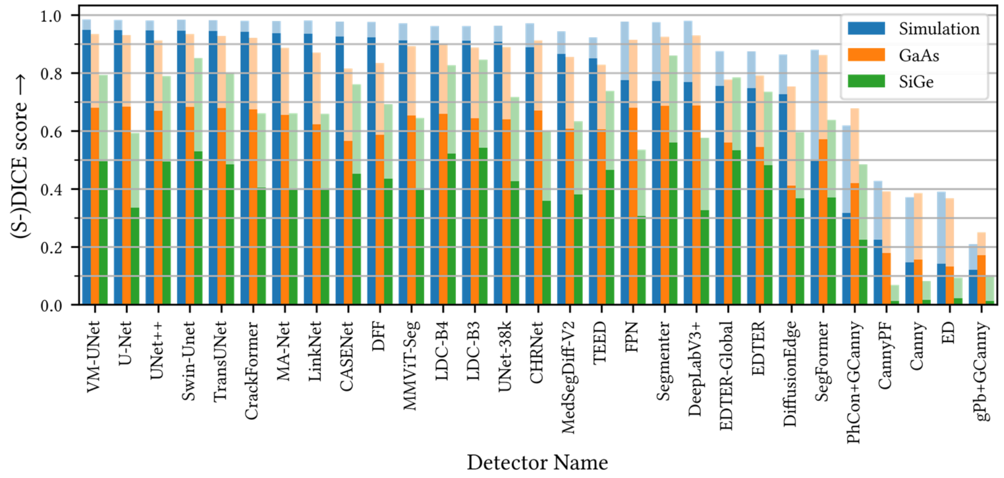
TOWARDS SCALABLE ROBUST CHARGE TRANSITION DETECTION FOR QUANTUM DOT DEVICES

5 October 2025 | FABIAN ANTÓNIO HADER

JÜLICH Forschungszentrum | Integrated Computing Architectures ICA

Outline

- Background: Experimental Data
- Charge Transition Detection
- Efficiency Refinement with Improved Sensor Dot Tuning
- Outlook



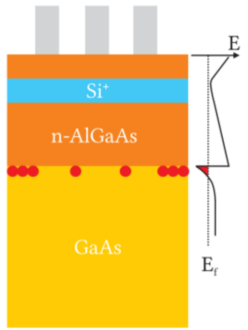
Fabian António Hader
f.hader@fz-juelich.de
www.fz-juelich.de/profile/hader_f

Integrated Computing Architectures (ICA | PGI-4)
www.ica.fz-juelich.de

JÜLICH Forschungszentrum | Integrated Computing Architectures ICA

Background

Experimental Data

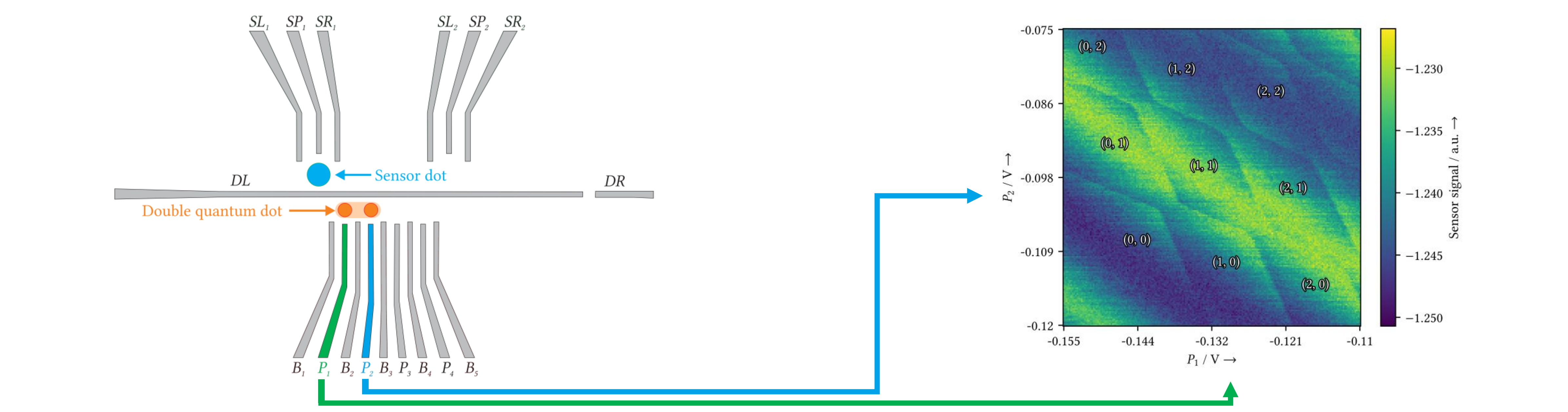


Present Case:

