JANUARY 2025

TEXAS
The University of Texas at Austin

A Compact Optical Neuron Based on Multi-Operand Microring Resonators

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DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

The University of Texas at Austin

SPIE. PHOTONICS WEST

Outline

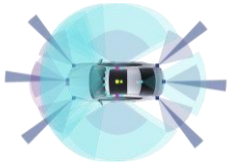
1. Background of Photonic AI
2. Hardware-efficient design for Optical Neural Networks
3. MRR-based Multi-Operand Optical Neuron (M^2OON)
4. Experimental Results of M^2OON with Tunable Nonlinear Active Functions
5. Summary

Photonic AI keeps growing

Why Photonic AI ?

- High computation speed and low power consumption
- High bandwidth in the **analog** domain
- Unique multiplexing techniques, *e.g.*, **WDM**
- Integrated photonics bring new opportunities…

AI influences various aspects of our lives

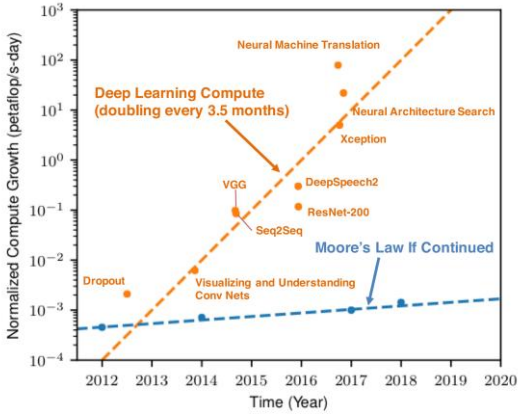


Autonomous driving

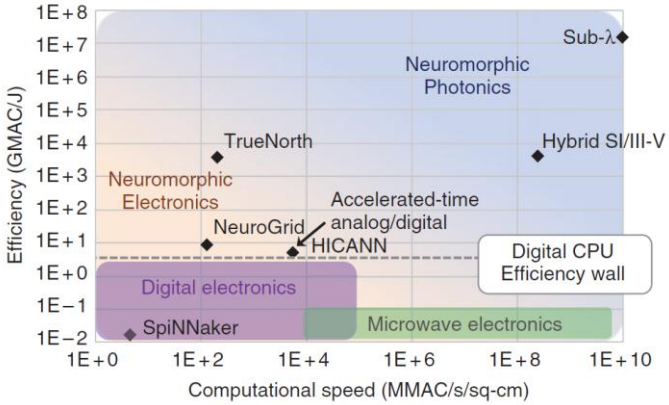
Data centers

ChatGPT

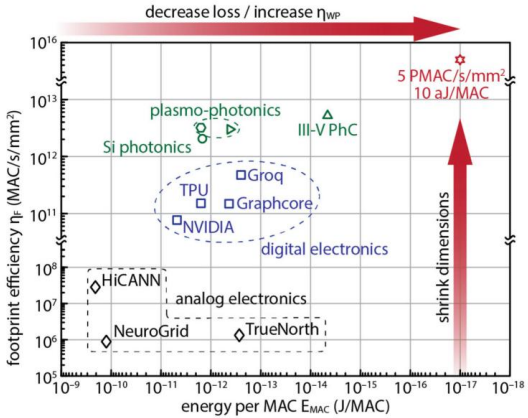
General Language Model



[Lima+, 2020]



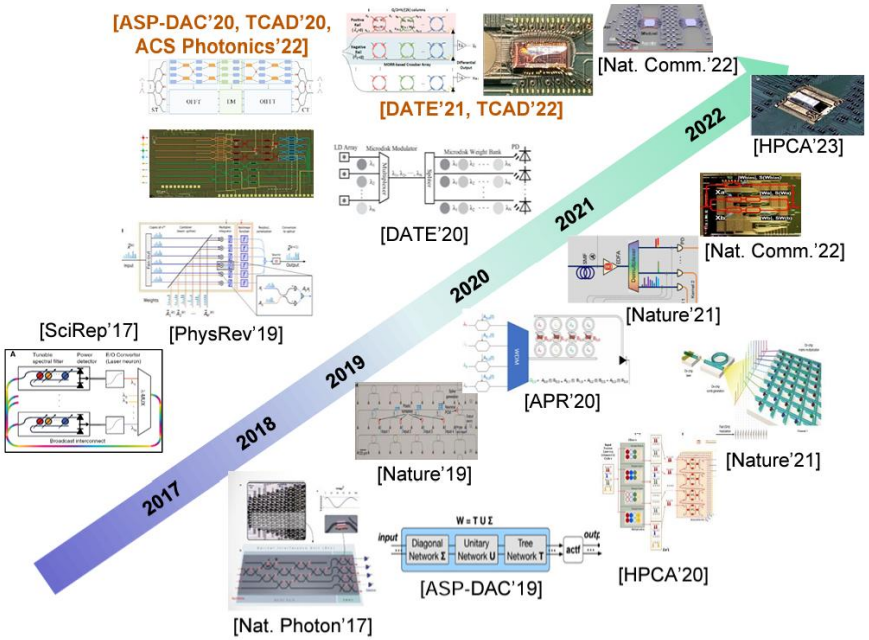
[Lima+, 2017]



[Totovick+, 2017]

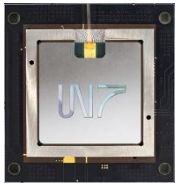
Photonic AI keeps growing

Photonic Neural Network Trends in Academia



Foundry / EPDA Support in Industry

Photonic Computing Chip Designs



LIGHTMATTER
LIGHTELLIGENCE
SALIENCE LABS
LUMINOUS
OPTIUS light powered computing
Lighton

Design Automation / Simulation Tools

Ansys LUMERICAL
SYNOPSYS OPTICAL & PHOTONIC SOLUTIONS
cadence
COMSOL

PDKs / Foundry

amf ADVANCED MICRO FOUNDRY
AIM PHOTONICS
SiEPIC FAB OpenEBL
tsmc
GlobalFoundries

Challenges and Concerns:

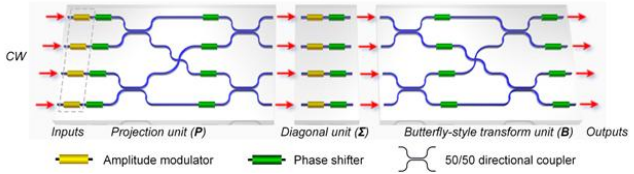
- Large footprints of optical devices in PICs → **Scalability**
- Inefficient electrical-optical (E-O) interfaces → **Efficiency**
- Training for hardware-based ONNs…

The absence of on-chip nonlinearities, which are critical for NNs, necessitates additional E-O/O-E conversion!

