NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

Deep Learning-based Analysis of Microscopic IC Images for Hardware Assurance

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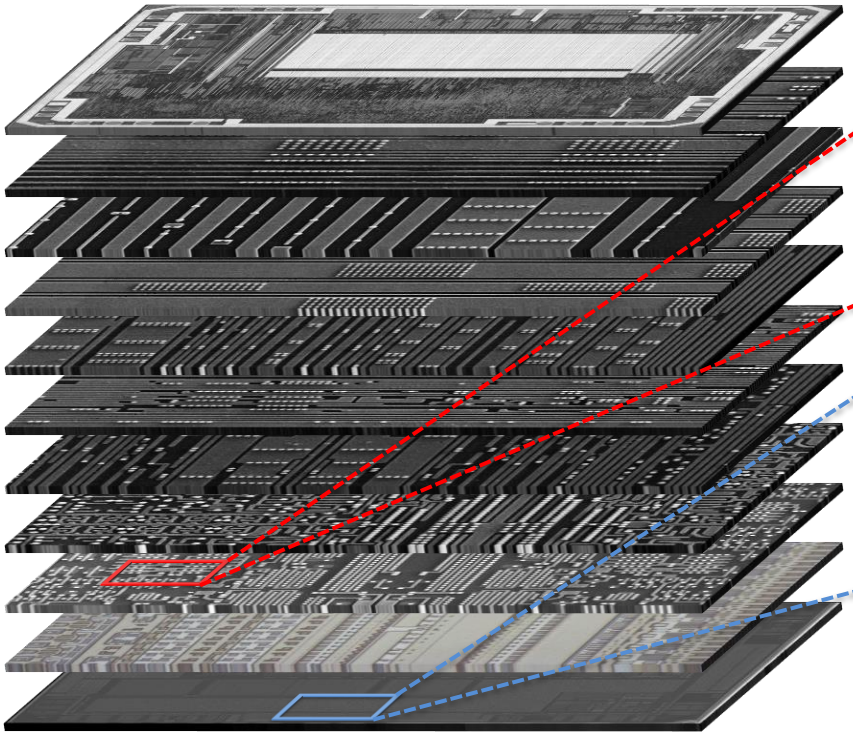
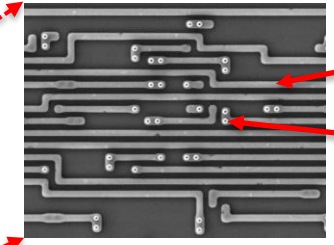
Outline

- **Introduction to Microscopic IC Image Analysis**
  - Background and Motivation
  - Key Tasks and Challenges
- **Deep Learning-based IC Image Analysis**
  - An Overview of Our Deep Learning-based Image Analysis Framework
  - Self-supervised Anomaly Detection with Generative Adversarial Network (GAN)
- **Conclusions**

