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AN ENSEMBLE OF SUPERVISED LEARNING AND IMAGE INPAINTING FOR MURA DETECTION

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ABSTRACT

Mura refers to surface defects or areas of uneven brightness that can occur during factory panel production. Mura can vary in size and shape and be categorized as "light Mura" or "serious Mura." To optimize the repair process, factories aim to differentiate between the two types of Mura before sending the panels for repair. However, current Mura detection models focus only on identifying "normal" and "Mura," resulting in poor performance in distinguishing between light and serious Mura. To address this issue, we propose an ensemble approach called the Ensemble Image Inpainting and Supervised Modeling Mura Detection System (EISMDS), which combines supervised and image inpainting models to differentiate between the two types of Mura. Experimental results show that our approach improves the True Positive Rate (TPR) by 11% under a high True Negative Rate (TNR) compared to a single supervised detection model.

***Index Terms*—** Mura detection, image inpainting, SEResNeXt101, U-Net.

1. INTRODUCTION

The Mura detection system is required to ensure the quality of the panels during production. Just Noticeable Distortion (JND) is used to judge light Mura and serious Mura, as shown in Fig. 1 and Fig. 2. There are two Mura repair stations. All panels with Mura are sent to the first station for initial repair. If a panel is deemed to have severe Mura, it must be sent to a secondary station for further restoration. The time and repair cost increase since all panels are repaired at the first station. If there is an AI model to distinguish light Mura and serious Mura before the panel enters the repair station and sends the corresponding panel to the appropriate station, it can speed up the production process of factories.

However, current AI models mainly differentiate between "Normal" and "Mura," but not differentiated "light Mura" and "serious Mura". The only variation between the two is the degree of brightness unevenness. Besides, Mura is usually small and low in contrast. Due to these factors, AI models have difficulty accurately identifying the severity level of Mura.

Fig. 1: Light Mura.

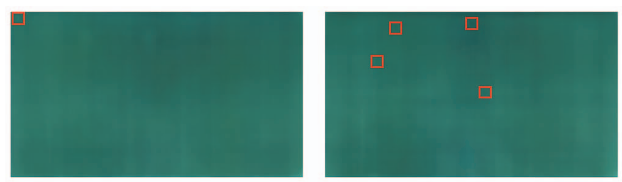

Fig. 2: Serious Mura with black or white block.

In this paper, we propose an ensemble approach called Ensemble Image inpainting and Supervised modeling Mura Detection System (EISMDS), combining the supervised model and image inpainting model to distinguish two types of Mura. We create a two-dimensional plane. The x-axis is the anomaly score of the inpainting model, and the y-axis is the confidence score of the supervised model. We find a straight line with the highest recall under the specified TNR through greedy search as the threshold for judging light Mura and serious Mura. Our contributions in this work are as follows,

- We combine the image inpainting model and the supervised model to differentiate light Mura and serious Mura.
- The proposed EISMDS intensively increases the TPR with high TNR of Mura detection.
- EISMDS helps factories save the time and repair cost of the Mura repairing process and optimizes the panel production process.

2. RELATED WORKS

2.1. Defect Detection

Defect detection can be roughly divided into supervised learning and unsupervised learning. While supervised learning requires a significant amount of labeled serious Mura data, common classification models include ResNet [1], Xception [2], and SEResNeXt101. However, using supervised models may not produce desirable results due to insufficient serious Mura data. The deep neural network structure of a generative adversarial network (GAN) was proposed, and the generated network and the discriminative network were opposed to each other, so the generated image was similar to the original image. Skip-GANomaly [3] combined the two models of U-Net and GANomaly and used the network structure of skip connection. Res-UnetGAN [4] was a GANomaly model. The particular point was that its generator used ResNet50 as an encoder for feature extraction and used U-Net as the decoder. Since the GAN models mentioned above were primarily designed for distinguishing between normal and abnormal, their effectiveness in distinguishing between light Mura and serious Mura may be limited. Therefore, to address this issue, we try image inpainting models.

2.2. Image Inpainting

Several image inpainting models have been proposed to address the limitations of GAN-based models in distinguishing between light Mura and serious Mura. PEN-Net [5] 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. Shift-Net [6] incorporated a shift-connection layer based on U-Net to enhance the details of the filled area. LaMa [7] added Fast Fourier Convolution (FFC) to the inpainting network, enabling the model to have a full-picture receptive field in the shallow layer. [8] added the GMSD and SSIM similarities between the original and reconstructed images to the training loss function.

To overcome the limitations of GAN-based models, we combined SEResNeXt101 with PEN-Net, Shift-Net, and LaMa to improve performance in defect detection. The following section will introduce our proposed method in detail.

