

Deep Learning Reconstruction of Optoacoustic images on FPGA

Name: **Habib Ben Abda**

Exam: **System on Chip for Data Analytics and Machine Learning**

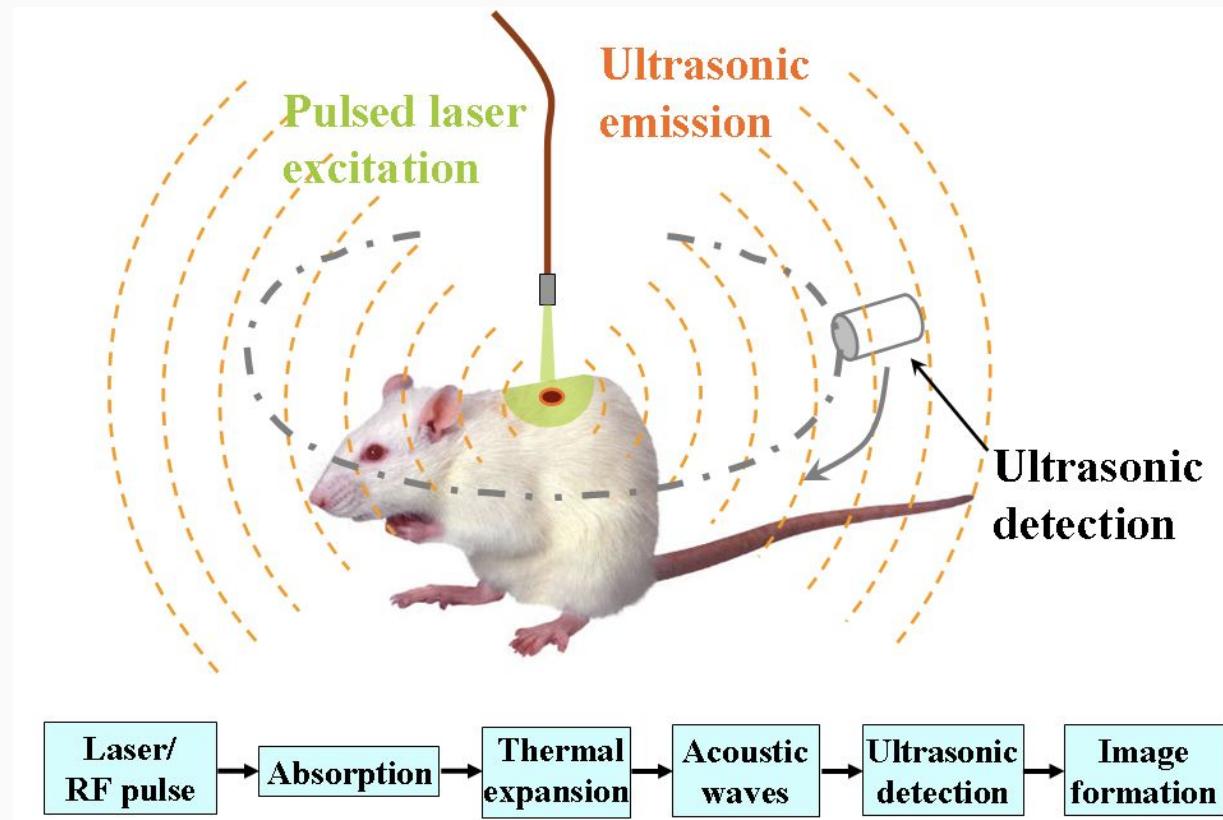
Date: **21/08/2025**



Kria KR260

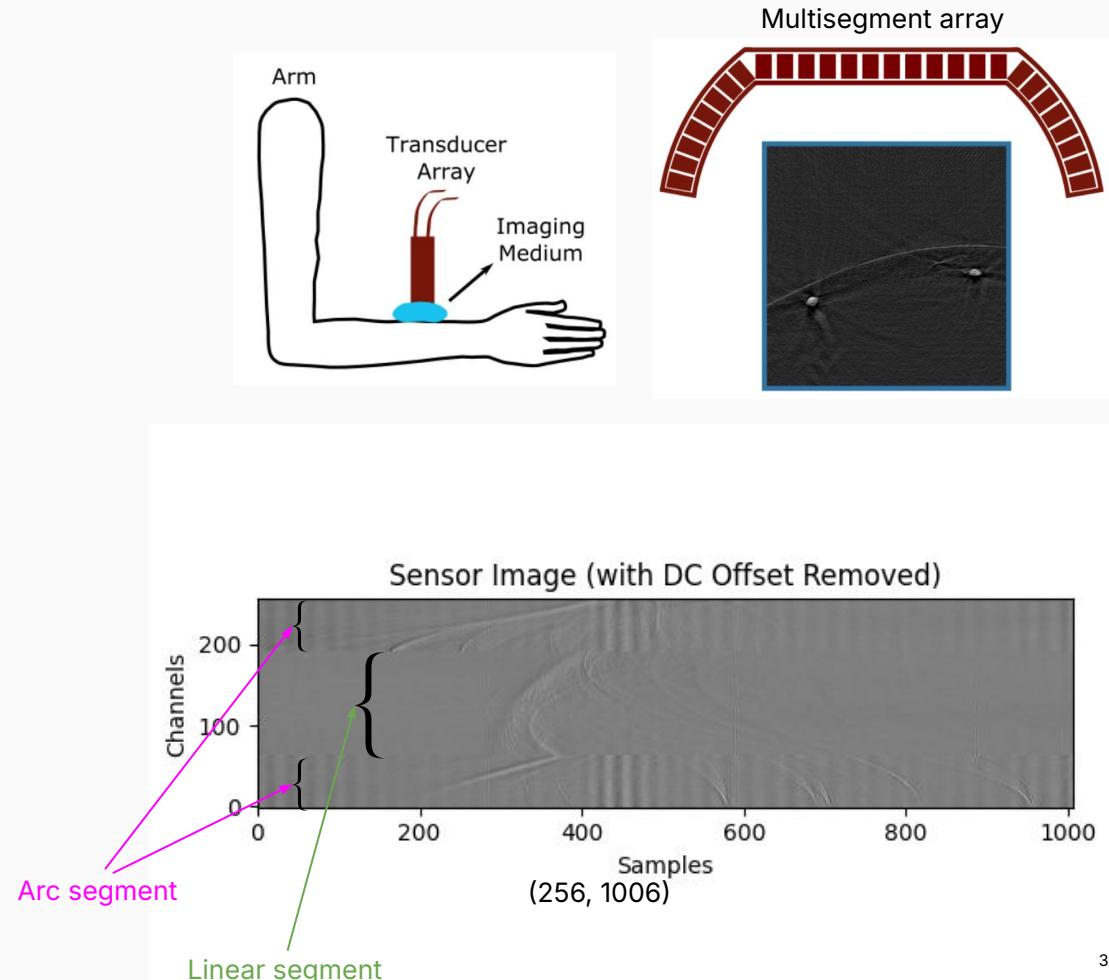
Optoacoustic Imaging

1. Laser pulse generates thermal expansion
2. Pressure wave from expansion detected by ultrasonic receiver



Dataset

- Prof. Dr. Daniel Razansky's Lab
- 4 recordings:
 - Right arm normal
 - Right arm parallel
 - Left arm normal
 - Left arm parallel
- ~ 5500 images
- Float32
- 256 channels, 1006 time samples



