Fast and accurate automatic wafer defect detection and classification using machine learning based SEM image analysis

SPIE.

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INTRODUCTION

Performing accurate and timely SEM image analysis to identify wafer defects is crucial as it directly impacts manufacturing yield. Traditional analysis done by human experts is prone to error due to long hours of focus required. Software with rules may be used to overcome this, but still faces the issue to construct them, since image quality varies from process to process and layer to layer. In this work, **an ML based approach for analyzing SEM images to locate and classify wafer defects is proposed**. A state-of-the-art one-stage objection detection model called YOLOv8 is used as it offers a good balance between accuracy and inference speed.

METHODS

Model

As shown in Figure 1, YOLOv8 is trained to receive as input a SEM image and its corresponding aligned design layout image, and to predict defect locations along with defect types.

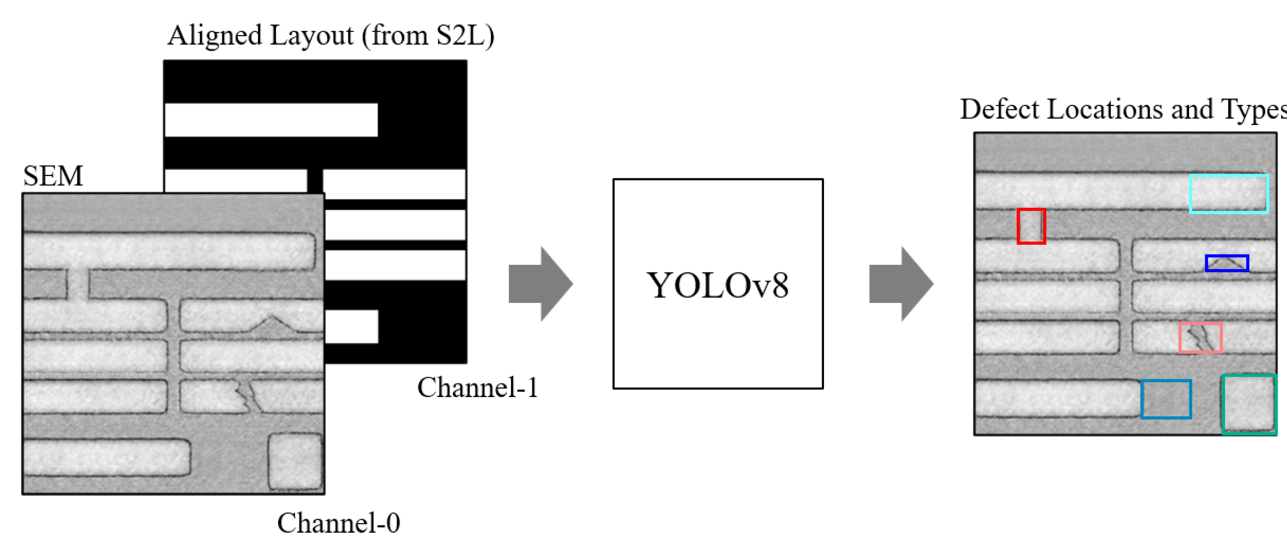

Fig. 1 Training YOLOv8 to predict defect locations and types.

To potentially improve accuracy, multiple variants of YOLOv8 are trained, and a subset of those models are used collectively for ensemble prediction, as shown in Figure 2.