3. PROPOSED METHOD

To enhance the ability of the model to identify light Mura and serious Mura panels, we propose EISMDS. Fig. 3 is our system architecture. First, the panel images will enter the supervised Mura detection module and the image inpainting Mura detection module. After their respective preprocessing, They will be input into the individual model and get the confidence and anomaly scores from their model outputs. We will combine these two scores and put them on a two-dimensional plane. After that, we will find a straight line on the plane as the threshold for judging light Mura and serious Mura.

Since some defects in the panel data are small compared to the whole panel picture, we designed the supervised Mura detection module and image inpainting Mura detection module to solve this problem. We will explain this in detail following subsections.

3.1. Supervised Mura Detection Module

In the preprocessing part, we first resize the panel image to 256*256 pixels. Then, we randomly flip the image. It can increase the probability of Mura appearing in different positions and enhance the variability of the data. Next, we convert the image to grayscale and filter the edge information of the x-axis and y-axis of the image through the Sobel operator. Finally, we combine the grayscale image, X-axis, and Y-axis edge images into a three-channel image as the input.

We use SEResNeXt101 as the classification model. SEResNeXt101 adds the Squeeze-and-Excitation module based on ResNeXt101, which helps the model understand the relationship between feature channels and improves performance. Since the ratio of light Mura to serious Mura is quite imbalanced, we choose α-balanced Focal loss[9] as the model loss function, which can make the model focus on the sparse class and is often used to solve the problem of data imbalance. After we put the image into the model, we will get the confidence score output from the model.

3.2. Image Inpainting Mura Detection Module

In the preprocessing part, if we resize the panel image to 256*256 pixels, the defect is too small after resizing, leading to too small changes in the anomaly score calculation. Thus, we first resize the panel image into 512*512 pixels. Then, we crop the image to get many 64*64 pixels patches and make 32*32 pixels masks in the center of each patch. These patches are the input image of the model.

Regarding the image painting models, we use three different GAN-based image painting models, PEN-Net, Shift-Net, and LaMa, to fill the mask of the patches. The GAN-based image painting models can fill the masked part of the patches more naturally and realistically. After we put these patches into the model, we will get the reconstructed patches. We calculate the mean square error (MSE) between the reconstructed and original patches in each image and take the average as the anomaly score.

3.3. Ensemble Supervised and Image Inpainting Model

After the panel image input into the supervised Mura detection module and the image inpainting Mura detection module, we will get these models' scores, respectively. Then, we will create a two-dimensional plane, the x-axis is the anomaly

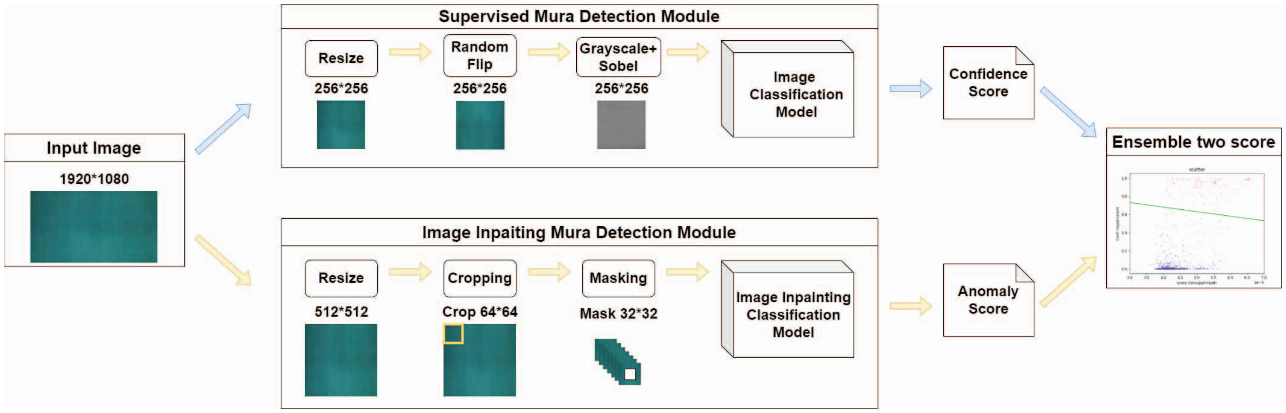

Fig. 3: The overview of the proposed EISMDS architecture.