Standard Reconstruction

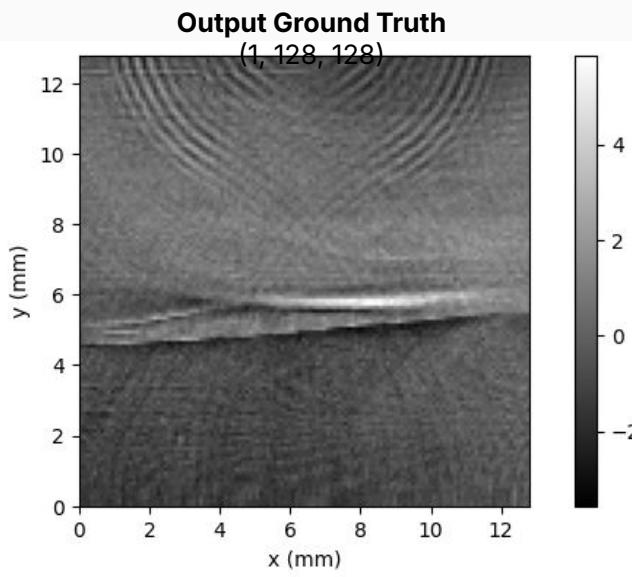
Delay and Sum:

```
for each pixel (x,y):  
    for each channel:  
        d = dist(receiver, pixel)  
        delay = d / speed_of_sound  
        pixel_value += time_signal(delay)
```

- Inverse problem with high computational load
- Data dependency: each pixel involves signals from many sensors
- Inefficient GPU utilization (non-trivial indexing and irregular memory access)

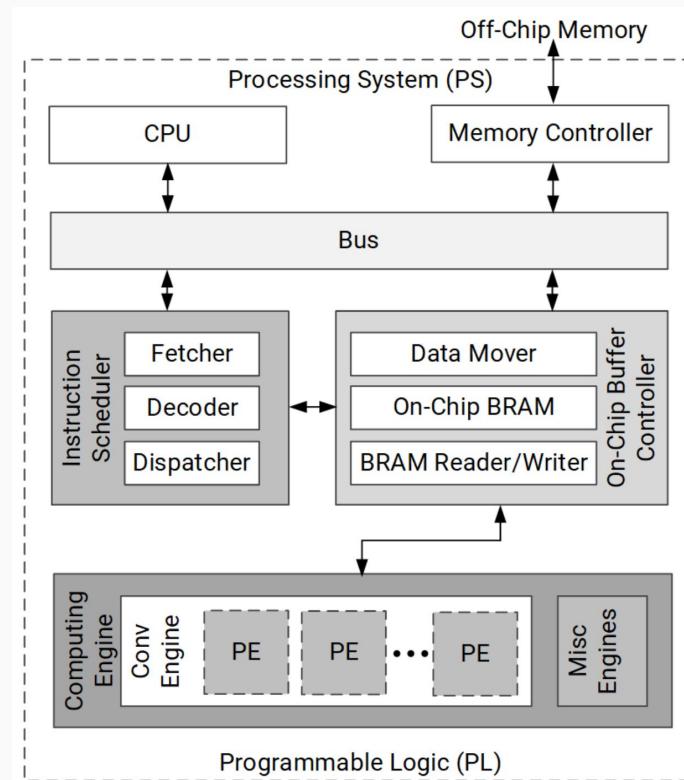
Objective:

- Real time implementation on embedded device
- Use Deep Learning interesting for fast inference



