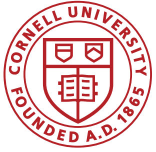
LVX
VERITAS
VIRTVS



Role of Artificial Intelligence in Nanomanufacturing

Photolithography and Plasma Etch

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Acknowledgment

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- DARPA PAI program
- SEMI-FlexTech/ARL
- DARPA NZERO program

CNF facility:

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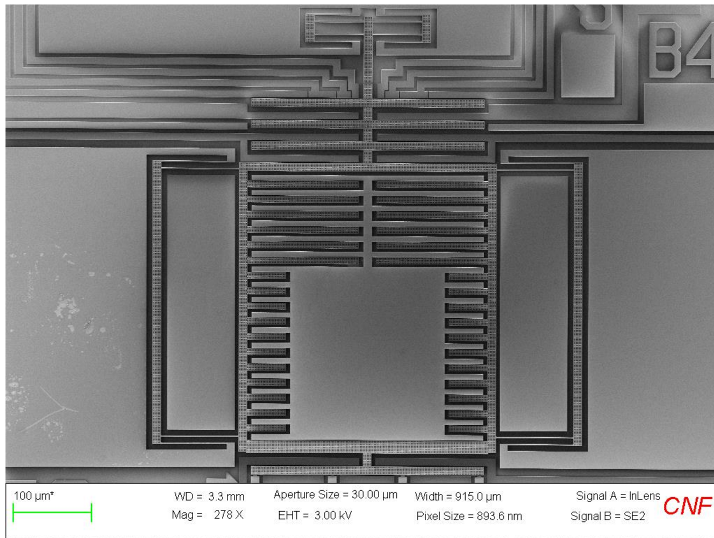
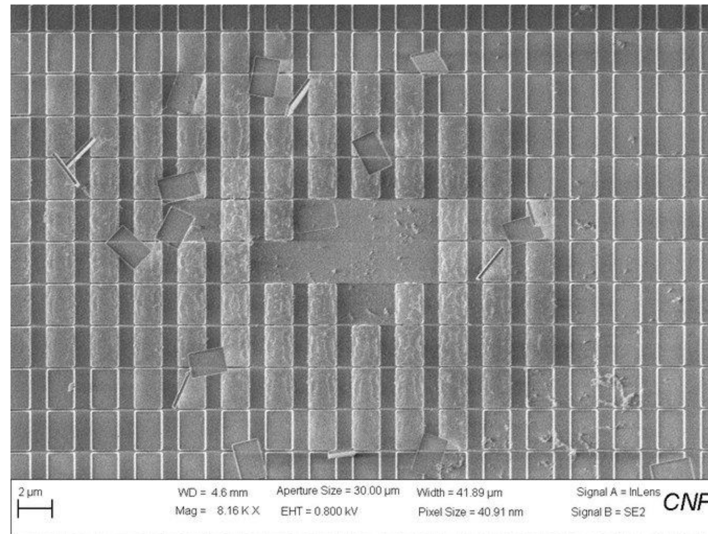
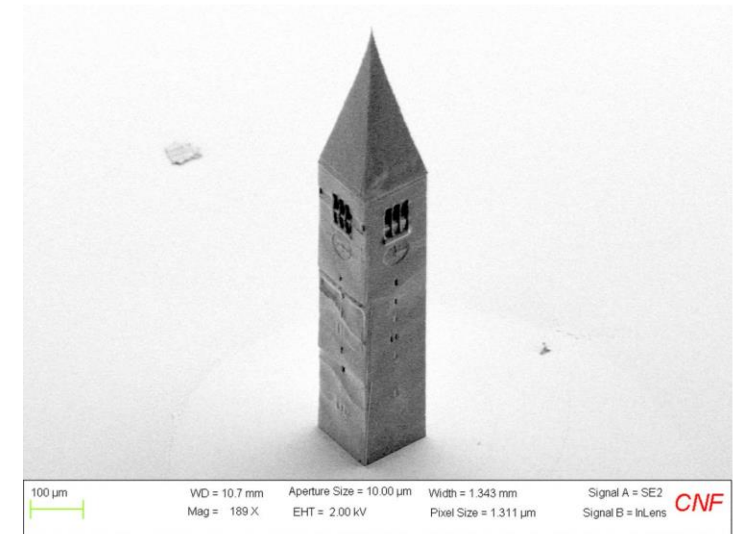
You can build *anything* at Nanofab .....CNF!



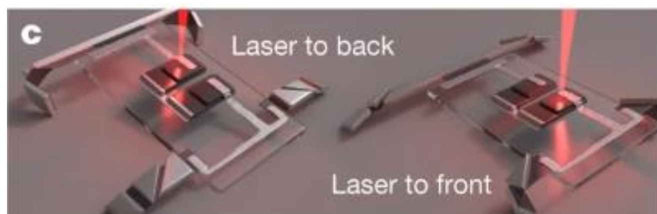
SonicMEMS, 2019

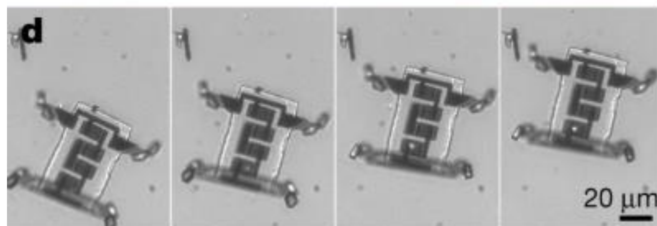


Shvets group, 2021

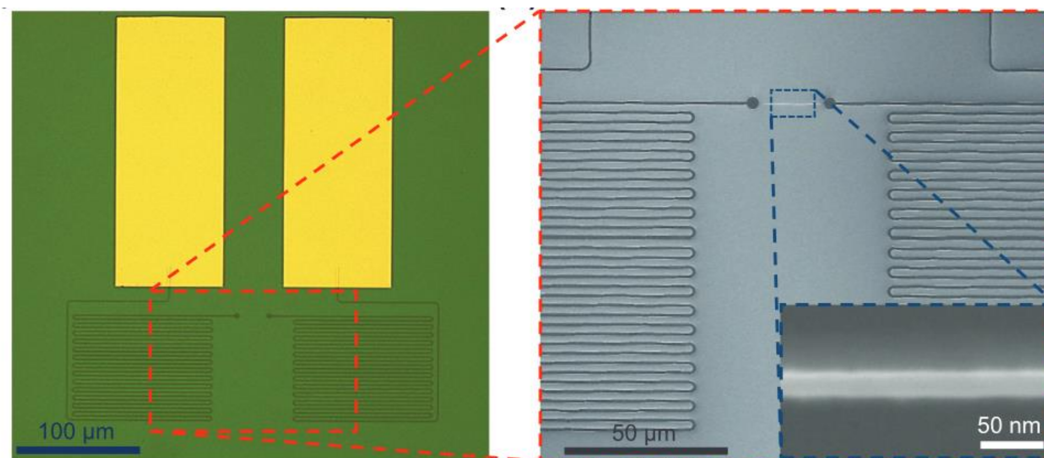


CNF, 2021

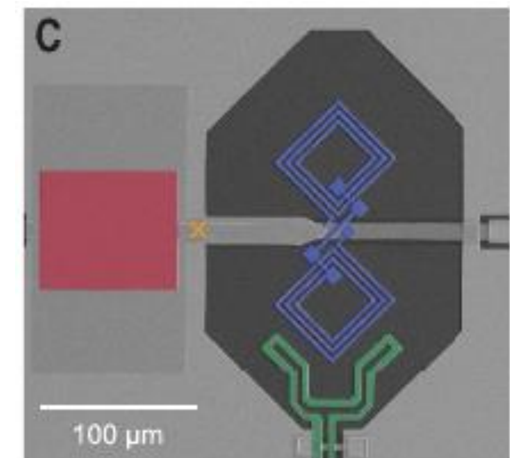




McEuen/Cohen groups, 2020



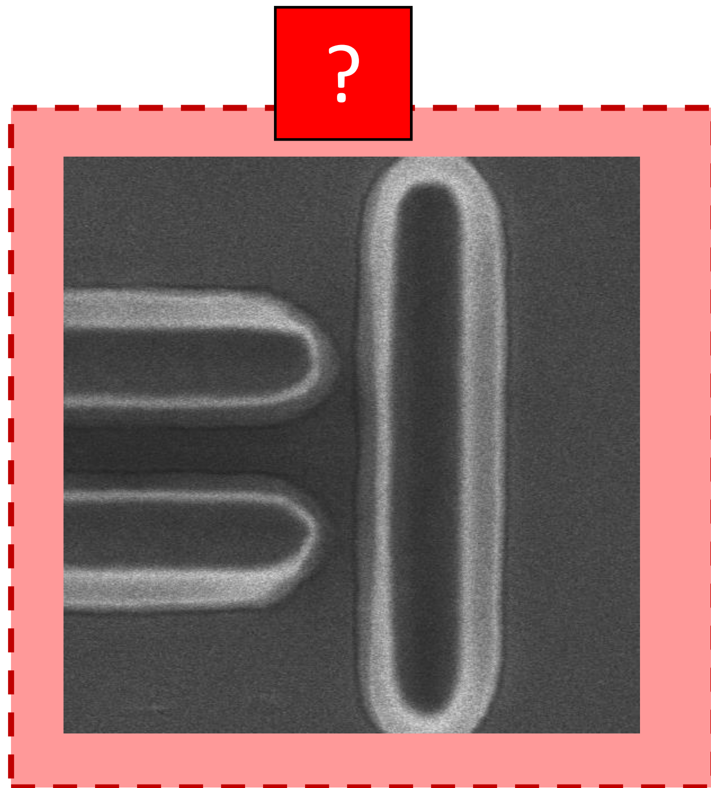
Jenna-Xing groups, 2020

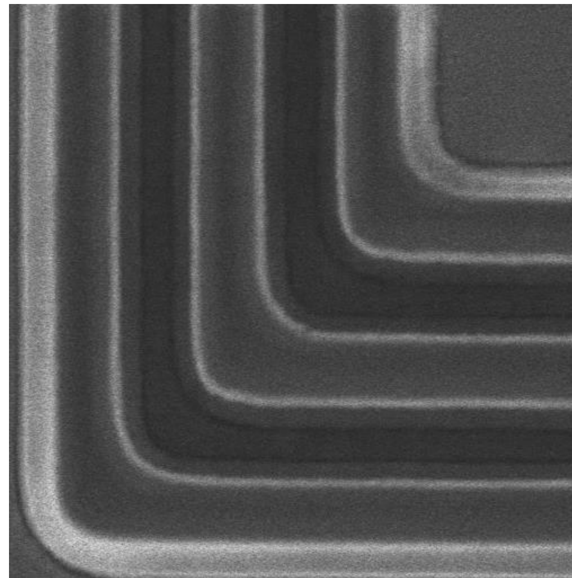


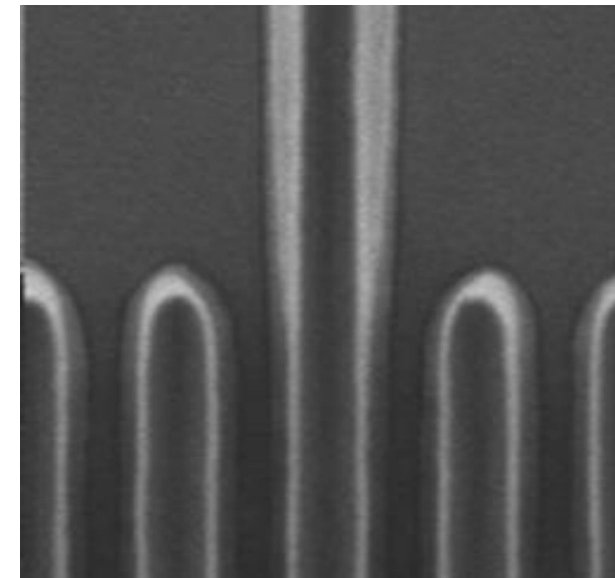
Plourde group, 2018

Which image is a real SEM?

Process: (HBr+Ar) ICP-etched Si nanostructures, with UV210 resist mask.







These are all AI predictions!

SEM images shows a 2 x 2 um.

[SEMI master class #6, 2021]

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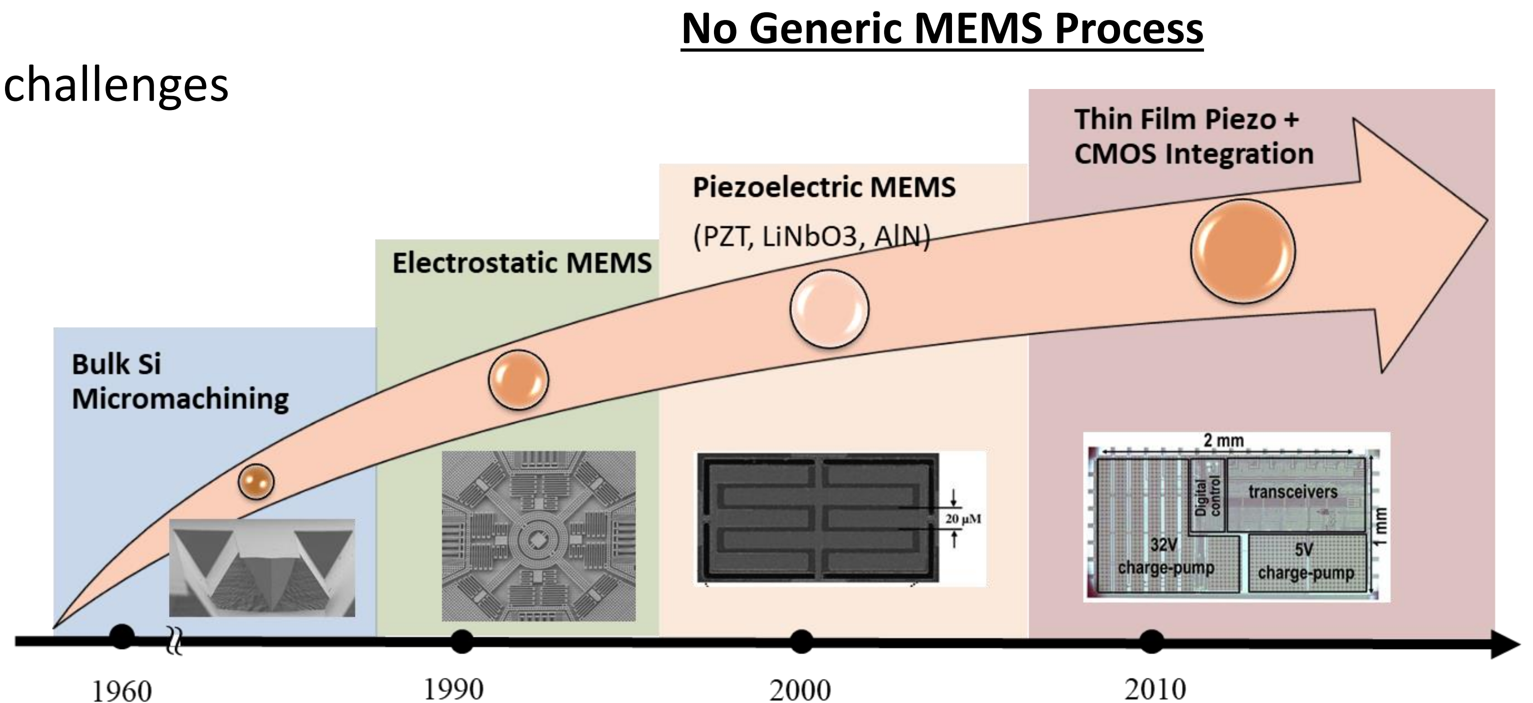
Advances in Artificial Intelligence and Machine Learning

- ML and AI have made a lot of progress in recent years due to **algorithmic advances and large datasets** all enabled by **computational resources** (e.g., HPC, GPUs, TPUs …)
- Example areas where AI already has impact includes: **E-commerce**, **face recognition** and **autonomous vehicles**
- AI and ML is being used in **material science**
- AI is being used to enhance the **computation** and **pattern recognition** efficiency on the data collected by micro and nanosystems (e.g, **IoT**, **edge devices**)
- But application of AI to **micro and nanofabrication** and **device design** is in its infancy

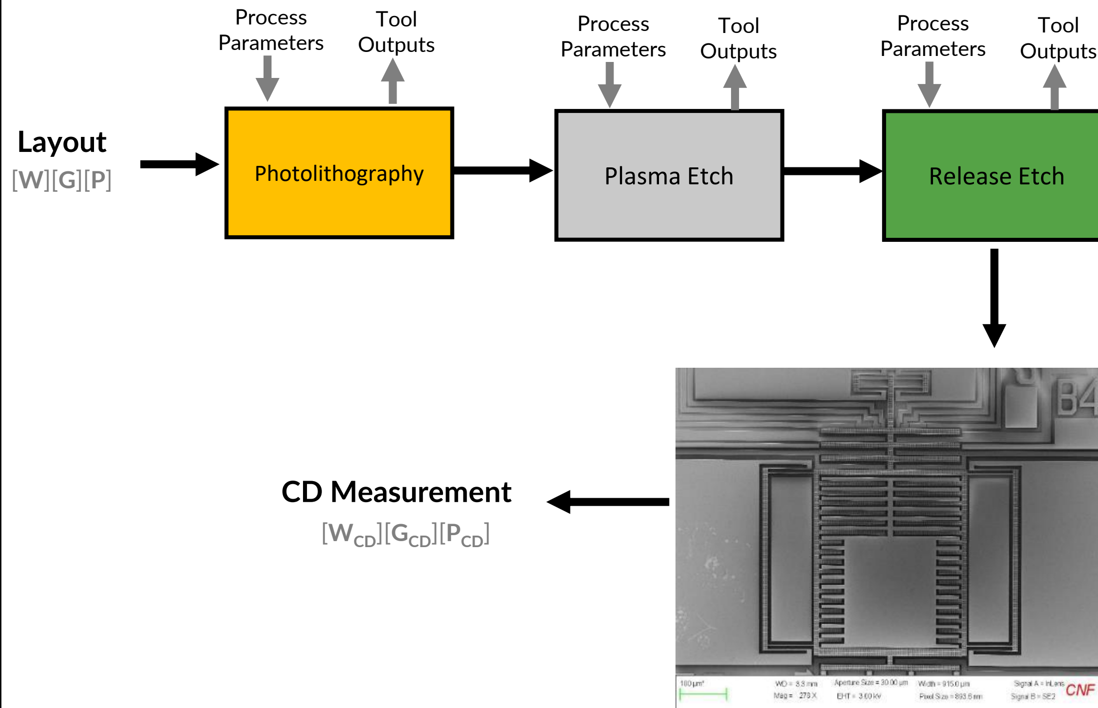
Can AI/ML solve nanofabrication challenges?

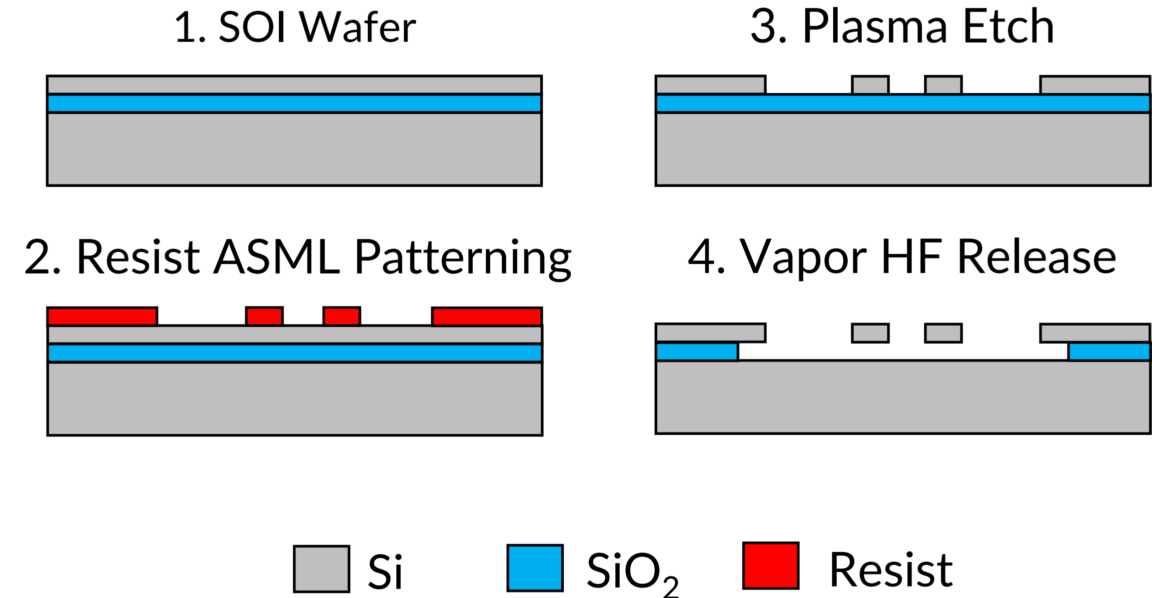
Nanodevices design and manufacturing challenges:

- Excessive effort and time for new device development
- Lack of standard/generic processes
- Novel materials and process development challenges
- Lack of process connection with CAD tools
- Growing demand for integration
- Multiple foundry implementation challenges



Example: Si NEMS switch fabrication





[Ruyack, 2018]

NEMS radio switch

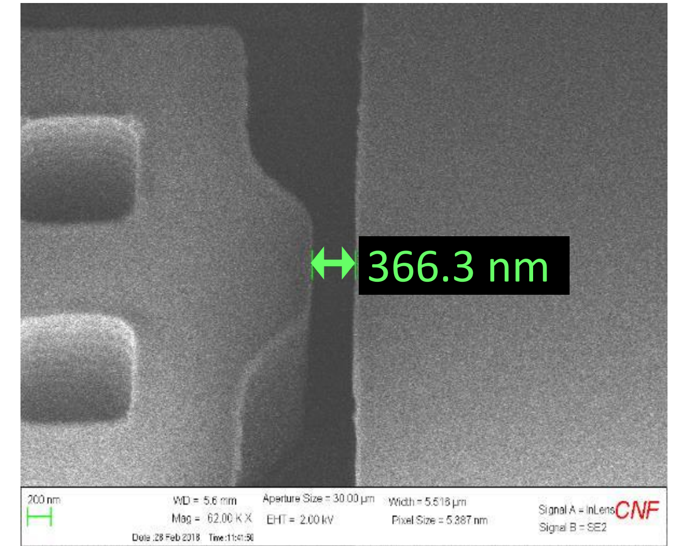
~93 nm

Pt Pt

1 µm

Down to 20 nm possible

HV 5.00 kV | WD 5.0 mm | tilt 45 ° | mag 12 061 x | curr 1.6 nA | det TLD | 2 µm



y
x

[Ruyack, 2018]

Learning outcome of nanofabrication

Device Layout
[G][W][P]

Photolithography
[F][E]

CD-SEM

Wafers

Plasma Etch
[MFC_1,...MFC_n][P]
[T][ICP][RIE][t]

CD-SEM

Wafers

NEMS Switch

Predict Results

Predict Etch Results

Process Parameters

Process Data (Leveling, focus, alignment, ...)

Process Parameters

Process Data (DC_{bias}, OES, ...)

