Improving CNN-based Pad Defect Classification with Enhanced Preprocessing Techniques

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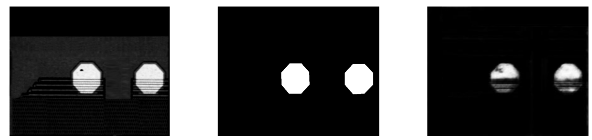
***Abstract*—In the domain of binary classification, Convolutional Neural Networks (CNNs) are a well-established technique, evidenced by numerous studies highlighting their superior accuracy and generalizability compared to other methods. We try to use CNNs on a semiconductor manufacturing company's pad defect dataset to evaluate their effectiveness in classification. However, due to the significant influence of noise, the results are unsatisfactory. Thus, we propose a preprocessing technique, which includes U-Net pad feature extraction and dilation operation in this work. This preprocessing technique allows the model to identify the features of pad defects more accurately, minimizing the impact of background interference. Consequently, the proposed approach is more adaptable across various production lines in that company.**

***Index Terms*—pad defect, binary classification, background removal**

I. Introduction

As semiconductor companies strive to manufacture increasingly smaller transistors, the number of defects has increased proportionally. Classifying these defects can identify critical sections in the manufacturing process that need improvement [5]. Pad defects, in particular, are a crucial category due to their impact on the chip's electrical connectivity. Pads are typically light-colored and often have various shapes, such as rectangles or octagons. Light-colored pads contrast with the typically darker substrate of the chip, making them easier to be identified and aligned with testing probes. The choice of geometric shapes, like rectangles or octagons, is not arbitrary, but is based on the need to maximize surface area for connectivity while accommodating the spatial constraints of the chip layout. Pads function as essential interfaces linking the internal circuits of the chip to external circuits, supporting power supply and signal transmission. Therefore, any pad defects are unacceptable.

To classify images into different categories, Convolutional Neural Networks (CNNs) [2][4] are a commonly used technique. This paper focuses primarily on the preprocessing task before classification. The purpose of preprocessing is to eliminate non-essential features, thereby allowing the model to be trained solely on clean, relevant features [1][3][6]. U-Net [7] is a CNN architecture originally designed for biomedical image segmentation. It employs a unique structure that features both upsampling and downsampling pathways, capturing extensive contextual information. Its symmetrical scaling architecture enables the network to extract features while preserving critical spatial information. In this paper, U-Net is utilized for the pad feature extraction in our preprocessing technique. However, although U-Net can approximately determine the location and contours of pads, it lacks precision to classify pad defects because the real world dataset has a lot of external noise, such as camera quality or lighting conditions. Figure 1[1] presents an example of the pad feature extraction result using the U-Net model, which consists of the original image, the ground truth, and the result of pad feature extraction. The result in Figure 1(c) only roughly outlines the pads' contours, highlighting the difficulty in capturing details as precisely as the ground truth of Figure 1(b) does. Thus, we also propose a new approach to deal with this deficiency.



(a) (b) (c)

Figure 1: Pad feature extraction result. (a) Original image. (b) Ground truth of pad feature. (c) Pad feature extraction result.

In this paper, we propose two preprocessing techniques that include U-Net pad feature extraction and *dilation* operation. Additionally, we propose a more comprehensive flow that enables the model to identify images with pad defects in the dataset.

II. Proposed Approaches

Our classification approach consists of the following steps: (1) Preprocessing, (2) Pad Presence Examination, and (3) Pad Defect Examination. These steps are described in detail below.

A. Preprocessing

The U-Net pad feature extraction from images allowed us to capture contours related to the pads, but the result is not acceptable for the succeeding pad defect classification. Pad defect classification requires clearer information. Therefore, we propose a *dilation* operation to the images after the pad feature extraction process. The dilation operation is conducted as follows. Given a single white pixel in the image, the dilation operation expands this pixel by transforming the pixels in the surrounding neighborhood into white as well. Specifically, the neighborhood is defined as an $n \times n$ square centered on the original white pixel, and all pixels within this square become white. Figure 2 illustrates this operation: in Figure 2(a), the initial image contains one white pixel, and in Figure 2(b), the white pixel has been expanded into an $n \times n$ white square through the dilation operation.

The color of a pixel can be represented as a value ranging from 0 to 255. The values closer to 0 are darker colors while closer to 255 are lighter colors. We set a threshold value, say 127. Pixels in the image above this threshold value will be considered as white points. The dilation operation is applied to each white point (value > 127) in the image obtained by the pad feature extraction. Through the dilation operation, it can be observed that if a pixel is originally white, it will remain white. Additionally, if a pixel was originally black, it will

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[1]To comply with confidentiality agreements with the semiconductor manufacturer, only blurred images with two representative pads are provided.

