterizes the number of all records that are correctly classified, to the sum of all records. The metric is calculated using the following formula (1):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Intersection over union, IoU is used to evaluate the correctness of the defect position on the image. It is often used to evaluate Predicting the network model at the pixel level, the IoU value is calculated by formula (2), which characterizes the predicted defect area, over the actual defect area, and the unit is the number of pixels.

$$\text{IoU} = \frac{P_A \cap D_A}{P_A \cup D_A} \tag{2}$$

Where, TP— Number of true positive
FP— Number of false positives
TN— Number of true negative
FN— Number of false negatives
P_A — Predicted defect area
D_A — Actual defect area

IV. RESULTS AND DISCUSSIONS

The training curv for both U-Net and RM1024 is shown in the Fig. 1. The segmentation results for RM1024 is shown in Fig. 2. Fig1. Shows the plot of Accuracy vs Epochs. It can be observed that the proposed RM1024 is able to produce an accuracy of 99.56%. The segmentation result shows that the RM1024 is able to acieve an IoU of 0.611 while the original U-Net is able to achieve an IoU of 0.558. This shows the proposed architecture is able to identify the defect areas better.

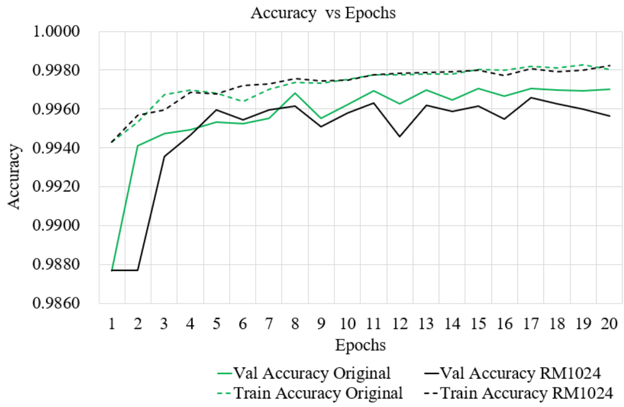

Fig. 1. Learning Curves

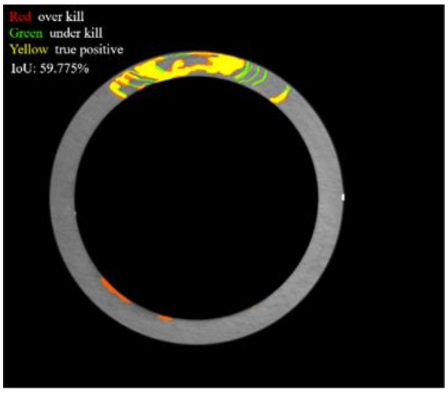

Fig. 2. Defect detection results

V. CONCLUSIONS AND OUTLOOK

This Study aims at detection of metal ring defects based on deep learning network and image processing. In studying the defect detection system, since the defect characteristics must be presented on the image, so the selection of the light source is very important. Than selecting a suitable detection method and network model based on the characteristics appeared by the defects is important. Due to the uneven brightness of bump damage defects, we proposes unwrapping the gasket and use a modified U-Net architecture to solve this problem, with an accuracy of 99.56% and an IoU of 0.611.

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