Image Inpainting with Self-Supervised Learning for Mura Detection System

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***Abstract*—Mura is usually caused by inhomogeneity and material defects in the manufacturing process. According to the JND value, it can be divided into light Mura and serious Mura. In order to optimize the repair process, the factory hopes to distinguish between light Mura and serious Mura before sending them to the repair site. However, the traditional AI model only distinguishes between normal and Mura and is ineffective in distinguishing between light Mura and serious Mura. To address this issue, we propose a Mura Detection System using an image inpainting model with a self-supervised technique and an attention module to distinguish light Mura and serious Mura. The experiment results show that the proposed method's Area Under Curve (AUC) can reach 0.854.**

I. Introduction

Panels often have Mura defects during the production process. We use the Just Noticeable Differences (JND) value to distinguish between "light Mura" as shown in Fig. 1 and "serious Mura" as shown in Fig. 2. The factory has two restoration sites. All panels must be sent to the first site for repair, and for serious Mura, they must be sent to the second site for further repair. This method will reduce the speed of shipment. Therefore, We want to add a Mura defect detection model in front of the first station, to distinguish whether the panel is light Mura or serious Mura in advance.

However, the early AI models, such as [1] and [2] were used to distinguish between normal and Mura, and the effect of distinguishing light Mura and serious Mura could have been better. Nevertheless, the autoencoder has too strong a rebuilding ability to restore Mura defects easily, so we use the image inpainting method. Furthermore, self-supervised learning increases the ability of the model to learn features. In this paper, we propose a Mura Detection System using an image inpainting model with a self-supervised technique and an attention module to distinguish two types of Mura.

We use a self-supervised module to improve the generalization ability of the image inpainting model and also add an attention module between the encoder and decoder to allow the model to focus on regions with Mura defects when reconstructing images. Our contributions to this work are summarized as follows,

- We propose a Mura Detection System using an image inpainting model with a self-supervised technique and an attention module to differentiate light Mura and serious Mura.

Fig. 1: Light Mura.

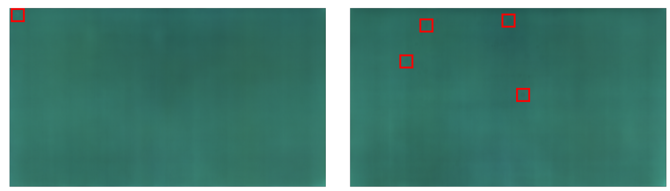

Fig. 2: Serious Mura with black or white block.

- The proposed method intensively increases the AUC of Mura detection.
- The proposed method optimizes the panel production process.

II. Methods

In order to further strengthen the model to distinguish between light Mura and serious Mura, we propose a Mura Detection System using an image inpainting model with a self-supervised technique and an attention module.

A. Self-Supervised module

Self-supervised learning can enable the model to learn a more robust and general feature representation, thereby improving the model's generalization ability. [3] proposed a new objective function to avoid collapse by computing the cross-correlation matrix of two identical network outputs. We use Barlow twins [3] as our pre-train model to achieve our purpose.

B. Image inpainting module

[4] utilized an ATN network to fill the hollowed-out areas of feature pyramids and combined the ATN network's features with the decoder's features using skip connections to reconstruct the filling area more effectively. [5] added Fast Fourier Convolution (FFC) to the inpainting network, enabling

the model to have a full-picture receptive field in the shallow layer. [6] incorporated a shift-connection layer based on U-Net to enhance the details of the filled area. Since Mura defects account for a relatively small proportion of the panel, we do the following pre-processing to help the image inpainting module. First, resize the image to 512*512, cut it into multiple 64*64 small patches, and hollow out the center 32*32 of each small patch as a mask. The image inpainting module fills in the hollowed-out parts of the image.

In the classification, we calculate the mean square error (MSE) between the reconstructed image of all small images of each image and the original image as the anomaly score of the image. We got better results in the experiment, as shown in Table I, so we chose [6] as our image inpainting model. In order to have better accuracy, we try to increase the attention module.

C. Attention module

Inspired by [7], adding an attention module between the encoder and decoder allows the model to focus on regions with Mura defects when reconstructing images. We try to add the attention module to the skip connections in U-Net. Skip connections can help the model better preserve image details and textures. Adding an attention module in each skip connection allows the model to focus on regions with Mura defects while preserving details and textures, thereby better recovering the details and textures of these regions.

In addition to adding attention modules in skip connections, consider adding global attention modules in the last layer of the encoder and decoder. That can help the model better understand the entire image and thus fix Mura's defects.

III. Experiment

A. Dataset description

The experiment data are high-resolution panel images. The resolution of the image is 1920*1080 pixels. All images are classified as light Mura and serious Mura. We split the data set into training and testing datasets. We used 4835 light Mura as the training dataset and 541 light Mura, and 143 serious Mura as the testing dataset for evaluation.

B. Evaluation metric

We use Area Under Curve (AUC) as our evaluation metric. AUC represents the area under the ROC curve, which can represent a standard statistical value of the predictive ability of the classifier. The higher the AUC, the higher the accuracy of the model.

C. Experiment setting

First, in the self-supervised module, we use Barlow twins as the pre-train model, and the network architecture is ResNet50.

Then comes the image inpainting module. The optimizer uses Adam, the scheduler uses CosineAnnealingLR, the batch size is 64, the learning rate is 5e-4, and the epoch is set to 100 according to the degree of convergence and fixed at 5000 steps. We have completed two experiments, using the image inpainting module with the self-supervised module and only using the image inpainting module. The result is shown in Table II.

TABLE I: Compare to other image inpainting models

Model	**AUC**
PEN-Net	0.782
LaMa	0.756
Shift-Net	0.83

TABLE II: Proposed Methods

Model	**AUC**
Shift-Net	0.83
Shift-Net with self-supervised module	0.854

IV. Conclusion

We proposed a Mura detection system using an image inpainting model with a self-supervised technique and an attention module to accurately distinguish light Mura from serious Mura. By leveraging the self-supervised module, we enhanced the model's generalization ability, while the attention module helped reconstruct the region's details and texture. Our proposed method achieved an impressive AUC of 0.854, indicating its efficacy in Mura detection. Overall, the proposed Mura Detection System optimizes the panel repair process in the factory. In the future, we will focus on the position of serious Mura to help the factory repair the panel better and improve the ability of the image inpainting model.

Acknowledgements

This work is jointly sponsored by AUO Corporation, AUO · NYCU Joint Research and Development Center, National Central University, Yuan Ze University, and National Science and Technology Council (NSTC) under the project NSTC 111-2622-8-A49-023 and NSTC 110-2222-E-008-008-MY3.

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