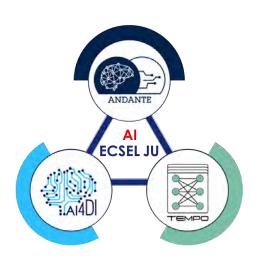


The International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)



An End-to-End Al-based Automated Process for Semiconductor Device Parameter Extraction

Dinu Purice Matthias Ludwig Claus Lenz





Vienna, Austria 25-26 July 2022

Presentation Outline





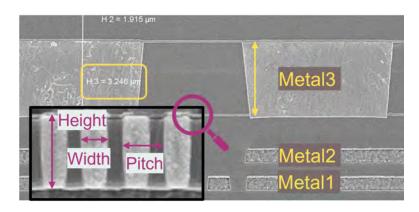
- Introduction and Background
- Task Overview
- Data Preparation Pipeline
- Semantic Segmentation
 - Architecture benchmark
 - Hyperparameters
- Parameter Extraction
- Synopsis and Overview

Introduction and Background

 Process automation for internal semiconductor device analytics and counterfeit detection



- Counterfeiting activities endanger safety, reliability and trust in critical systems
- Anti-counterfeiting methods: electrical testing, supply chain measures, design measures (PUF, logic locking, etc), **physical inspection**
- Relevant features for physical inspection:
 - Geometrical shapes and dimensions
 - Material-related properties



Counterfeit Electronic Parts:

A Multibillion-Dollar Black Market
by Brett Daniel, on Jul 27, 2020, 4:36:07 PM

Counterfeit Chips on the Rise

A more firms report finding phony chips, the danger they pose becomes clearer

By Celia Gorman

Combating Counterfeit Chips

How secure provisioning of cryptographic keys can fight the billions of dollars in counterfeit components.

AUGUST 6TH. 2020 - BY: PAUL KARAZUBA

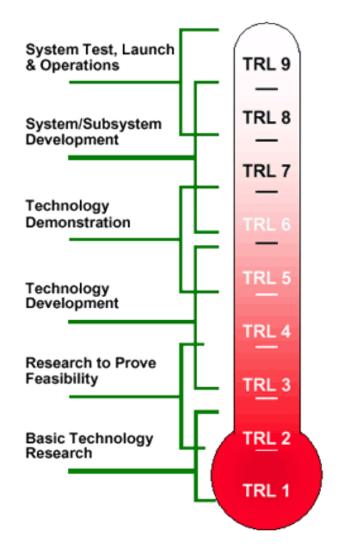
- [1] trentonsystems.com/blog/counterfeit-electronic-parts
- [2] spectrum.ieee.org/computing/hardware/counterfeit-chips-on-the-rise
- [3] semiengineering.com/combating-counterfeit-chips/

[1]

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Introduction and Background



- Workhorse in the field of automatization
- Constantly increasing rate of innovations
- Plethora of relatively low TRL methodologies with potential use-cases in industry
- AIM: Harness Al-based techniques and develop methodologies for subsequent quick and efficient use-case expansion



ARTIFICIAL INTELLIGENCE

Programs with the ability to learn and reason like humans

MACHINE LEARNING

Algorithms with the ability to learn without being explicitly programmed

DEEP LEARNING

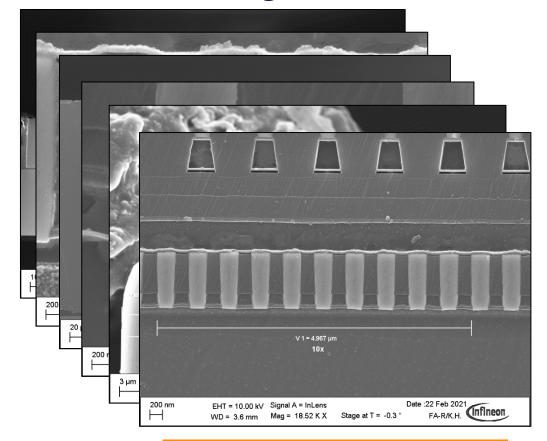
Subset of machine learning in which artificial neural networks adapt and learn from vast amounts of data

End-to-End Pipeline

Product

from:

• Task: Reverse Engineer the Technology



ABC Design House



Technology Definitions

Tech_A32_180
Tech_F53_90
Tech_D65_180_dti
Tech_V87_90
Tech_A21_180
Tech_V76_65
Tech_G09_250
Tech_C46a_180
Tech_C46b_90
:



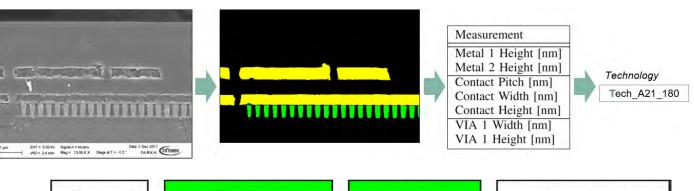
 Automate the process of transition from raw SEM images to techonolgical fingerprint

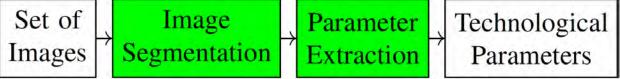
Application Overview

- Semantic Segmentation Stage
- Parameter Extraction Stage

- Technical Requirements:
 - Ability to measure cross section input images
 - Ability to categorize technologies (anti-counterfeiting use-case)
 - Ability to perform without user interaction
 - Ability to perform analysis within real-time



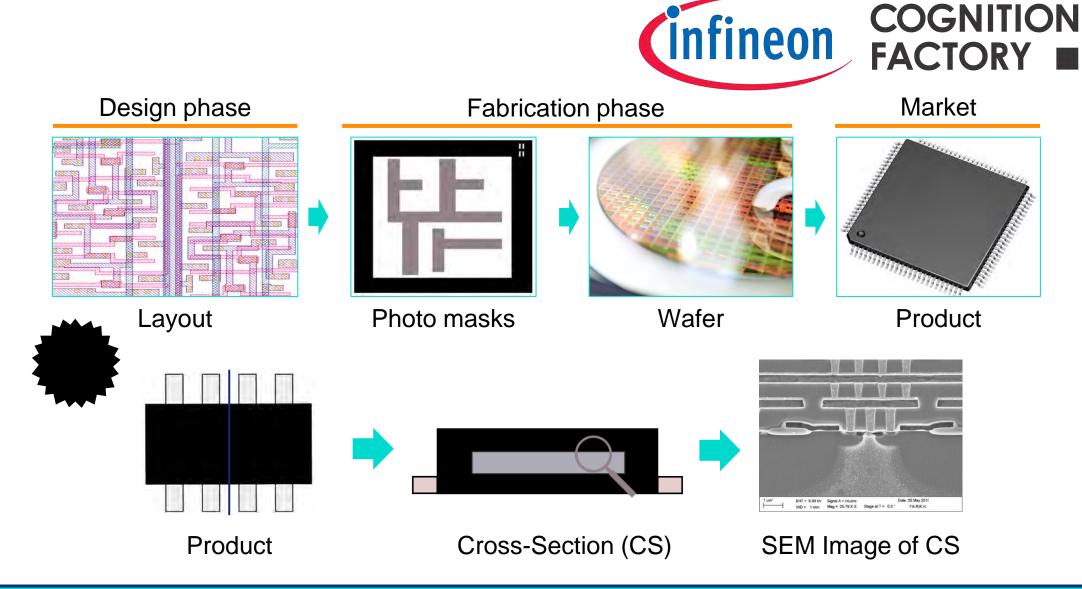




Data Acquisition

Production

Analysis

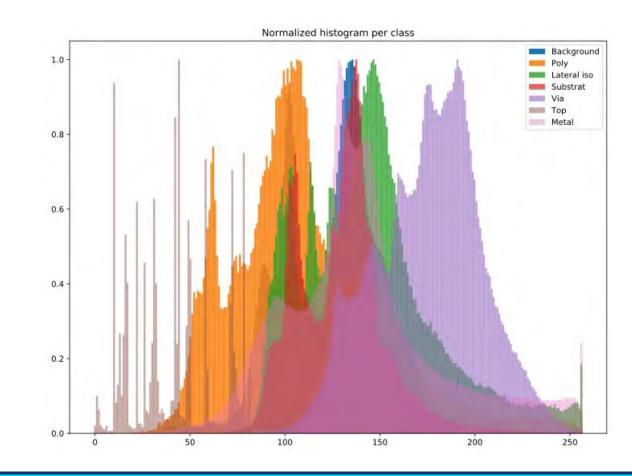


Dataset and Labels

Gray-scale images, acquired via SEM (1024 x 685)
 (Cu, Al-Tu technologies; 500nm – 40nm)

