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Unsupervised Autoencoder Approach for Precise Line-Type Mura Detection and Classification

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***Abstract*—Mura refers to surface defects or uneven brightness in panel manufacturing and is classified by severity into light Mura and serious Mura. Due to limited data, traditional object detection is not feasible. Instead, we propose an unsupervised method to classify serious Mura and accurately localize defects. We combine an autoencoder with computer vision to simulate a supervised model. This approach not only improves defect reconstruction quality but also achieves 90% precision while improving recall by 30%. Our method enhances defect detection accuracy, providing a data-efficient, scalable solution for quality control in panel manufacturing**

***Index Terms*—Anomaly localization, unsupervised learning, Autoencoder, mura detection**

I. Introduction

In panel manufacturing, Mura refers to non-uniform brightness or localized surface defects caused by material properties, equipment, or process conditions impacting display quality. Mura is classified by severity into serious and light types. Our observations further divide serious Mura into three shape-based categories: line types (Vertical, Horizontal), spot types (Whitespot, Blackspot), and Dirt, as shown in Fig. 1. The gray area represents the detection region, while the black border and white background indicate non-detection areas.

Mura detection requires classification and localization. We initially attempted object detection, but limited defect samples hindered our results, leading us to adopt an unsupervised approach. Lin et al. adopted both supervised and unsupervised methods for localization, but failed to classify Mura [1]. Effective localization and classification of serious Mura can reduce manual labeling and costs, but the limited defect data continues to challenge object detection effectiveness.

We propose a method for serious line-type Mura using a convolutional autoencoder with an algorithm for localization and classification. The model reconstructs input images, which are then analyzed with computer vision techniques.

In experiments, we compare our approach with more complex neural networks, such as Skip-GANomaly [2] and Res-unetGAN [3]. Skip-GANomaly is an unsupervised anomaly detection model that reconstructs normal images using a GAN with skip connections, highlighting anomalies through reconstruction errors. However, in low-contrast panel images, it often preserves defect features during reconstruction, resulting in lower recall. Res-unetGAN is a residual U-Net architecture that enhances feature extraction and image reconstruction. However, it reconstructs both normal and defective areas similarly, which reduces its effectiveness in isolating defects. Our method shows better performance in both precision and recall by concentrating on learning the key features of normal panels, thereby effectively reducing defect reconstruction.

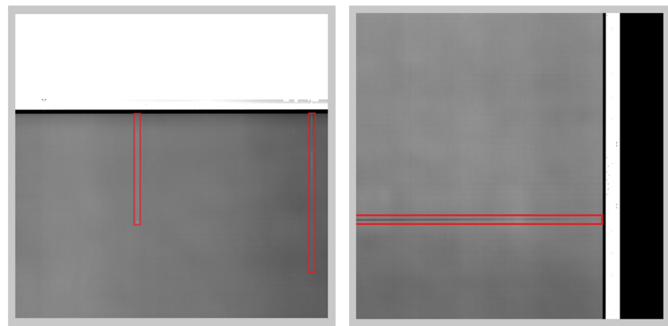

Fig. 1. **(a)** Vertical **(b)** Horizontal

Our method effectively learns the characteristics of datasets with low contrast between defects and background, making it less likely to reconstruct defects in the generated outputs.

II. Methods

A. Image Preprocessing

We classify the dataset into normal and Mura groups, dividing the panels into 1024×1024 pixel images. To improve Mura detection, we develop an algorithm to remove borders and background regions that could interfere with model training.

Pixels with intensity values greater than 180 and equal to 0 are marked as non-detection regions, identifying borders and background. Morphological erosion is used to reduce noise and enhance classification by shrinking bright areas. Pixels with intensity values greater than 250 are also classified as non-detection regions, with morphological dilation ensuring complete coverage. Finally, connected component labeling discards regions with fewer than 77,692 pixels, retaining only relevant areas for Mura detection.

