Machine Learning Based SEM Image Analysis for Automatic Detection and Classification of Wafer Defects

Sanghyun Choi[a], Qian Xie[b], Frederic Huguennet[c], Nathan Greeneltch[b], Mohan Govindaraj[b], Srividya Jayaram[b], Mark Pereira[d], Sayani Biswas[d], Samir Bhamidipati[d], Ilhami Torunoglu[b]

(a) Siemens Digital Industries Software, Korea
(b) Siemens Digital Industries Software, USA
(c) Siemens Digital Industries Software, France
(d) Siemens Digital Industries Software, India

SIEMENS

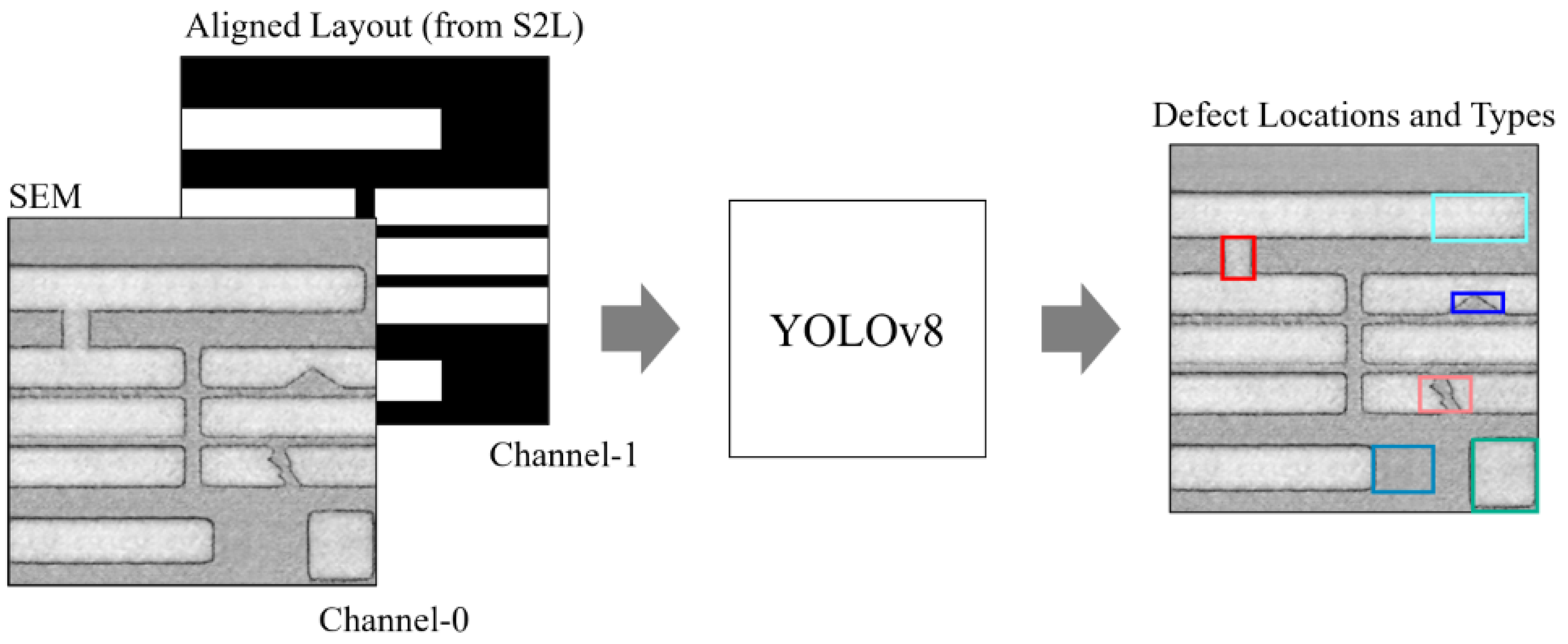
Introduction

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. This work presents of YOLOv8 [1] machine learning (ML) object detection model for:

- Defect detection
- Defect localization
- Defect identification and labeling

Background

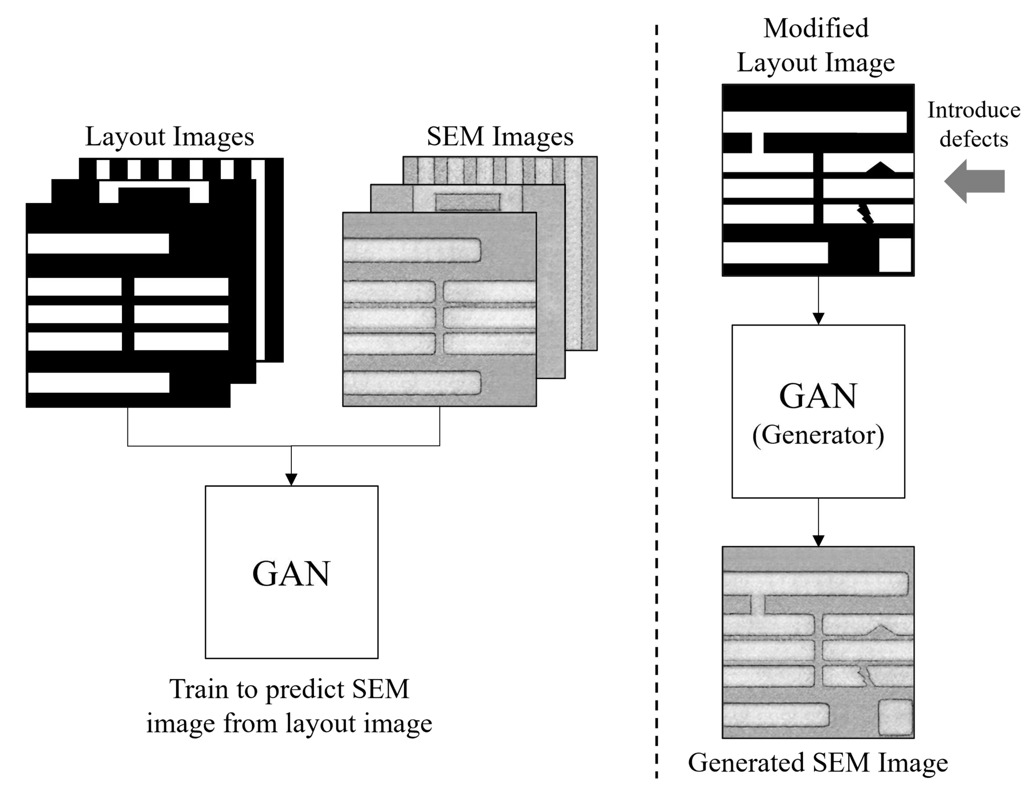
YOLOv8 model is trained to receive as input a multichannel image with 1) SEM image in first channel, and 2) aligned design layout clip in second channel, and to predict as outputs 1) defect locations (via bounding boxes) and 2) defect types. Based on this training scheme, the model is expected to learn abnormalities in SEM images by using layout images as reference. Five different size model architectures were tested, ranging from extra-small to extra-large.



