Meeting Note

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Summary
Wafer Map Failure Detection [1, 2, 3, 4].
Wafer Failure Detection Coding.

Plan for Next Week
Implement text-to-text and image-to-image CLIP models, and use the models to test zero-shot text-to-text and image-to-image retrieval.
Implement a multi-label CLIP model.

Problems
Wafer map failure detection by human has only about 80% of accuracy, so we need to use machine learning to improve the detection process [1, 2, 3, 4].

Details
Zheng et al. [1] introduce a failure detection method using deep convolution neural network (DCNN). In this paper, the authors use WM-811K as the dataset, and make comparisons with some vision deep learning networks, such as VGG16, ResNet50, EfficientNetB0, etc. The experimental result shows that the specialized DCNN provided by authors performs the best among all the other vision models.
The interesting part of this paper is that all models, including the proposed DCNN, couldn't detect the failure pattern of "local" well, some of the model has even around 0.6 F1 score on this failure pattern.

Jeong et al. [2] proposed a novel approach which combines the Radon transform and kernel flipping techniques for archiving rotation and flip invariance. The following are the major steps: first, a feature map will be acquired from the Radon transformer and kernel flipping module, second, the feature map will be inputted into a CNN-based model, finally, the fully connection layers will output the predicted classes of wafer failures.

Sakaguchi et al. [3] introduce an ensemble learning methods for wafer map classification. The main idea of their approach is using the CNNs (especially VGG16 in this study) as binary classifiers, that is, for each failure pattern, there is a VGG16 classifier. This method could be expensive since it must train or fine tune many models, and the result shows that the F1 score is around 0.5 to 0.7. The order of each pattern classifier is another problem, different order may lead to different prediction. But there still some benefits with the architecture, one is that this method has the capability to detect the unknown failure patterns of wafer map.

Conclusion

There are many machine learning methods to handle the wafer map detection task, most of them are just using CNN-based model, but there are still limited researches on using masks with CNNs to enhance the detection process.
Based on this, we can use multiple CNNs and different patterns of masks (e.g. mask the edge area to detect the central failures and mask the central area to detect the edge failures) to detect the wafer map failures.
Our current work, the wafer failure detection, we use a novel approach which uses different mask shapes to mask the input image, and then uses CNNs to extract the feature maps. The experimental result shows that it has the capability to archive an acceptable performance – 99.67% accuracy on testing set.

References

[1] Zheng, H.; Sherazi, S.W.A.; Son, S.H.; Lee, J.Y. A Deep Convolutional Neural Network-Based Multi-Class Image Classification for Automatic Wafer Map Failure Recognition in Semiconductor Manufacturing. Appl. Sci. 2021, 11, 9769. https://doi.org/10.3390/app11209769

[2] Jeong, I., Lee, S.Y., Park, K. et al. Wafer map failure pattern classification using geometric transformation-invariant convolutional neural network. Sci Rep 13, 8127 (2023). https://doi.org/10.1038/s41598-023-34147-2

[3] S. Sakaguchi, H. Kawanaka, and T. Wakabayashi, "A Study on Feature Extraction and Ensemble Learning for Wafer Map Classification and Detection of Unknown Defects," presented at the Mie University Graduate School of Engineering, Japan.

[4] Shinde, Prashant & Pai, Priyadarshini & Adiga, Shashishekar. (2022). Wafer Defect Localization and Classification Using Deep Learning Techniques. IEEE Access. 10. 1-1. 10.1109/ACCESS.2022.3166512.