OPC + EPC

AI Engine (Device Level)

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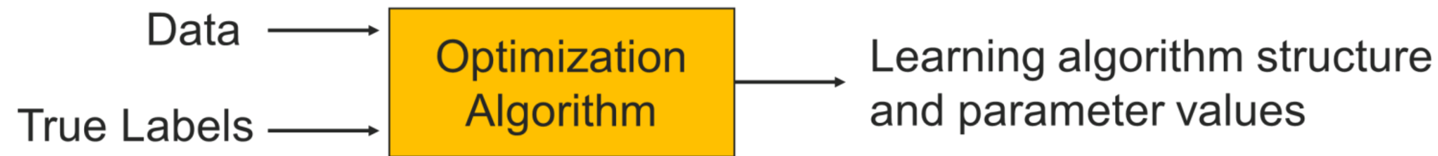
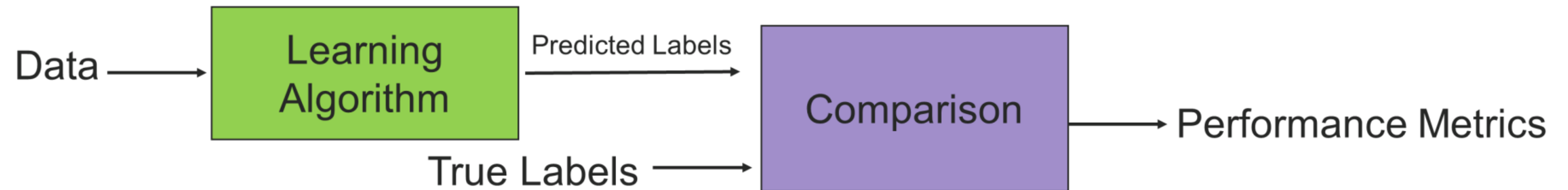
Machine learning = Learning from examples

Three Phases:

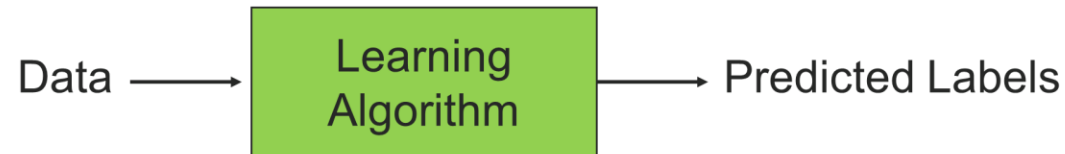
1. Train:



2. Test:



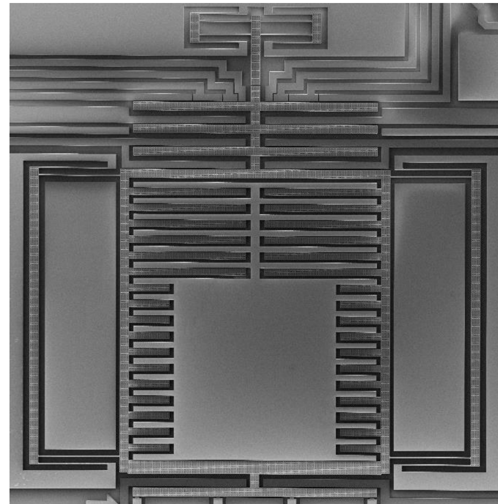
3. Use:

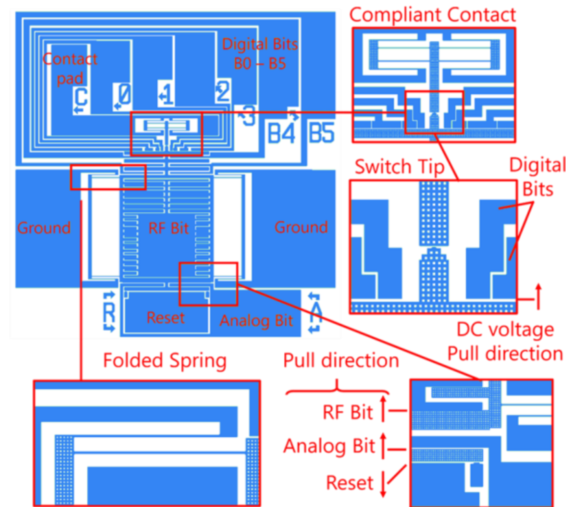


- The Learning Algorithm approximates the unknown function that maps **Data** to **Labels**.
- Accurate **True Labels** are important! Otherwise, the Learning Algorithm is trying to find a mapping of "one" to "many".
- **Example data** must match eventual **Use data**! ("transfer learning")

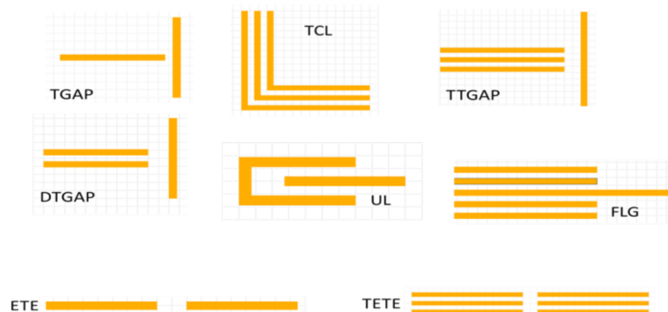
Training dataset motivated by NEMS switch

NEMS RF switch layout:

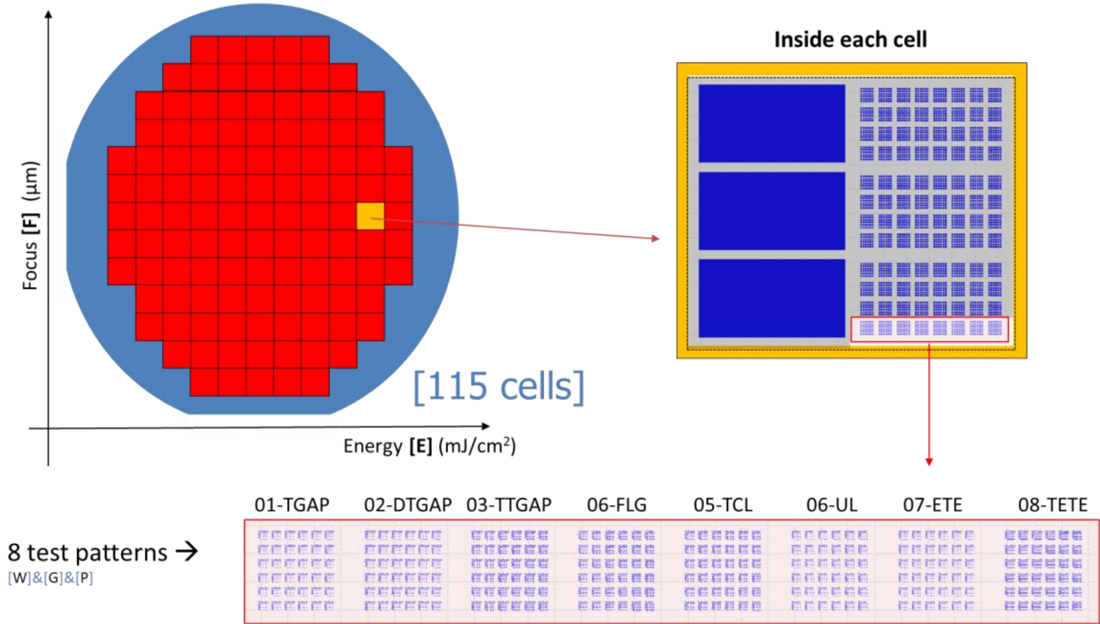




Fragments of mask layout:



Wafer layout:



Structures on the PAI Wafer:

115 x 8 x 4 x 2 x 6 x 6 x 18 = 4,769,280

[cell] x [L] x [P] x [Po] x [W] x [G] x [rep.]

Measured CD-SEMs for PAI program:

115 x 8 x 1 x 1 x 6 x 6 x 1 = 33,120

[L]: layout pattern (8 patterns)
[P]: pitch (line/space ratio: 1,1.25,1.5&2)
[Po]:polarity of patterns (positive and inverted)
[W]: width of lines (150-400 nm)
[G]: gap size (150 - 400 nm)
[rep.]: number of repeated structures (3x9)

[SEMI master class #6, 2021]

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Nanofabrication Tools Used for NEMS Switch

SUSS – Gamma Cluster

SussTec Gamma Photoresist Cluster
Automated Spin-coater
Automated Develop (Spray/Stream)
Multiple Proximity Hot Plates and Chill Plate
Genmark Robotic Wafer Handling
Alta Spray Coating Module
200mm – 100mm Wafer Capability

ASML – DUV Stepper

ASML PAS 5500/300C
248nm DUV
0.63-0.40 Variable NA
AERIAL Illuminator
3D-Align Back Side Alignment
200mm - 3" Capability

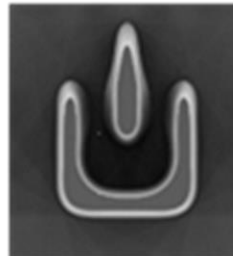
Oxford-ICP Etcher

Oxford ICP Cobra Etcher
Automatic Process Log Transfer
Multiple viewports for spatial variability (RP Camera Installed)
Optical Emission Spectroscopy (OES) for plasma species variability
100 mm Capability

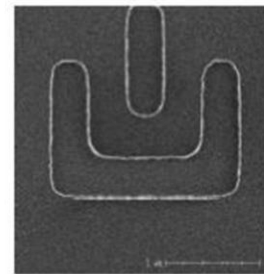
CD-SEM Images and Preprocessing

Mask layout

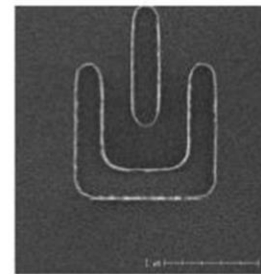
Physics-based model



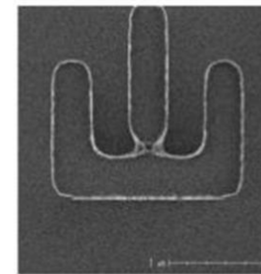
Photoresist pattern on wafer (CD-SEM)



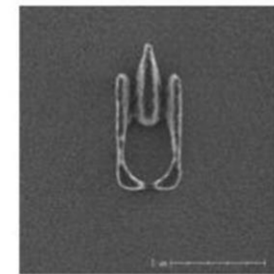
Success



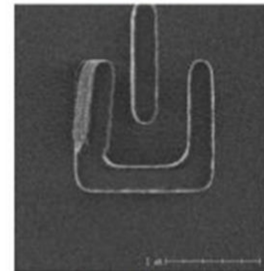
Success



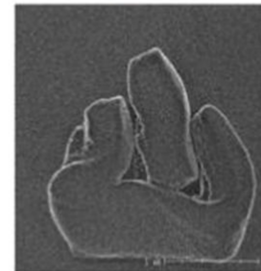
Connection



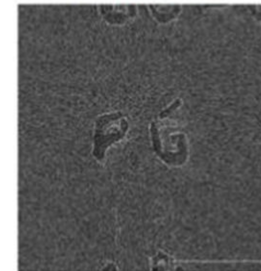
Broken



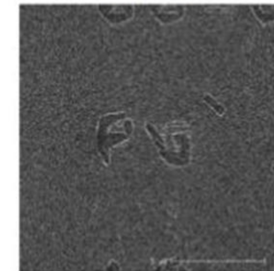
Collapse



Collapse



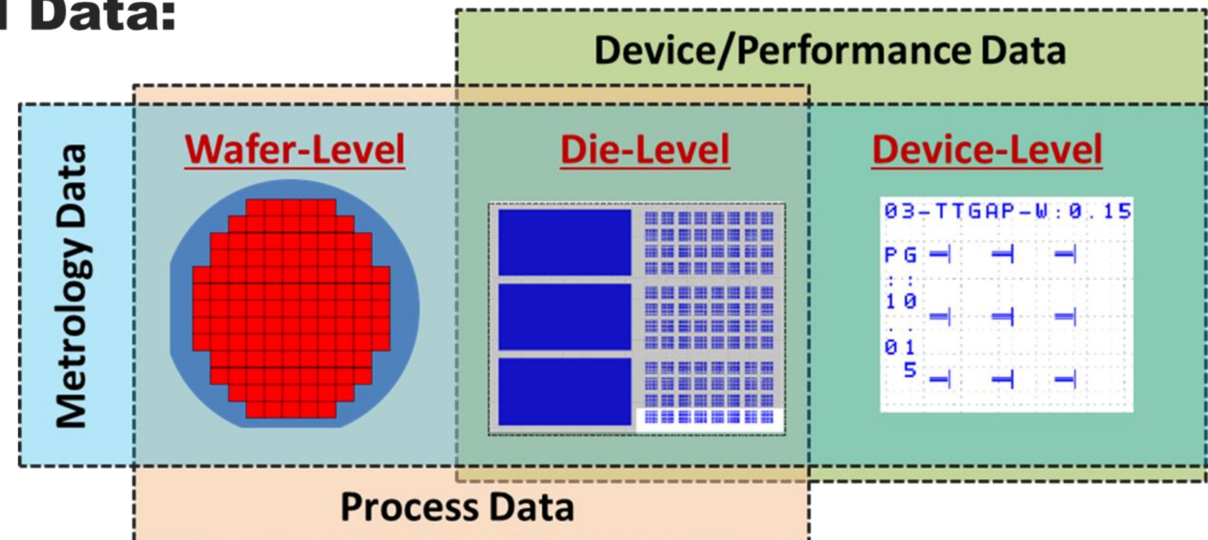
Text not device



Text not device

Data Format & Dimensionality

Multi-dimensional Data:

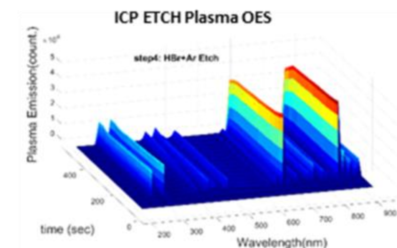


Multi-format Data:

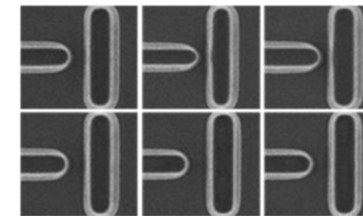
HBr-PR Etch DOE				
Run	RIE (W)	ICP (W)	Pre (m Torr)	Ar (sccm)
0	20	1500	5	4
1	20	1500	5	4
2	20	1700	8	7
3	20	1900	11	10
4	30	1500	11	7
5	30	1700	5	10
6	30	1900	8	4
7	40	1500	8	10
8	40	1700	11	4
9	40	1900	8	7

Numerical

Structured Text



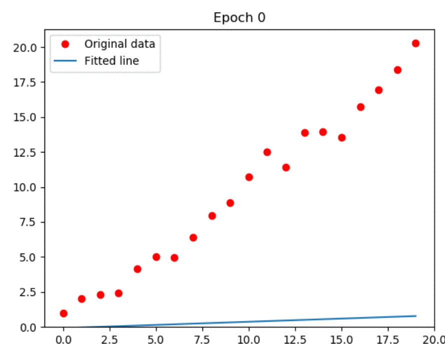
Time Series



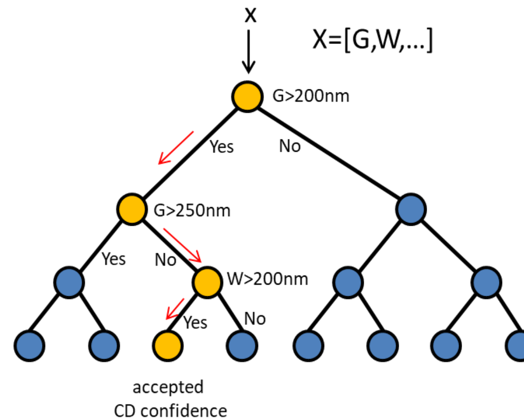
Images(2D data)

(1) Feature-based ML approaches

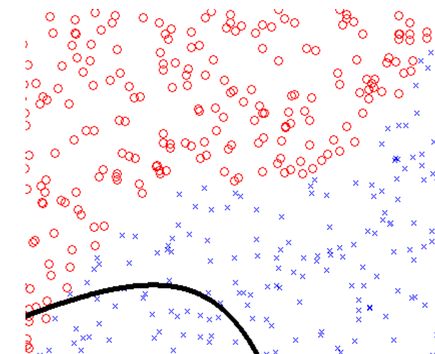
Linear Models



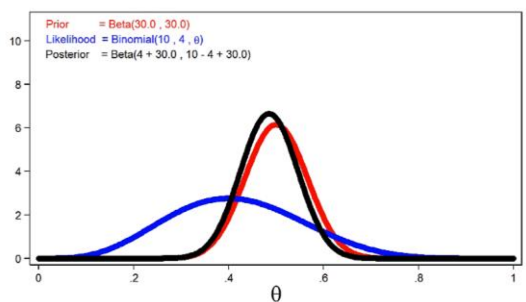
Decision Trees



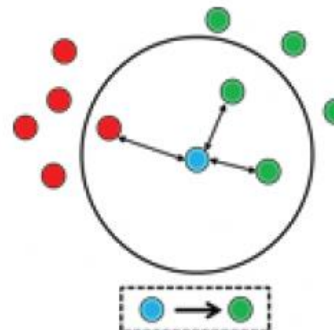
Support Vector Machines



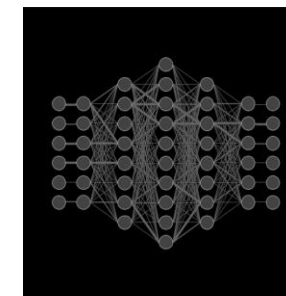
Naïve Bayesian Classification



K-nearest Neighbor

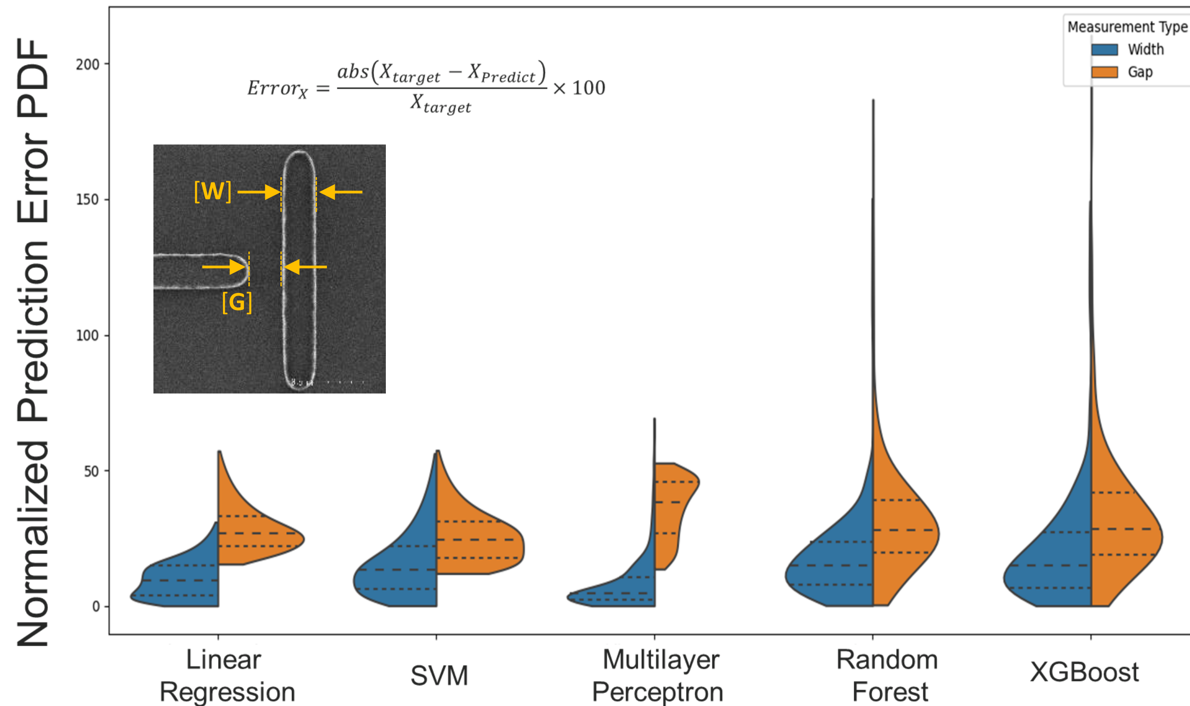


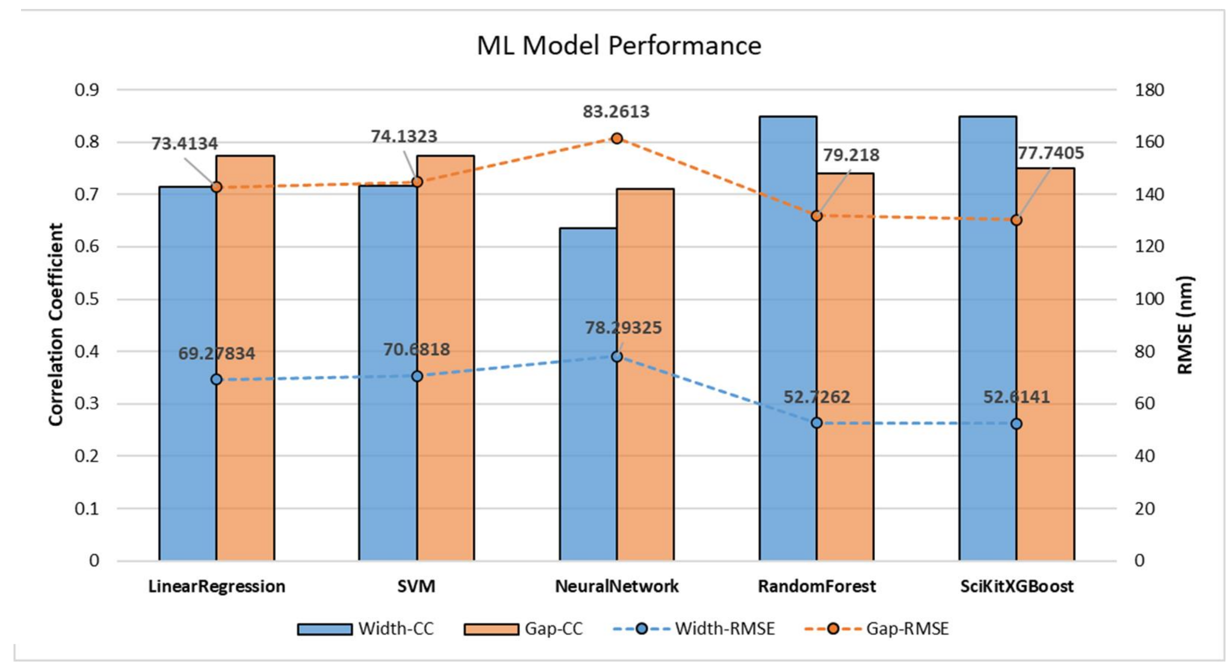
Neural Networks



[SEMI master class #6, 2021]

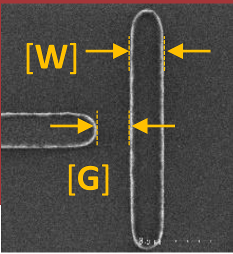
ML based regression applied to design



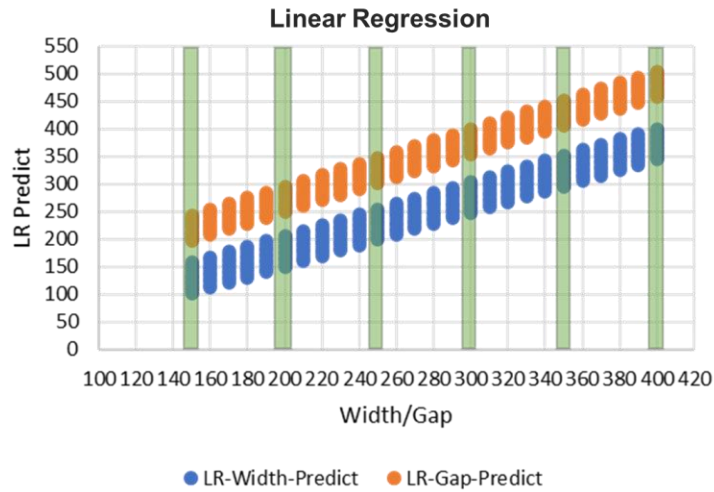


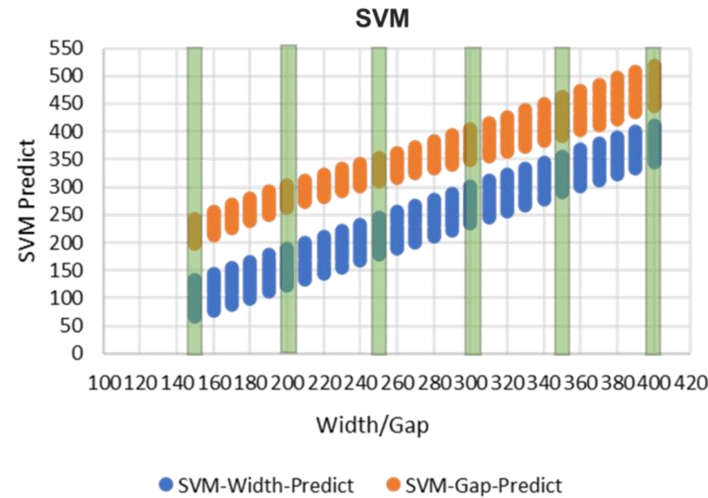
[SEMI master class #6, 2021]