Target Device: AMD Kria™ K26 SOM

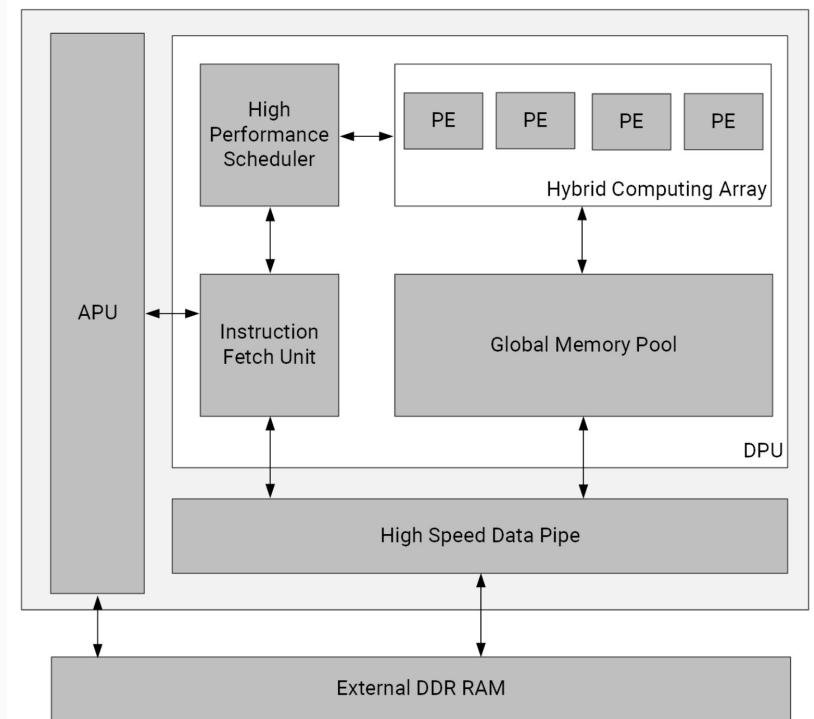
FPGA Fabric	Xilinx Zynq UltraScale+™ MPSoC EV (XCK26)
Deep Learning Processing Unit (DPU)	Up to 1.4 TOPS (peak performance)
CPU	Quad-core Arm® Cortex®-A53 MPCore™ up to 1.5 GHz
Memory	4 GB DDR4 RAM



DPU: microcoded compute engine, optimized instruction set, can support most CNN networks

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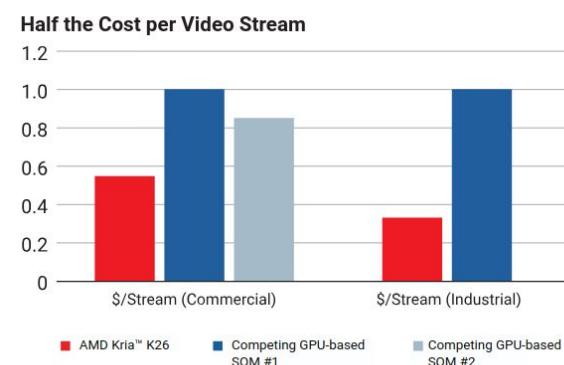
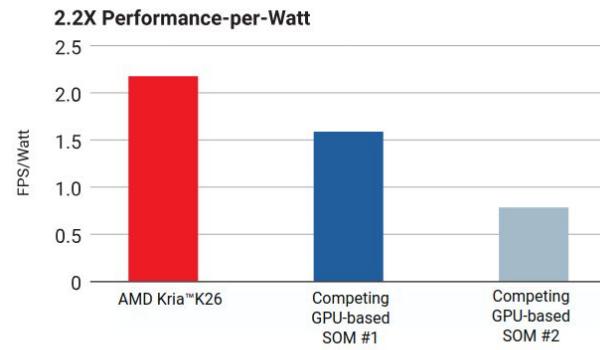
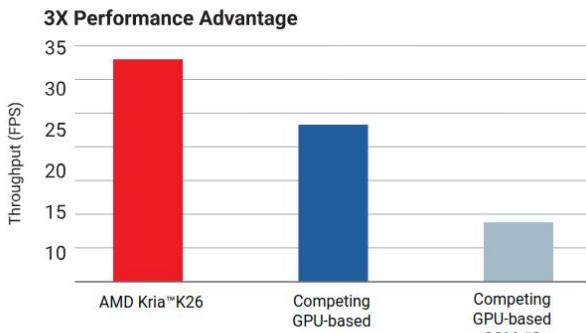