Introduction to Microscopic IC Image Analysis





Metal Line

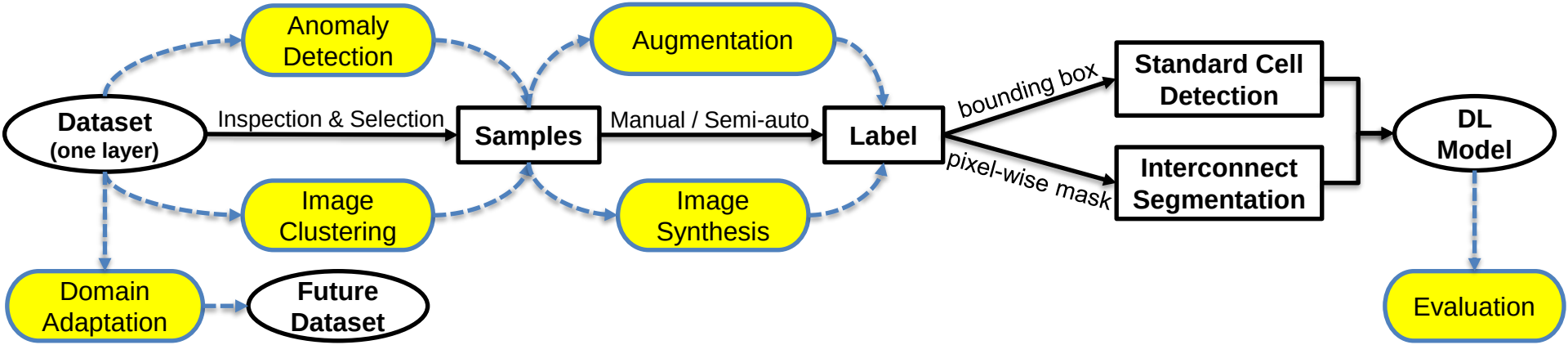
Via

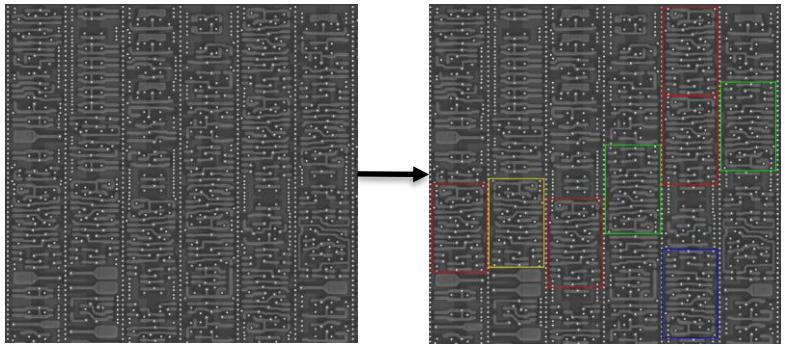
Standard Cells

Major Challenges:

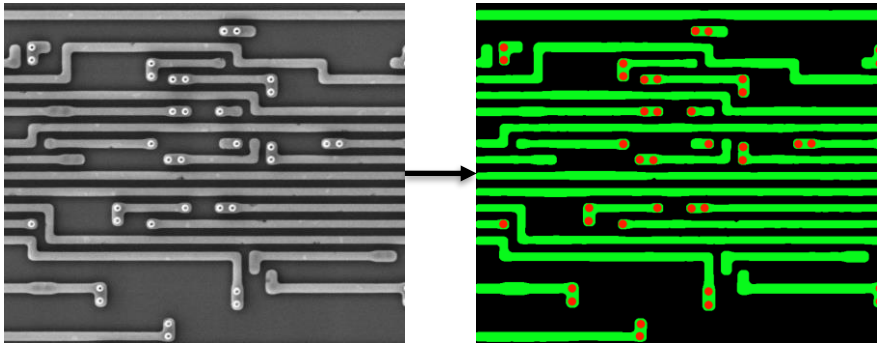
- Millions of images per layer
- Image variations across layers and regions
- Anomalies from sample preparation & imaging
- Small feature size / narrow gap between features