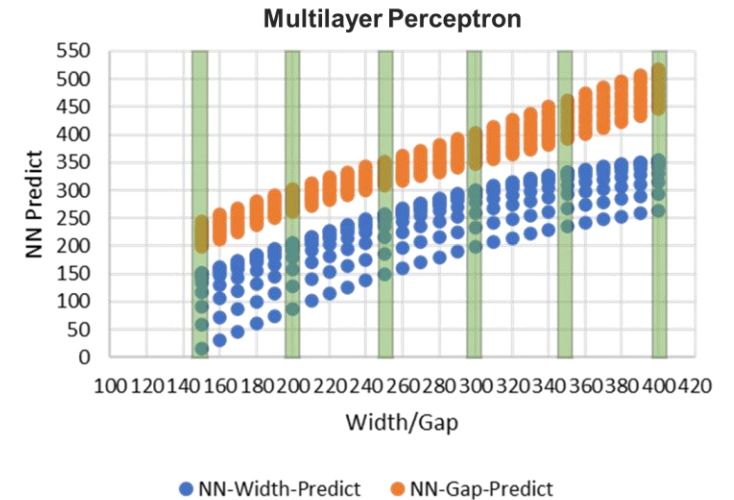
ML for design: width & gap interpolation

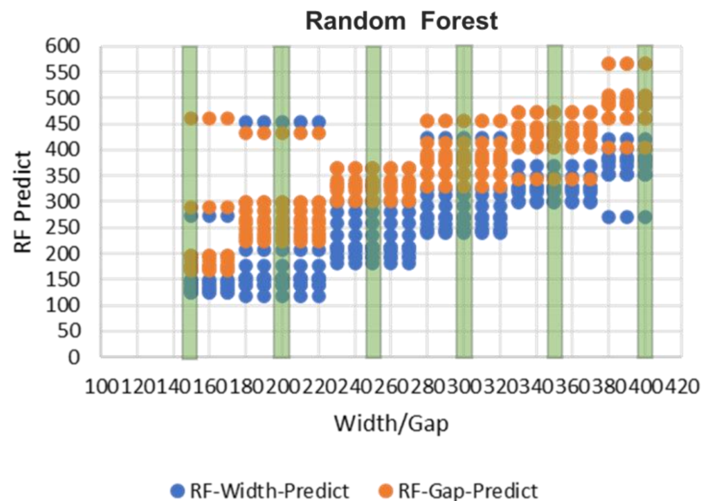


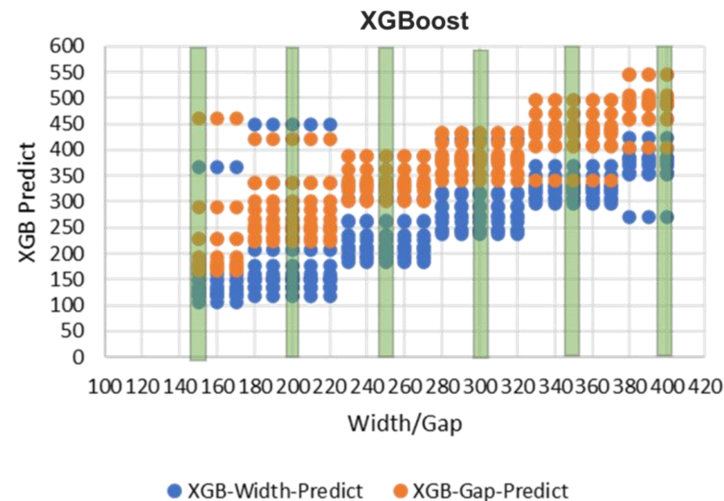
Green=Training data

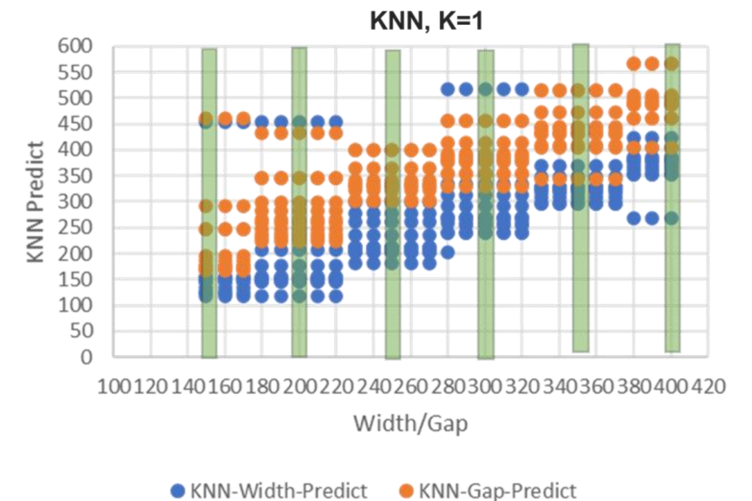






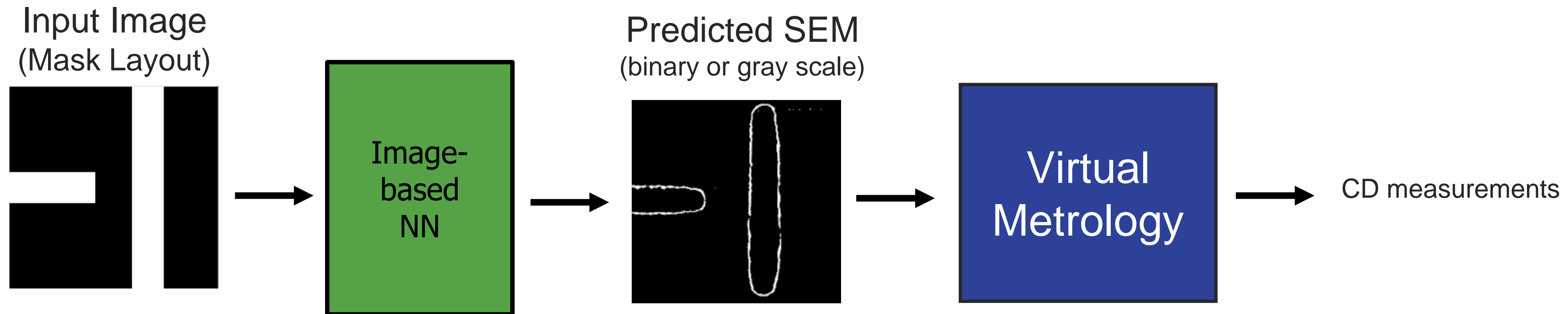






(2) Deep learning for image-to-image translation

Overall Plan:



One approach: Pix2Pix method for image-to-image translation:

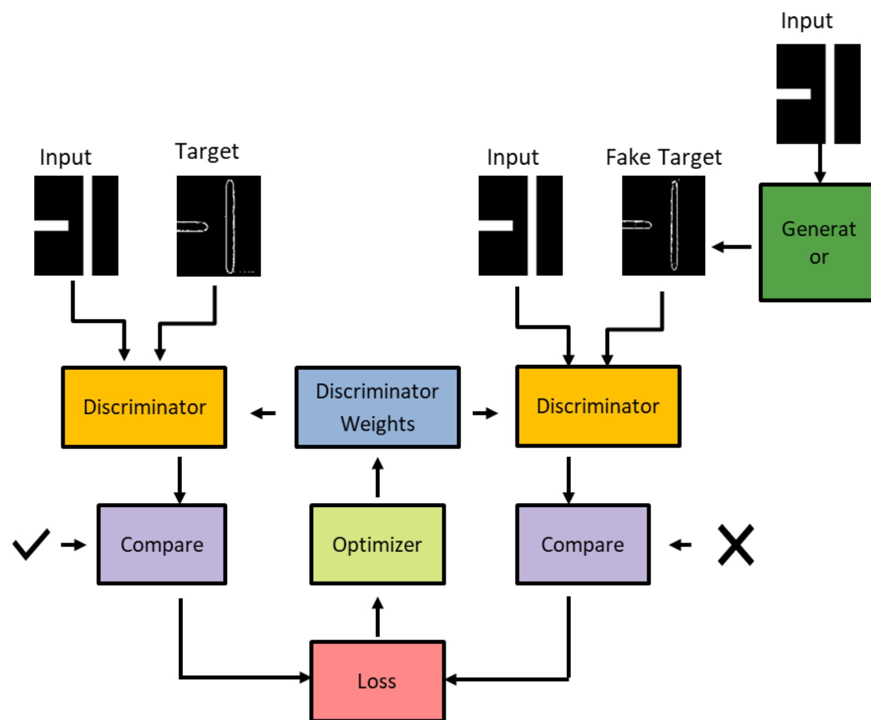
Ref: [arXiv, 1611.07004]

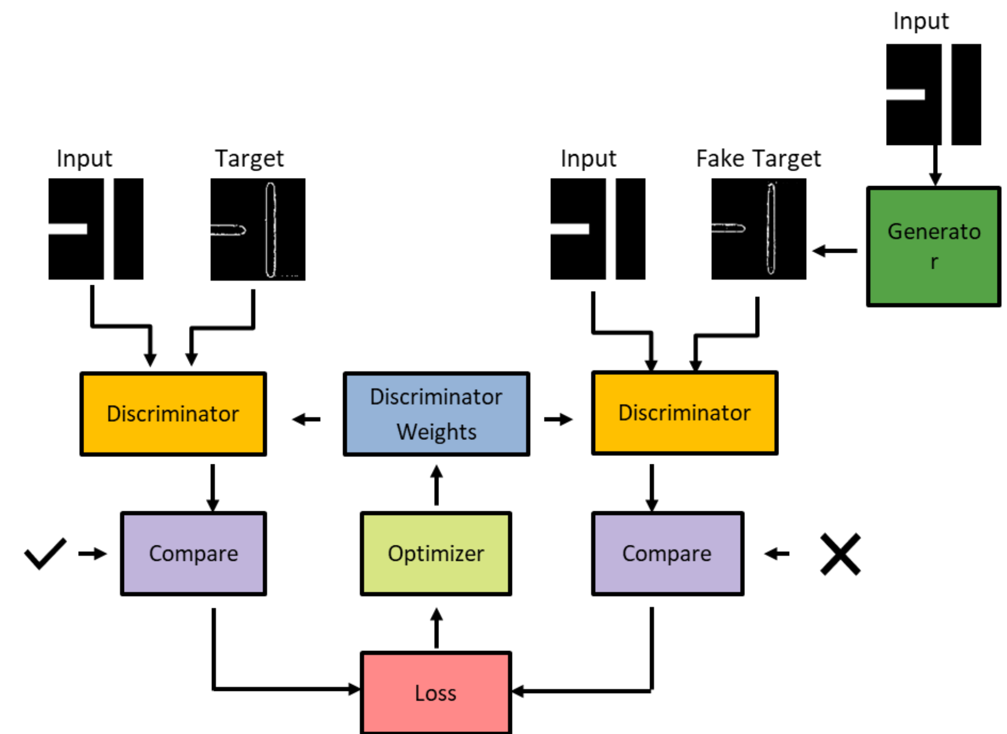
Summary of Pix2Pix method:

- Conditional Generative Adversarial Network (cGAN)
- Two main parts:
  - **Discriminator:** measures the similarity of the input image with an unknown image (either comes from the real target image or the output image from the generator) and guess if this unknown image is produced by the generator
  - **Generator:** predict the output image from the input image
  - In **use mode** we only use the generator.

[SEMI master class #6, 2021]

Pix2Pix Training: Generator and Discriminator





Ref: [arXiv, 1611.07004]

[MEMS 2022]

Pix2Pix Method: Training & Testing versus Using

Training and Test:

Run trained model

Input Mask Image

512*512
3.9 nm/pixel

Down sampling

256*256
7.8 nm/pixel

Matching CD SEM

512*512
3.9 nm/pixel

Binarizatio
n

512*512
3.9 nm/pixel

Down sampling

256*256
7.8 nm/pixel

+

Optimize Pix2Pix Network
(Generator & Discriminator)

Predicted CD SEM

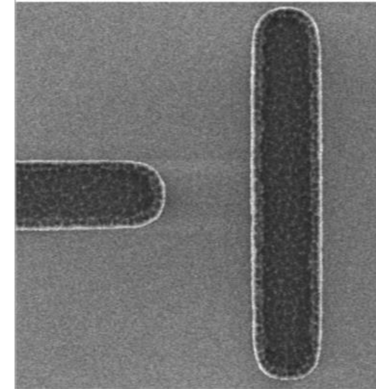
et Weights

[MEMS 2022]

Learning process outcomes and prediction by Pix2Pix

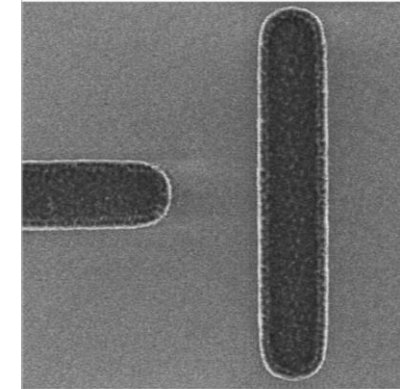
DUV Lithography Process

Mask Layout
Binary



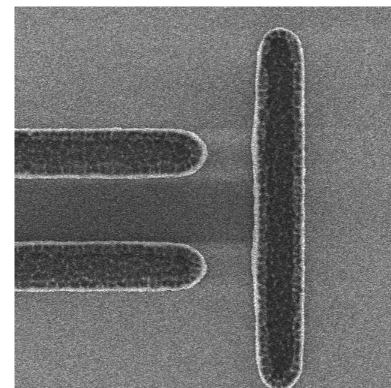
Resist Profile
UV 210- 500nm

Pix2Pix Prediction

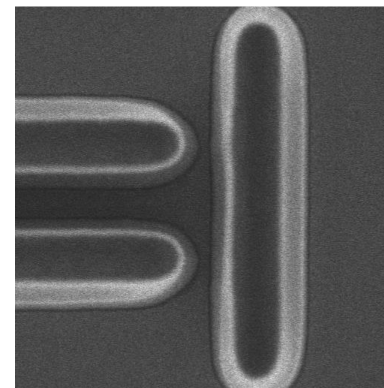


Prediction
Synthesized SEM

ICP Plasma Etch

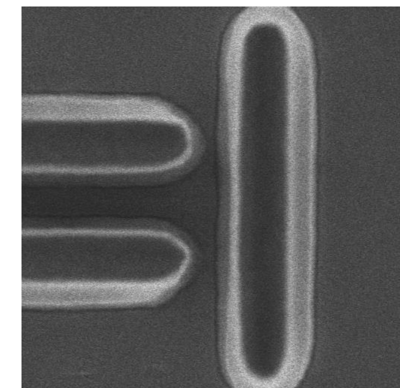


Pre-Etch
Resist Profile



Post-Etch
Si Profile

Pix2Pix Prediction



Prediction
Synthesized SEM

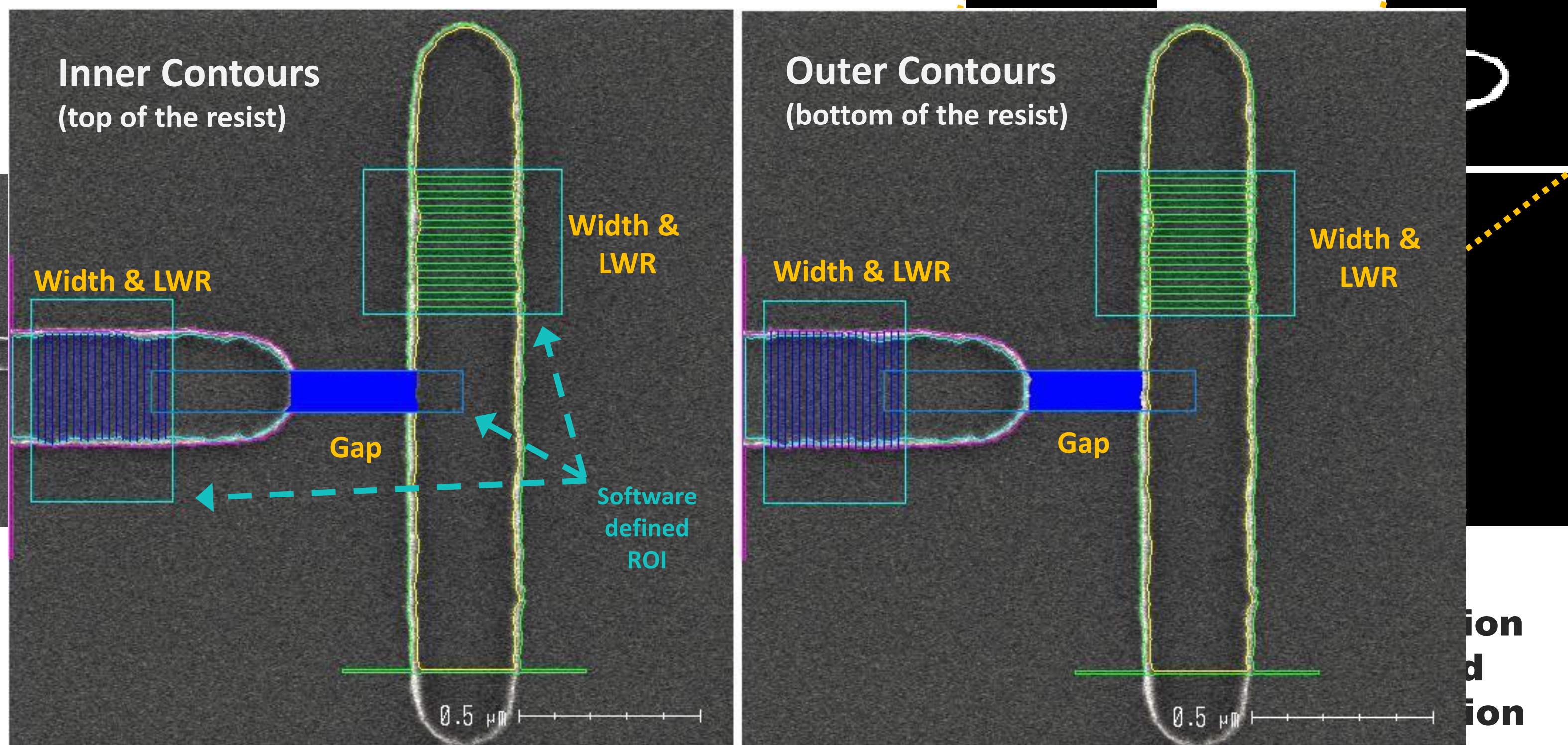
SEM images shows a 2 x 2 um area.

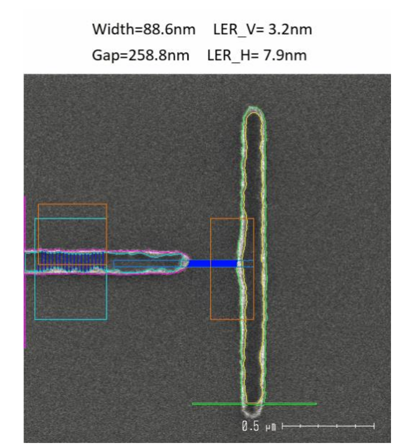
[MEMS 2022]

What AI can do for …

- Quantification and Metrology
- Learning process parameters
- Reverse direction
- AI-powered autonomous nanostructure design tool
- AI-powered autonomous device design tool

Virtual Metrology: Resist CD-SEM



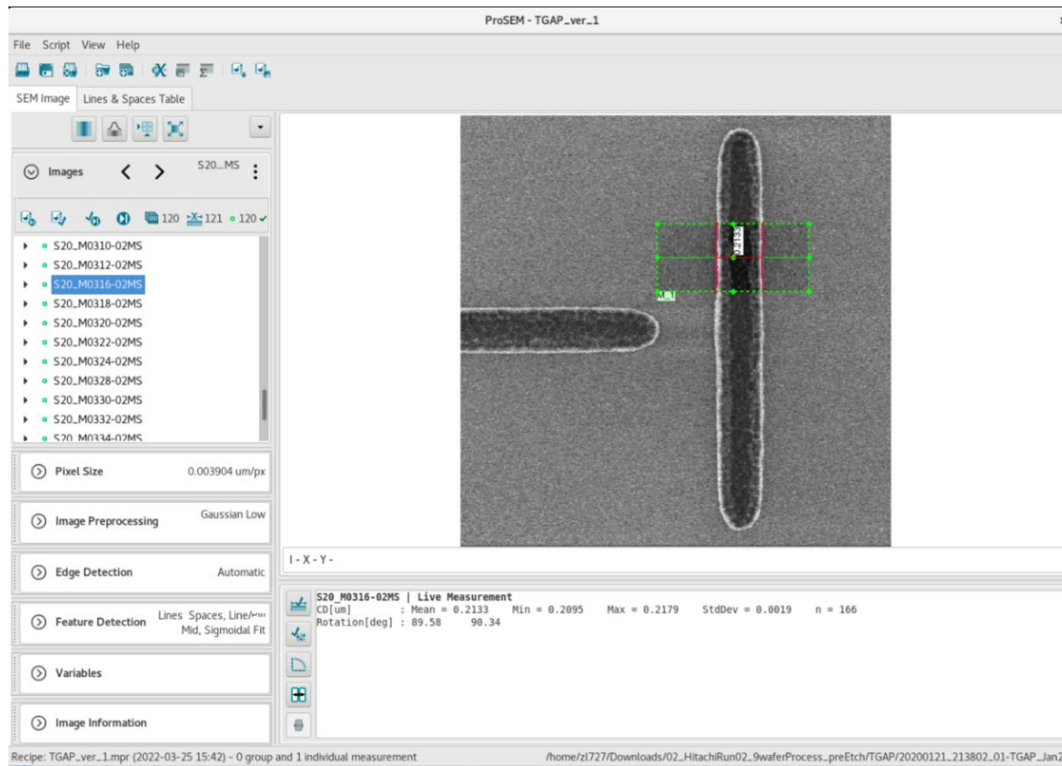


CD Values

	CD-SEM images	filtering and edge detection	PR sidewall
TGAP			
DGAP			
TTGAP			
FLG			
TCL			
UL			
ETE			
TETE			

Virtual Metrology Verification

Goal: ProSEM will serve as a gold standard to compare the accuracy of measurements



Scripting interface (Python) for automation

ProSEM measurement results

Edge Mode	Fine Mode	Cd Pos	Auto Conti	Filter Type	Gauss X	Gauss Y	Line Scan A	LL X[um]	LL Y[um]	UR X[um]	UR Y[um]
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.1154	1.6436	1.431
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.241	1.6436	1.5567
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.0525	1.6436	1.3682
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.2882	1.6436	1.6038
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9897	1.1625	1.6907	1.4782
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.0682	1.6436	1.3839
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.1154	1.6436	1.431
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.974	1.3196	1.675	1.6353
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9269	1.0997	1.6278	1.4153
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.2568	1.6436	1.5724
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.1311	1.6436	1.4467
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9426	1.1625	1.6436	1.4782
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.9269	1.1782	1.6278	1.4939
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.974	1.1154	1.675	1.431
Automatic	Sigmoidal	Mid	On	Gaussian	1	3	0	0.974	1.1154	1.675	1.431

Automatic measurement on large batch of data is possible.