B. Generate Diffenece Map

We input the image into a trained autoencoder, which generates a reconstructed version. The difference between the original and reconstructed images forms a difference map, which may contain noise. To reduce noise, we set a threshold based on each image's characteristics. If the difference map has a high average value, indicating brighter areas and noise, we apply a stricter threshold. Additionally, we consider the standard deviation to dynamically adjust the threshold.

C. Serious Mura Localization and Classification

This stage analyzes the image by examining rows and columns separately. We compute the mean for each using a filtered difference map, identify the 30 highest mean values, and merge closely spaced points to address defect lines across multiple pixels. A threshold is set based on the mean and standard deviation of these top values, as shown by the red line in Fig. 2. The previous stage reduces major noise, but some may remain. We apply a new threshold for further filtering: columns exceeding it are marked as defects, indicated by the orange line in Fig. 2. Defects are classified based on row and column characteristics. If row mean values include a few disproportionately large peaks while most remain near zero, resulting in a high standard deviation, and column means are relatively uniform, the defect is classified as horizontal.

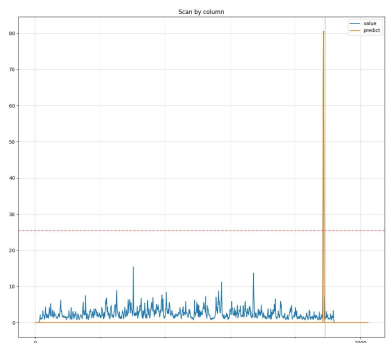

Fig. 2. Threshold.

TABLE I
INFERENCE ON VERTICAL AND HORIZONTAL LINES

Metric	Skip-GANomaly	Res-unetGAN	Proposed Method (AutoEncoder)
Vertical Line			
Precision	0.83	0.75	**0.88**
Recall	0.25	0.30	**0.75**
F1-score	0.39	0.43	**0.80**
Accuracy	0.87	0.5	**0.94**
Horizontal Line			
Precision	1	0.43	0.88
Recall	0.34	0.6	**0.78**
F1-score	0.51	0.50	**0.82**
Accuracy	0.95	0.90	**0.97**

III. EXPERIMENT

The dataset, provided by a panel manufacturer, comprises 3,992 normal images and 5,345 with serious Mura defects. Of the normal images, 90% (3,628) are used for training. The remaining 10%, along with all serious Mura images exhibiting line-type defects, form the test set, which includes 24 such defective samples.

Prediction accuracy is evaluated using the ground truth and the previously defined threshold. A detected point is considered correct if it exceeds the threshold and falls within a 2-pixel margin of the ground truth; otherwise, it is classified as a false detection.

The proposed method is compared with SkipGANomaly [2] and Res-unetGAN [3]. Table 1 compares different models' performance on vertical and horizontal line detection. AutoEncoder outperforms both SkipGANomaly and Res-unetGAN, achieving the highest recall and precision for both vertical and horizontal lines. While SkipGANomaly has perfect precision (1.0) for horizontal lines, its recall remains low (0.34), indicating that it misses many defects. Res-unetGAN performs better in recall than SkipGANomaly, but its precision is lower. Our method outperforms the others by effectively learning to extract only the most important features of normal panels and discarding non-essential details. In contrast, the other approaches retain too many details during reconstruction, leading to defects and lower recall. The AutoEncoder achieves superior performance in both metrics, especially in recall, indicating it effectively detects defects while maintaining accuracy.

IV. CONCLUSION

We proposed an unsupervised autoencoder approach to localize and classify defects with limited data. The method integrated an autoencoder with computer-vision techniques for defect detection. While it maintained precision comparable to other models, our approach improved recall by approximately 30%, enabled better detection of subtle defects, and mitigated defect-reconstruction issues observed in existing models. This improvement enhanced quality control in manufacturing and provided a scalable, data-efficient solution for defect inspection and classification.

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