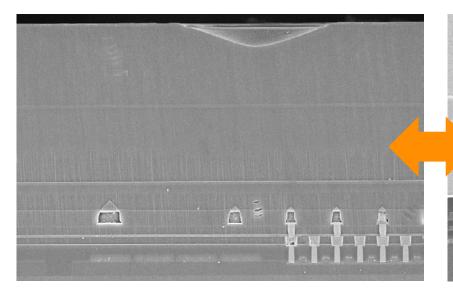


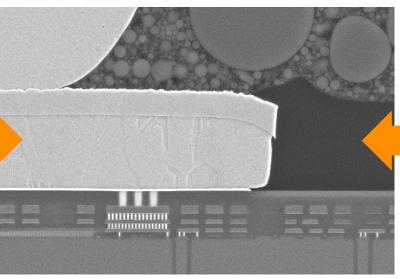
- Manually labelled:
 - Metal
 - Vertical interconnect access (VIA)
 - Poly
 - Lateral isolation/shallow trench isolation
 - Deep trench isolation
- Dataset size (60/20/20 split):
 - Benchmark stage: 202 images
 - Development stage: 2192 images

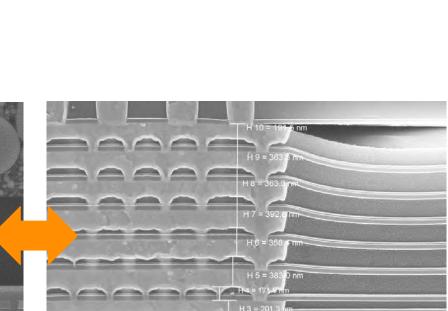


Dataset characteristics

- Strong dependence on domain knowledge
- High input variances (both inter- and intra-image)
- Very high class imbalance





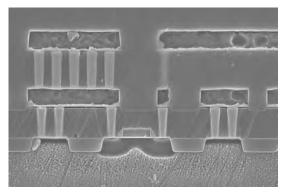


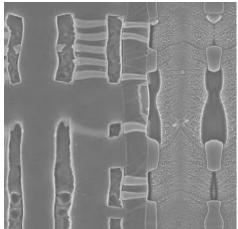
FACTORY

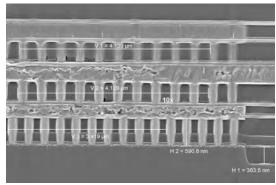
(infineon

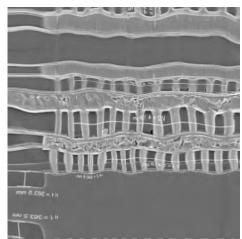
Data Augmentation

- Augmentation Procedures:
 - x90 Rotation, inversion, reflective padding
 - Elastic transforms
 - Grid distortion





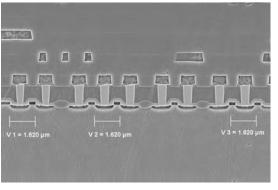






COGNITION FACTORY

Accuracy improvements >15%



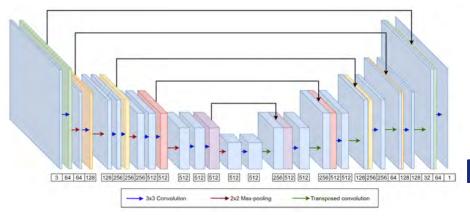
Original



Augmented

Benchmark Candidates

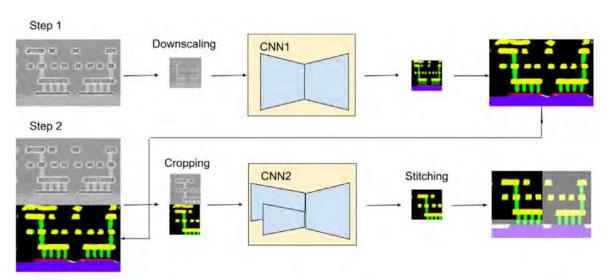
U-Net

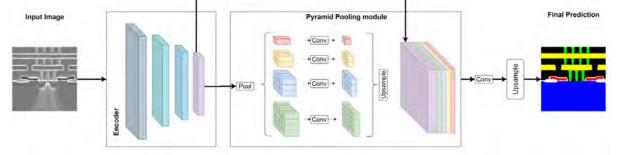




Pyramid Scene Parsing Network (PSPNet)