Table 1: Supervised model and our ensemble approach

Model	TPR with TNR 0.987
SEResNeXt101	0.559
SEResNeXt101 + PEN-Net	0.664
SEResNeXt101 + Shift-Net	**0.671**
SEResNeXt101 + LaMa	0.573
SEResNeXt101 + Skip-GANomaly	0.566
SEResNeXt101 + ResUNetGAN	0.608

Table 2: Ensemble approach with different supervised model

Model	TPR with TNR 0.987
SEResNeXt101 + Shift-Net	**0.671**
ResNet50 + Shift-Net	0.455
Xception + Shift-Net	0.552
ConViT + Shift-Net	0.385

score, and the y-axis is the confidence score. Each panel image is projected onto this plane according to its score, and we will find a straight line with the highest recall under the specified TNR through greedy search as the threshold for judging light Mura and serious Mura.

4. EXPERIMENT RESULTS

4.1. Dataset Description

We use the high-resolution panel images from the manufactory as our dataset. The original resolution of the panel images is 1920*1080 pixels, and there are two classes of light Mura images and serious Mura images.

We divided the dataset into training and testing datasets to conduct our experiments. Specifically, we used 4835 light Mura images and 1328 serious Mura images as the training dataset for both the supervised and image inpainting models. It is worth noting that we only utilized light Mura images for training the image inpainting model. Subsequently, we employed 541 light Mura images and 143 serious Mura images as the testing dataset for evaluation.

4.2. Experiment Setting

Our experiments utilize SEResNeXt101 as a supervised model and PEN-Net, Shift-Net, and LaMa as image inpainting models. Since differentiating light Mura can save costs, factories want to identify as many light Mura panels as possible. Moreover, light Mura and serious Mura panel data are imbalanced. It is not appropriate to use TPR as an evaluation metric. Therefore, we aim to increase the TPR as much as possible while maintaining a high TNR. In our experiments, we fix the TNR to 0.987, the minimum standard acceptable to factories, and evaluate the TPR performance of each model.

4.3. Experiment Result

This section compares different models, including the supervised model, the GAN-based autoencoder model, the GAN-based image inpainting model, and our proposed ensemble method. The results are shown in Table 1 and Table 2.

The TPR of the ensemble SEResNeXt101 and Shift-Net model is 0.671 when the TNR is fixed to 0.987, which increases TPR by 11% compared to SEResNeXt101. Furthermore, the performance of the ensemble model is superior to that of the single models, demonstrating that our proposed ensemble method can effectively enhance the serious Mura detection performance.

To verify that the image inpainting model can effectively avoid reconstructing serious Mura, we select a patch containing serious Mura at the center and demonstrate the inpainting effect using PEN-Net, Shift-Net, and LaMa, as shown in

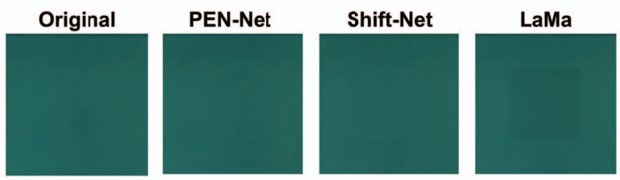

Fig. 4: Results of different image inpainting models.

Table 3: Our ensemble approach with different preprocessing

Model	TPR with TNR 0.987
SEResNeXt101 + Shift-Net	0.266
SEResNeXt101 w/Sobel + Shift-Net	0.406
SEResNeXt101 w/grayscale + Shift-Net	0.559
SEResNeXt101 w/grayscale&Sobel + Shift-Net	**0.671**

Fig4. We observe that the serious Mura is removed by these image inpainting models, resulting in a large mean squared error (MSE) between the reconstructed and original patch, improving the model's ability to distinguish between light Mura and serious Mura.

4.4. Ablation Study

The first experiment aims to ensemble different supervised models with Shift-Net. We evaluate the performance of four supervised models, namely SEResNeXt101, ResNet50, Xception, and ConViT. From Table 2, the ensemble of SEResNeXt101 and Shift-Net achieves the highest True Positive Rate (TPR) when the True Negative Rate (TNR) is 0.987.

Besides, we investigate the effects of the preprocessing module in the ensemble of SEResNeXt101 and Shift-Net. We compare four preprocessing methods: no preprocessing, grayscale, Sobel, and grayscale with Sobel. Table 3 shows that the TPR is the lowest without any preprocessing. The TPR increases when using a single preprocessing method, such as grayscale or Sobel. The combination of grayscale and Sobel method achieves the highest TPR 0.671.

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5. CONCLUSION

In this paper, we proposed EISMDS, which ensembled the supervised and image inpainting models to optimize the panel repair process in factories. Besides, we designed specific preprocessing steps based on the features of Mura, such as combining grayscale with Sobel and cropping the image into small patches. The experiments showed that EISMDS effectively increased the TPR by approximately 11% when the TNR was 0.987 compared to a single supervised model. The proposed EISMDS can help factories save the Mura repairing cost and optimize the panel production process.

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