Deep Learning (DL)-based Image Analysis Framework



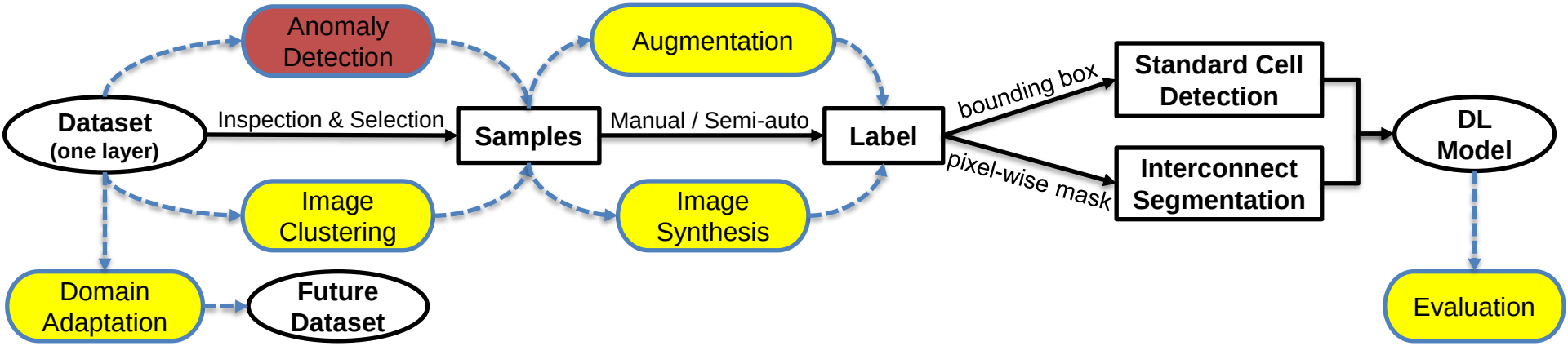


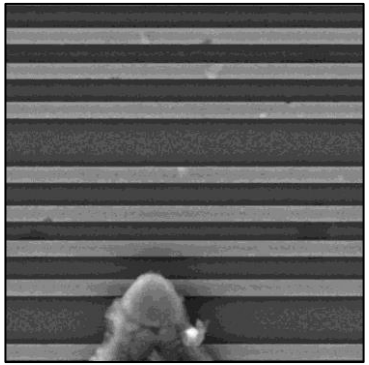
Standard Cell Detection in Poly Layer

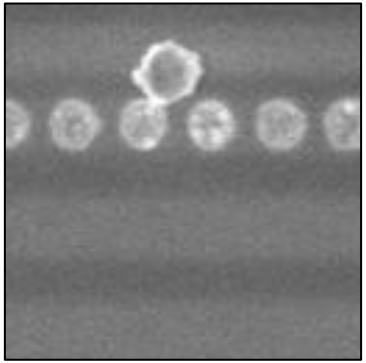


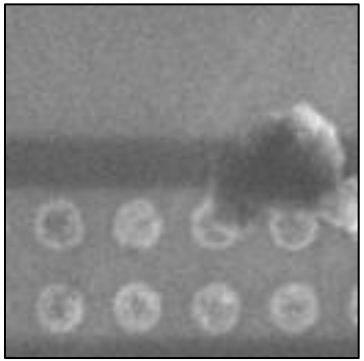
Interconnect Segmentation in Metal Layers

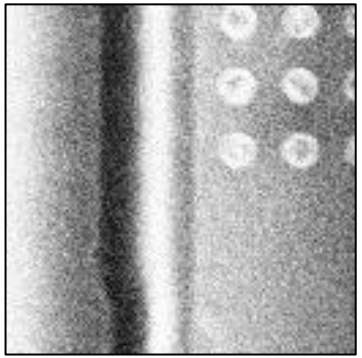
Deep Learning (DL)-based Image Analysis Framework