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BENCHMARKS

Video Pipeline with AI

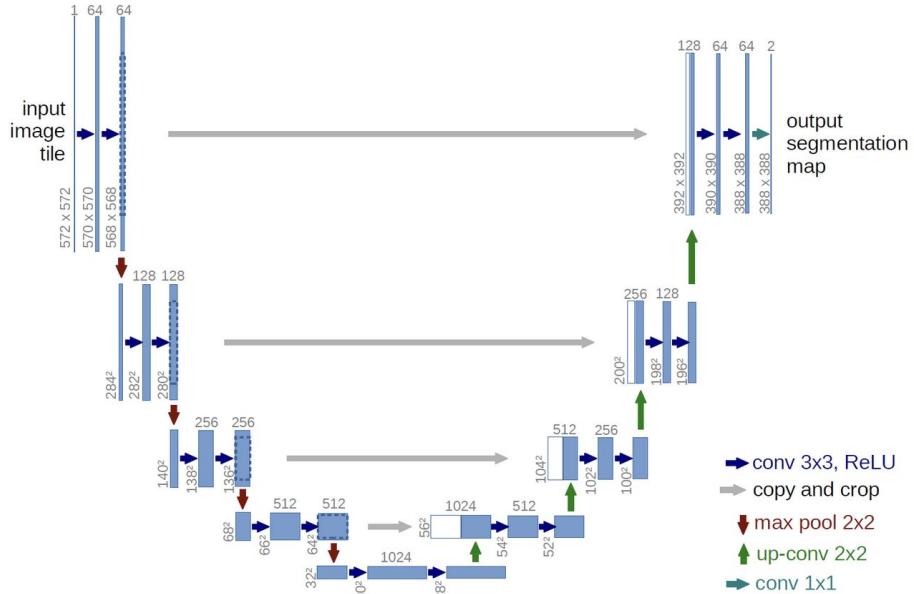


Model choice: U-Net

- One of the best networks for biomedical image segmentation/reconstruction since 2015
- Fast & precise
- CNN based

Can't use directly. Need some adjustments

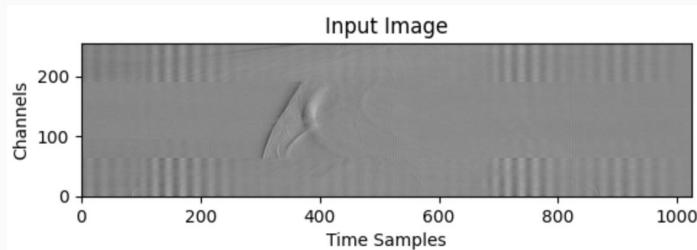
- Different size input and output
- Different number of channels



Preprocessing Pipeline

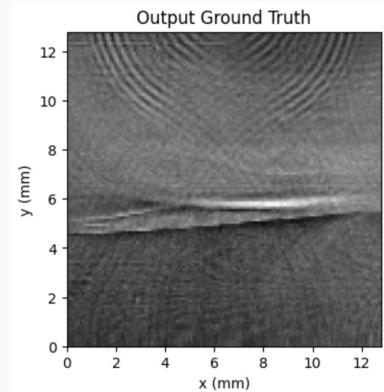
Input:

- Remove DC offset
- Median padding time signal (256,1006) → (256,1024)
- Normalizing (zero mean, unit variance)
- Removing outliers (first ~150 images of each recording)



Generated Labels:

- $(C, H, W) = (1, 128, 128)$
- Corresponds to 250 μ m resolution
- Normalization (zero mean, unit variance)