(a) (b)

Figure 2: The dilation operation. (a) A white pixel. (b) An $n \times n$ square after the dilation operation.

(a) (b) (c)

Figure 3: Combined result of original image and dilation operation result. (a) Original image. (b) Pad feature extraction result after the dilation operation. (c) Combined result.

turn white if there is a white pixel within a $\sqrt{2}n$ range (since the longest distance in a square with a side length of n is diagonal, which is $\sqrt{2}n$); otherwise, it will remain black. The result of pad feature extraction after dilation operation is shown in Figure 3(b). However, from Figure 3(b), we observe that each pad area appears completely white with no defects. Therefore, we map these white areas back to the original image, as shown in Figure 3(a), after the dilation operation and obtain the combined result. The combined result, as shown in Figure 3(c), provides more precise information about pads. This process enables us to obtain better features for succeeding pad defect classification.

Moreover, the choice of parameters for the dilation operation is crucial for the classification results. Excessive dilation may cover much irrelevant area, leading to ineffectiveness. Conversely, insufficient dilation might fail to highlight key features adequately.

B. *Pad Presence Examination & Pad Defect Classification*

In the pad presence examination step, we classify images to distinguish between those with pads and those without pads. We preprocess the original images and then use the combined results as inputs to train the model. This enables the model using the key features from the combined results to classify whether a pad is present, which reduces the impact of background from different production lines. With the pad presence examination, we reduce the number of images that the succeeding pad defect classification needs to deal with. As for the pad defect classification, we determine whether defects occur on the pads. We use the combined results again as inputs to train the another model for pad defect classification. Finally, within the entire dataset, images classified as having no pad present during the pad presence examination and images classified as having no pad defect during the pad defect classification are grouped as No-pad-defect (NPD), while images classified as having a pad defect in the pad defect classification are grouped as Pad-defect (PD).

III. Experimental Results

The proposed approach was implemented using Python and was executed in an Ubuntu 18.04 environment on a machine with an NVIDIA 4090 GPU, an Intel Xeon Gold 6248R CPU, and 64GB of RAM. The benchmark dataset from a semiconductor manufacturing company is shown in Table I. We use ResNet18 [2] as the baseline CNN model for comparison. The ResNet18 model parameters are as follows: Adam optimizer, learning rate is set to 0.001, batch size = 64, 10 epochs, and the loss function is cross entropy. The proposed approach employs our preprocessing technique, which integrates U-Net pad feature extraction and dilation operation to obtain combined results. In the dilation operation, we set the color threshold value to 127 (values > 127 are considered white pixels) and the side length parameter of square to 35 pixels. We implemented a preprocessing on the ResNet18 model to evaluate its impact on the classifier's effectiveness. As shown in the accuracy results of Table II, while there is little difference in the No-pad-defect category, there is a significant improvement in the Pad-defect category.

Table I: Summary of |PD| and |NPD| counts across different product lines.

	3QA	**9MA**	**24W**
|PD|	23	1089	144
|NPD|	115	5445	720

Table II: The accuracy of three product lines.

	3QA		9MA		24W		Average	
	PD	NPD	PD	NPD	PD	NPD	PD	NPD
[2]	28.71	93.52	66.75	95.75	49.85	95.5	48.43	94.92
[2] + preprocessing	42.09	92.34	78.05	95.42	58.15	95.8	59.43	94.52

Table III: The precision and recall of three product lines with pads.

	3QA		9MA		24W		Average	
	Prec.	Rec.	Prec.	Rec.	Prec.	Rec.	Prec.	Rec.
[2]	0.47	0.28	0.76	0.67	0.69	0.5	0.64	0.48
[2] + preprocessing	0.52	0.42	0.77	0.78	0.73	0.58	0.67	0.59

Precision (Prec.) and recall (Rec.) are two commonly used metrics that are crucial for evaluating the performance of classification models. Precision is defined as the ratio of true positive predictions (Pad-defect category) to the total number of positive predictions. Recall is defined as the ratio of true positive predictions to the total number of actual positives. These metrics are particularly important in the imbalanced dataset, as they provide insight into how well the model performs in identifying minority class instances. As shown in Table III, our approach provides better precision and recall compared to the baseline.

IV. Conclusion

In this paper, we present a complete flow for pad defect classification, which includes preprocessing, pad presence examination, and pad defect classification. In the preprocessing, we propose using U-Net pad feature extraction combined with a dilation operation, addressing the issue of label scarcity in the dataset. Subsequently, we employ a ResNet18 model for pad presence examination to alleviate dataset imbalance. Finally, we employ a ResNet18 model for pad defect classification. The experimental results demonstrate that our approach outperforms the baseline in pad defect classification.

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