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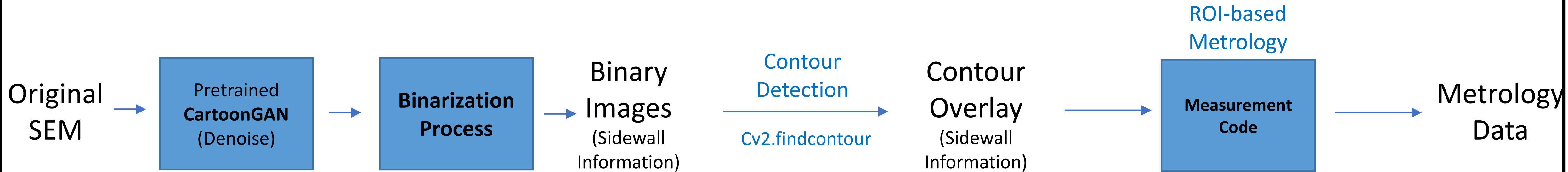
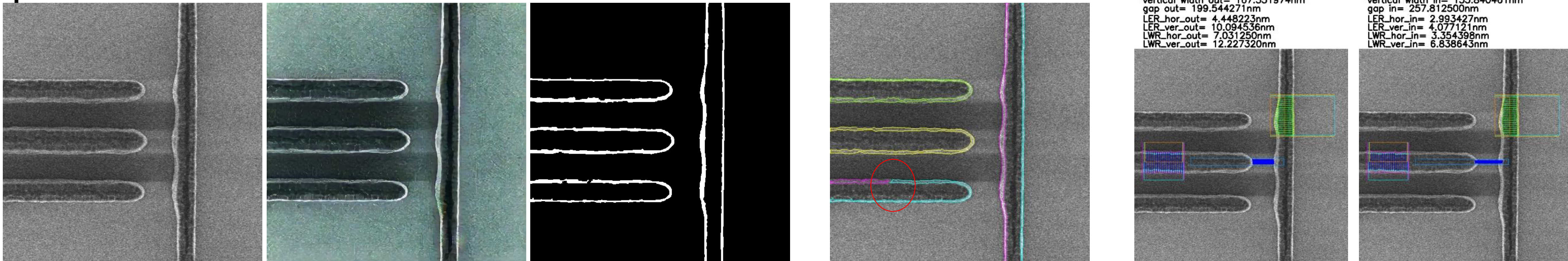
DNN1: cartoonGAN + Thresholding





Binarization Process

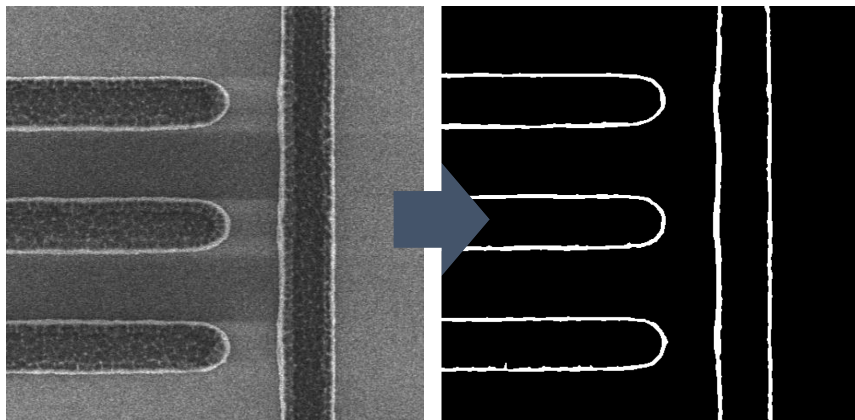
- Median Filter + **Adaptive Thresholding** + Remove Small Connected Components +Erosion Dilation
- Median Filter + (**Sobel Edge Detection** + **Absolute Thresholding)** + Remove Small Connected Components + Erosion dilation

Deep Learning Training Dataset

Training Dataset Part 1:

Raw SEM images and Binary image from DNN1 are paired to form a **train & test dataset** for Pix2Pix and BasNet

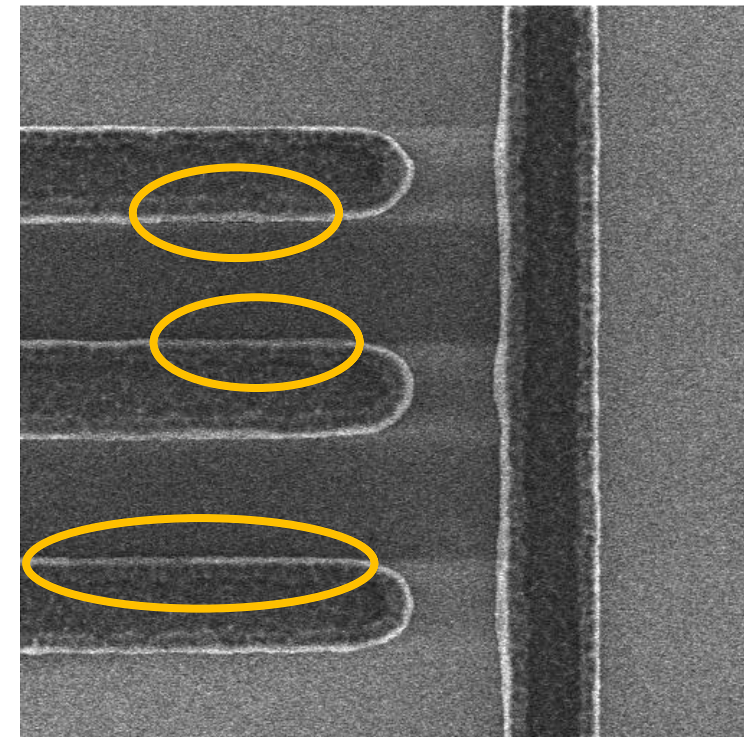
Only Well-connected results are included



A- The final trainset has **5572** image pairs including all eight structures from **wafer 1 to wafer 8**
B- The testset has **908** image pairs including all eight structures from **wafer 9**

Training Dataset Part 2:

Data Augmentation
Reduced contrast of selected areas of sidewalls



Note: Augmented SEM with reduced contrasted is paired with well-connected binary image in the training dataset.

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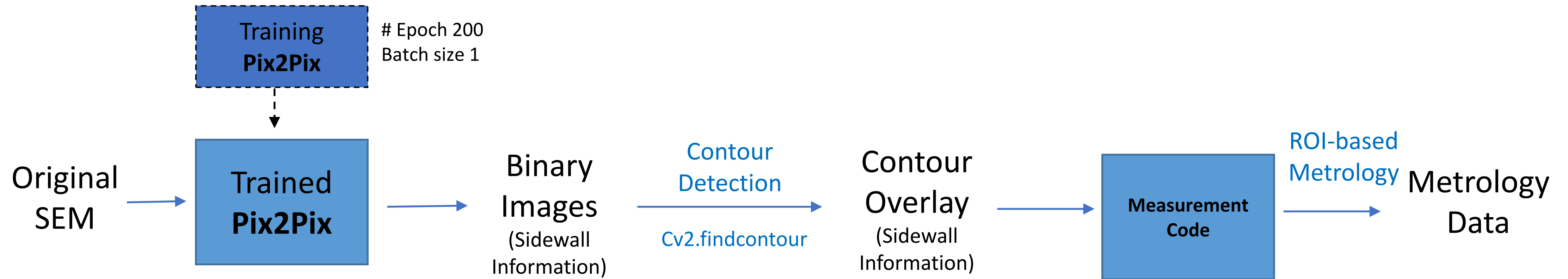
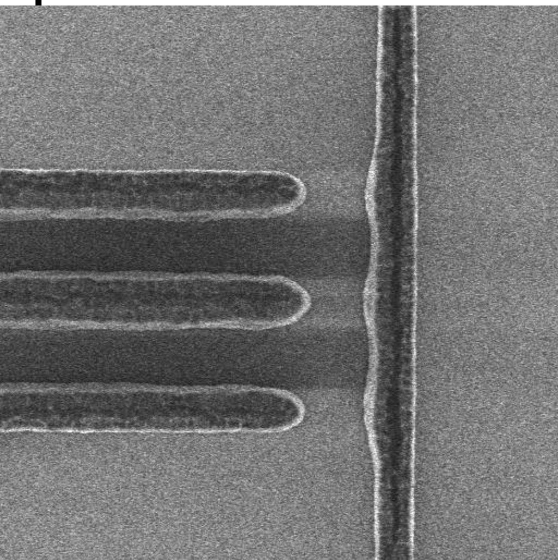
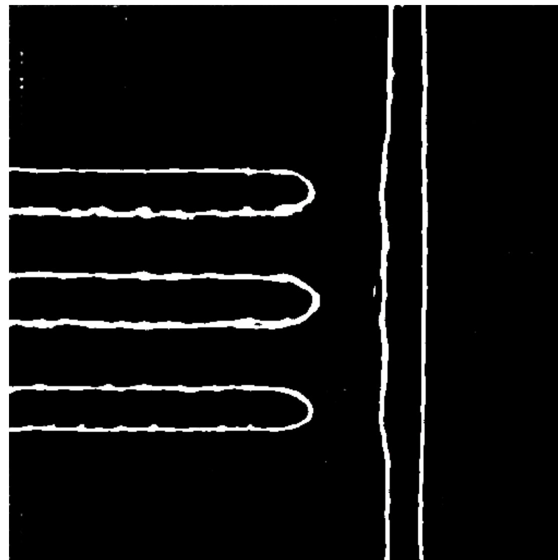
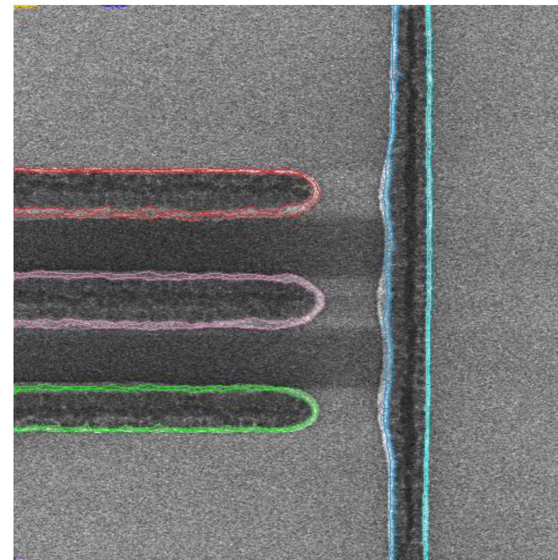
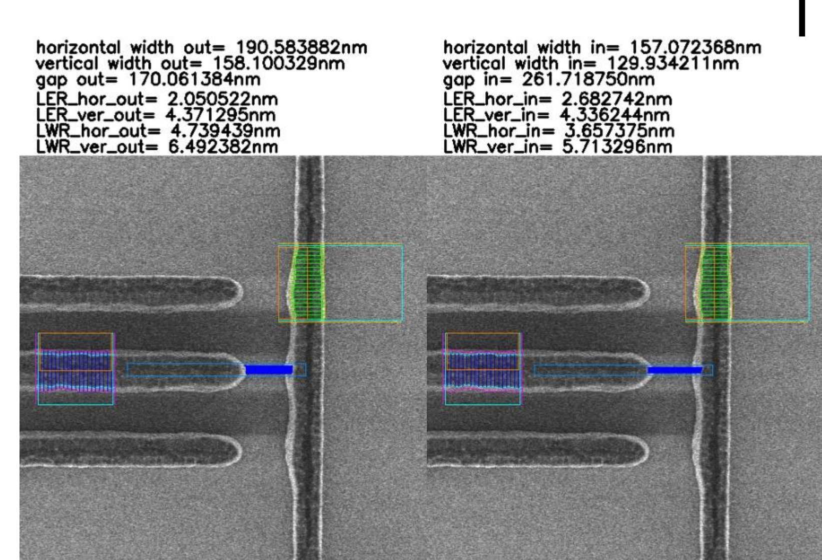
DNN2: DNN1 + Pix2Pix



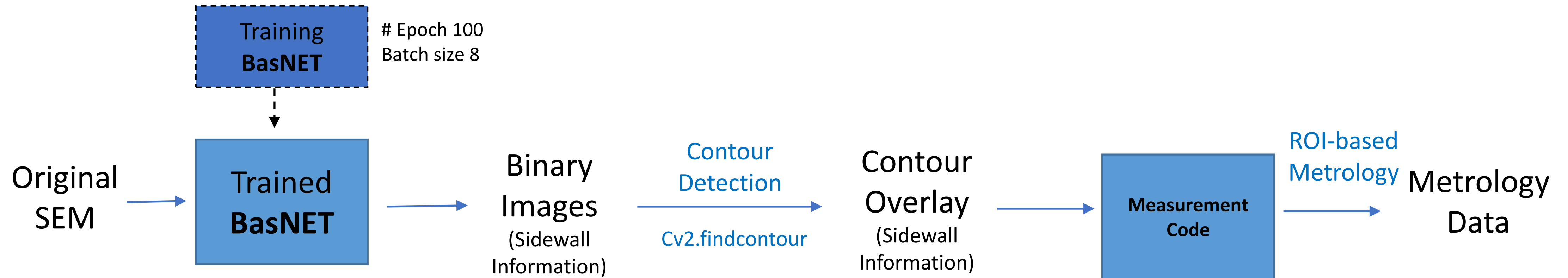








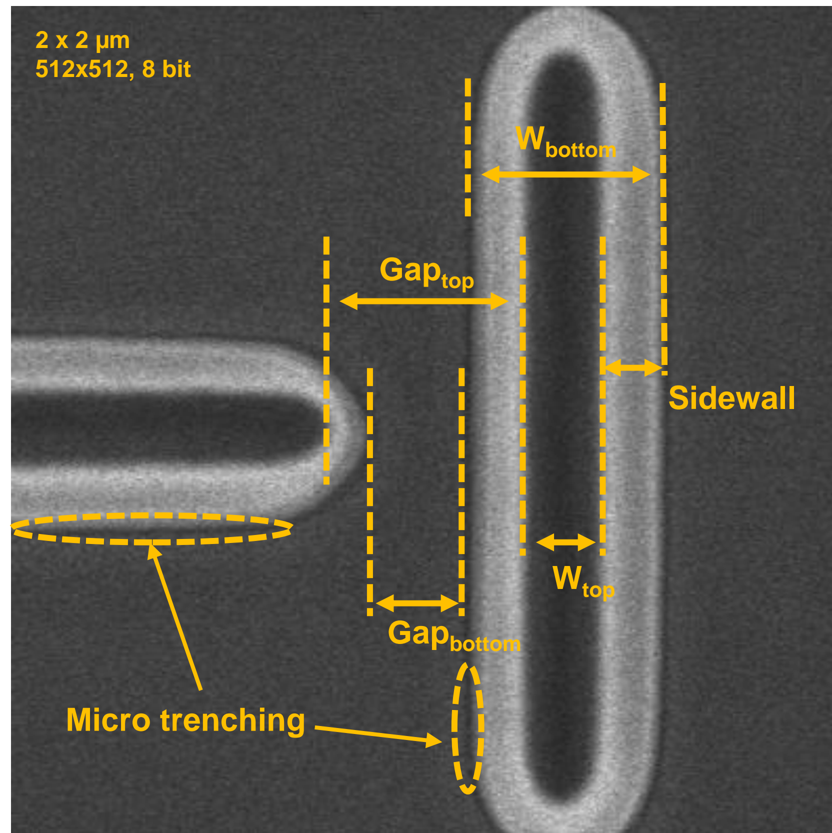
DNN3: DNN1 + BasNET



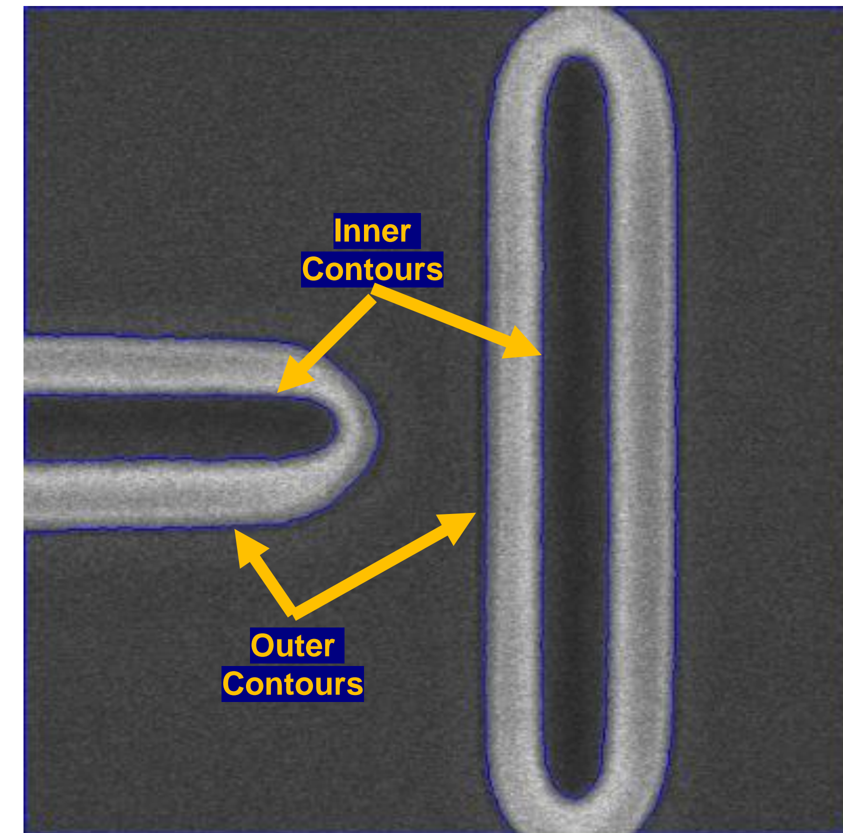
horizontal width in= 146.587171nm
vertical width in= 125.616776nm
gap in= 266.183036nm
LER_hor_in= 2.898742nm
LER_ver_in= 3.958200nm
LWR_hor_in= 4.847645nm
LWR_ver_in= 6.211046nm

horizontal width out= 205.180921nm
vertical width out= 174.958882nm
gap out= 184.495192nm
LER_hor_out= 3.469811nm
LER_ver_out= 9.814132nm
LWR_hor_out= 5.648373nm
LWR_ver_out= 10.820637nm

Virtual Metrology: Post-Etch CD-SEM

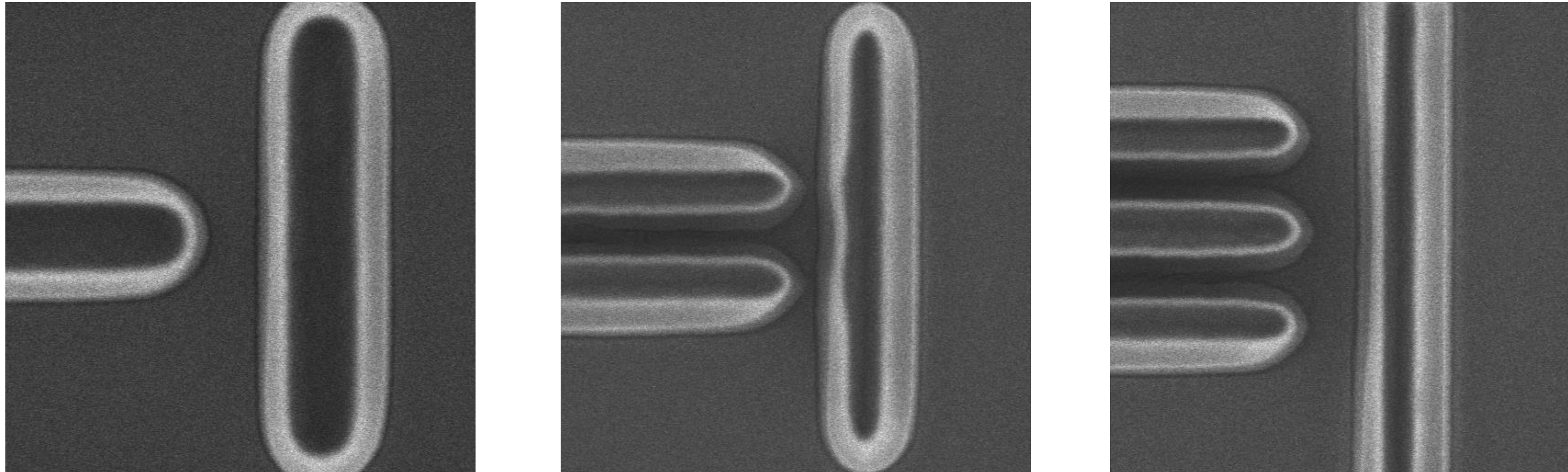


Active contour

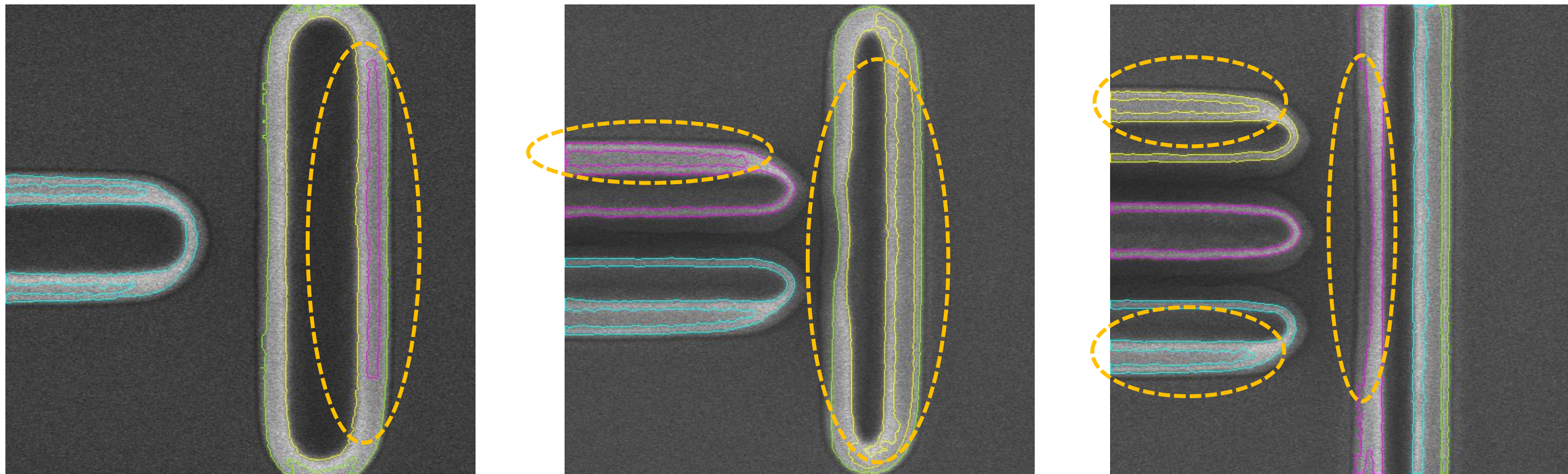


Virtual metrology challenges with complexities of post-Etch CD-SEMs

Post Etch
CD-SEM Images



Virtual Metrology
Results
(using Pre-Etch
algorithms)