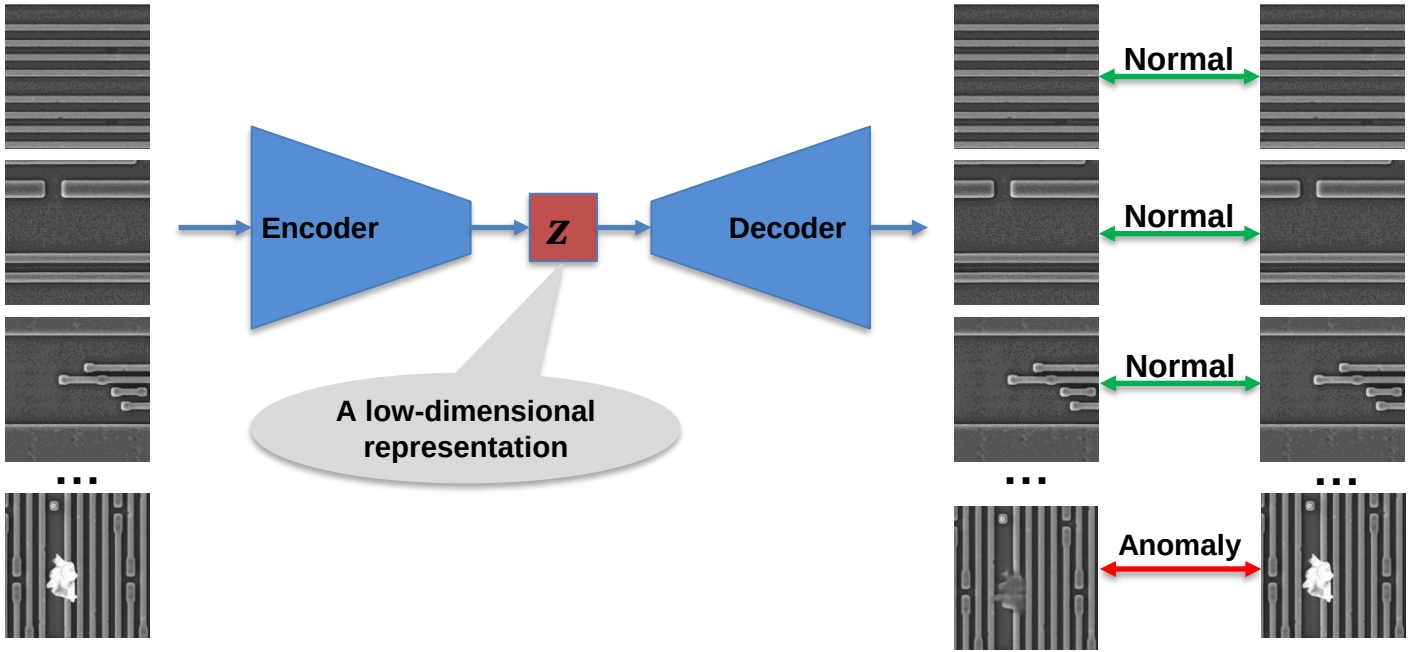




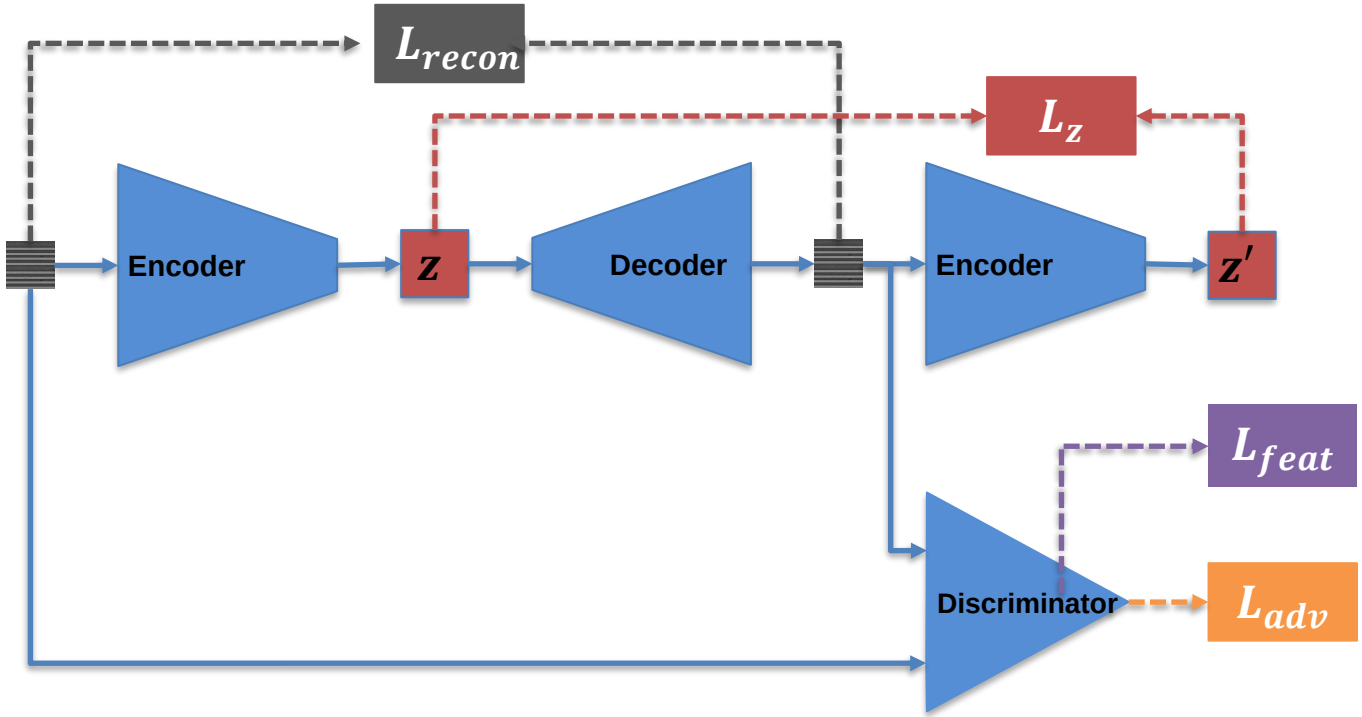




Self-supervised Anomaly Detection with GAN



Self-supervised Anomaly Detection with GAN



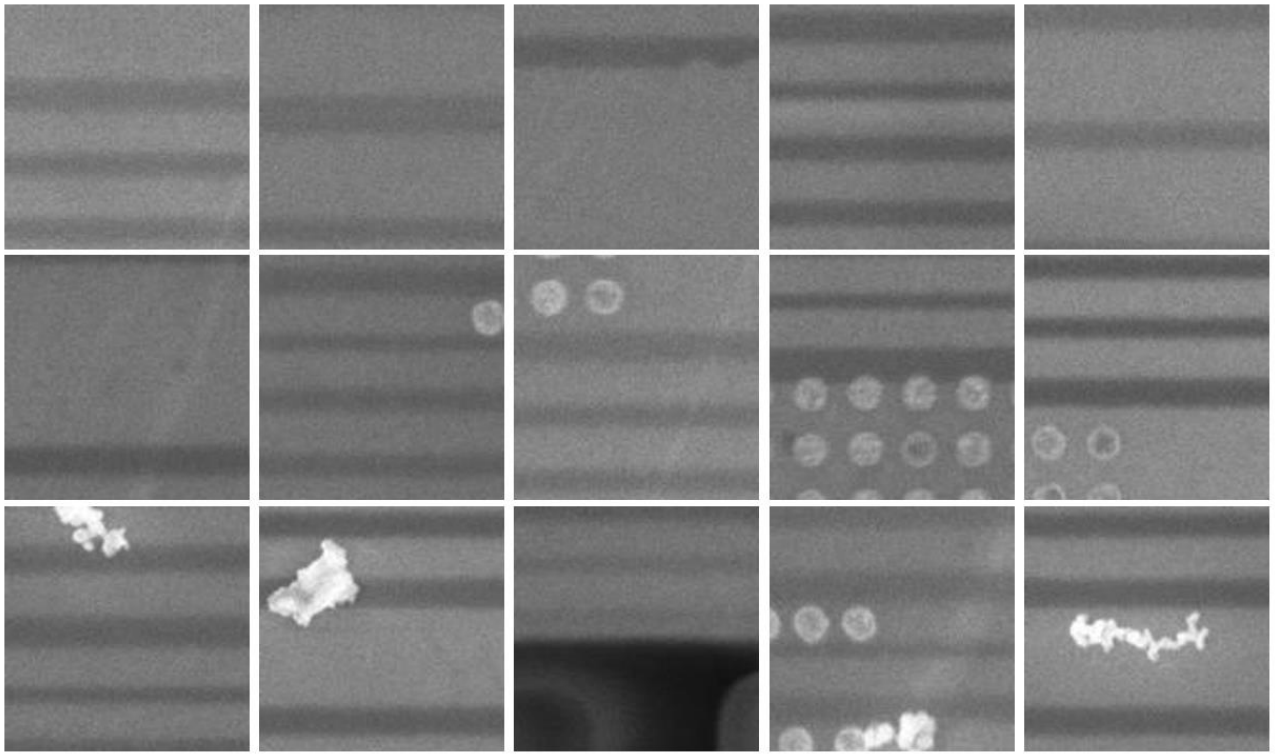
Training Stage:

- Alternating training between Encoder/Decoder (Generator) and Discriminator
- Generator is optimized with weighted sum of 4 loss terms
- Discriminator is optimized with adversarial loss

Testing Stage:

- Reconstruction loss, z-loss, and feature loss are computed for patches of input images
- 3 loss values are normalized as anomaly scores to determine anomalous images.