- **Plunger-Plunger-Scans**
- Mainly influencing dot potentials

Used for **charge state analysis**

→ Lines provide information about charge transitions



Charge Transition Detection

Motivation

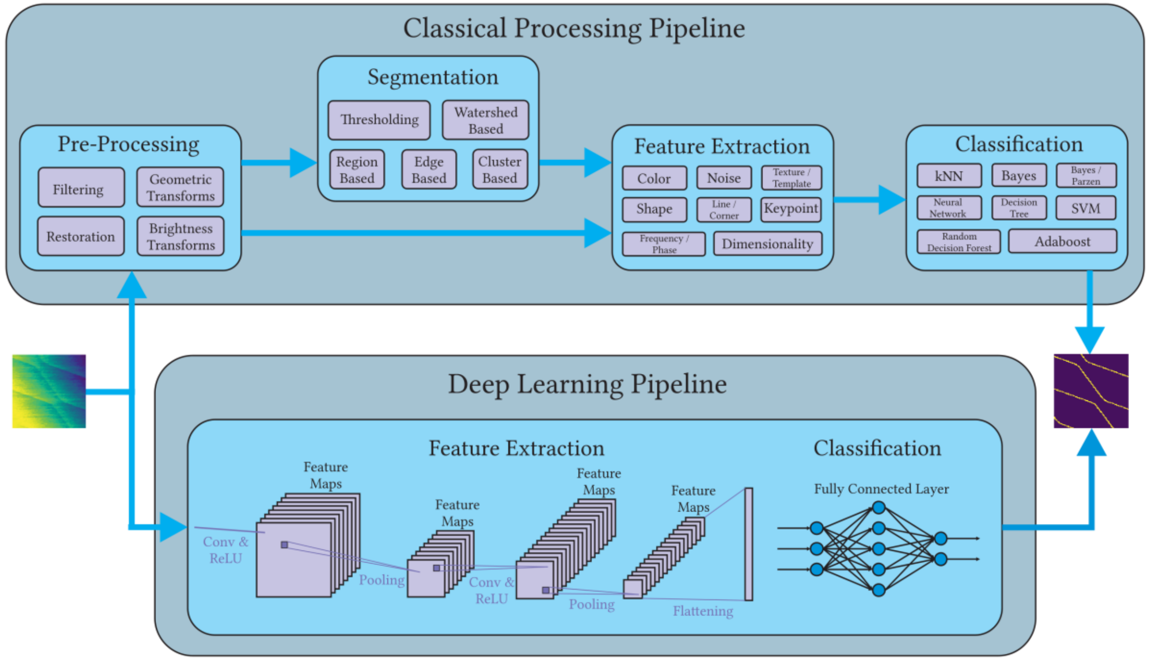
Can CT detection be **integrated close to the qubits**, to reduce data transmission?

- Approaches must operate in cryogenic environments
- **Power dissipation** impacts qubit fidelity

Does ML offer a (robust) advantage?

- Collect & compare different classical & ML approaches
- **Training** with **simulated data** (SimCATS)

Goals:
1. Good generalization
2. Reduce approach complexity



Charge Transition Detection

Collected Approaches

Approaches intended for:
- Edge Detection
- Segmentation / Object Detection

Classical Approaches:

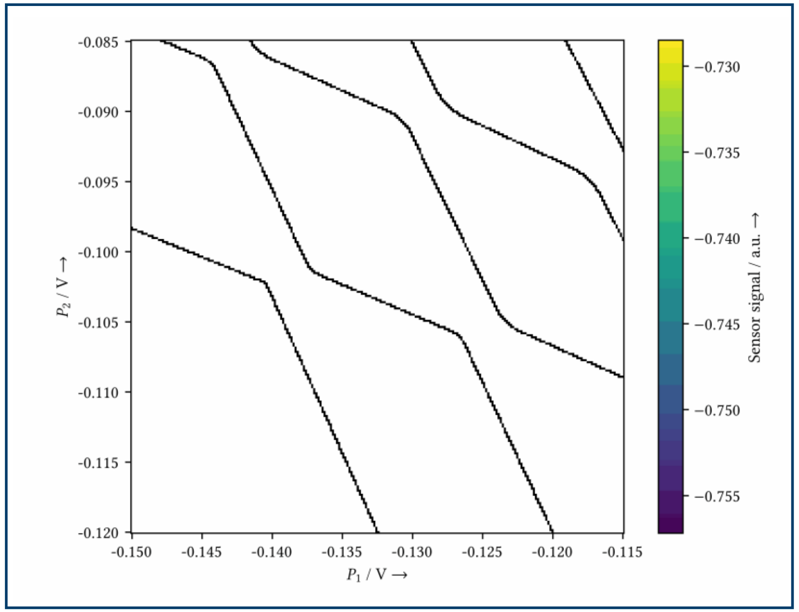
- Canny, CannyPF, ED, PhCon+GCanny, gPb+GCanny