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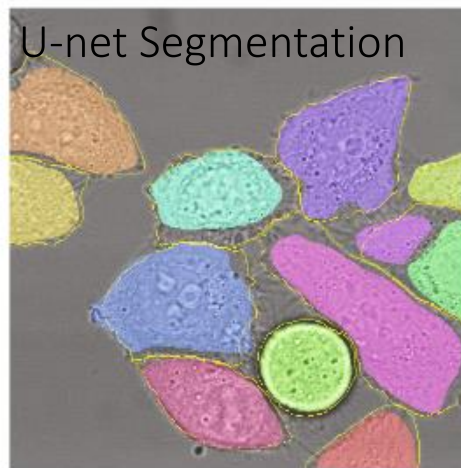
U-net for image segmentation

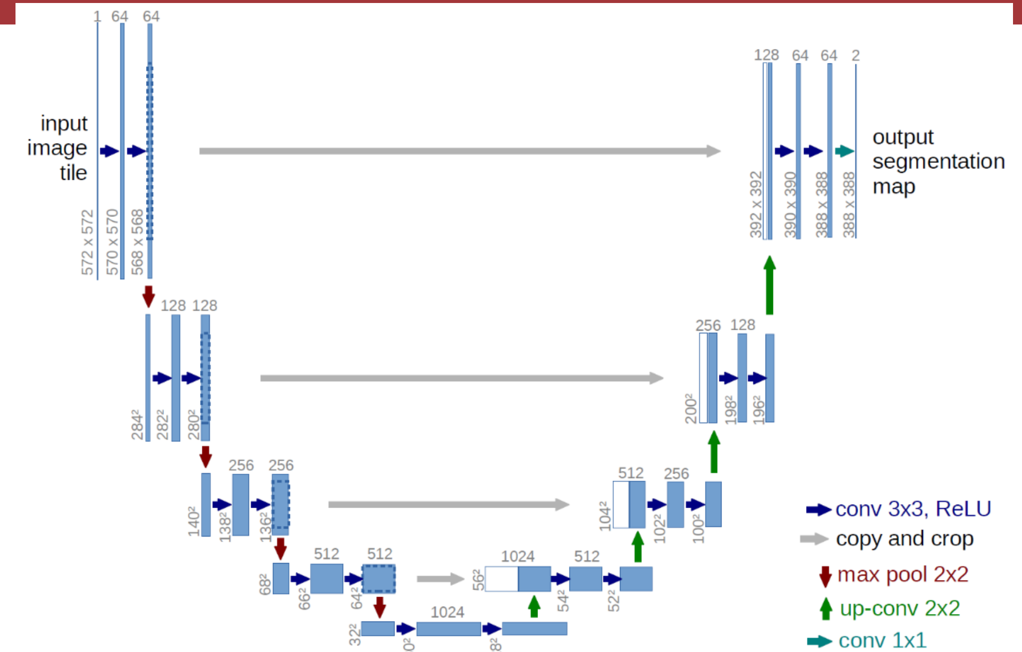
Goal: automatic and robust segmentation of sidewalls in post-etch CD-SEM images

Progress: training U-net with successful results of simple segmentation algorithms

Differential Interference Contrast (DIC)
Image-HeLa Cells



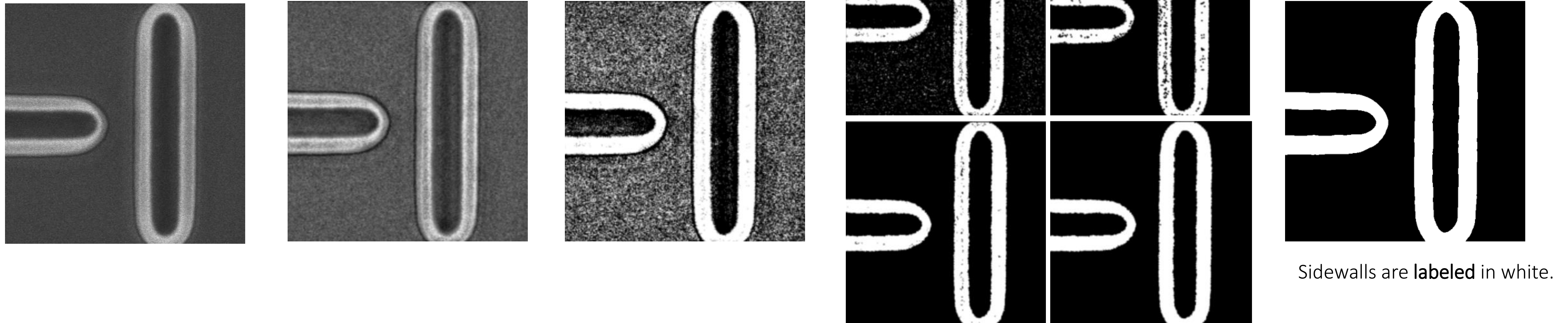
U-net Architecture



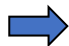
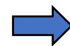
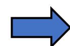
https://link.springer.com/content/pdf/10.1007%2F978-3-319-24574-4_28.pdf

Post-Etch binarization process

Goal: automatic labeling to train a U-net for image segmentation



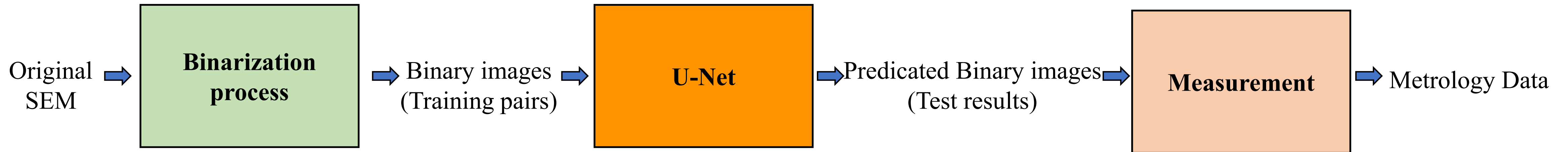
Sidewalls are labeled in white.

CD-SEM RAW image  **Histogram equalization**  **Thresholding** 

1.Erosion
2.Small contours removal
3.Dilation
4.Small contours fill

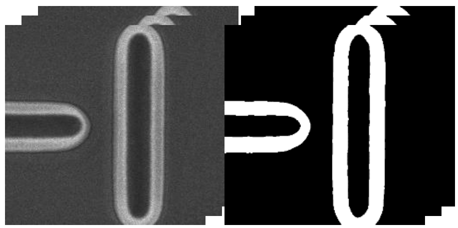
Median filter

U-net: one structure type (TGAP/DTGAP)



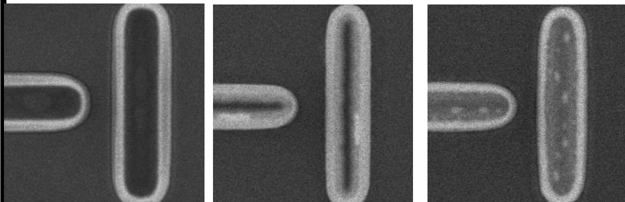
Train set

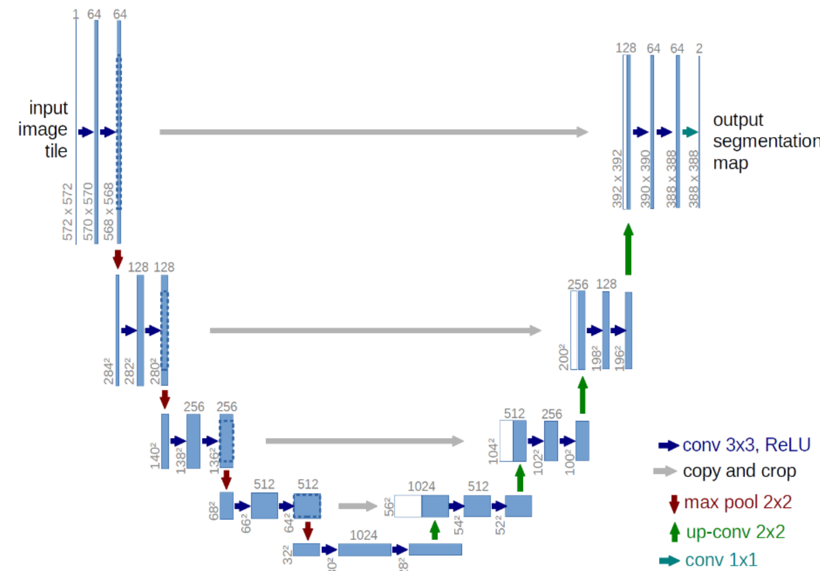
TGAP W1 104 pairs



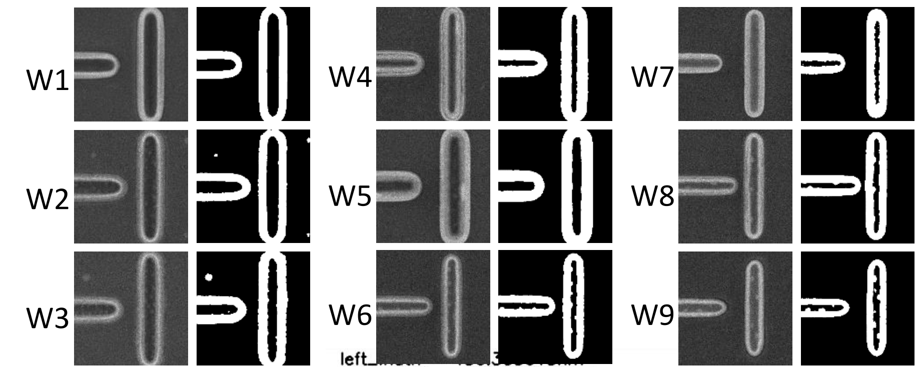
Test set

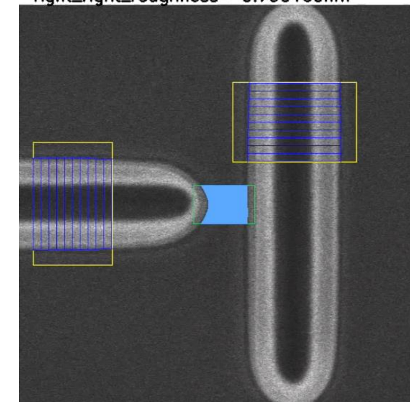
TGAP W1-9





Predicted binary images





Using RGB channels to merge process parameters with CD-SEM data

Exposure

1e8

Cell Location (A)

1.4
1.2
1.0
0.8
0.6

0.6 0.7 0.8 0.9 1.0 1.1 1.2 1.3

1e8

Cell Location (A)

1.4
1.2
1.0
0.8
0.6

0.6 0.7 0.8 0.9 1.0 1.1 1.2 1.3

1e8

Cell Location (A)

Focus

CD-SEM

Concatenated RGB image

Train Pix2Pix

Preliminary Results:

Concatenated RGB Layout

Predicted

Real CD-SEM

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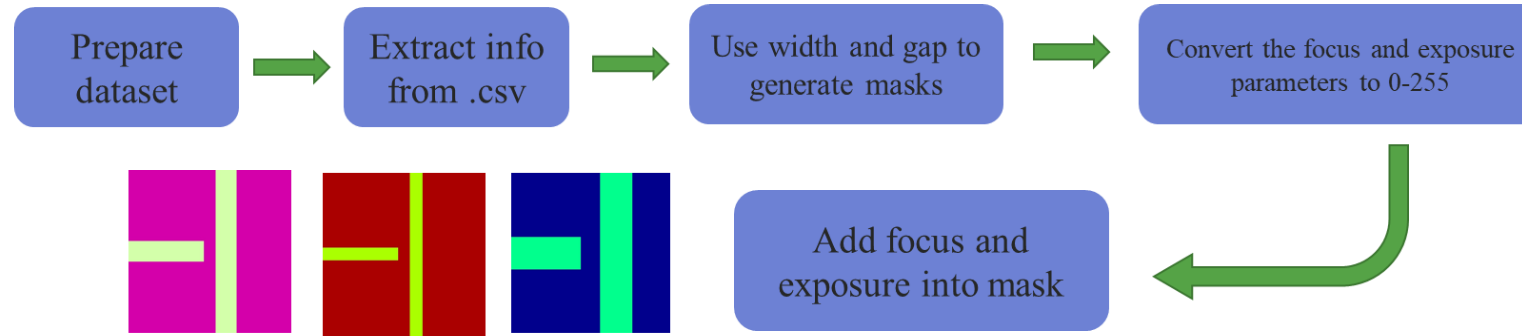
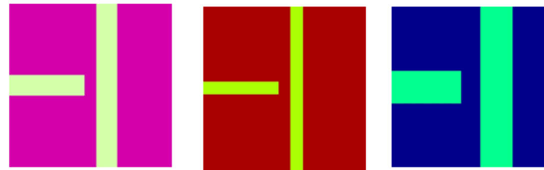
Training dataset: pseudo-colored layouts

- Layout + Process Parameters



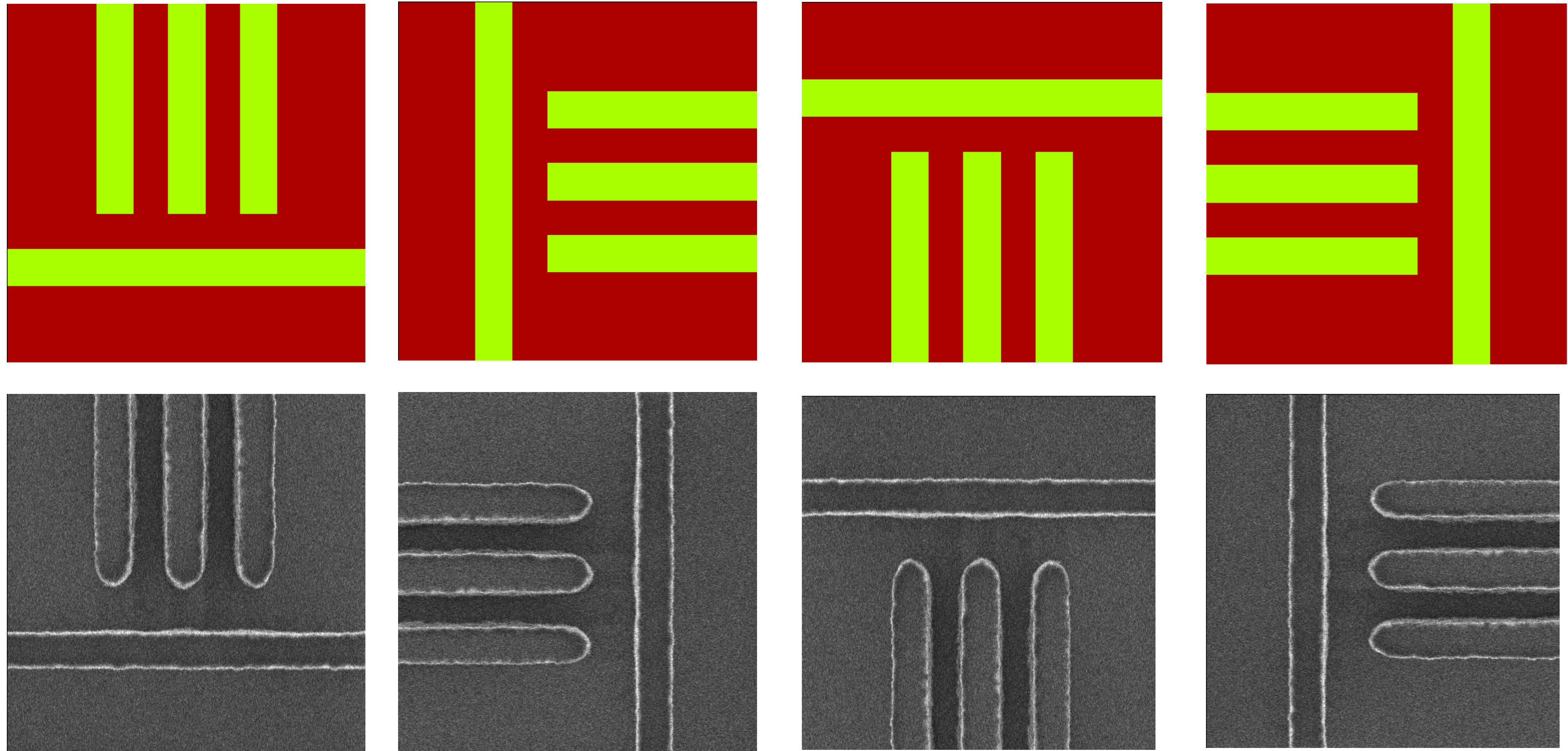


S15_M0001-01 MS.tif S15_M0003-01 MS.tif S15_M0005-01 MS.tif S15_M0007-01 MS.tif S15_M0009-01 MS.tif S15_M0011-01 MS.tif S15_M0013-01 MS.tif
S15_M0015-01 MS.tif S15_M0017-01 MS.tif S15_M0019-01 MS.tif S15_M0021-01 MS.tif S15_M0023-01 MS.tif S15_M0025-01 MS.tif S15_M0027-01 MS.tif
S15_M0029-01 MS.tif S15_M0031-01 MS.tif S15_M0033-01 MS.tif S15_M0035-01 MS.tif S15_M0037-01 MS.tif S15_M0039-01 MS.tif S15_M0041-01 MS.tif
S15_M0043-01 MS.tif S15_M0045-01 MS.tif S15_M0047-01 MS.tif S15_M0049-01 MS.tif S15_M0051-01 MS.tif S15_M0053-01 MS.tif S15_M0055-01 MS.tif

S15_M1093-01 MS.tif S15_M1095-01 MS.tif S15_M1097-01 MS.tif S15_M1099-01 MS.tif S15_M1101-01 MS.tif S15_M1103-01 MS.tif S15_M1105-01 MS.tif
S15_M1107-01 MS.tif S15_M1109-01 MS.tif S15_M1111-01 MS.tif S15_M1113-01 MS.tif S15_M1115-01 MS.tif S15_M1117-01 MS.tif S15_M1119-01 MS.tif
S15_M1121-01 MS.tif S15_M1123-01 MS.tif S15_M1125-01 MS.tif S15_M1127-01 MS.tif S15_M1129-01 MS.tif S15_M1131-01 MS.tif S15_M1133-01 MS.tif

S15_M1687-01 MS.tif S15_M1689-01 MS.tif S15_M1691-01 MS.tif S15_M1693-01 MS.tif S15_M1695-01 MS.tif S15_M1697-01 MS.tif S15_M1699-01 MS.tif
S15_M1701-01 MS.tif S15_M1703-01 MS.tif S15_M1705-01 MS.tif S15_M1707-01 MS.tif S15_M1709-01 MS.tif S15_M1711-01 MS.tif S15_M1713-01 MS.tif
S15_M1715-01 MS.tif S15_M1717-01 MS.tif S15_M1719-01 MS.tif S15_M1721-01 MS.tif S15_M1723-01 MS.tif S15_M1725-01 MS.tif S15_M1727-01 MS.tif
S15_M1741-01 MS.tif S15_M1743-01 MS.tif S15_M1745-01 MS.tif S15_M1747-01 MS.tif S15_M1749-01 MS.tif S15_M1751-01 MS.tif S15_M1753-01 MS.tif

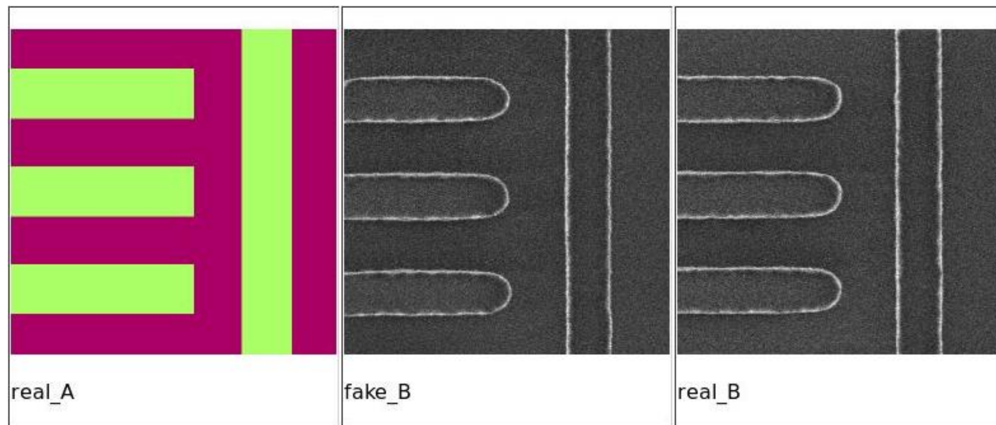
Augmentation to enhance the learning (rotation example)

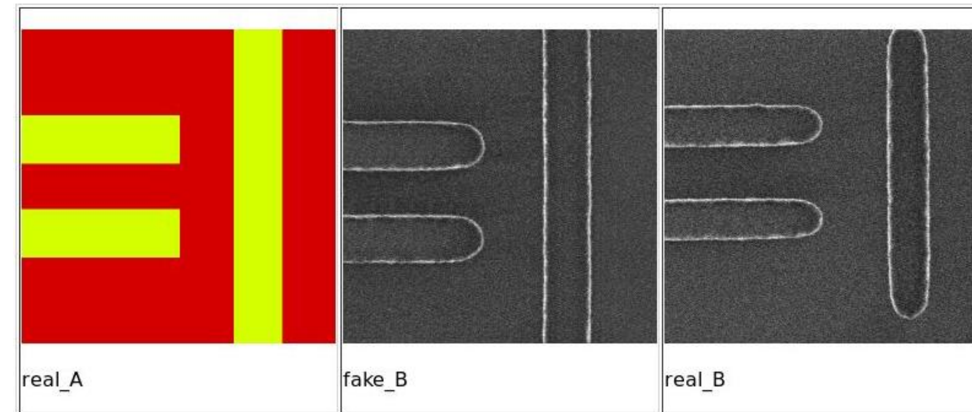


Results: with augmentation (16X)

Best result parameters for pix2pix: with augmentation

Crop_size = 256
batch_size = 16
N_epoch = 400
Epoch_decay = 100
Learning_rate = 0.0001
Augmentation: Rotated 90° 180° 270°, randomly cropped (4 times each)

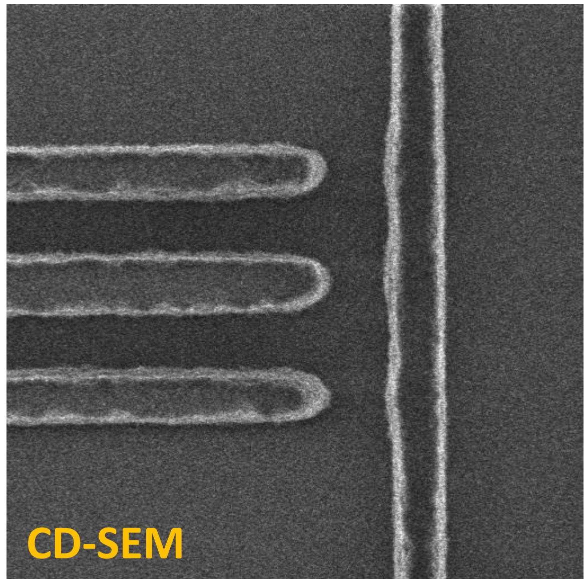




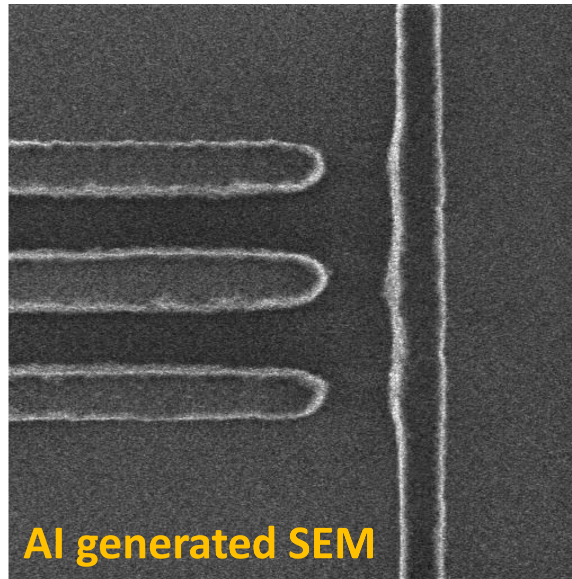
Test results for other layout (Not included in the training set)