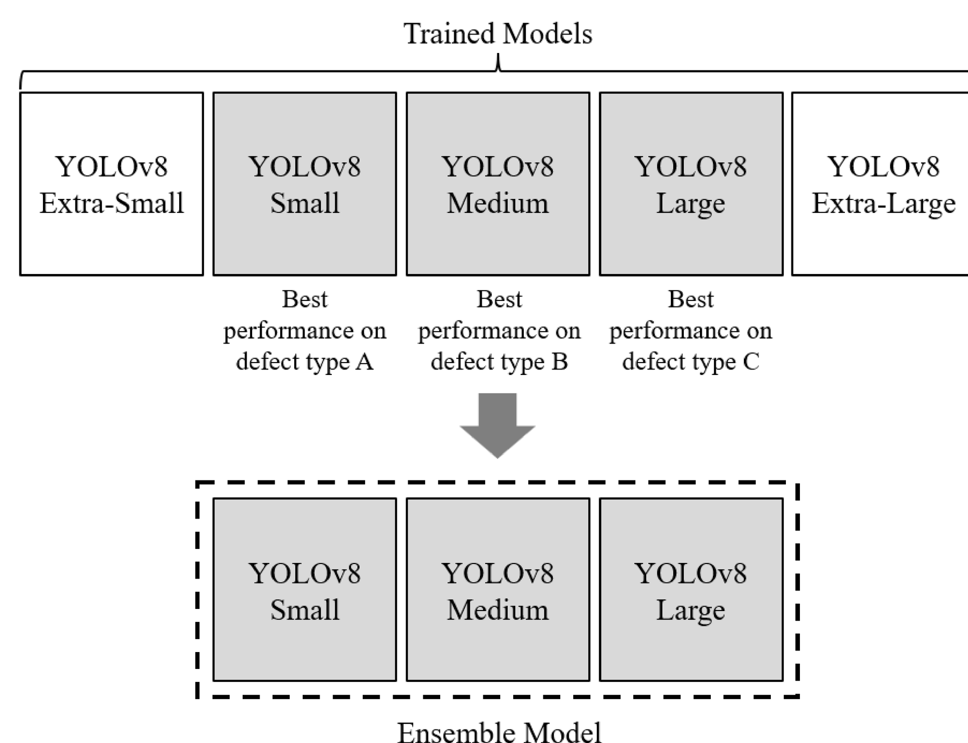

Fig. 2 Using multiple models for ensemble prediction.

Defect Types

Model is trained to classify missing pattern (M), added pattern (A), pinch (P), line-end extension (LE), line-end pullback (LP), and bridge (B) defects. See Figure 3 for samples of defects.

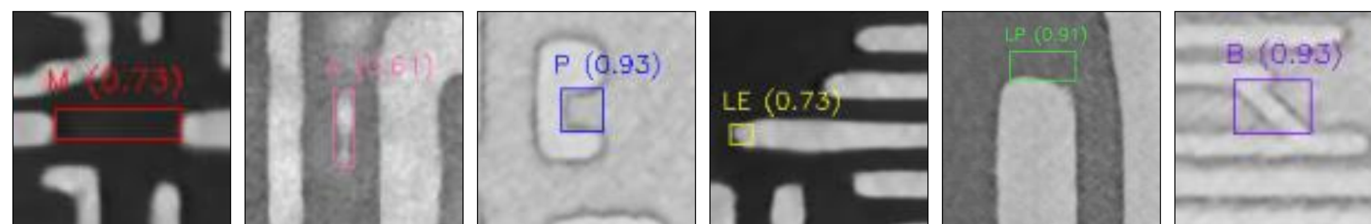

Fig. 3 Sample prediction for each of 6 defect types.

Dataset

To overcome scarcity of data, a Conditional GAN (cGAN) for image-to-image translation is used to generate synthetic SEM images with desired defects (Figure 4). All images shown in Figure 3 are synthetic images generated using this method.