Machine Learning Approaches:

- **Convolution-Based:**
  - CASENet, CHRNet, DeepLabV3+, DFF, FPN, LDC, LinkNet, TEED, U-Net, U-Net++
- **Transformer-Based:**
  - CrackFormer, EDTER, MA-Net, MMViT-Seg, SegFormer, Segmenter, Swin-Unet, TransUNet
- **State-Space-Model-Based:**
  - VM-UNet
- **Diffusion-Based:**
  - DiffusionEdge, MedSegDiff-V2

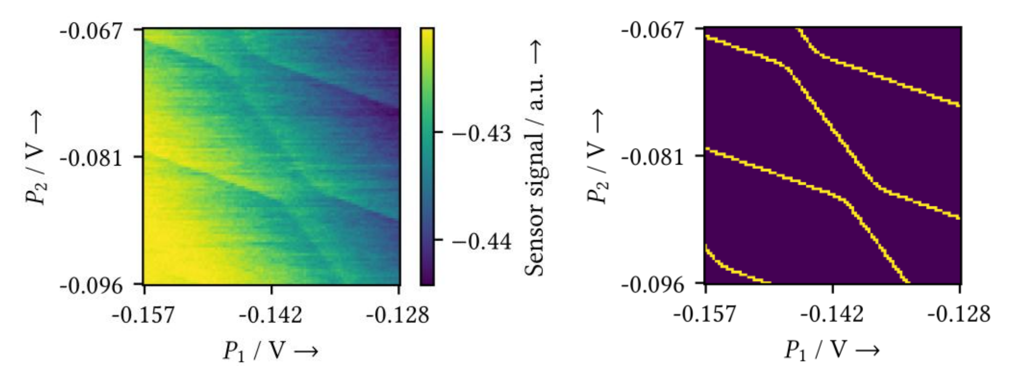
Charge Transition Detection

Datasets & Training



Datasets

- **Simulated**
  - **Parameter ranges** extracted **from** RWTH **GaAs** sample
  - Random variations of TCTs, sensor, and distortion parameters
  - 10.000 randomly sampled configs with 100 CSDs each
- **Experimental**
  - **GaAs DQD** data & **SiGe single QD** data



CSD **Charge Transitions**

Training

- Classical & ML approaches **optimized on simulated data**
- **ML models trained** using **original settings**, and using **AdamW, OneCycleLR, and dice loss**

Charge Transition Detection

Dice Similarity Coefficient

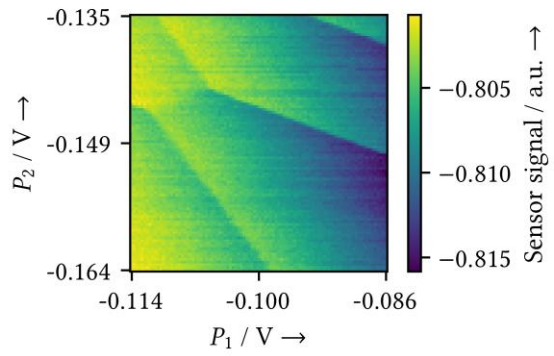
Used **Dice Similarity Coefficient for Evaluation**:

$$\boldsymbol{DICE} = \frac{\mathbf{2}|\boldsymbol{X} \cap \boldsymbol{Y}|}{|\boldsymbol{X}| + |\boldsymbol{Y}|}$$

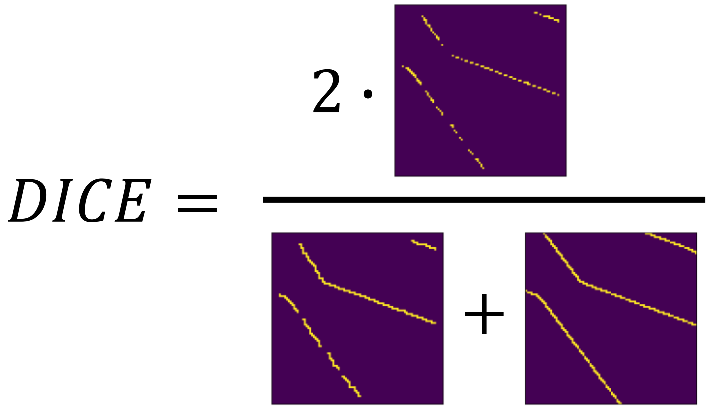
→ **Quantifies** the **similarity** between
the **predicted segmentation mask** X
and the **ground truth segmentation mask** Y