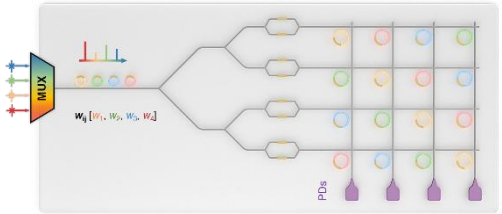
How to improve?

Toward Hardware-Efficient Optical Neural Networks (ONNs)

Circuit-level optimization

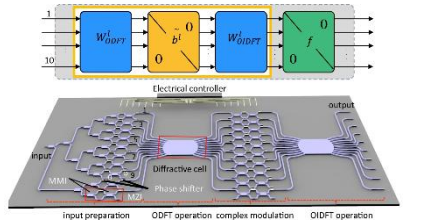


Butterfly-style photonic mesh [Feng+, 2022]

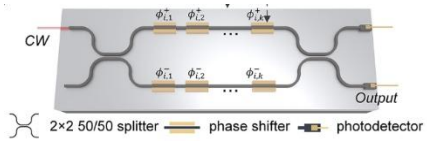


Structured compression approach [Ning+, 2024]

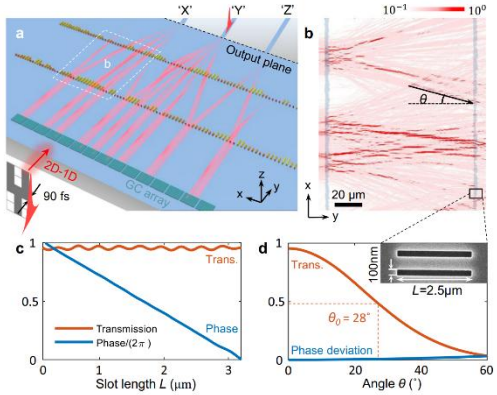
Deployment of compact device-level tensor cores



Star-coupler-based ONN [Zhu+,2022]



Multi-operand MZI [Feng+,2022]



Metasurface-based ONN [Wang+,2024]

Multi-Operand Modulators — *Squeeze operation on single device*

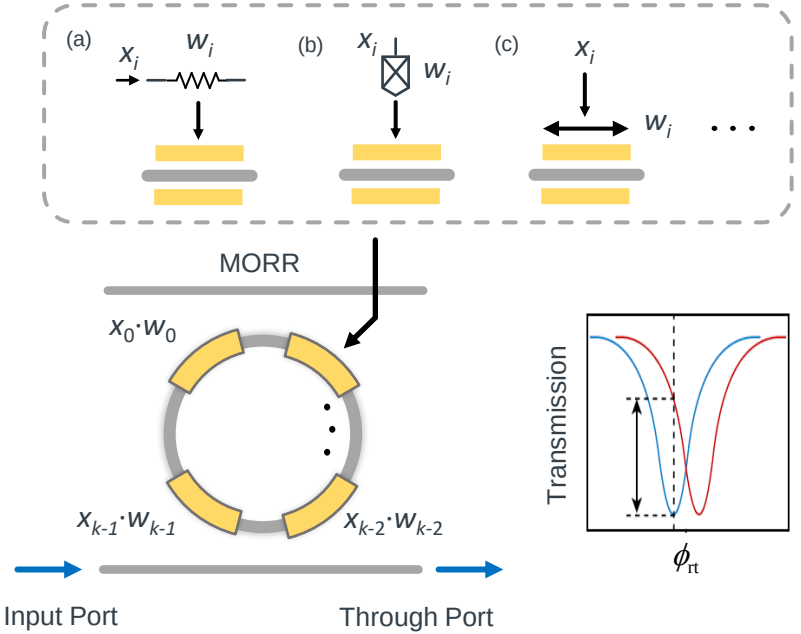
Multi-Operand Micro-ring Resonator (MORR)

- MORR has ***k*** active actuators controlled simultaneously by independent electrical signals.
- Squeezes a length-*k* tensor operation within a single device.

  k ×area/power/wavelength saving than MRR arrays
- Multiplication could achieve by (a) programmable resistors, (b) tunable amplifiers/attenuators, (c) adjusting modulation length, *etc*.

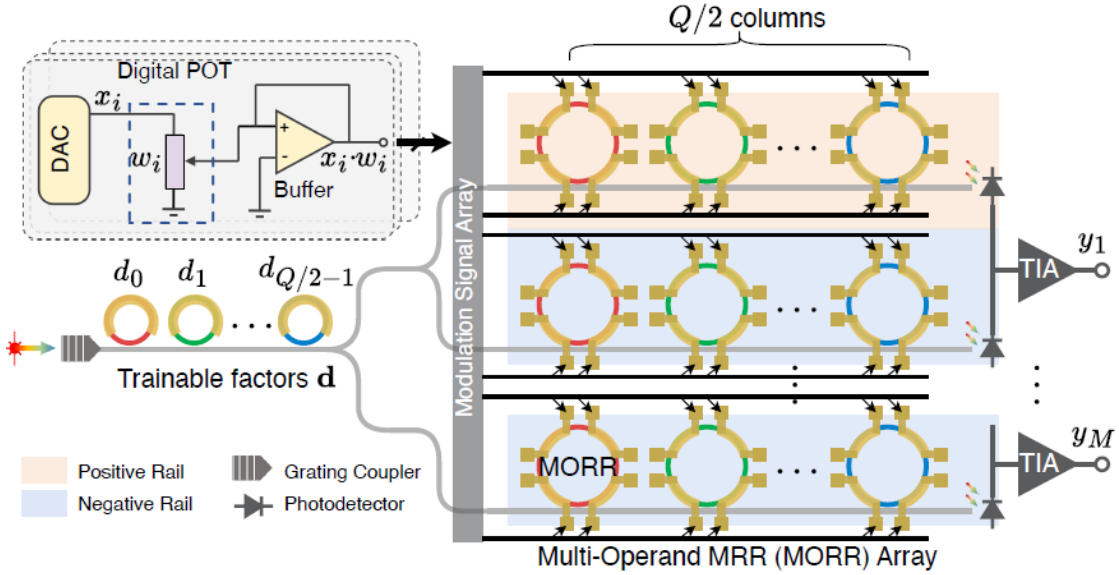
$$\phi_{rt} = \sum_{0}^{k-1} g_{\mathrm{mod}}\left(w_i \cdot x_i\right)$$