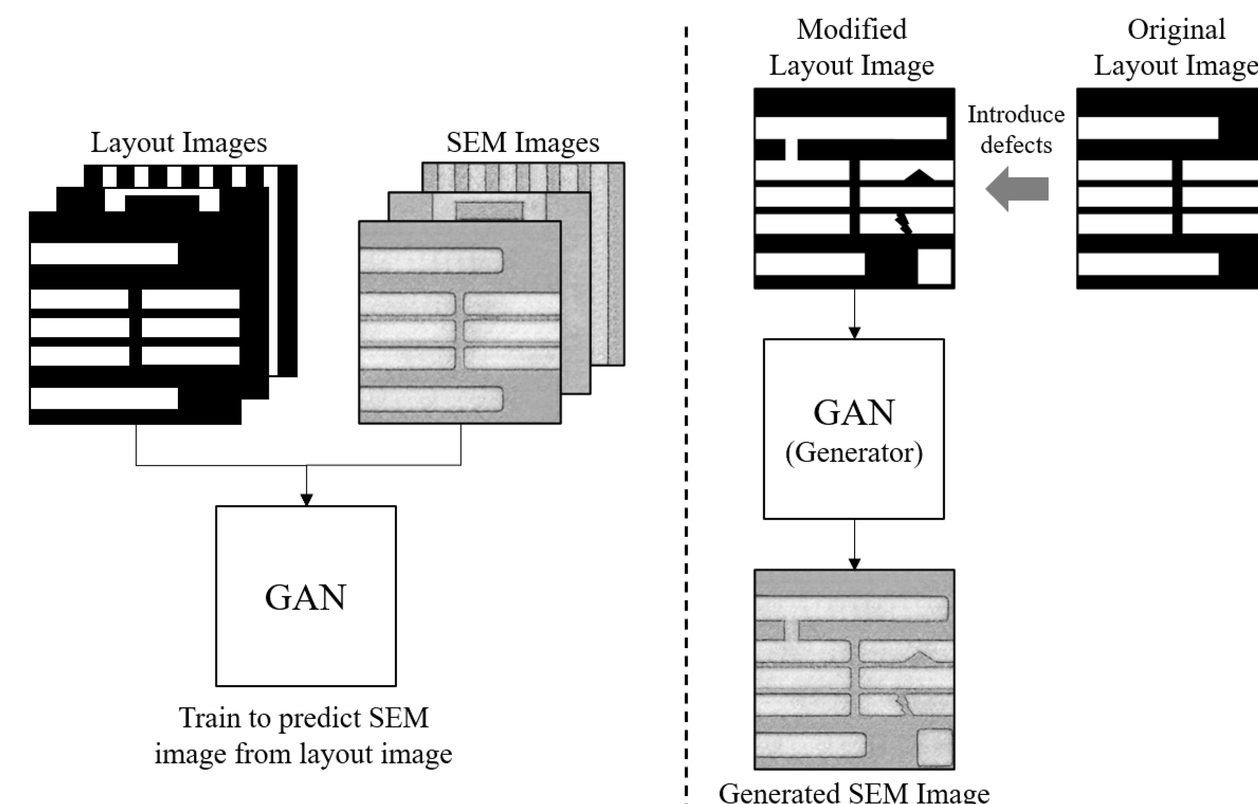

Fig. 4 Training GAN models to generate synthetic SEM images.

The final dataset used consists of 355 real-world images from 5 wafer fabs, and 1,302 synthetic images (20% of actual images are used as test set).

RESULTS

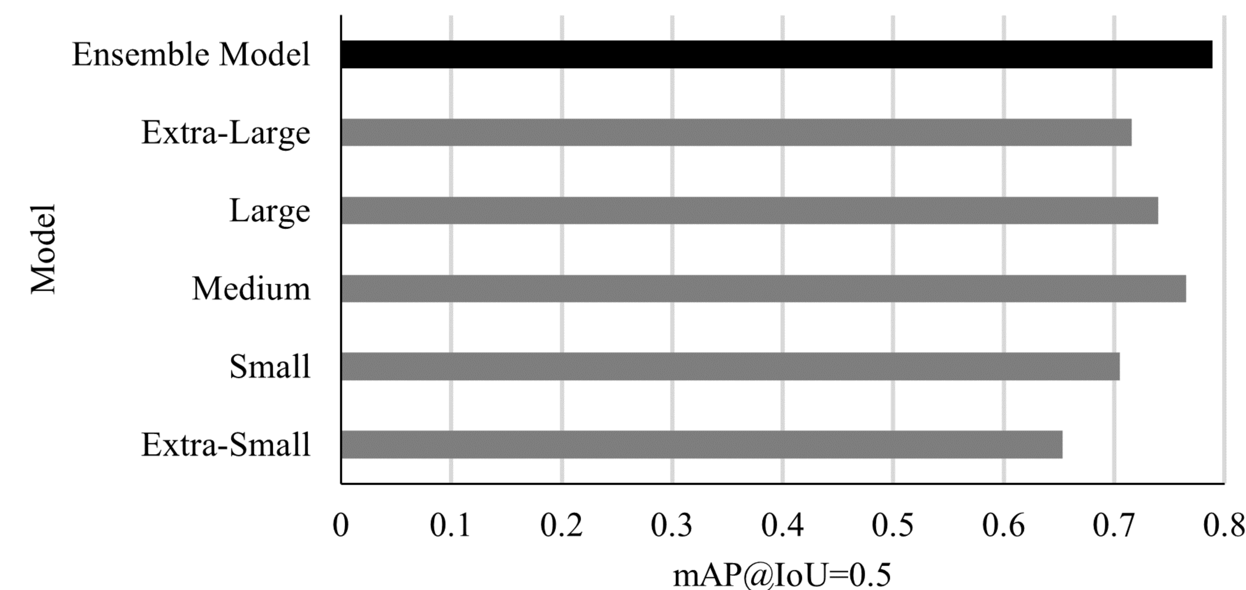

Fig. 5 Performance on test set (66 real-world SEM images) for each YOLOv8 variant and ensemble model.