Siamese Network

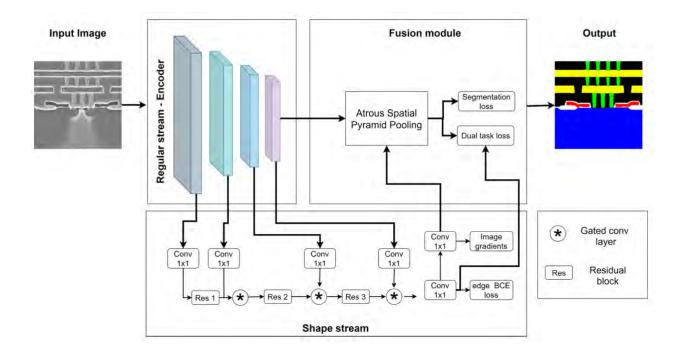




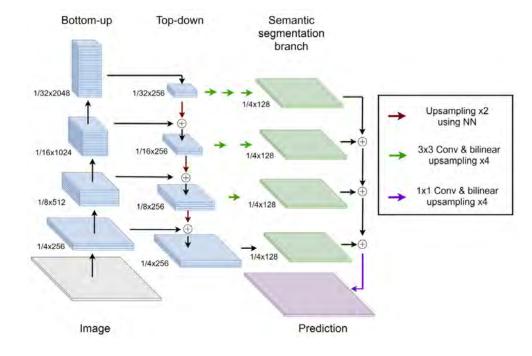
Benchmark Candidates

Gate-Shape Convolutional Neural Network (GSCNN) (infineon

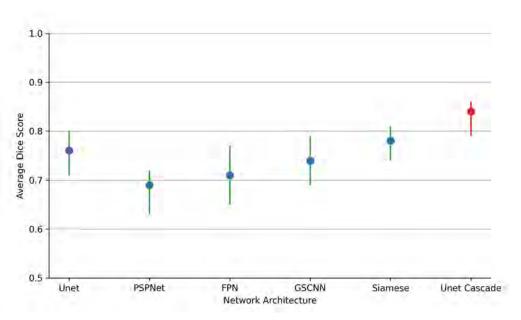




Feature Pyramid Network (FPN)

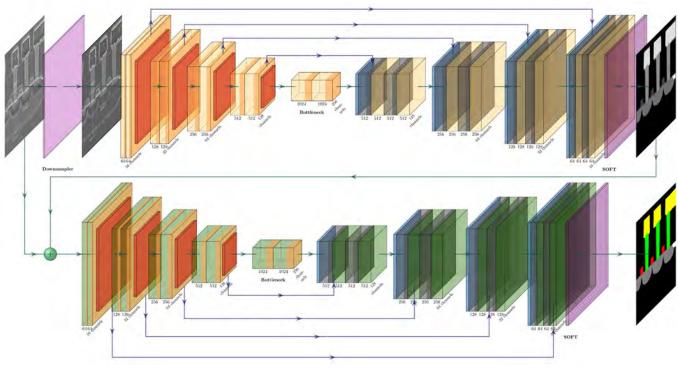


Benchmark Results



- UNet and Siamese networks most promising
- Cascaded UNet architecture
 - UNet generalisation capabilities
 - 2-step analysis inspired by Siamese architecture





Cascaded architecture of 2D and 3D UNets

Hyperparameters

Focal Tversky Loss [metal]