- Introduces ***on-chip nonlinearity*** by leveraging the intrinsic transmission characteristic of MRR.



$$T_t = f\left(\phi_{rt}\right) = \left|\frac{t_1 - t_2\alpha_{rt}e^{-j\phi_{rt}}}{1 - t_1 t_2 \alpha_{rt} e^{-j\phi_{rt}}}\right|^2 = f\left(\sum_{i=0}^{k} g_{\mathrm{mod}}\left(w_i \cdot x_i\right)\right)$$

MRR-based Multi-Operand Optical Neuron (M²OON)



Schematic of M²OON and proposed ONN architecture.

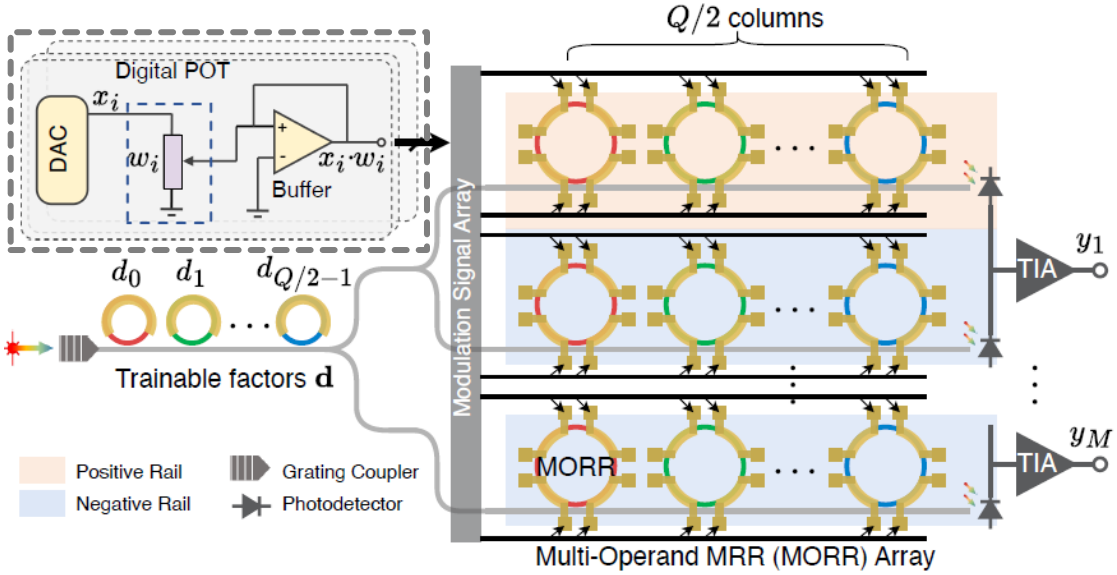
- $M \times N$ weight matrix is partitioned into $P \times Q$ blocks with a size of k
- To achieve full-range MVMs, the Q multi-operand MRRs for each row are split into **positive** and **negative** rails.
- Introduce a **learnable** balancing factor ***d*** to scale each MORR's output range adaptively, enhancing the expressivity of network.
- The output of each row can be expressed as

$$y_{m,+/-} = \sum_{q=0}^{Q/2-1} f_{\mathrm{MORR}} \left(\sum_{i=0}^{k-1} g_{\mathrm{mod}} \left(w_{mqi} \cdot x_{qi} \right) \right) d_q$$

Depend on modulation mechanism, e.g., thermal

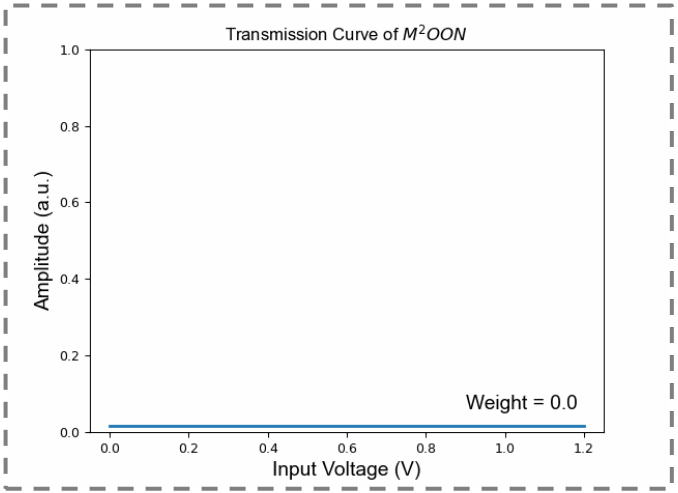
$d_q > 0$ for positive rail; $d_q < 0$ for negative rail

On-chip nonlinearity of an M²OON



Schematic of M²OON and proposed ONN architecture.

