Defective Wafer Map Classification for Unknown Patterns Using Image Generation Model - Seima Sakaguchi

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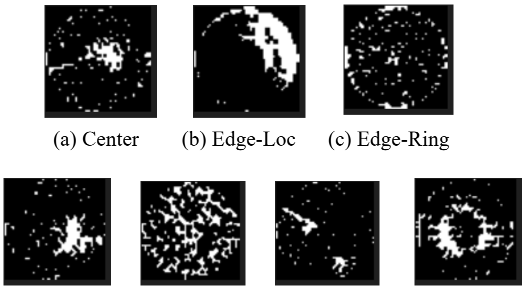
In semiconductor manufacturing, chips on silicon wafers are inspected in various ways, and the distribution of defective chips is obtained as a wafer map. The obtained patterns of wafer maps heavily depend on the causes of the manufacturing process. Therefore, classifying wafer map patterns and identifying their causes are very important from the viewpoint of production control. Currently, plenty of studies on wafer map classification have been reported. However, as far as we know, the conventional methods only focused on known wafer map patterns that had occurred in the past, so they could not detect "Unknown" patterns that occur unexpectedly at actual manufacturing sites. It is crucial to not only classify the known patterns but also detect unknown patterns from the viewpoint of manufacturing control. Therefore, in our previous study, we discussed a possibility of an ensemble classification model using binary classifiers. The proposed method worked well in the experiments with actual wafer maps. But, the detection accuracy of unknown classes in the existing model was about 30%. This is not sufficient for practical use. In this paper, we aimed to improve its classification accuracy by using an image generation model for unknown patterns.

This paper used Kaggle's WM-811K wafer map repository as experimental material. All given labels in the dataset were checked and revised when the given label was incorrect. Fig. 1 shows examples of wafer maps. The given data were expressed as numerical data, and we converted the data into gray-scale images. we used 5252 wafer map data. In the experimental session, 502 known-pattern and 32 unknown-pattern images were used for evaluation, respectively. We define 32 Donut images as unknown images and used them for evaluation. They were not included in the training data.

We used an ensemble classification model with binary classifiers[1]. An overview of the classification model can be found in [1]. The classification model consists of binary classifiers to detect specific (i.e., known) wafer map patterns. This method used SVM as a binary classifier, and the SVMs were connected based on their classification performance. The above scheme can only pick up known classes, e.g., Center, Edge-Loc, etc.; a given pattern not picked up by any SVMs was regarded as an unknown pattern. The feature extraction approach heavily depends on each wafer map pattern, so we fixed the most effective approach through preliminary experiments.

To improve the classification accuracy, we employed an image generation model (VAE/GAN)[2] to generate pseudo-unknown images, and the generated images were added to the training set for the binary classifiers. VAE/GAN is a generative model combining a variational autoencoder (VAE) and an adversarial network (GAN). The method generates unknown images by inputting the generated feature vectors into a trained VAE/GAN decoder. We generated feature vectors that did not belong to any known label by randomly adding noise to the feature vectors of known patterns.

Tables 1 and 2 show the accuracy of the existing and proposed methods, respectively. Table 3 summarizes the classification accuracy of known patterns and the purity of the unknown clusters in the case of each method. In this table, the classification accuracy for known patterns indicates how accurately the method classified the 502 known patterns. The purity of the unknown cluster shows a ratio of unknown (Donut) images contained in the Unknown cluster. From the obtained results of the comparative experiments, we confirmed that the purity of the unknown cluster was improved by 12% compared to the existing method, even though the classification accuracy of the proposed method was 0.6% lower than the existing method. Table 4 shows the confusion matrix of the proposed method. As a result of experiments, 10 Loc data were classified as Unknown. The classification accuracy of binary classifiers for Loc is not sufficient for practical use. Advanced investigations will be required to improve the accuracy of the proposed method.



(a) Center (b) Edge-Loc (c) Edge-Ring

(d) Loc (e) Random (f) Scratch (g) Donut

Fig.1 Example of Wafer Map for each Label

Table 1 Accuracy of each Classifier of Existingl Method (%)

	C	EL	ER	L	R	S
Recall	82.4	86.9	95.7	76.8	85.3	85.5
Precision	78.9	57.0	97.1	27.3	73.9	87.7
F1 Score	80.6	68.8	96.4	40.3	79.2	86.6

(C: Center, EL: Edge-Loc, ER: Edge-Ring, L: Loc, R: Random, S: Scratch)

Table 2 Accuracy of each Classifier of Proposed Method (%)

	C	EL	ER	L	R	S
Recall	86.8	97.6	95.7	79.3	86.2	86.7
Precision	75.6	51.9	97.1	25.7	73.0	88.9
F1 Score	80.8	67.8	96.4	38.8	79.1	87.8

(C: Center, EL: Edge-Loc, ER: Edge-Ring, L: Loc, R: Random, S: Scratch)

Table 3 Classification Accuracy for Test Data (%)

	Existing Method	Proposed Method
Classification Rate for Known Patterns	78.1	77.5
The purity of Unknown Cluster	32.5	45.2

Table 4 Confusion Matrix of Proposed Method

		Predicted Label						
		C	EL	ER	L	R	S	U
True Label	C	59	0	0	6	3	0	0
	EL	0	67	2	0	10	5	0
	ER	0	0	66	1	2	0	0
	L	9	23	0	30	7	3	10
	R	10	2	0	5	95	1	3
	S	0	1	0	5	1	72	4
	D	3	0	0	7	8	0	14

(C: Center, EL: Edge-Loc, ER: Edge-Ring, L: Loc, R: Random, S: Scratch, D:Donut,

U:Unknown)

Reference:

[1] S. Sakaguchi *et al*., "A Study on Detection Method Using 2-Class Classifiers for Defective Wafer Maps," *2022 International Symposium on Semiconductor Manufacturing (ISSM)*, Tokyo, Japan, 2022, pp. 1-4, doi: 10.1109/ISSM55802.2022.10026916.

[2] Larsen, A.B.L, Sonderby, S, Larochelle, H. and Winther, O., “Autoencoding beyond pixels using a learned similarity metric”, arXiv: 1512.09300v2, 2016.