Requires pixel-precise segmentation

→ Surface Dice (**S-DICE**) **allows deviation**



CSD

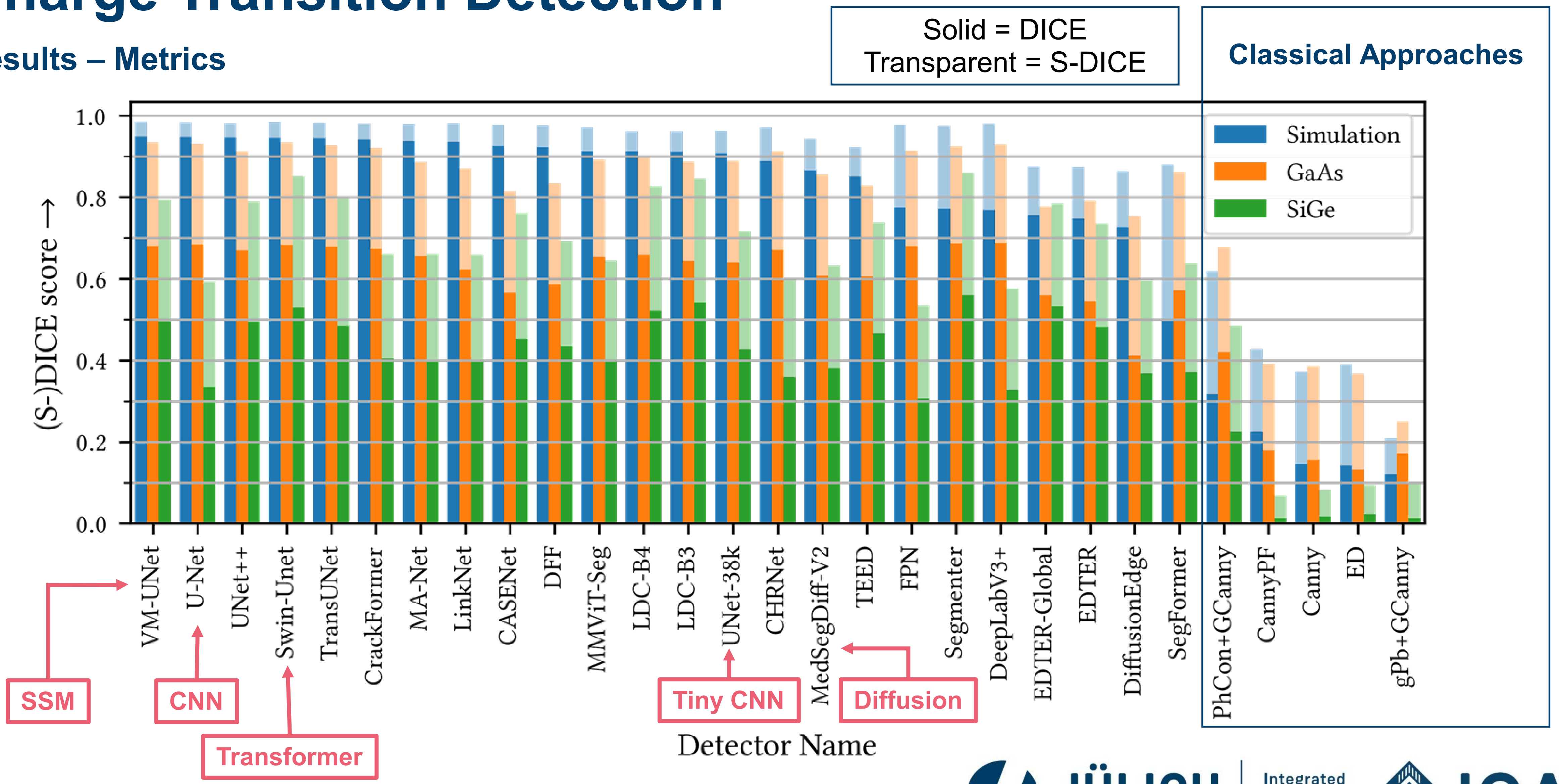


DICE Calculation

Charge Transition Detection

Results – Metrics

Solid = DICE
Transparent = S-DICE



Charge Transition Detection

Results – Exemplary Predictions

Low Noise, High Sensitivity

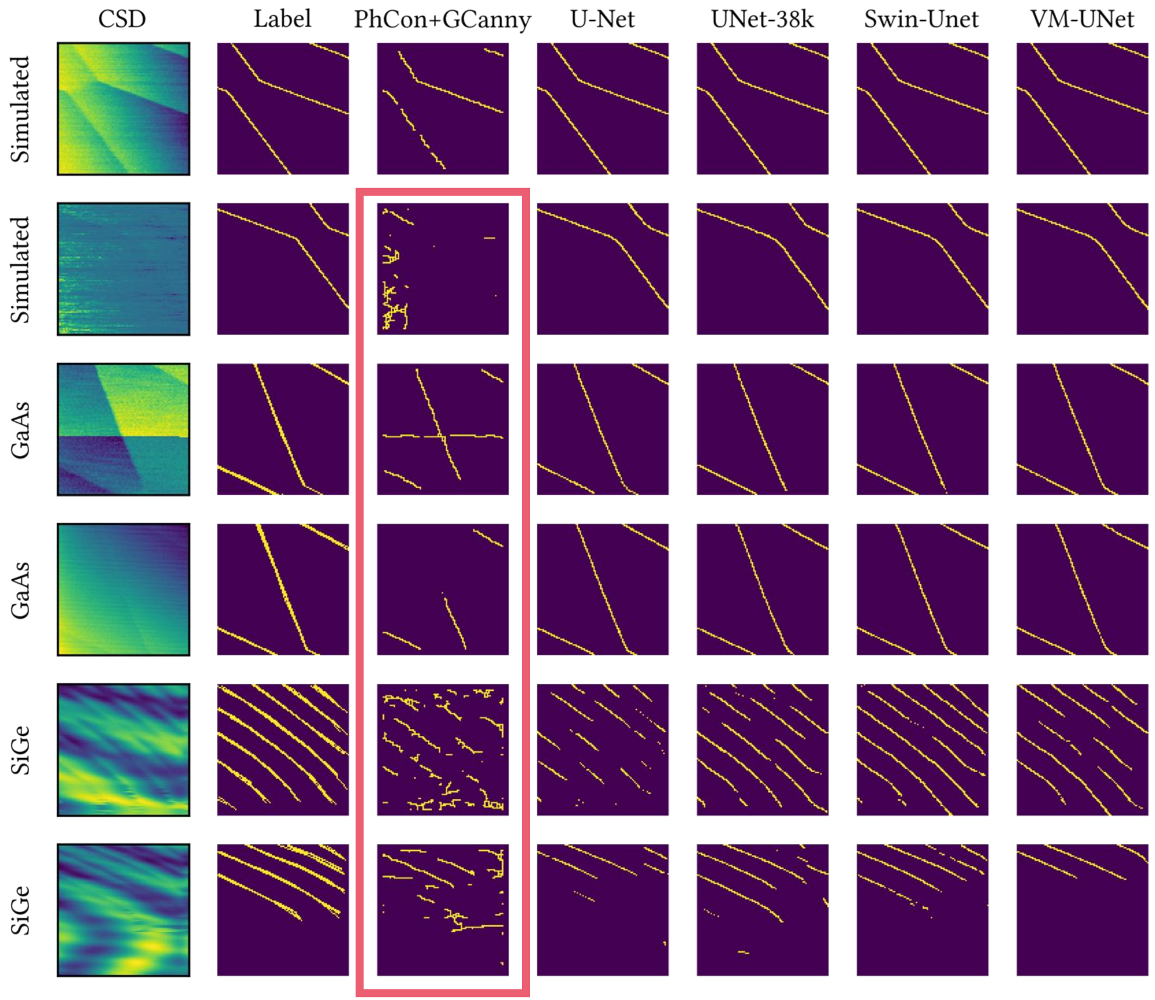
High Noise, Low Sensitivity

Random Telegraph Noise

Low Noise, Low Sensitivity

Blurred Transitions, Single Dot

Different Angle, Single Dot



Classical approach not robust