Response of ***Weights***

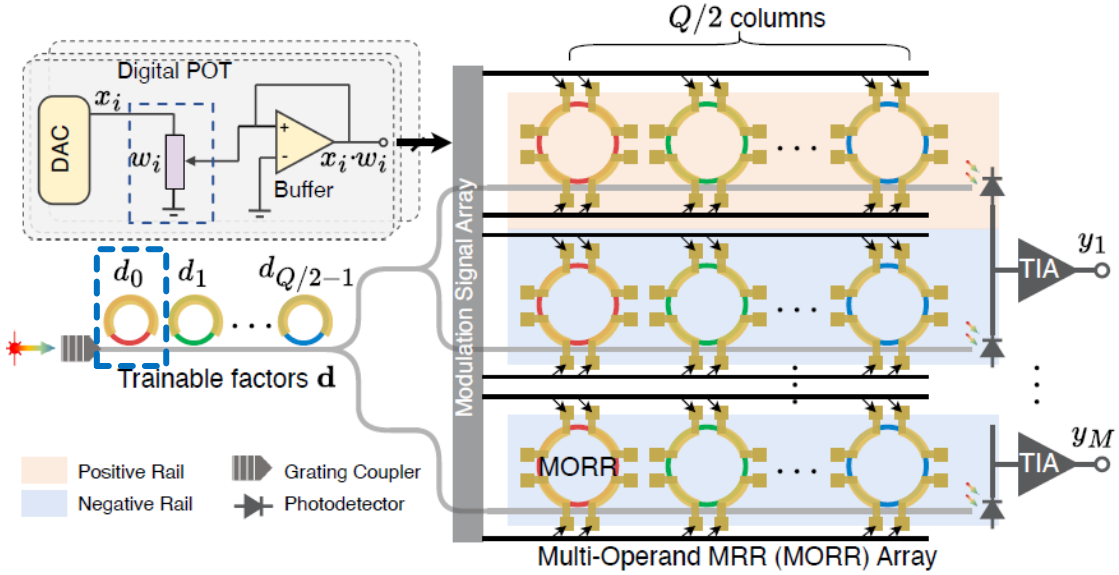


$$y_{m,+/-} = \sum_{q=0}^{Q/2-1} f_{\mathrm{MORR}} \left(\sum_{i=0}^{k-1} g_{\mathrm{mod}} \left(w_{mqi} \cdot x_{qi} \right) \right) d_q$$

w *are programed by digital potentiometers*

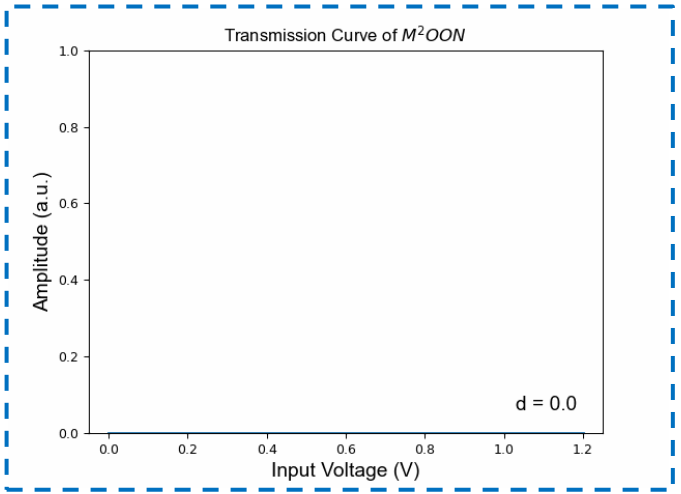
* All actuators are set to the same voltage for demonstration purposes

On-chip nonlinearity of an M²OON



Schematic of M²OON and proposed ONN architecture.

Tune Nonlinearity by ***d***

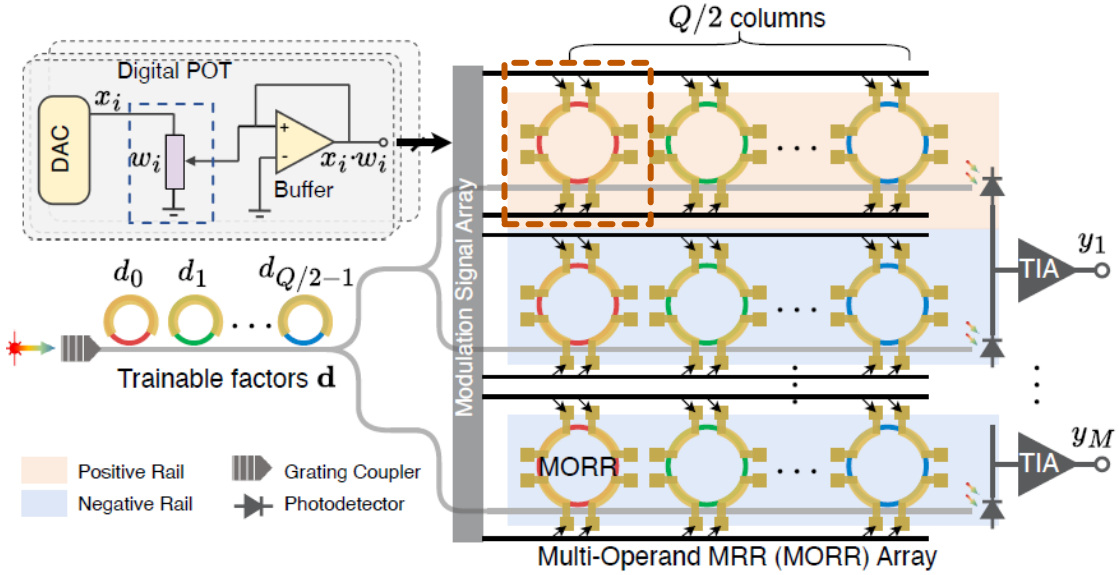


$$y_{m,+/-} = \sum_{q=0}^{Q/2-1} f_{\text{MORR}} \left(\sum_{i=0}^{k-1} g_{\text{mod}} \left(w_{mqi} \cdot x_{qi} \right) \right) d_q$$

d *are programed by regular MRRs*

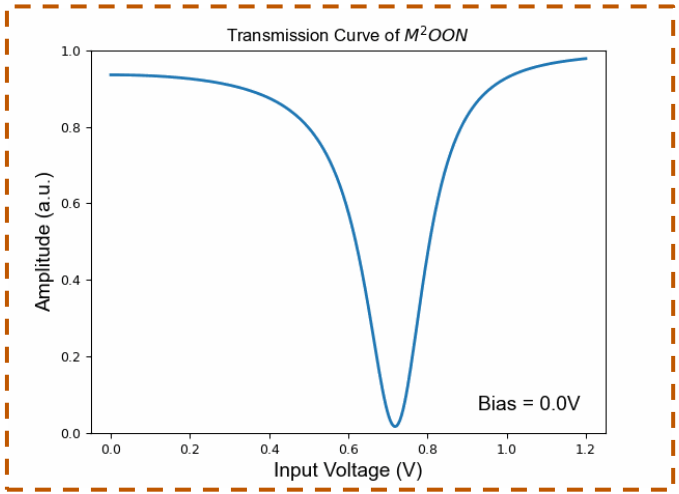
* All actuators are set to the same voltage for demonstration purposes

On-chip Nonlinearity of an M²OON

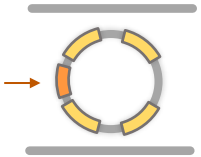


Schematic of M²OON and proposed ONN architecture.