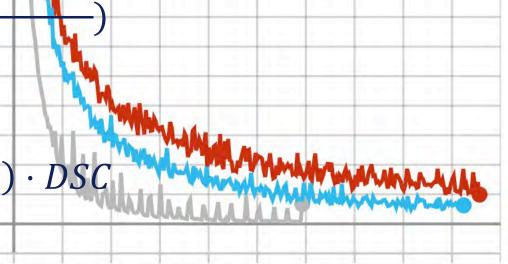
$$FTL = (1 - TI)^{\gamma}, TI = \frac{TP}{TP + \alpha FN + \beta FP}$$

LogCosh Loss [VIA, Poly]

$$LCh = \frac{1}{\alpha} \log(\frac{e^{\alpha DSC} + e^{-\alpha DSC}}{2})$$

Combo Loss [Lateral ISO, Deep Trench ISO]

$$CoL = w \cdot CE - (1 - w) \cdot DSC$$



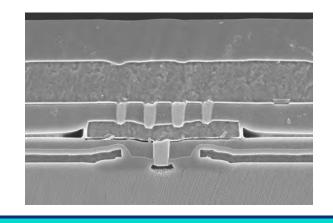
Hyperparameters

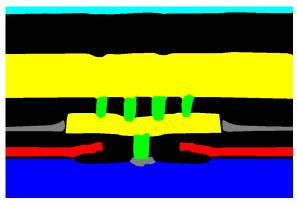
More complex Loss functions:

+Accuracy increase ≈15-20%

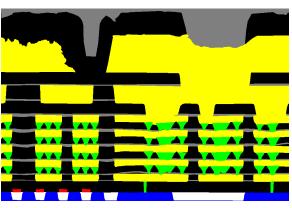


- More training time
- More tune-able hyperparameters
- -Higher GPU requirements (batch sizes 4 times smaller)







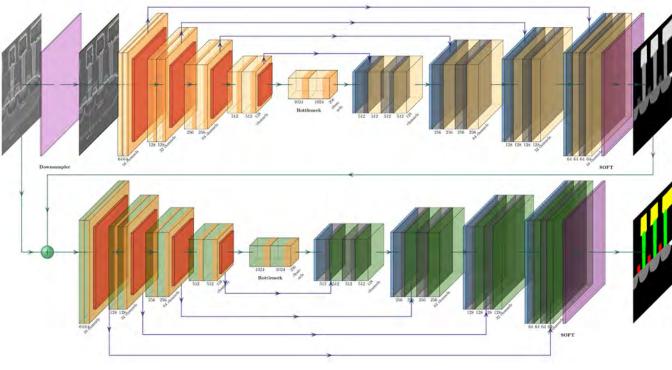


Benchmark Results

Label of Interest	Validation Dice Score
Metal	0.93
VIA	0.91
Poly	0.88
Lateral ISO	0.82
Deep Trench ISO	0.76