Charge Transition Detection

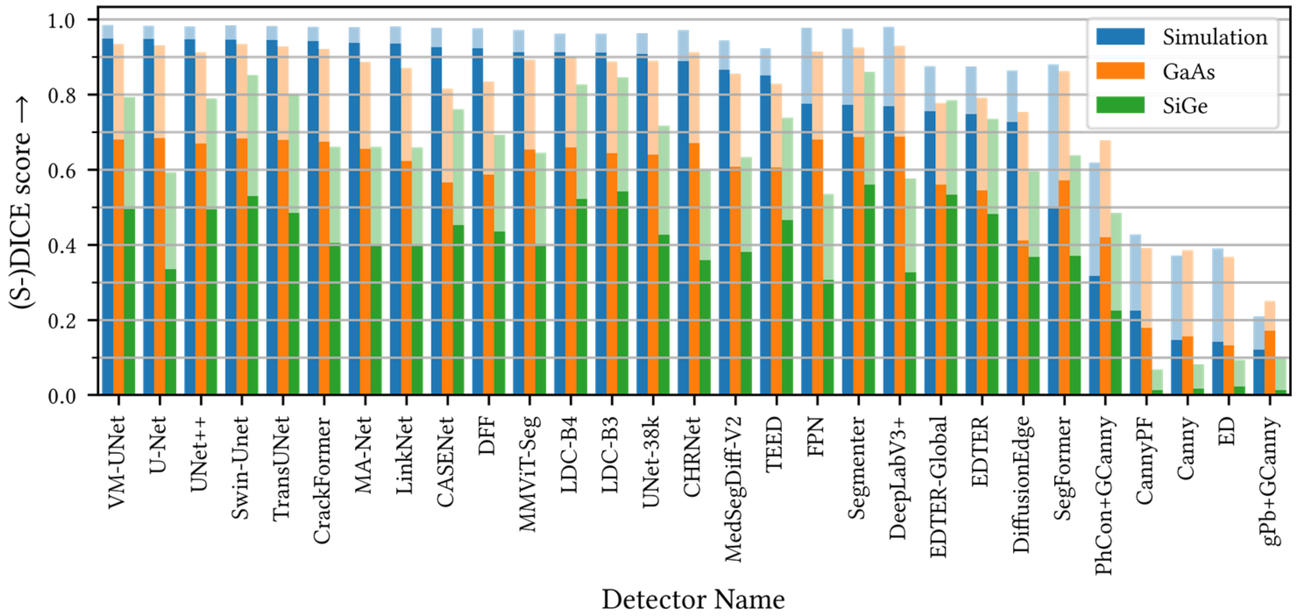
Summary

Machine learning clearly outperforms classical approaches

- Models trained on simulated generalize well to experimental data

Model size & complexity can be reduced

- **How can we further reduce?**



F. Hader et al., "Automated Charge Transition Detection in Quantum Dot Charge Stability Diagrams“

Published in IEEE TQE, **DOI: 10.1109/TQE.2025.3596392**

Efficiency Refinement with Improved SD Tuning

Sensor Compensation – Effects on Data Quality