Tune Nonlinearity by ***Bias***

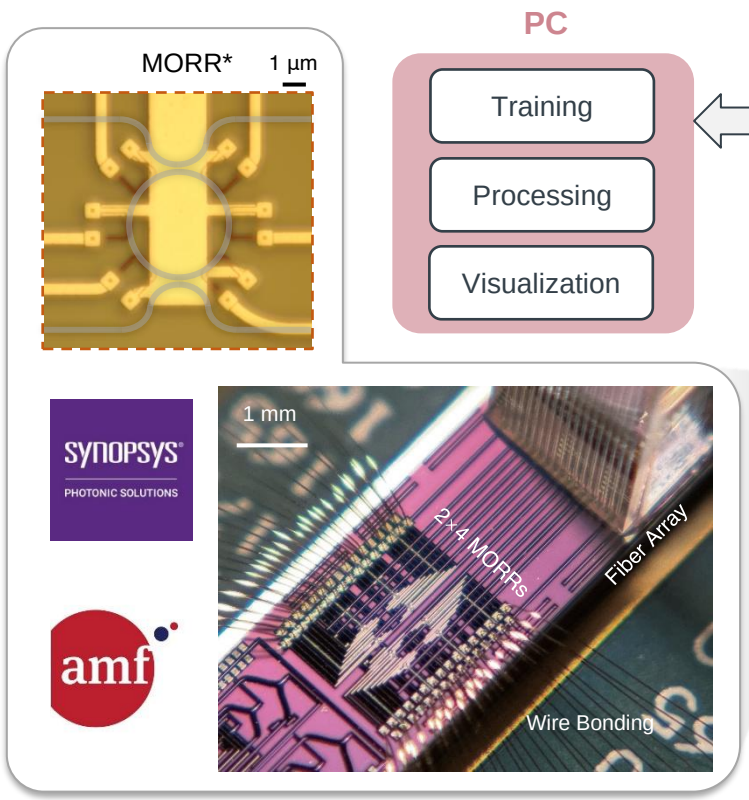


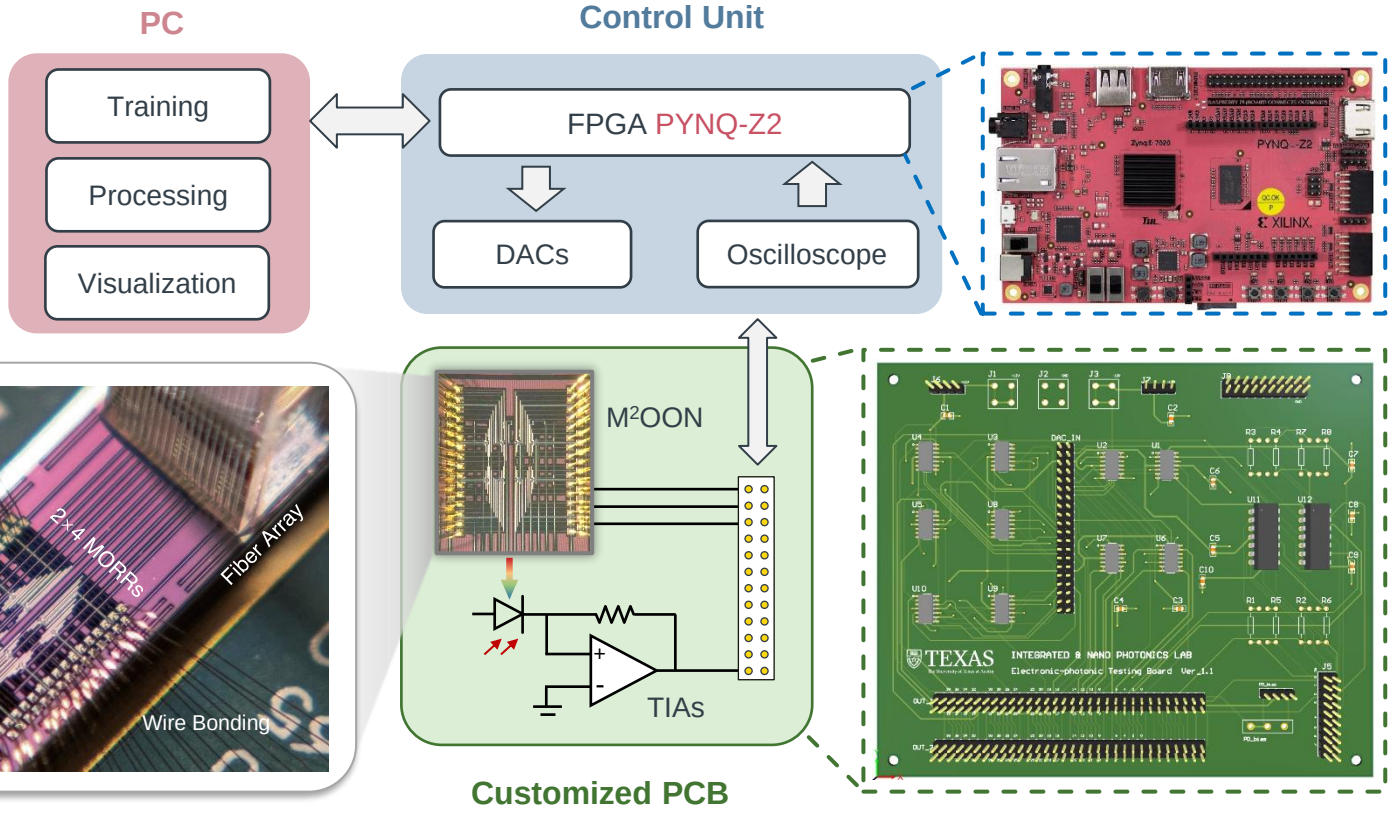
Bias *is applied to an additional* actuator, *besides the k* actuators *used for computation*