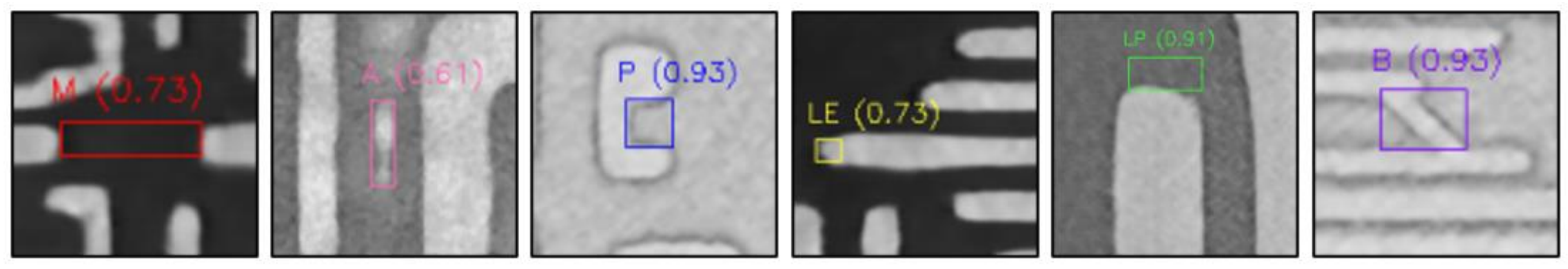
Data

Dataset: 355 actual images from 5 wafer fabs, and 1,302 synthetic images. 80% of actual images and 100% of synthetic images are used for training and the remaining for testing.

GAN-based data augmentation technique was employed to grow and have more control over the input set. Specifically, Conditional GAN (cGAN) [2] for image-to-image translation is used. Defects were then added to layout images to obtain synthetic SEM images. To add realistic variety to the synthetic set, multiple cGAN models were trained to generate SEM images from different vendor sources, wafer fabs, and process conditions.



Training set defect types from left to right: missing pattern (M), added pattern (A), pinch (P), line-end extension (LE), line-end pullback (LP), and bridge (B)



Results

Dataset	Defect Type	Scores for each YOLOv8 Variant (mAP@IoU=0.5)				
		Extra-Small	Small	Medium	Large	Extra-Large
Train	M	0.805	0.885	**0.892**	0.88	0.87
	A	0.928	0.959	**0.969**	0.958	0.959
	P	0.815	0.858	**0.879**	0.835	0.814
	LE	0.662	0.795	0.779	**0.803**	0.776
	LP	0.719	0.824	**0.83**	0.808	0.816
	B	0.934	**0.989**	0.985	0.979	0.976
Test	M	0.653	0.705	**0.765**	0.74	0.716
	A	0.451	0.436	0.477	**0.478**	0.407
	P	0.78	0.785	**0.832**	0.78	0.801
	LE	0.751	0.827	**0.883**	0.817	0.793
	LP	0.835	0.77	**0.849**	0.825	0.846
	B	0.95	0.856	0.901	**1.000**	1.000

The table above shows metric mean Average Precision (mAP) at IoU=0.5 results, with best performing model size for each defect mode highlighted in bold blue. ML object detection is shown to be feasible for various defect modes.

Single Model					
	Extra-Small	Small	Medium	Large	Extra-Large
TP Rate (%)	78.8	82.3	85.8	81.4	82.5
FP Rate (%)	15.3	15.4	15.9	14.4	15.9

Ensemble with (V # of votes) Threshold					
	V=1	V=2	V=3	V=4	V=5
TP Rate (%)	92.9	88.8	84.5	77.5	68.4
FP Rate (%)	28.4	15.1	11.6	7.7	5.2

The tables above shows different model sizes perform better for different defects, so a voting classifier was applied to combine model sizes. Results of voting is shown above :

Conclusion

ML-based SEM defect detection and classification is feasible. Custom model sizes and architectures may be required on a per-defect basis, but a simple voting classifier can be used to combine output from various models

References

[1] Redmon, J., Divvala, S., Girshick, R. and Farhadi, A., “You Only Look Once: Unified, Real-Time Object Detection” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016, pp. 779-788 doi: 10.1109/CVPR.2016.91.

[2] Isola, P., Zhu, J-Y., Zhou, T., Efros, A., “Image-to-image translation with conditional adversarial networks”. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017 pp. 5967–5976. doi: 10.1109/CVPR.2017.632

Frederic.Huguennet@siemens.com