SD is **disturbed** by the **voltages** applied to the DQD gate electrodes

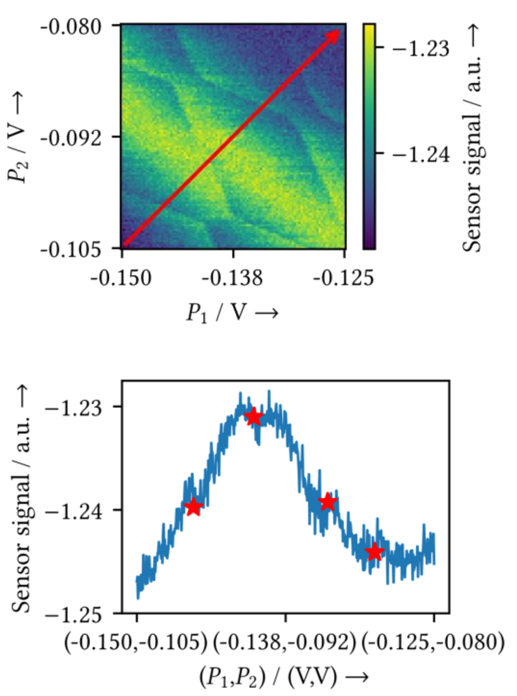
Effect can be mitigated by using **virtual gates**

- Combination of several physical gates
- Effect of DQD gates on the SD is compensated
- SD **signal** shows **stepwise characteristic**

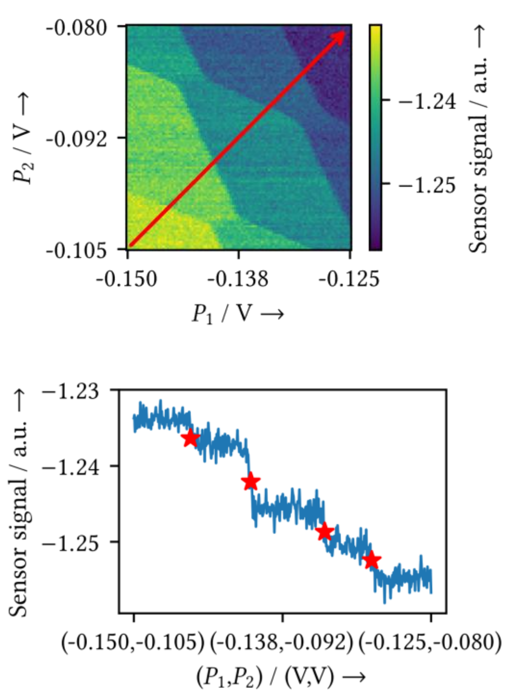
  → Reduces complexity in signal interpretation

Task: Evaluate if **compensated SD data improves 2D** U-Net model performance and **enables ray-based (RB)** detection