* All actuators are set to the same voltage for demonstration purposes

On-chip testing of a 4-operands M²OON





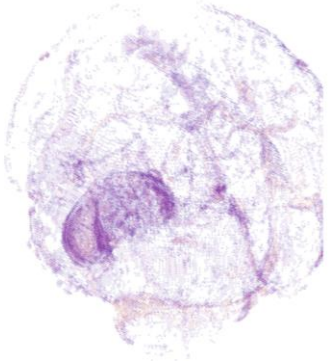
* 4 operands and 2 microheaters for calibration/tunable nonlinearity

Results: On-chip demonstration for nonlinear convolution process

- Input images: Human brain MRI image (3D) *from BraTS2020 Dataset*
- Convolve each slice with the 3 × 3 sobel kernel (on-resonate, *i.e.*, bias=0)
- For demonstration purposes, a threshold is set for 3D visualization
- Inherent tunable nonlinearity of M²OON allows for more **effective feature extraction**

On-chip Covn results

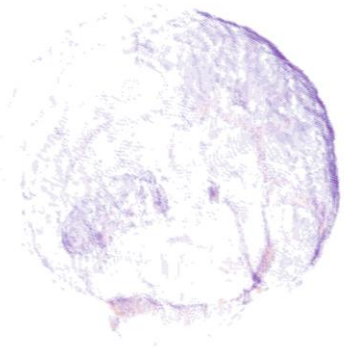
(output > 0.35)



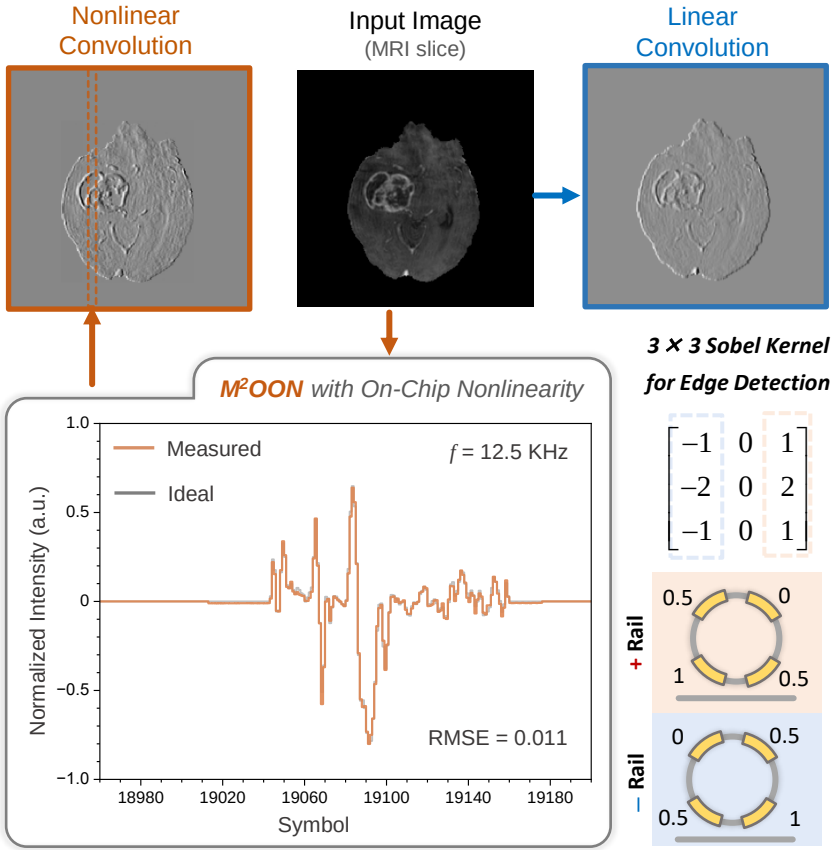
Tumor region is extracted

Linear Covn results

(output > 0.35)

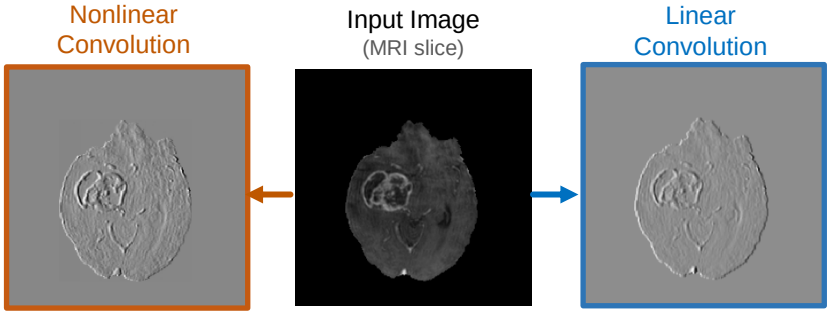


Tumor region is Vague



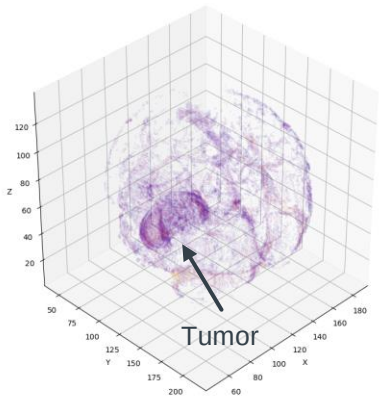
Results: On-chip demonstration for nonlinear convolution process

- Input images: Human brain MRI image (3D) *from BraTS2020 Dataset*
- Convolve each slice with the 3 × 3 sobel kernel (on-resonate, *i.e.*, bias=0)
- On-chip nonlinearity emphasize the boundary, increases contrast
- Inherent tunable nonlinearity of M²OON allows for more effective **feature extraction**