As shown in Figure 5, 'Ensemble Model', consisting of 'Small', 'Medium', and 'Large' models, achieved the best performance among all models – **0.79 mAP at IoU=0.5**. Note that 'Medium' model achieved the best performance among five YOLOv8 variants.

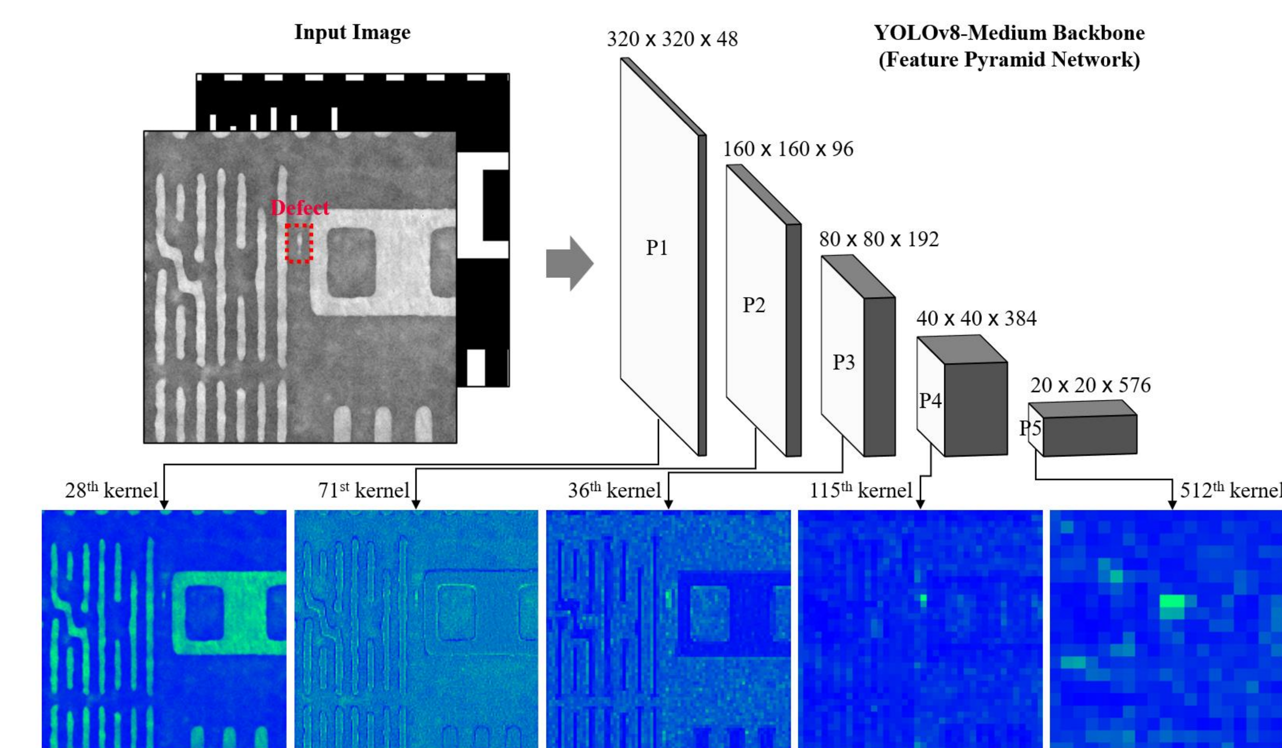

Fig. 6 Visualization of feature maps from trained 'Medium' model.

To better understand how trained model detects defects, feature maps from feature extractor layers are visualized in Figure 6. In the earlier layers, some form of contour extraction is taking place, while in the later layers, an isolated region that nearly coincides with the defect region is activated.

CONCLUSIONS

1. **With ML based ADC, defects in SEM images (that have various image qualities) can be detected with high accuracy.**
2. **This ML model may be integrated into failure analysis to increase the accuracy of root cause analysis and for faster problem solving.**
3. **Certain limitations must still be addressed, such as, model's weak performance on SEM images that are drastically different from trained images. Training the model at customer-site will be considered.**

REFERENCES

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