Toward assessment of learning outcomes

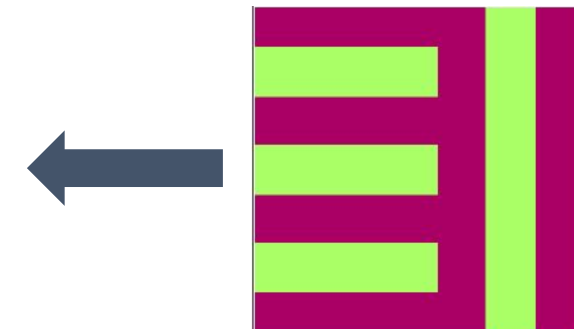
Experimental Image
S15_M2740-02MS.tif



Process-aware AI Predicted Image



Pseudo-colored layout with process parameters



Process Parameters: E=21 J/cm^2, F=-0.5 µm
SEM images show 2x2 µm area (3.9 nm/pixel)

Reverse direction: process diagnostics

Experimental CD-SEMs

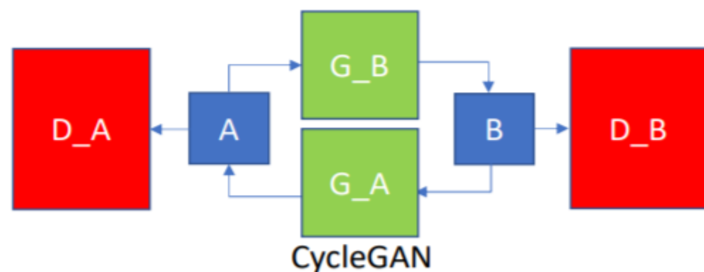
Training:

Test:

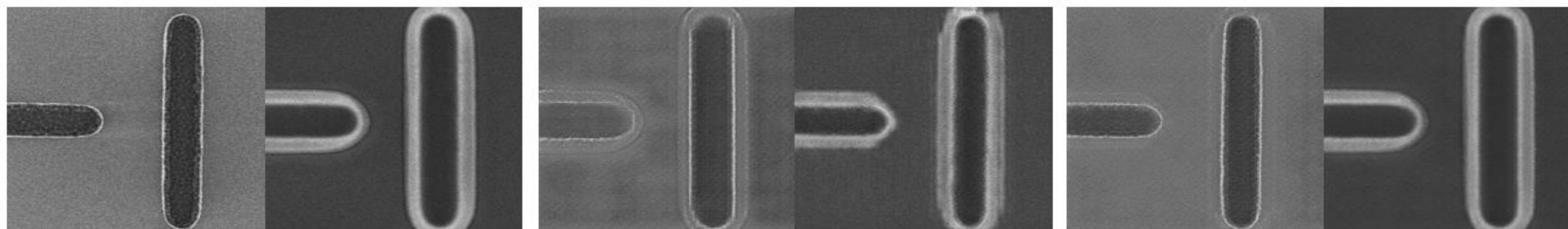
Pix2Pix Prediction

Pix2Pix-Generated CD-SEMs

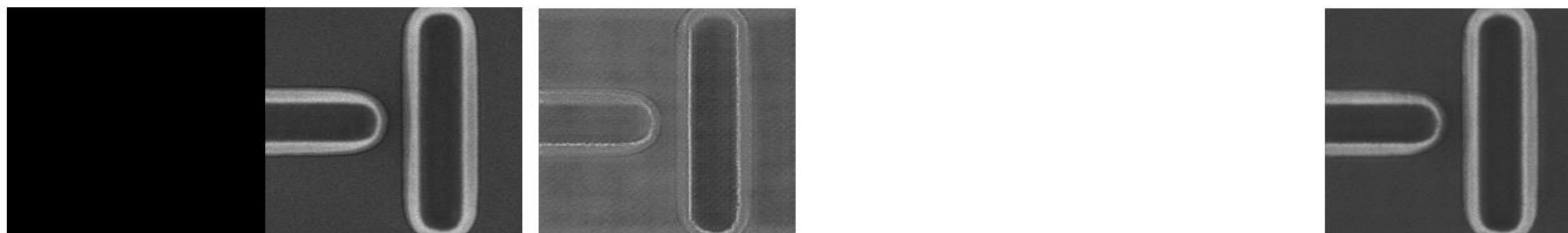
CycleGAN and Cycle Consistency



Training:



Test:

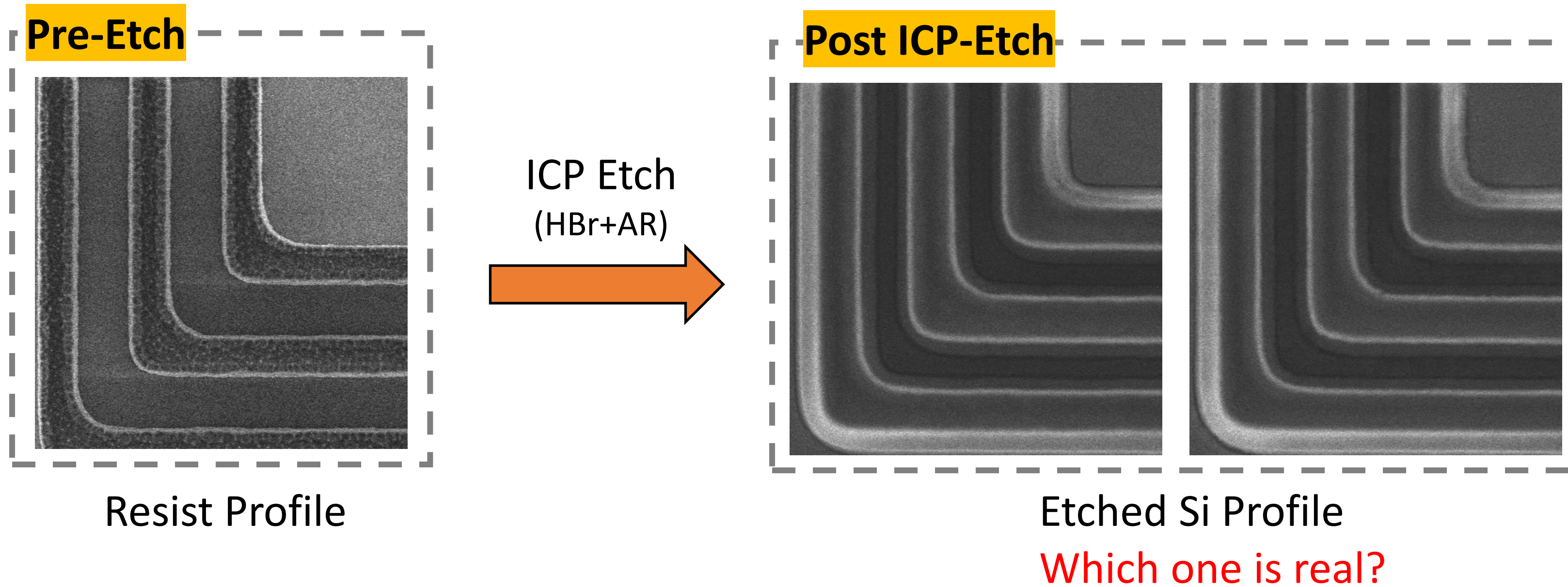


A	B	$G_A(B)$	$G_B(A)$	$G_A(G_B(A))$	$G_B(G_A(B))$
Pre-Etch	Post-Etch	Fake Pre-Etch	Fake Post-Etch	Recovered Pre-Etch	Recovered Post-Etch

Can **AI** make nanodevice fabrication **Ubiquitous?**

- We developed ML models to learn the DUV lithography process and we demonstrated interpolation beyond training dataset
- We trained deep learning models to learn and predict the outcomes of DUV lithography and Plasma Etch Processes
- AI models can be used as a design tool (mask, process parameters,….) for micro and nanofabrication
- AI potentially simplifies integration of multiple foundries working on one device, which potentially provides privacy gains at hardware level
- AI driven design improvement are not limited to MEMS and can be applied to IC industries, printed electronics, optics, and so forth

What do you think?



* SEM Images are 2x2 µm, 512x512, 8 bit

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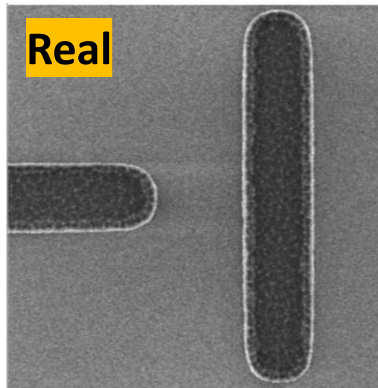
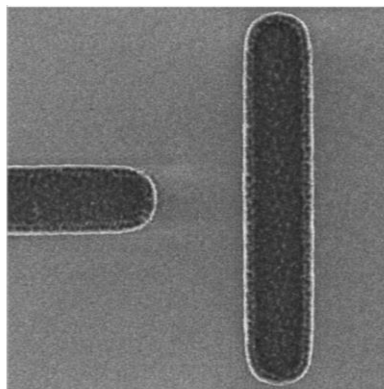
UNIVERSITY
NORTHEASTERN UNIVERSITY
LVX VERITAS VIRTVS
FOUNDED
BOSTON, MASSACHUSETTS

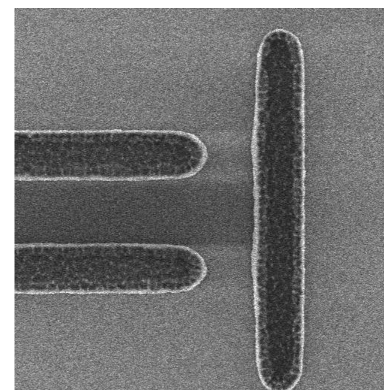
Mask Layout

Experimental DUV Lithography

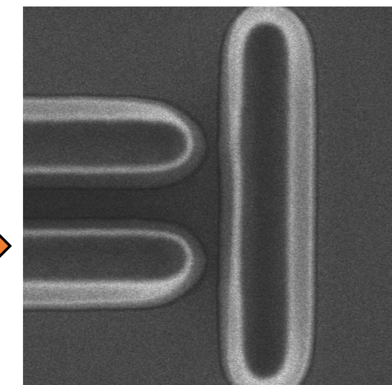


Pix2Pix Prediction

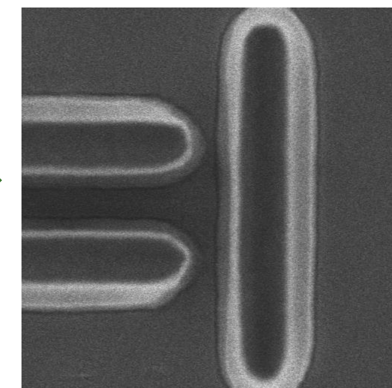



Resist Pattern

Experimental Plasma Etch



Pix2Pix Prediction



Back UP Charts: TA1-AI

This section contains the supporting data and charts to support extended discussions and the Q&A section.

- Pix2Pix details
- Augmentation
- Quantification and virtual metrology
- Process parameters

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DUV lithography prediction by trained Pix2Pix

Mask	CD_SEM	CD_SEM Binary		CD_SEM Predicted
E04_M0002-02MS				
S08_M0128-02MS			Pix2Pix Prediction	
E06_M0134-02MS				

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Learning outcomes Plasma Etching by Image Translation

Experimental SEM

Resist CD-SEM → Training AI Model

Plasma Etch CD-SEM → Training AI Model

Experimental SEM

Resist CD-SEM → Trained AI Model → Predicted CD-SEM → Virtual Metrology → Features

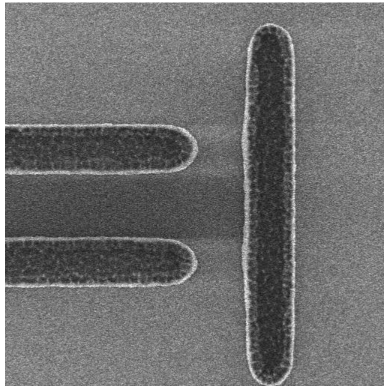
Experimental or Synthesized SEM

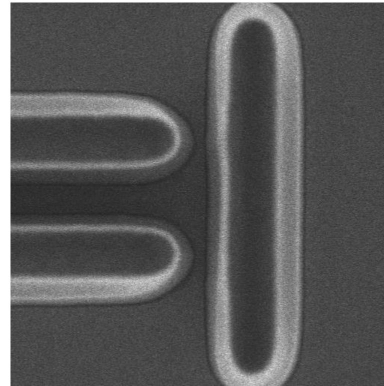
Predicted SEM

[this work, unpublished preliminary results]

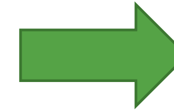
Pix2Pix Results for Plasma Etch

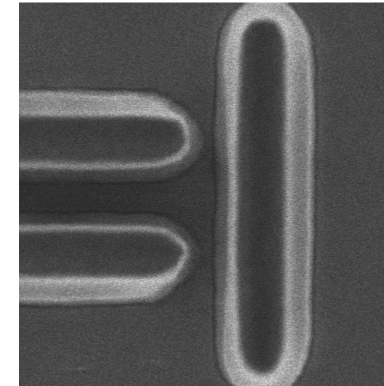
DTGAP



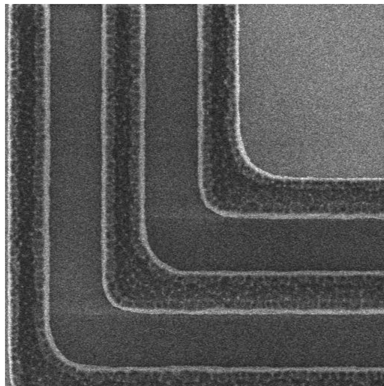


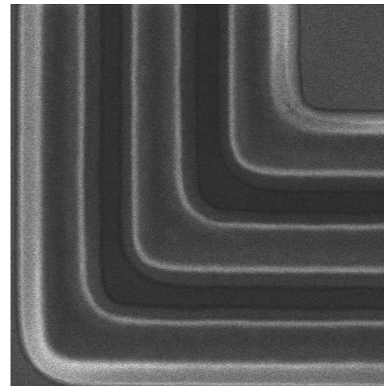
Pix2Pix Prediction

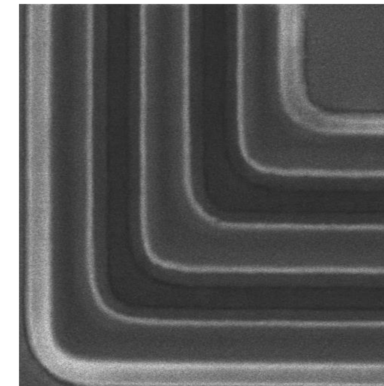




TCL







Pre-Etch Resist Profile | **Post-Etch Si Profile** | **Prediction Synthesized SEM**

SEM images shows a 2 x 2 um area.

[SEMI master class #6, 2021]

Summary

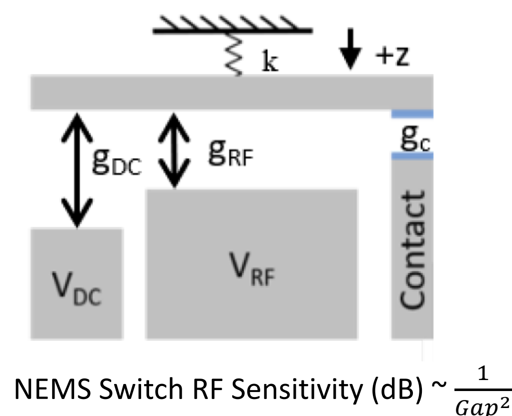
- ML feature-based model for DUV lithography process
- Pix2Pix model to learn to predict the outcomes of the DUV Lithography and Plasma Etch

Future Directions:

End-to-End implementation: adjusting layout to achieve target performance metric

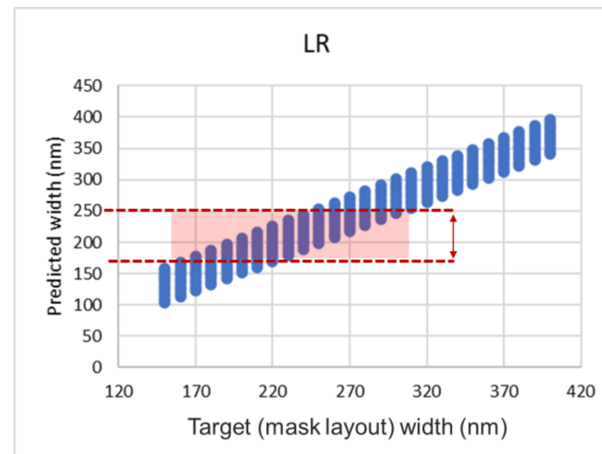
OES feature-based plasma etch improvement

Design tool to improve the electrical and mechanical performance

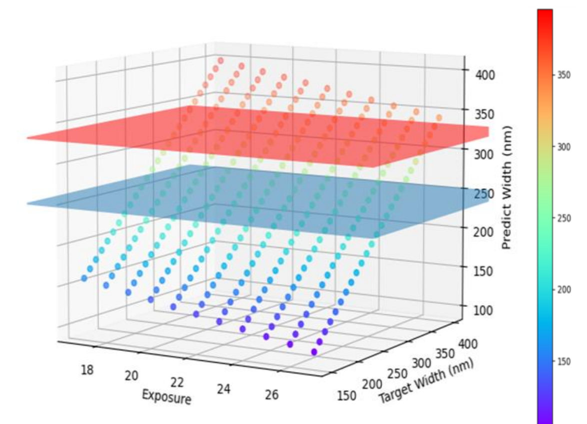


NEMS Switch RF Sensitivity (dB) ~ $\frac{1}{Gap^2}$

Selected feature



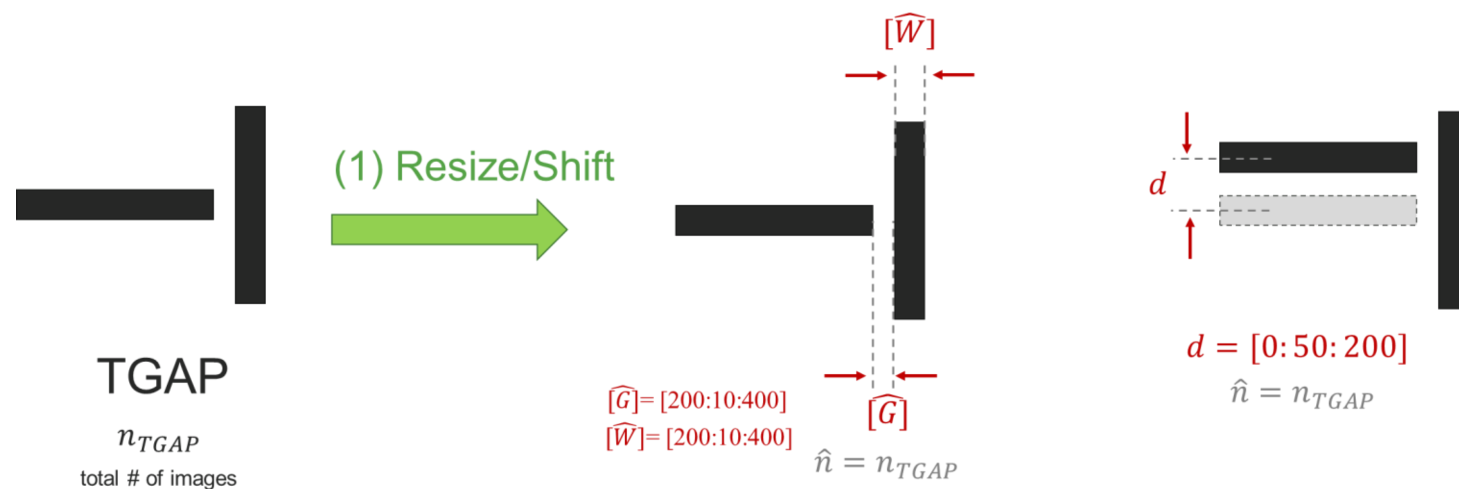
Process window

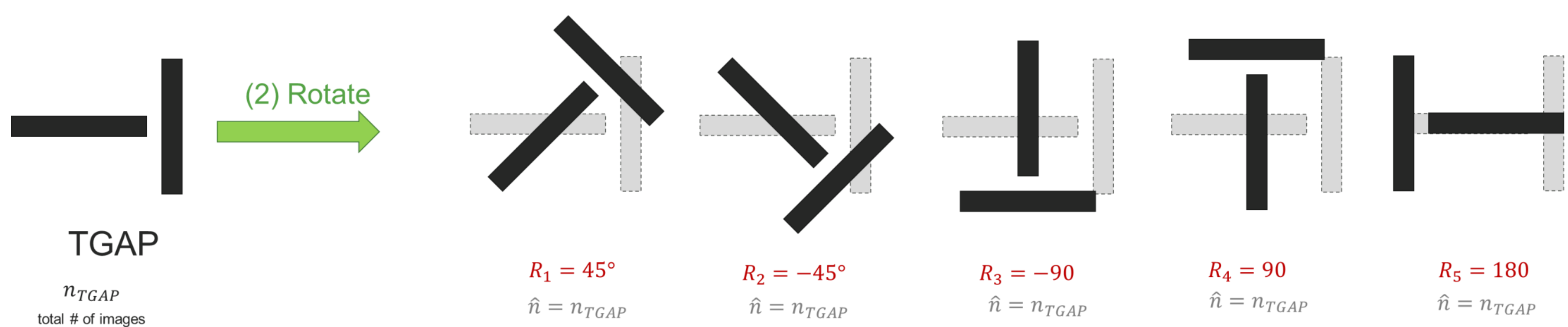


Summary

- AI can improve design (mask, process parameters,….) for micro and nanofabrication
- AI driven design improvements can be used for microcalorimeter and Ultrasound microdevices that are also important applications
- AI potentially simplifies integration of multiple foundries working on one device, which potentially provides privacy gains at hardware level
- AI driven design improvement are not limited to MEMS and can be applied to IC industries, printed electronics, optics, and so forth