→ **Target benchmark: S-DICE ≥ 0.95** on simulated data



Uncompensated



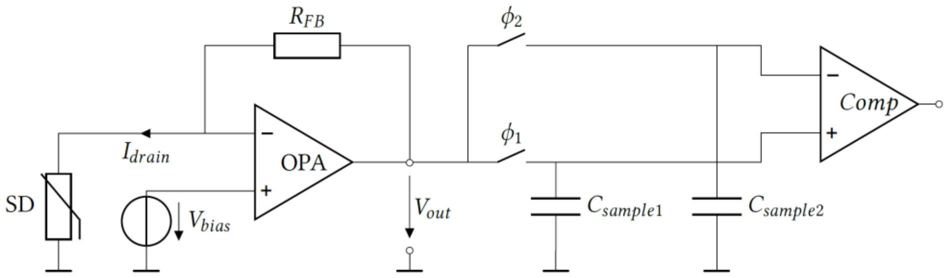
Compensated

Efficiency Refinement with Improved SD Tuning

Sensor Compensation – Approaches & Optimization

Considered Approaches:

- **U-Net**
  - **Full size & Unet-38k**
  - **Further reduced-size Variants**
  - **RB Versions** of the smallest U-Nets
- **Classical Methods**: PhCon+GCanny, First-Order Derivative (FOD) filter
- **HIAT Circuit**: Hardware integrated averaging and thresholding (scalable on-chip detection)



HIAT Schematic

Datasets:

- Simulated with compensated SD
- Simulated with compensated SD & superior data quality (top 10% of parameter range)

Efficiency Refinement with Improved SD Tuning

Sensor Compensation – Results

Sensor compensation improves detection quality

- **ML models improved** (U-Net & Unet-38k)
- **Models up to 2 orders of magnitude smaller** became viable
- Classical approaches improved, but are still inferior

RB detection did not reach the targeted benchmark of S-DICE ≥ 0.95

- ML based RB detection outperforms 2D classical approach
- **HIAT not robust enough** for local detection

Category	Detector Name	DICE	S-DICE
2D	U-Net	0.9935	0.9999
	UNet-38k	0.9906	0.9998
	UNet-4k	0.9805	0.9979
	UNet-447	0.9558	0.9884
	PhCon+GCanny	0.4886	0.9160
RB	UNet-1k-RB	0.8662	0.9926
	UNet-179-RB	0.7571	0.8971
	FOD filter	0.4429	0.8914
	HIAT	0.3256	0.8861

Efficiency Refinement with Improved SD Tuning

Sensor Compensation – Results Superior Data Quality

Superior data quality further improves detection quality

- All 2D ML models achieved optimal S-DICE scores
- Classical approaches improved, but did not match target

RB detection became viable

- **ML based RB detection** achieves **optimal S-DICE score** (Unet-1k-RB)
- Classical variants & **HIAT** still **not robust enough**

  → **HIAT** may perform reliably with further improved data quality and dual averaging times

UNet-447 and UNet-179-RB show declining S-DICE

→ **Further downsizing** not advisable

Category	Detector Name	DICE	S-DICE
2D	U-Net	0.9935	0.9999
	UNet-38k	0.9906	0.9998
	UNet-4k	0.9805	0.9979
	UNet-447	0.9558	0.9884
	PhCon+GCanny	0.4886	0.9160
RB	UNet-1k-RB	0.8662	0.9926
	UNet-179-RB	0.7571	0.8971
	FOD filter	0.4429	0.8914
	HIAT	0.3256	0.8861

Efficiency Refinement with Improved SD Tuning

Energy Efficiency of Scaled Machine Learning Models

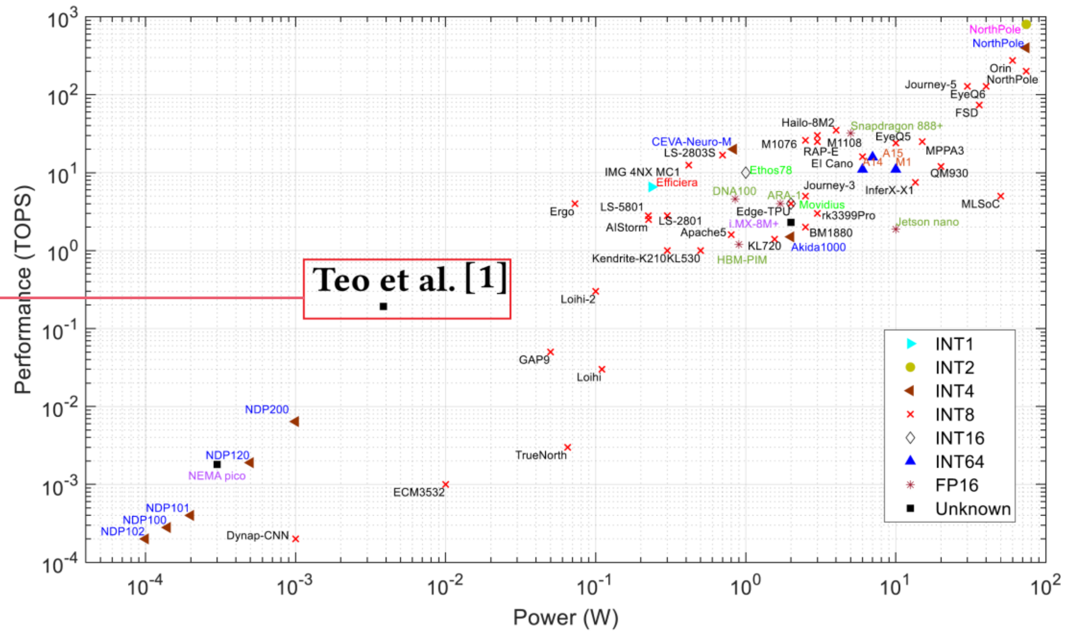
Required **Power for Tuning Procedure**:

$$P_{tune} = \frac{N_{ops/csd} \cdot n_{csd}}{E_{unet} \cdot t_{tune}}$$

- $N_{ops/csd}$: number of operations per CSD inference
- $n_{csd} = 10^7$ CSDs (or $6 \cdot 10^7$ ray-based measurements)
- $E_{unet} = 50.62 \left[\frac{TOPS}{W}\right]$
- $t_{tune} = 6h$: time requirement of the tuning procedure

Category	Model	Parameters	FLOPs	Power [W]
2D	U-Net	17,261,825	$1.124{\cdot}10^{10}$	$1.028{\cdot}10^{-1}$
	UNet-38k	38,041	$7.701{\cdot}10^{7}$	$7.043{\cdot}10^{-4}$
	UNet-4k	4,193	$2.404{\cdot}10^{7}$	$2.199{\cdot}10^{-4}$
	UNet-447	447	$4.471{\cdot}10^{6}$	$4.089{\cdot}10^{-5}$
RB	UNet-1k-RB	1,481	$1.374{\cdot}10^{7}$	$7.855{\cdot}10^{-6}$
	UNet-179-RB	179	$2.207{\cdot}10^{6}$	$1.262{\cdot}10^{-6}$

Power vs. Performance of AI Edge Processors



Adapted from DOI: 10.3390/electronics13152988

[1] Teo et al., „U-Net Hardware Accelerator“; IEEE Computer Society, 2024
DOI: 10.1109/MCSoC64144.2024.00063

JÜLICH Forschungszentrum | Integrated Computing Architectures ICA

Efficiency Refinement with Improved SD Tuning

Summary

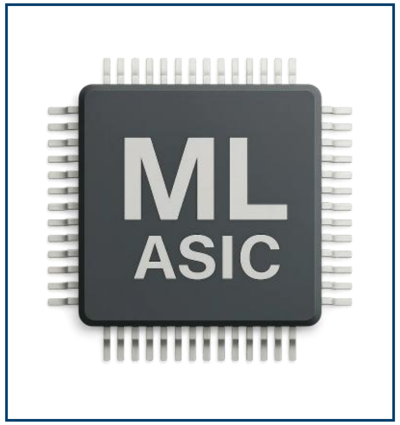
Reliable **SD compensation** is essential for scalable and accurate CT detection

RB approaches are only viable under consistently superior data quality

Category	Model	Power	Data Quality: uncompensated, contemporary	Data Quality: compensated SD	Data Quality: compensated SD, superior data quality
2D	U-Net				
	UNet-38k		★		
	UNet-4k				
	UNet-447			★	
	PhCon+GCanny				
RB	UNet-1k-RB				★
	UNet-179-RB				
	FOD filter				
	HIAT				

★ = Selected Candidate

Outlook



Is detection at the **millikelvin** stage **more efficient than transfer**?

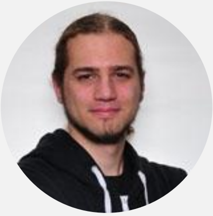
Can we realize a **more versatile demonstrator chip** for multiple tasks?

Category	Model	Power	Data Quality uncompensated, contemporary	 compensated SD	 compensated SD, superior data quality
2D	U-Net				
	UNet-38k		★		
	UNet-4k				
	UNet-447			★	
	PhCon+GCanny				
RB	UNet-1k-RB				★
	UNet-179-RB				
	FOD filter				
	HIAT				

★ = Selected Candidate

Acknowledgements

RWTH Aachen University
Quantum Technology Group
(Measurement Data)



Simon Humpohl

Tobias Hangleiter

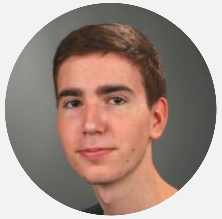
Till Huckemann

Forschungszentrum Jülich
ICA – Integrated Computing Architectures
(Charge Transition Detection)

Fabian Fuchs

Sarah Fleitmann

Karin Havemann



Benedikt Scherer

Jan Vogelbruch

Jonas Bühler

Lotte Geck

Stefan van Waasen