On-chip Covn results

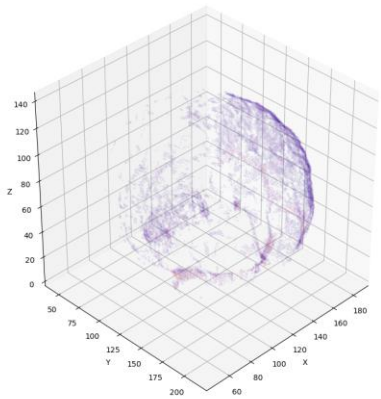
(output > 0.35)



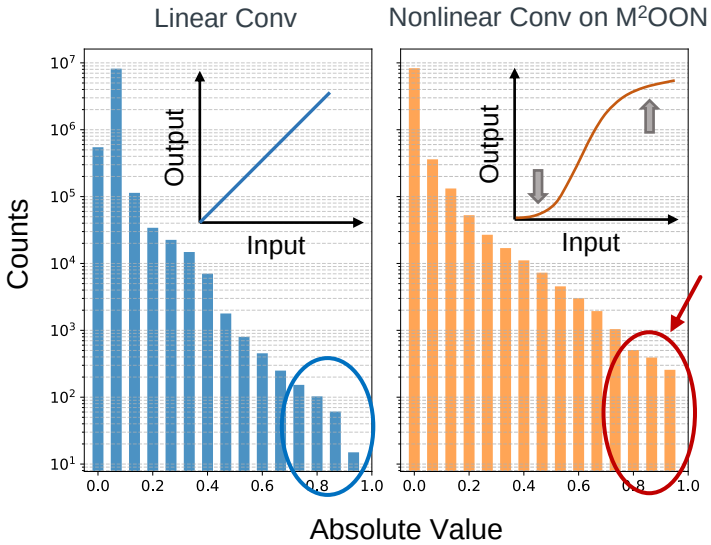
Tumor region is extracted

Linear Covn results

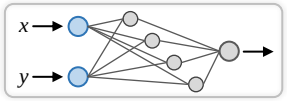
(output > 0.35)



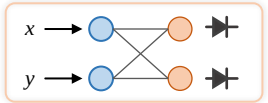
Tumor region is Vague



Results: On-chip demonstration for classification tasks



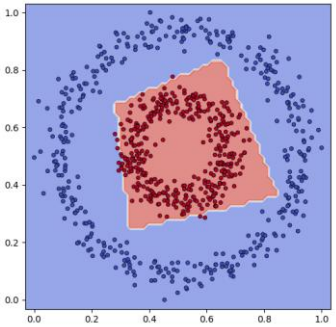
17 *trainable parameters for 2-layer NN*

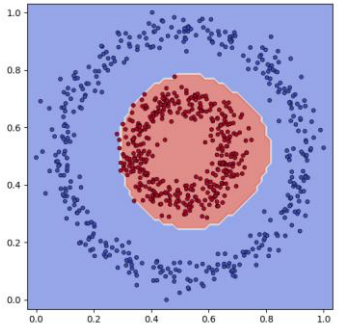


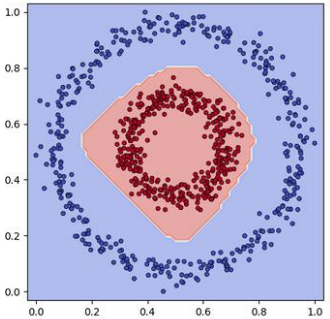
12 *trainable parameters for single-layer* ***ONN***

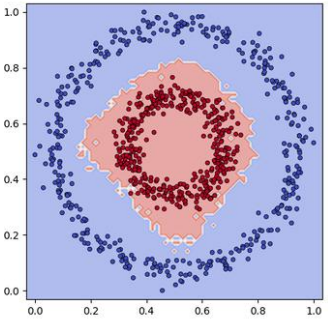
ReLU | Sigmoid | Simulation Result | Testing Result