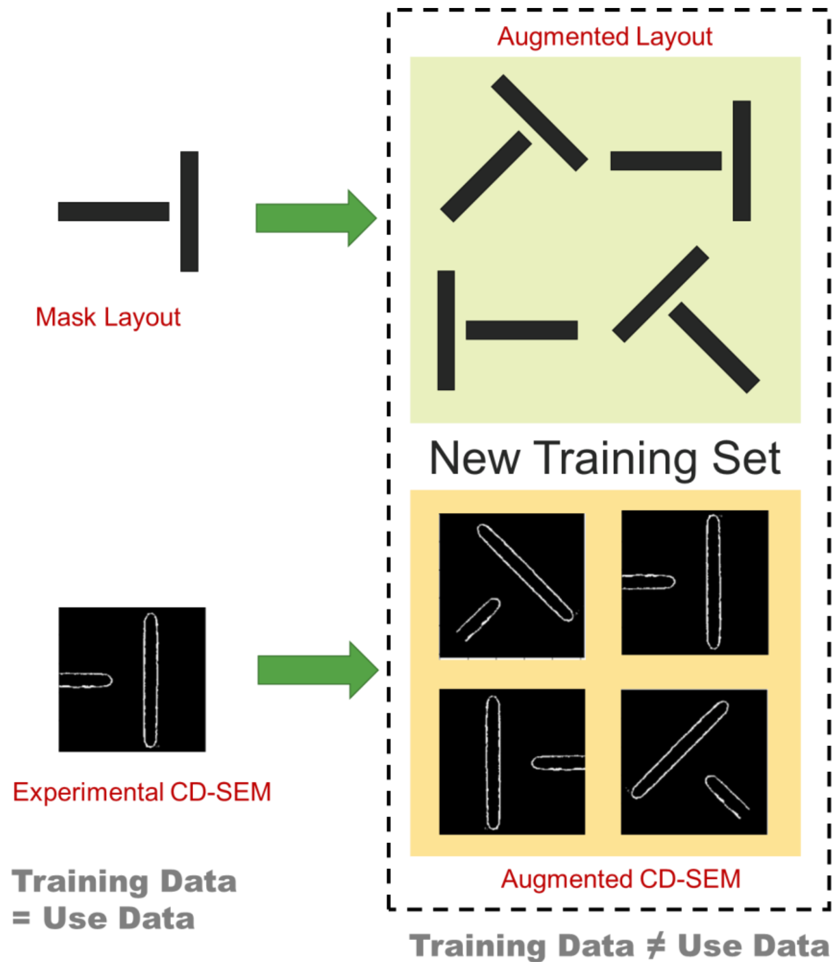
Beyond Training Database: Augmentation

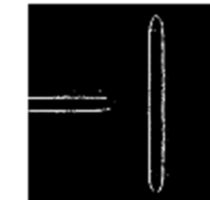




[this work, unpublished preliminary results]

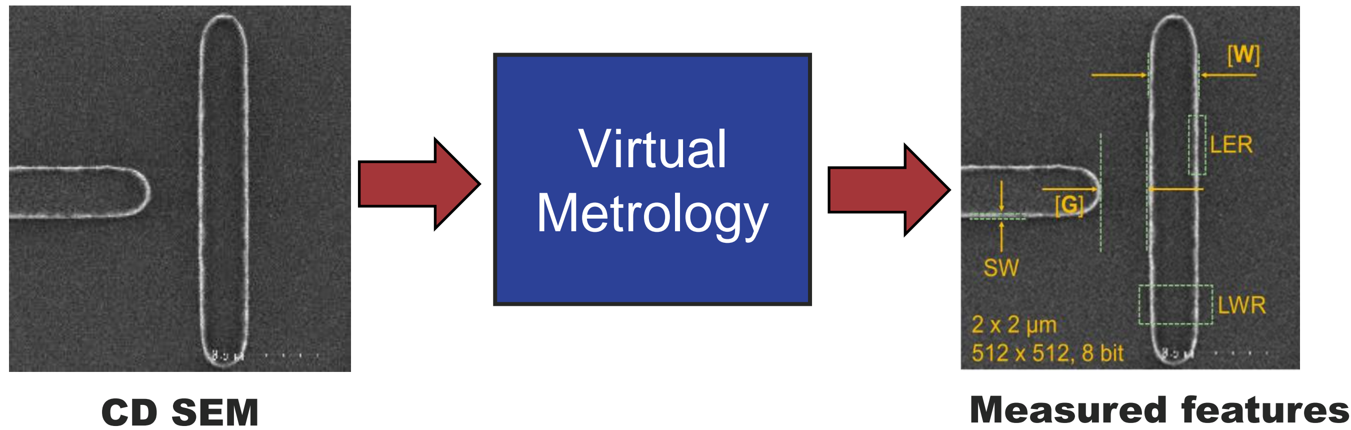
Augmented Data and Pix2Pix Results



Augmented Layout			
Prediction			
Augmented CD-SEM			

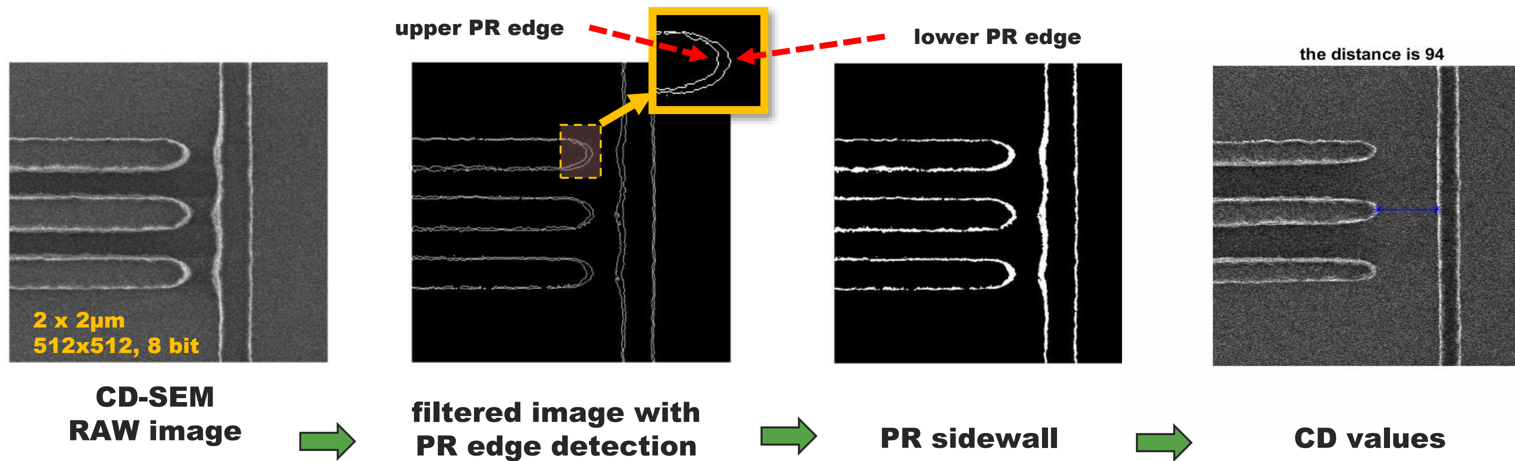
[this work, unpublished preliminary results]

Virtual Metrology



CD SEM

Measured features

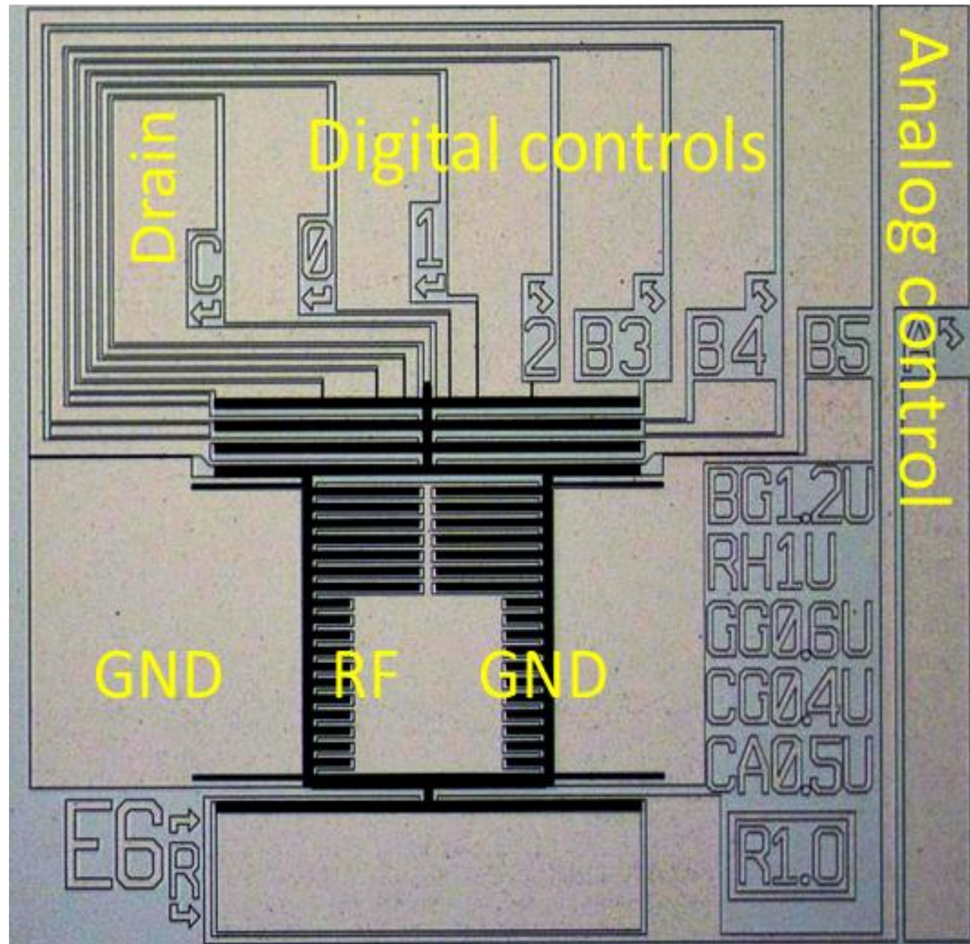


CD-SEM RAW image → **filtered image with PR edge detection** → **PR sidewall** → **CD values**

CD-SEM images
filtering and edge detection
PR sidewall

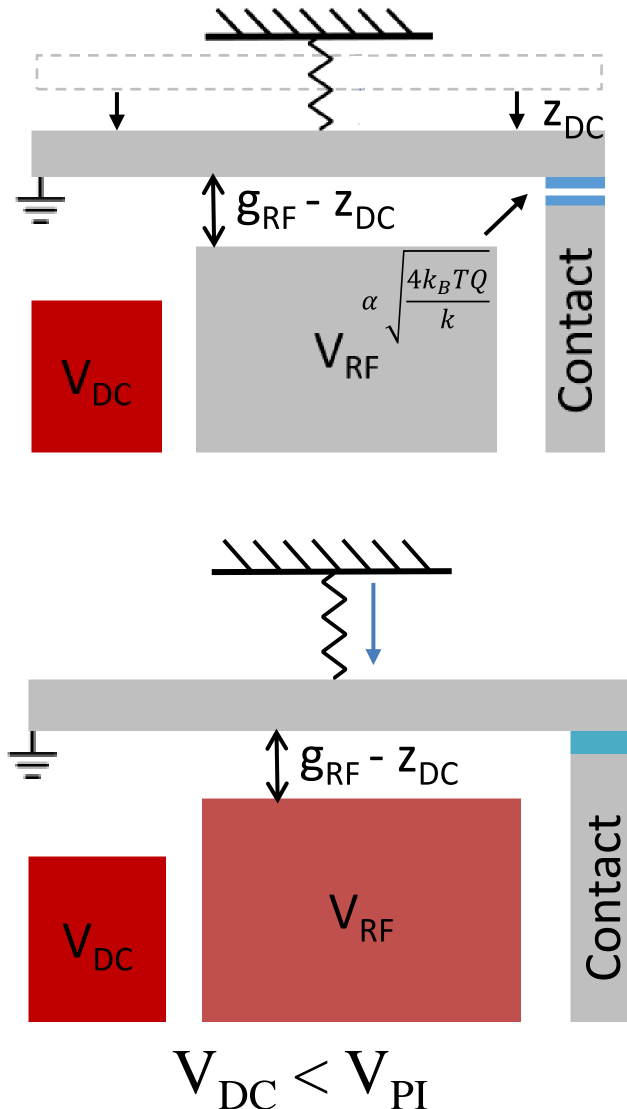
TGAP
DGAP
TTGAP
FLG
TCL
UL
ETE
TETE

Test vehicle: NEMS switch for RF wakeup



- NEMS switch can trigger at near zero power at the receipt of a specific very low RF signal
- Low power wakeup enables long-battery lifetime devices
- NEMS switch critical to ultralow signal wakeup radio – both for DOD and civilian IoT applications
- NEMS switch uses both lithography and etching for testing AI framework

Device Operation

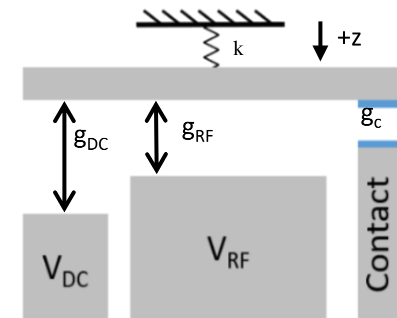


$V_{DC} < V_{PI}$

1. Pre-bias until the contact gap is within a few times the thermal noise displacement (z_n)

$$z_{DC} = g_c - \alpha\sqrt{\frac{4k_BTQ}{k}}$$

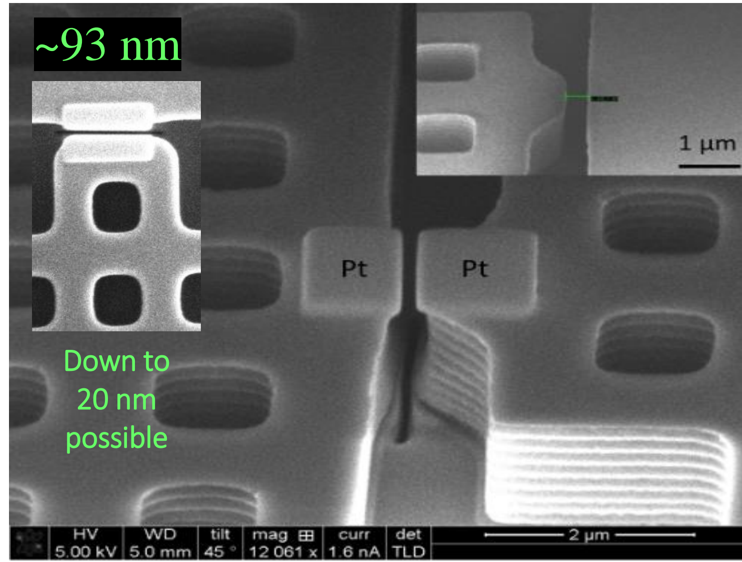
$$kz_{DC} = \frac{1}{2}\frac{\epsilon_0 A_{DC}}{(g_{DC} - z_{DC})^2}{V_{DC}}^2$$

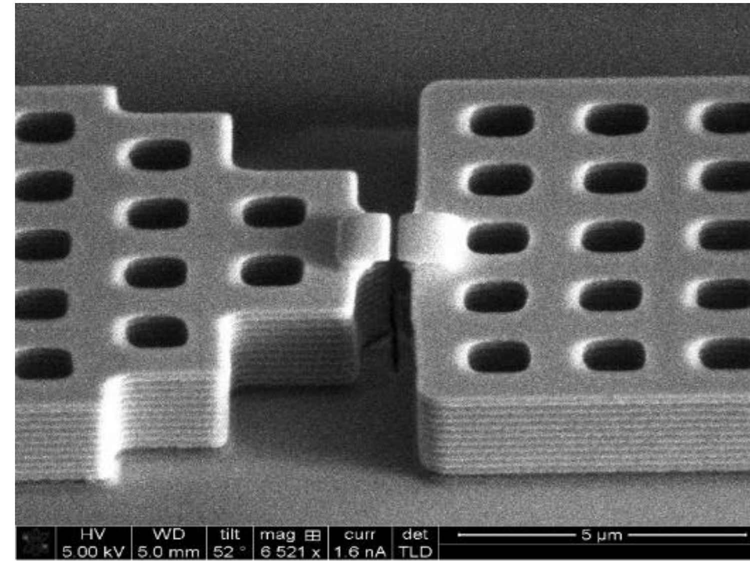


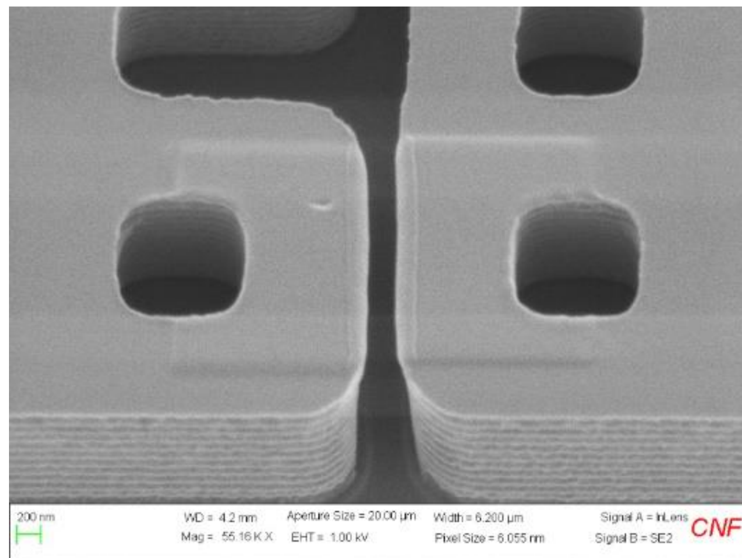
2. Use RF to close the gap completely

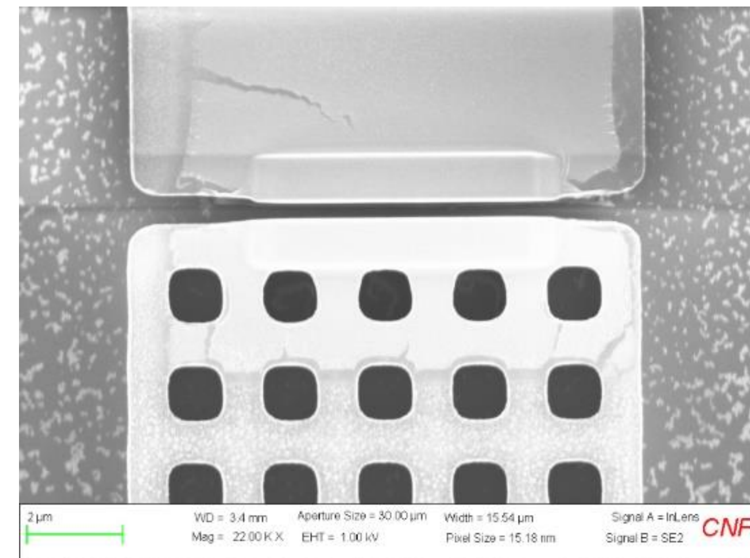
$$F_{RF} = \frac{Q}{4}\frac{\epsilon_0 A_{RF}}{(g_{RF} - z_{DC})^2}{V_{RF}}^2 = k\,\alpha\sqrt{\frac{4k_BTQ}{k}}$$

Focused Ion Beam (FIB) for Gap Control









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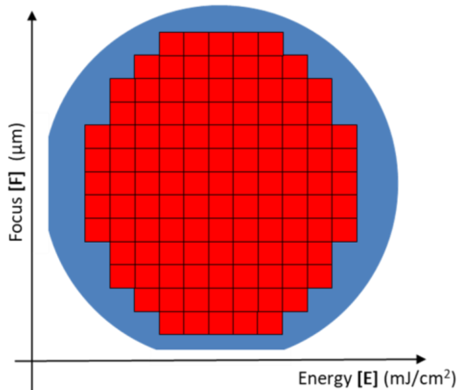
Lithography Results: Data Preparation

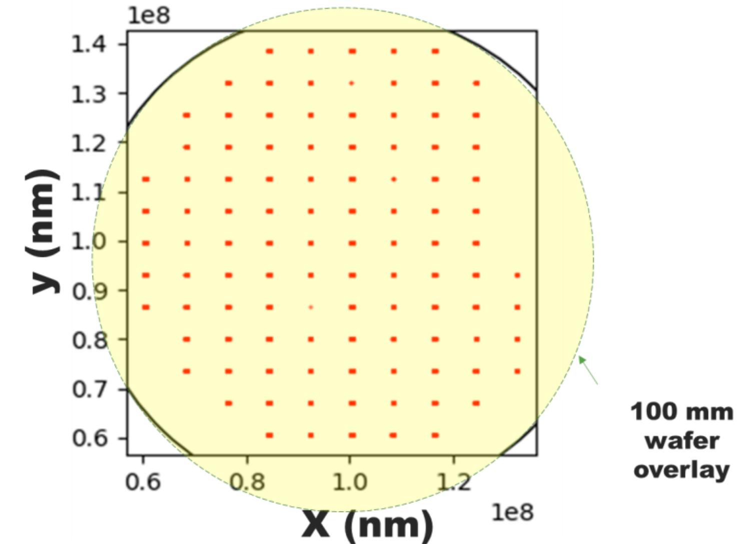
Spatial variation of focus and energy from ASML job file



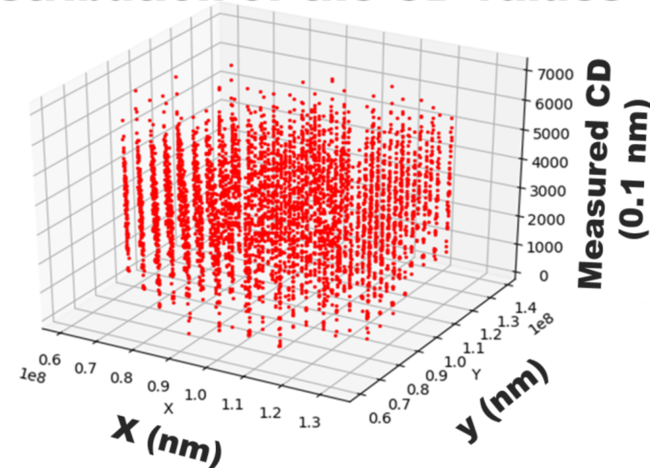
extracted from Hitachi meta data

"msr" text file

Spatial variations of accepted CD measurements on wafer



Distribution of the CD values



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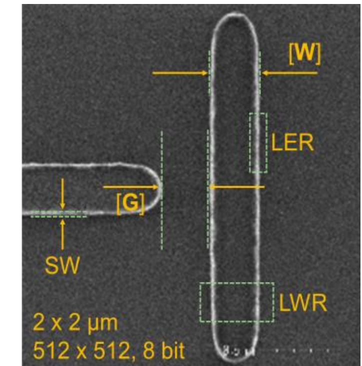
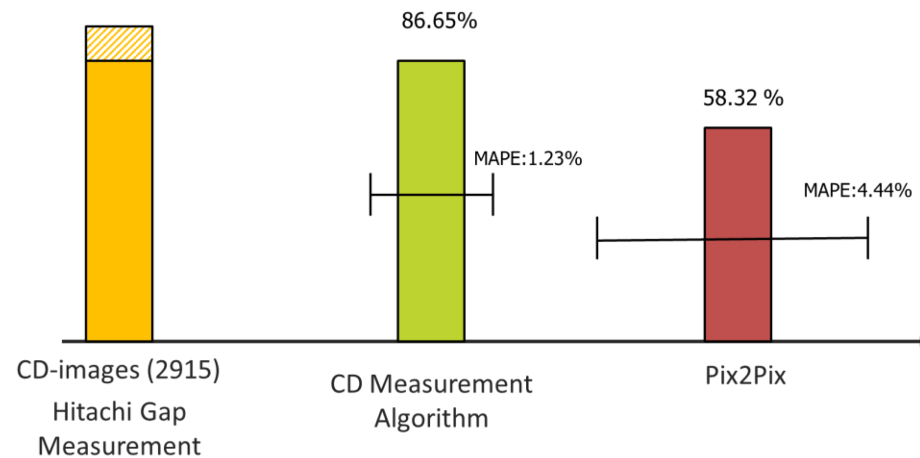
Limitations of Pix2Pix

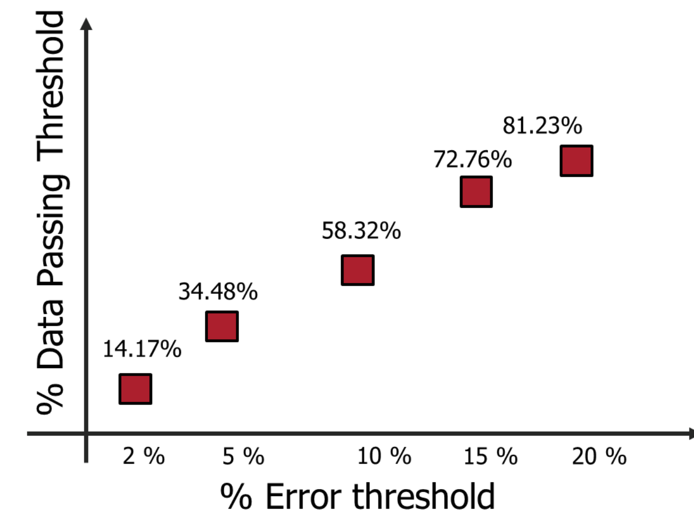
Input Mask	Experimental CD SEM	CD SEM Binary		Predicted CD SEM
			Pix2Pix Prediction	
		364.6 nm		302.6 nm

Gap Prediction Performance Quantification

- For TGAP **predicted CD SEM from masks**, 58.32% out of 2915 images for which Hitachi gave a CD value have a percentage error smaller than 10%, and MAPE is 4.44%.
- For TGAP **experimental CD SEM from wafers**, 86.65% out of 2915 images for which Hitachi gave a CD value have a percentage error smaller than 10%, and MAPE is 1.23%.
- **Algorithm parameters** (number of epochs and batch size) lead to +/- 5% change in performance.