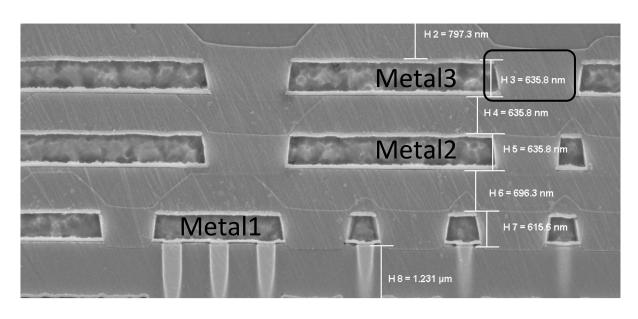


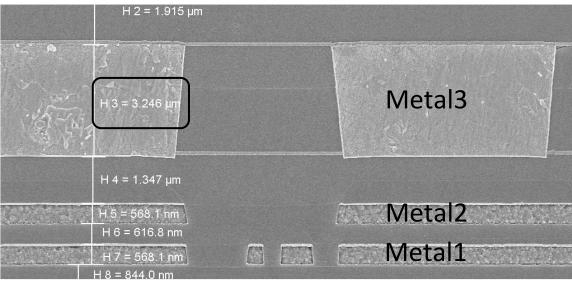


Cascaded architecture of 2D and 3D UNets

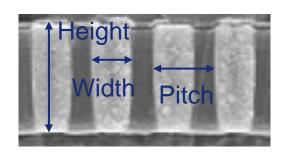
Differentiating Technologies



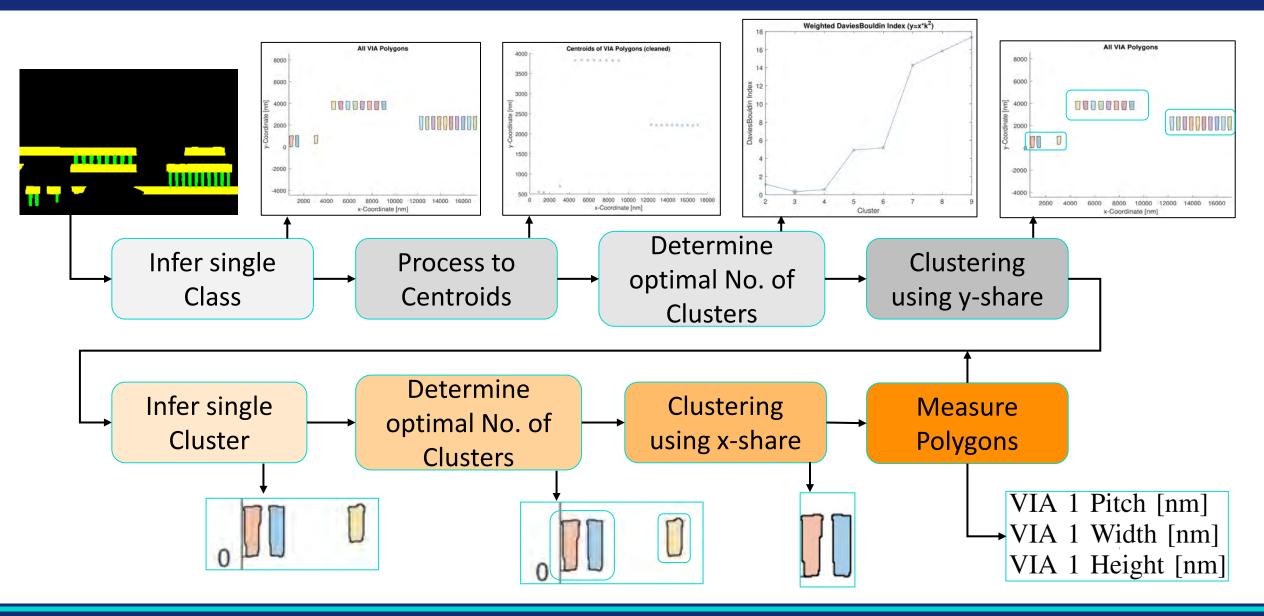




- In general, all features that allow an **inference of differences** between images (geometrical features, material-related features, even tool finger-printing)
- In the presented process, geometrical features (e.g. pitch, height, width) are measured



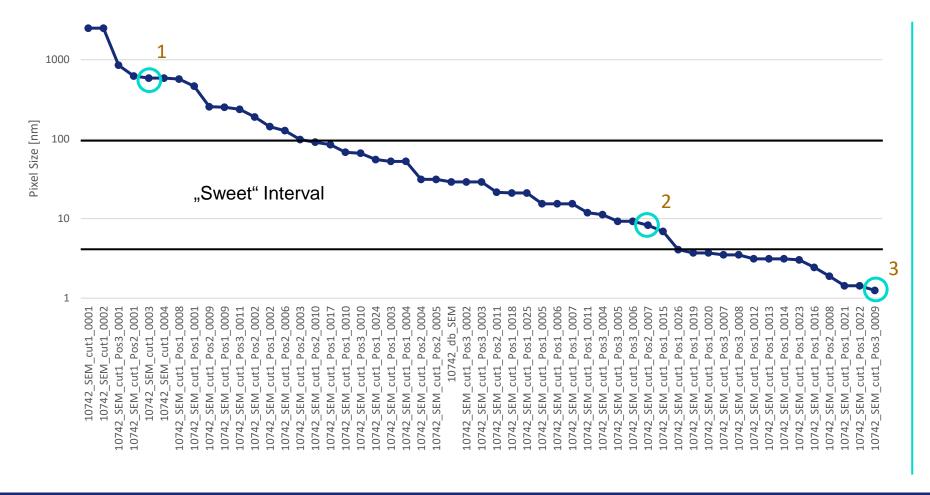
Interpretation of Results



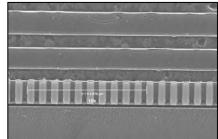
Sample: Overview

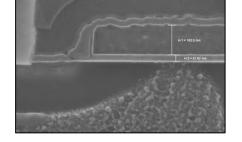
- Overall: 53 image taken on 3 locations of CS
- Extremely large variance in pixel size (~factor 2000)