Self-supervised Anomaly Detection: Score Ranking

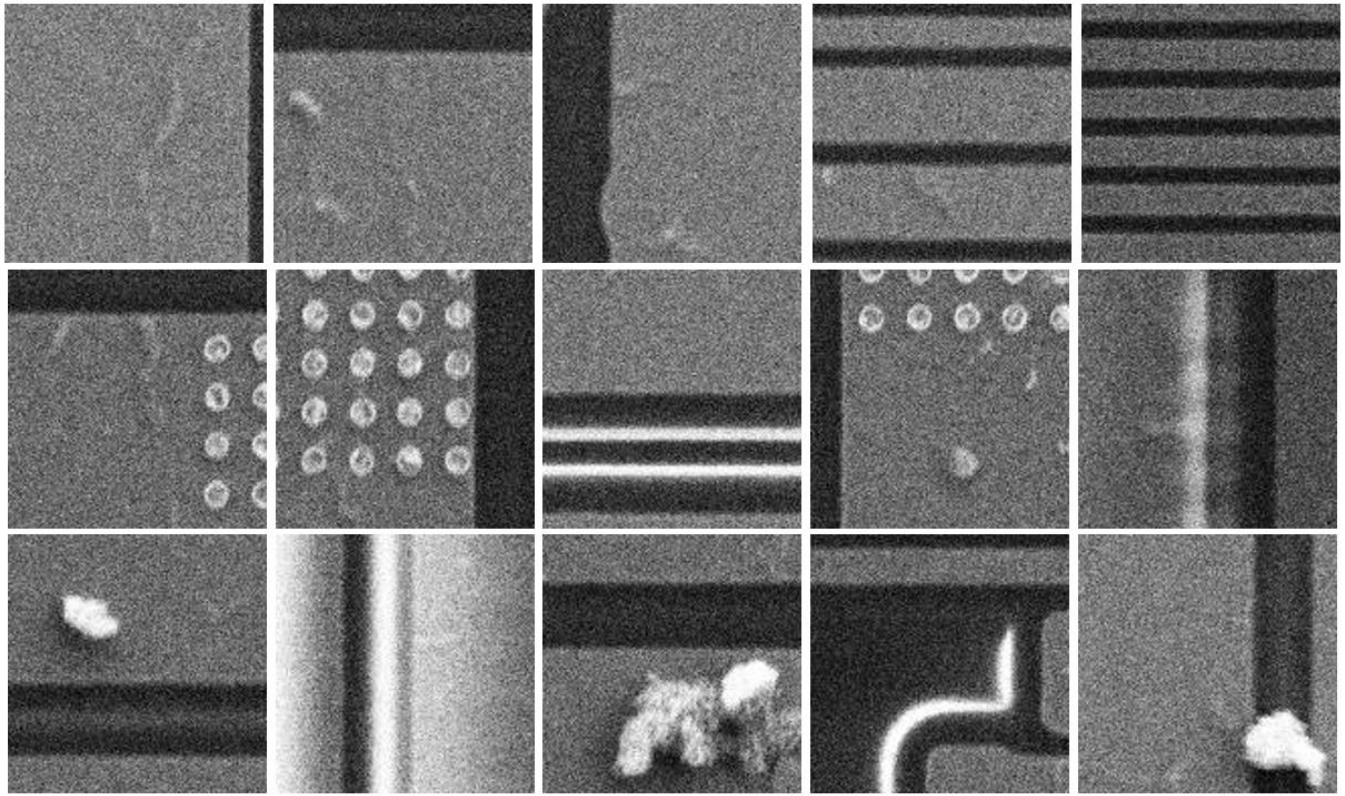


Low anomaly score

Medium anomaly score

High anomaly score

Self-supervised Anomaly Detection: Score Ranking

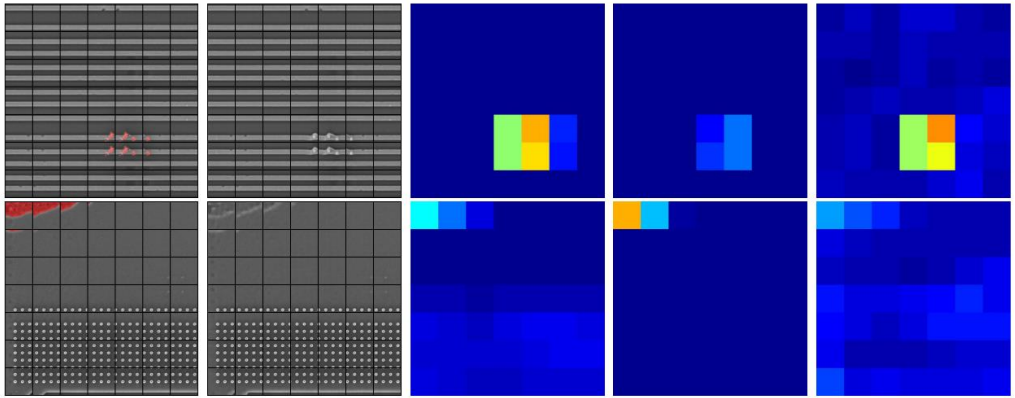


Low anomaly score

Medium anomaly score

High anomaly score

Self-supervised Anomaly Detection: Accuracy



Anomaly Groundtruth | Reconstructed Image | Reconstruction Score | Feature Score | Z-Score