Circle Distribution

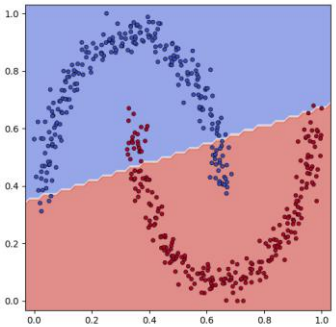


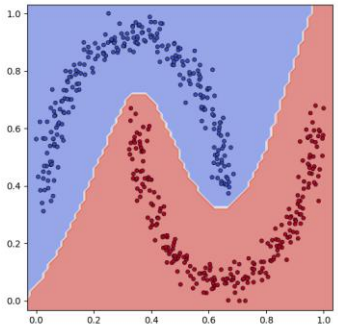


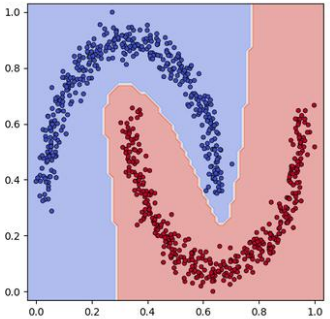


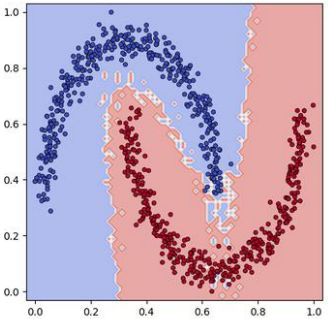


Hoof Distribution

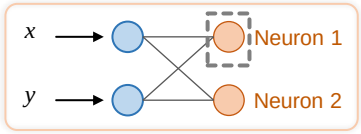


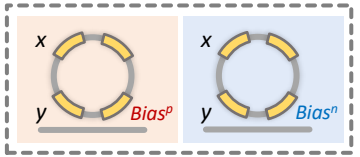




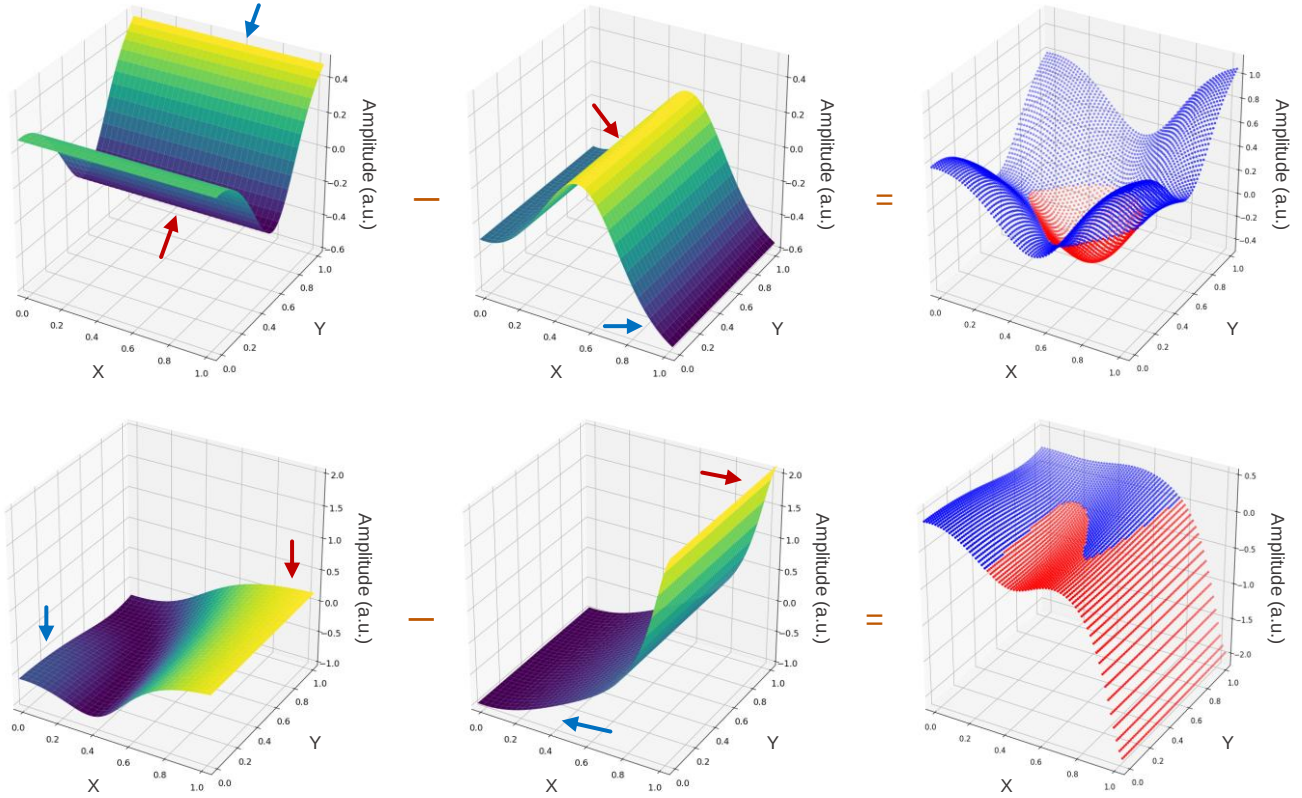


Results: Interpretability of M²OON-based ONN





Neuron 1 Neuron 2



Results: Image recognition with block-circulant optical neuron

Dataset: PTB-XL electrocardiography (ECG)

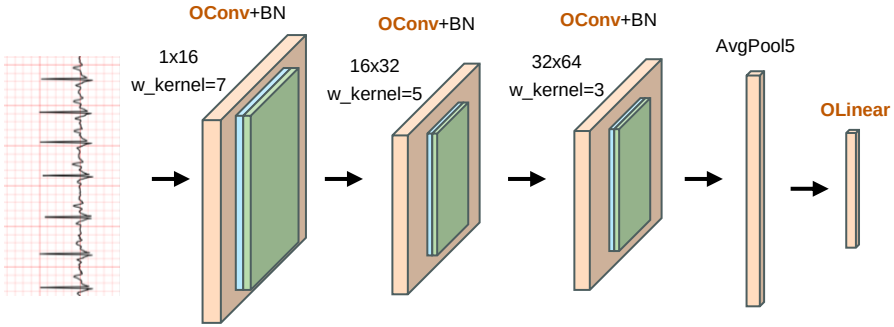
Structure: 3-layer CNN

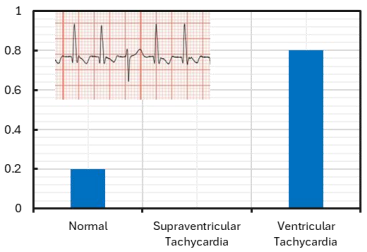
Results:

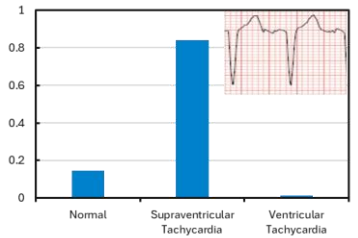
- ~95% measured accuracy for arrhythmia detection

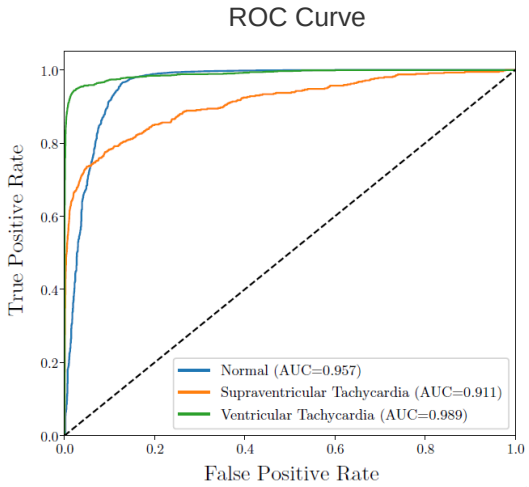
- 6-bit control precision for input encoding
- 8-bit control precision for weight encoding

More complicated datasets and analysis will be discussed in journal version









Summary

- We present a hardware-efficient ONN based on multi-operand MRR to implement tensor operations.
  - — Squeeze tensor operation on a single device
  - — on-chip tunable nonlinearity for higher representability of neural network
  - — >95% measured accuracy on arrhythmia detection task
- An FPGA-based ONN testing platform and AI-assisted hardware-aware training framework are developed.
- Experimentally demonstrated optical convolution process with emphasized features
- More details and complex tasks will be discussed in journal publication

Thank you !

Any Question?

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