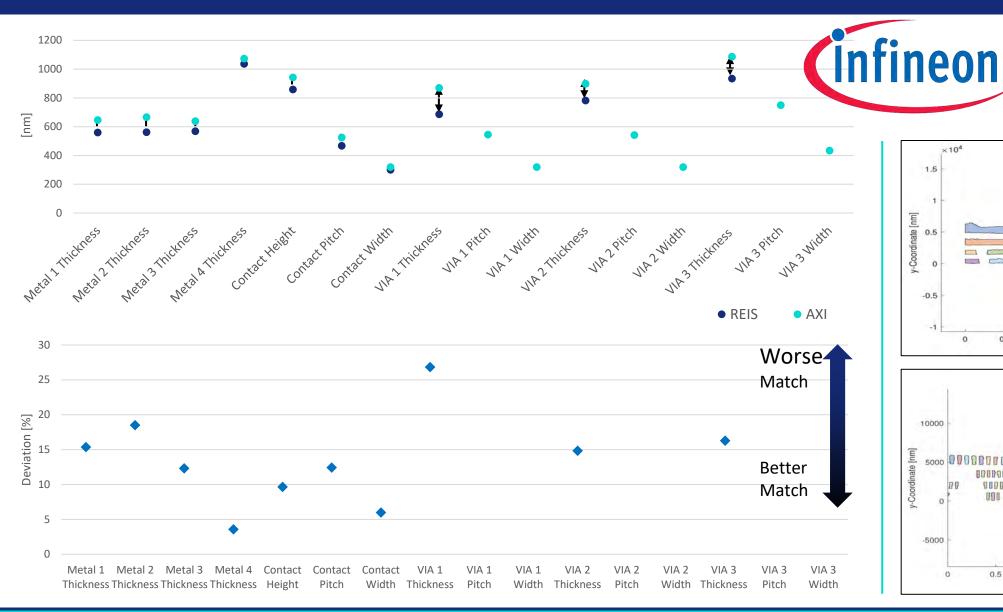


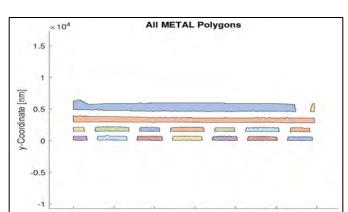


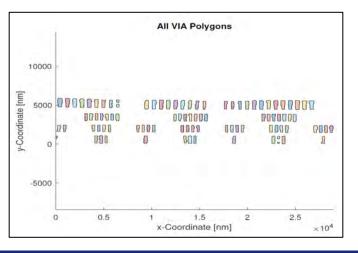




Extracted Technological Features







x-Coordinate [nm]

Synopsis and Future Work

Outcomes

 Approach will be used as an engineering solution for cross-section interpretation and technology inference within IFX reverse



- Image segmentation architecture can be used for future applications with similar scare availability of data
- Novel toolchain enabling big data processing for huge data bases that could not be handled manually
- Newly created data-set of segmented SEM images could foster similar use-cases in the semiconductor industry

Expected impact

- Contribution and extension of physical hardware verification methodology
- Step towards hardware assurance and trust via analysis capabilities
- Contribution for fraud detection on the silicon level

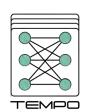
Event Organisers













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The AI4DI project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826060. The JU receives support from the European Union's Horizon 2020 research and innovation programme and the national authorities. www.ai4di.eu

The TEMPO project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826655. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Belgium, France, Germany, The Netherlands, Switzerland. www.tempo-ecsel.eu

The ANDANTE project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 876925. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Belgium, France, Germany, The Netherlands, Portugal, Spain, Switzerland. www.andante-ai.eu



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