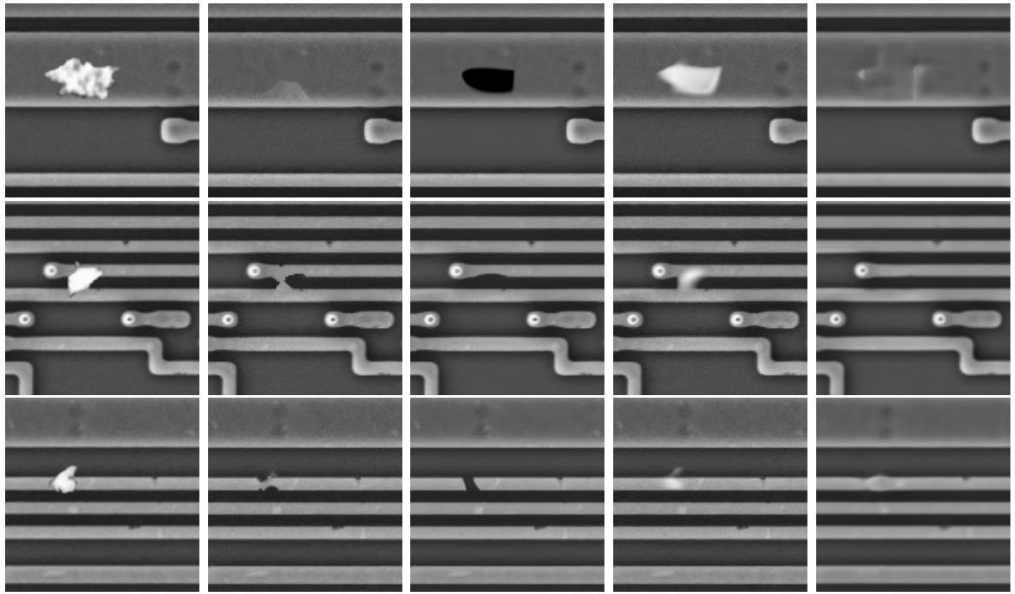
Anomalous regions are highlighted by high loss values (anomaly score).

Method	AUC	F1	TPR	FPR
ResNet f-anoGAN [17]	0.5623	0.3013	0.1896	0.0063
ConvNet f-anoGAN	0.5638	0.3165	0.1896	0.0008
GANomaly [18]	0.9334	0.7464	0.6724	0.0118
Ours (IAD only)	0.9728	0.8348	0.7845	0.0086

Better performance than reported methods, without supervision/data labeling.

Joint Task on Anomaly Detection & Inpainting

Concurrent anomaly detection and inpainting, by adding pairs of corrupted and corresponding clean images into training



Anomaly | IDBP | IRCNN | TSLRA | **Ours**

Model	PSNR	SSIM
IDBP [26]	31.3390	0.9575
IRCNN [6]	31.2245	0.9586
TSLRA [5]	30.4554	0.9563
Ours (IAD + Inpainting)	**34.4798**	**0.9627**

Good performance on image inpainting

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Ours(IAD+Inpainting)	**0.9927**	**0.9123**	0.8966	0.0063

Further improve image anomaly detection

Conclusions

- A deep learning-based framework for IC image analysis has been presented. Deep learning models can be effectively applied to retrieve the standard cells and interconnects in IC image analysis, concerning a wide variety of tasks and solutions.

- A major limitation of supervised learning models is their requirements on considerable amount of labelled data. Unsupervised or semi-supervised analysis can alleviate the data issue on certain tasks.

- A self-supervised GAN-based network has been presented for concurrent IC image anomaly detection and inpainting.