MAPE : Mean Absolute Percentage Error

Conditioning schemes for guiding image-2-image translation

conv Transpose conv FT PG

Input Guide concat Output

(a) Input Concatenation

Input Guide concat Output

(b) Feature Concatenation

Input Guide Output

(c) Uni-directional FT

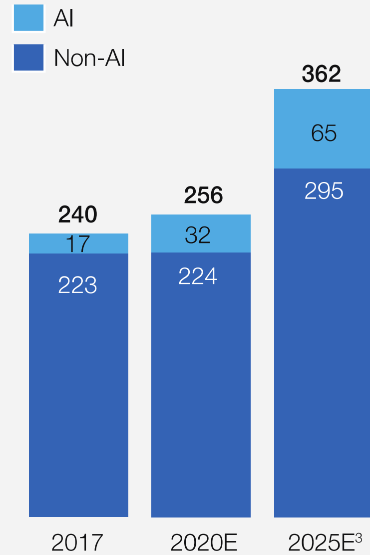
Input Guide Output

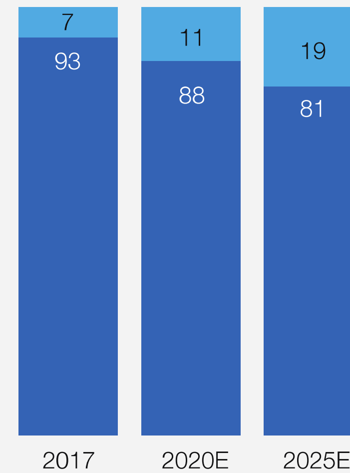
(d) Ours: Bi-directional FT

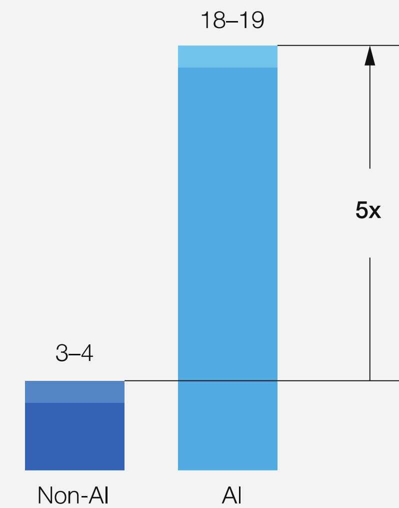
[B. Albahar, ICCV 2019]

Data & AI Projected impact on Semiconductor

Exhibit 3 **Growth for semiconductors related to artificial intelligence (AI) is expected to be five times greater than growth in the remainder of the market.**





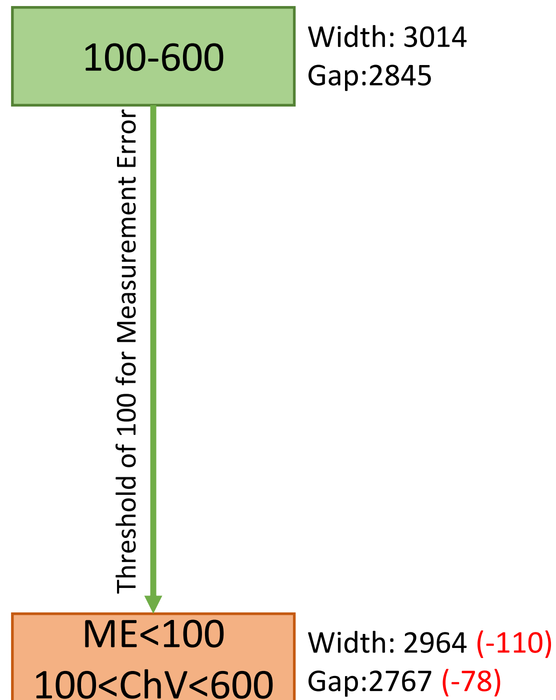


[1] Total available market includes processors, memory, and storage; excludes discretes, optical, and micro-electrical-mechanical systems.
[2] Compound annual growth rate.
[3] E = estimated.

Source: Bernstein; Cisco Systems; Gartner; IC Insights; IHS Markit; Machina Research; McKinsey analysis

KNN Performance per Feature Size

$$Error_{KNN} = \frac{(X_{Predict} - X_{Layout})}{X_{Layout}} \times 100$$



Width: 3014
Gap:2845

Width: 2964 (-110)
Gap:2767 (-78)

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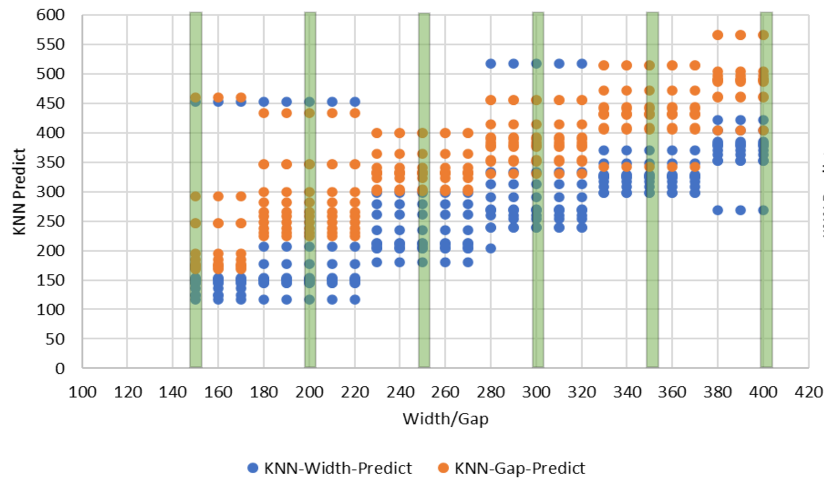
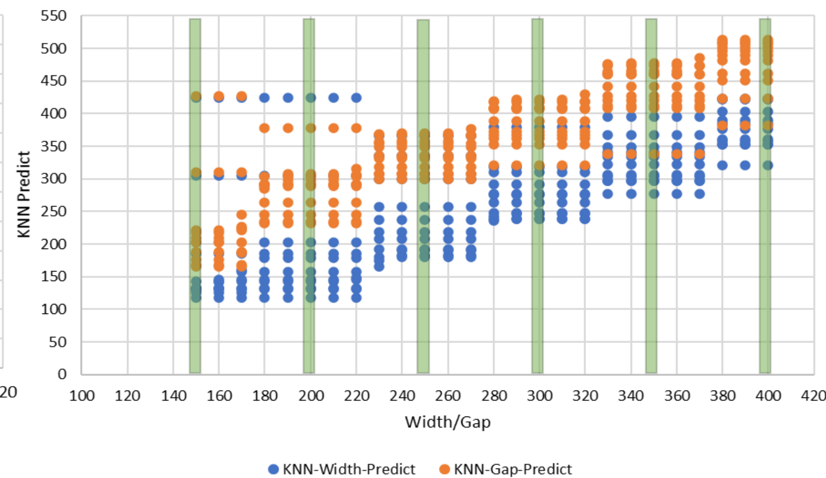
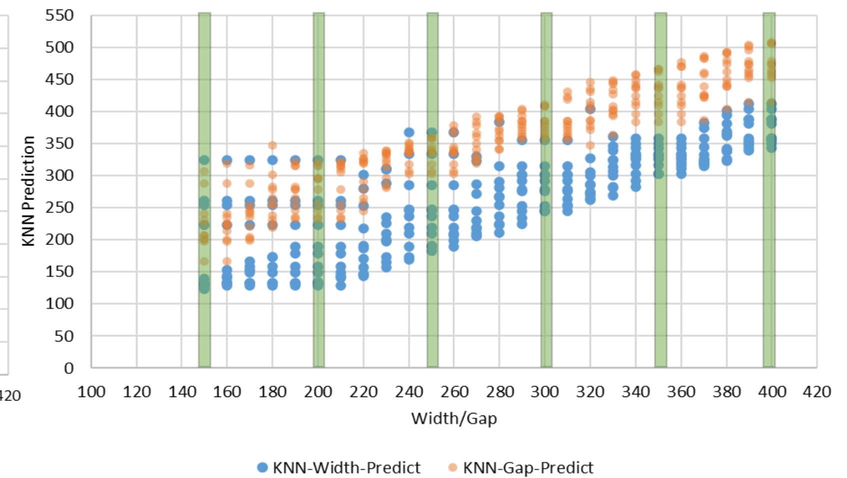
KNN Model for width & gap Interpolation



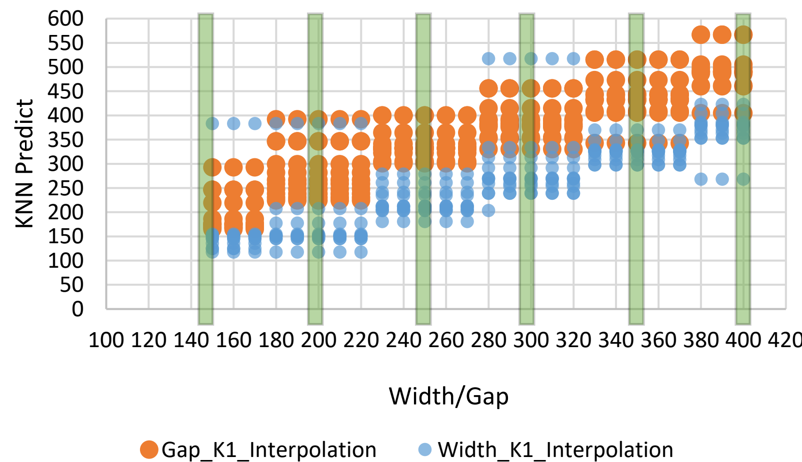


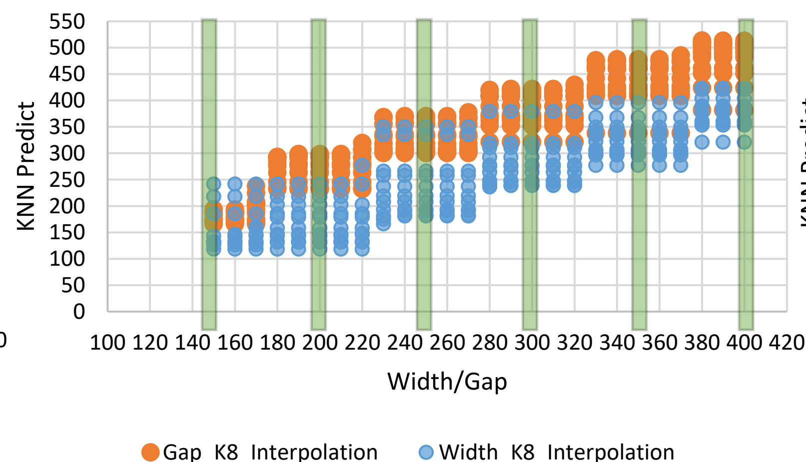


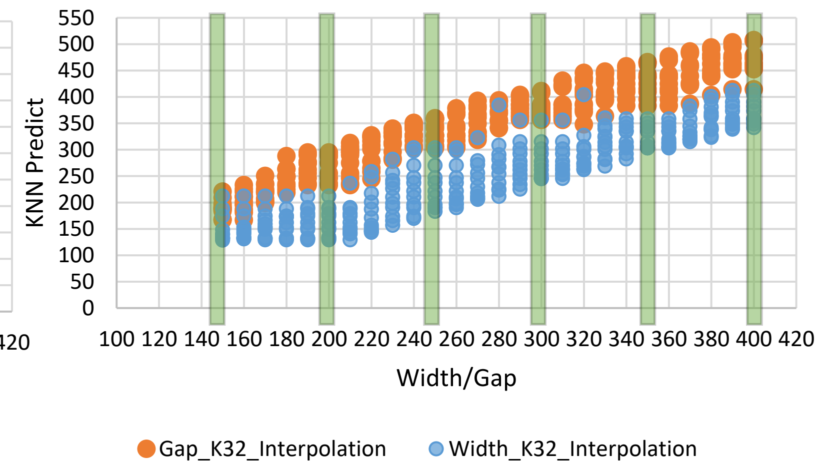
K=1

K=8

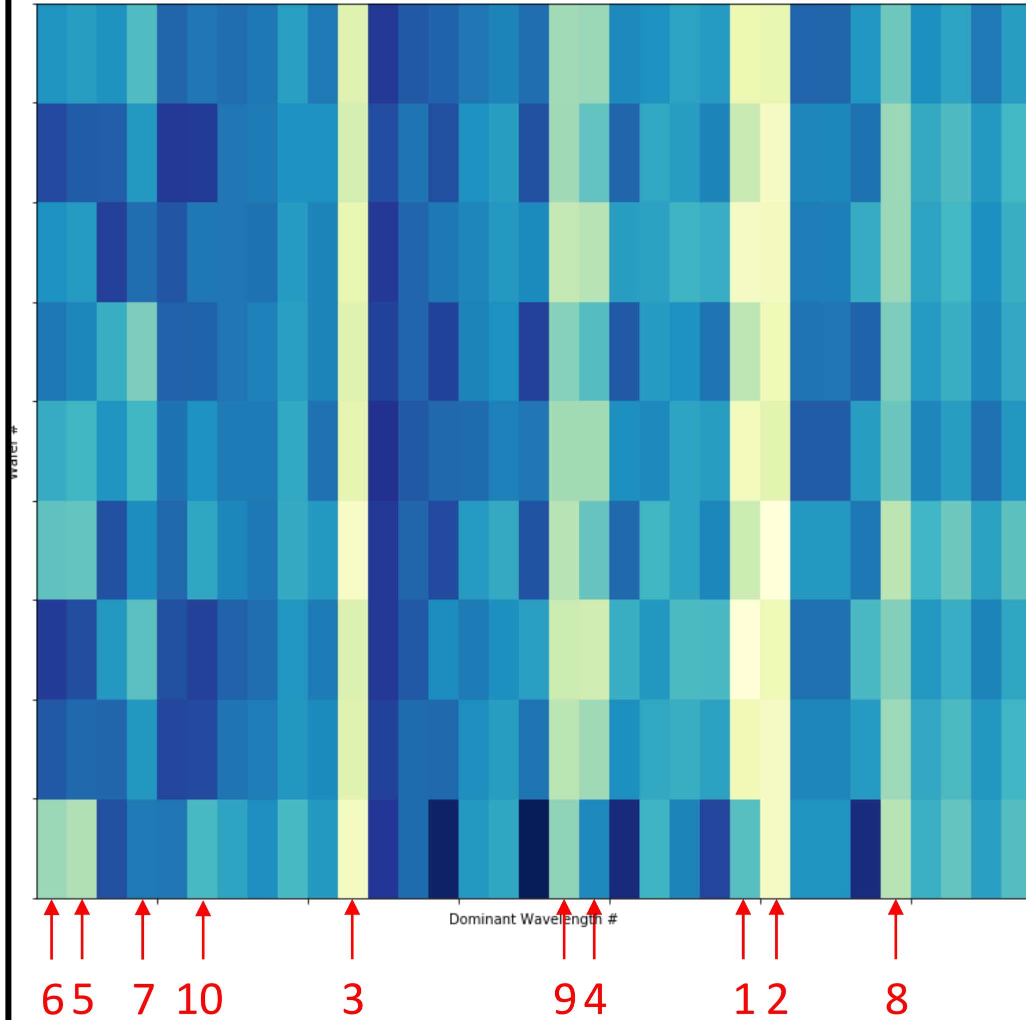
K=32







OES



−1.6
−1.8
−2.0
−2.2
−2.4
−2.6
−2.8

Time-Average Log Peaks for Different Wafers & Same Wavelengths (Normalized, Selected By MAD)

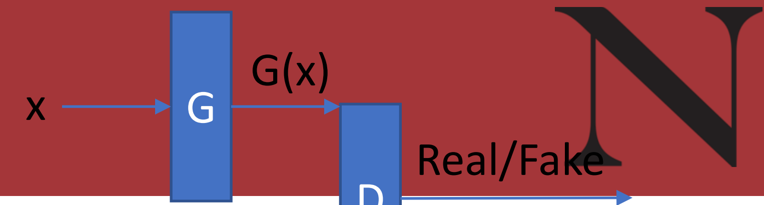
Wafer #

Dominant Wavelength #

6 5 7 4 9 3 1 2 10 8

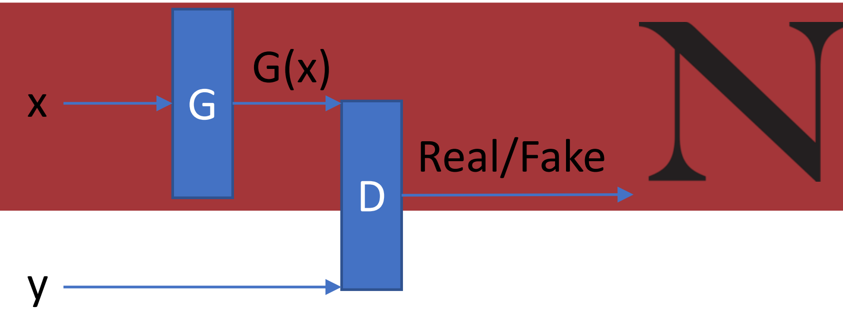
−1.6
−1.8
−2.0
−2.2
−2.4
−2.6
−2.8

GAN Evaluation Metrics

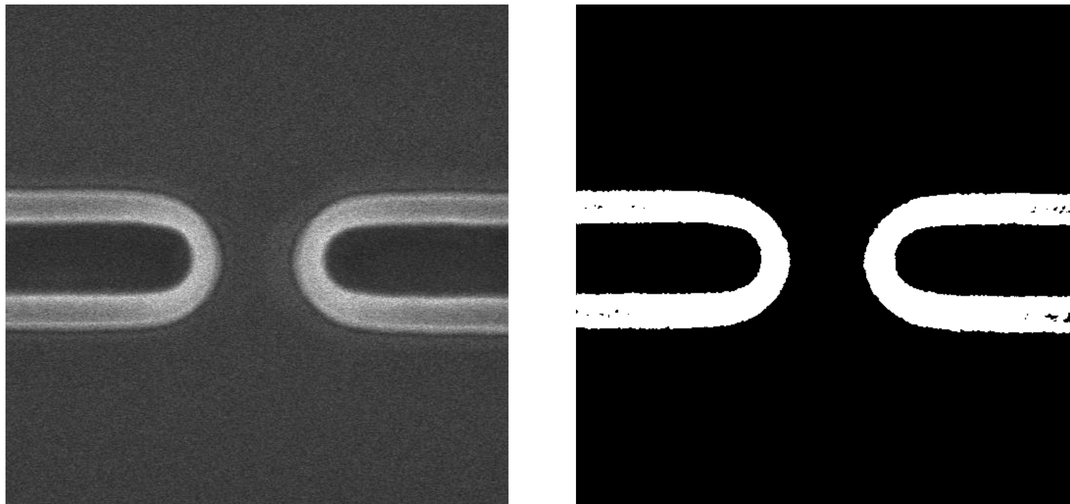


- Goal: for each input/output image pair (x,y), quantitatively evaluate "how good" the fake output G(x) is – difficult in general.
- Several approaches taken in previous work:
  - **Segmentation-Based:** if x is a segmentation of y, compute segmentation of G(x) using FCN. Then, segmentation metrics indirectly evaluate generator performance (pix2pix, mAP).
  - **Frechet Inception Distance:** using pretrained CNN, retrieve output layer vectors for each y (placing in set Y) and for each G(x) (in set X). Compute Frechet distance between the resulting sets Y, X (FID).
  - **Human Perceptual Study:** allow individuals to select which of y, G(x) looks more natural in controlled study (pix2pixHD)
  - **Analyze L1 Loss:** take average (over all images) of the L1 distance between y, G(x). Already able to do this, but distance is different from quality of fake.

Segmentation-Based



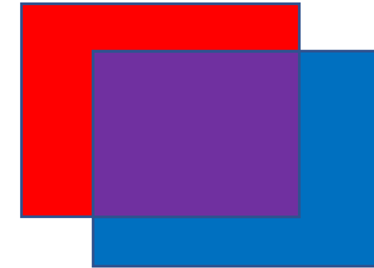
- Let s be the segmentation of G(x) the fully connected network (FCN) gives.
- Compare **ground truth** (x) and **prediction** (s) using segmentation metrics, taking results as a pseudo-metric for quality of the generator.
- Idea: our x is not a segmentation of y, but binary segmentation of post-etch images (y) is relatively easy via heuristic. Segment & compare y, G(x).



Heuristic (Otsu Thresholding & 3x3 Median Filter)

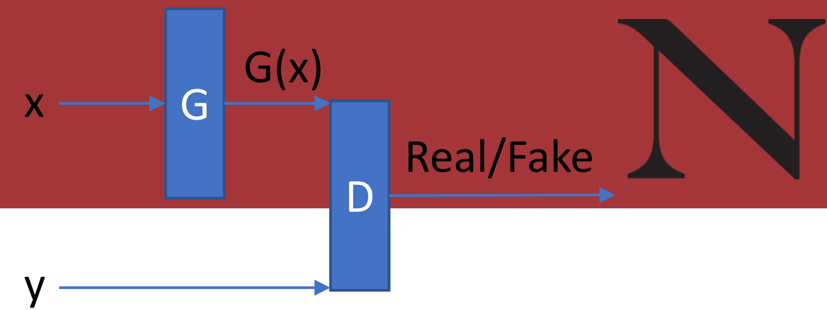
Segmentation Metrics

- Compare set of predicted foreground to ground truth for single image.
- <u>Average Precision (AP):</u>
  - Assume that the final step of the segmentation algorithm is a simple threshold.
  - For a set of n thresholds between min and max graylevels, evaluate the precision and recall we get for each (cf. precision-recall curves).
  - $$AP = \sum_{k=1}^{n} (Recall_k - Recall_{k-1}) \cdot Precision_k$$
- Take the mean over all images for a score with any of these metrics (mAP, mIoU, …)



- $\text{IoU} = \frac{A \cap B}{A \cup B}$
- $TP = |A \cap B|$
- $TN = |A^C \cap B^C|$
- $FP = |A^C \cap B|$
- $FN = |A \cap B^C|$
- $\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$
- $\text{Precision} = \frac{TP}{TP+FP}$
- $\text{Recall} = \frac{TP}{TP+FN}$

Frechet Inception Distance



- Load InceptionV3 classification network, pre-trained on the ImageNet dataset (or possibly another CNN).
- Form sets **X** = {set of Inception v3 output activation vectors for each G(x)}, **Y** = {set of Inception v3 output activation vectors for each y}.
- Compute Frechet Distance between **X** and **Y**:

$$d^2 = ||\mu_X - \mu_Y||^2 + tr(C_X + C_Y - 2(C_X C_Y)^{1/2})$$

  - Where μ_S, C_S are the sample mean and covariance of a set S.
- Lower FID indicates that sets X,Y are more similar, and thus that our generator produces better fakes.