Vitis-AI

IDE to deploy AI models and accelerate AI inference on AMD hardware platforms

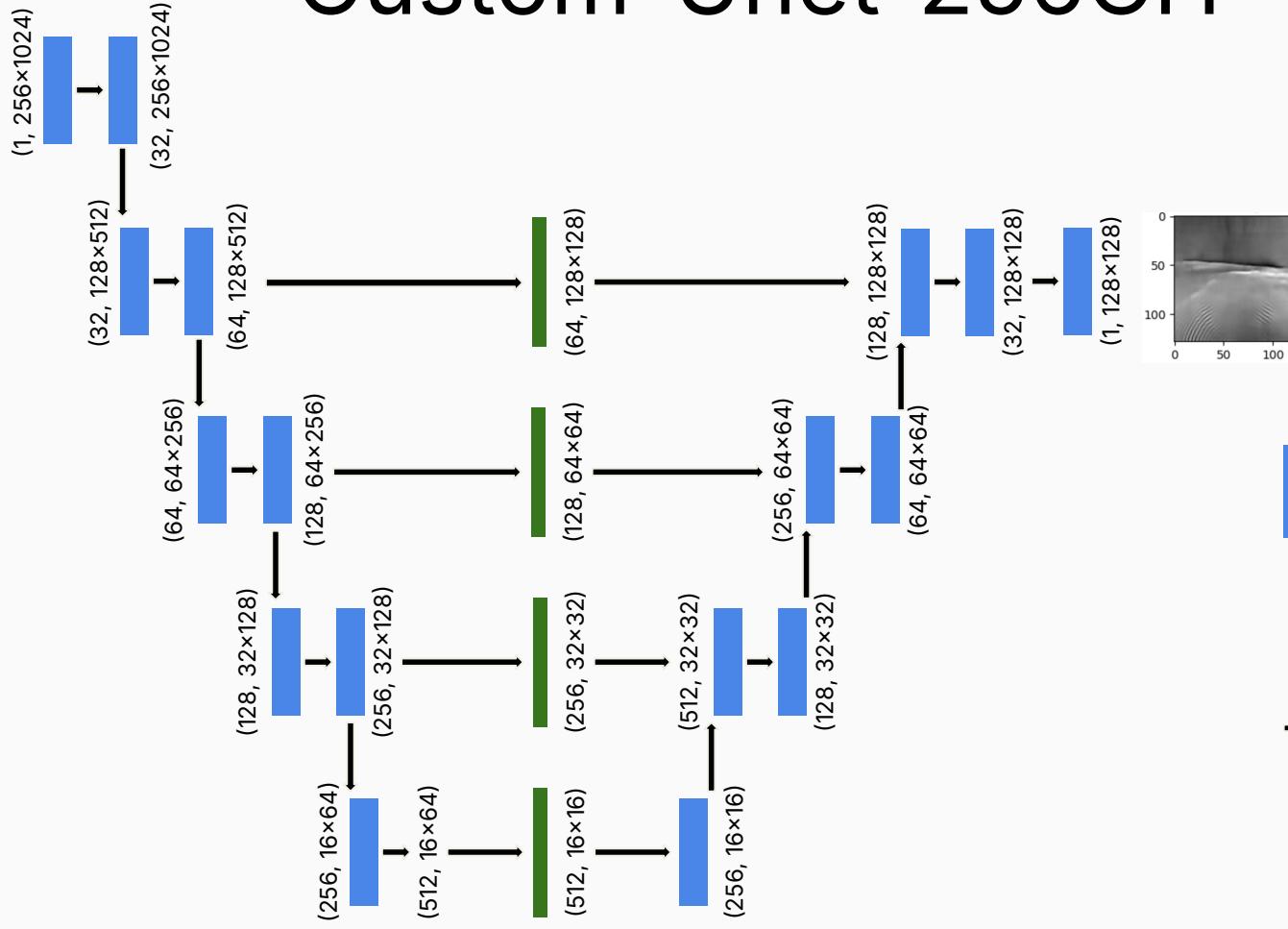
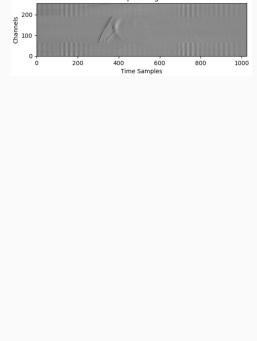
Vitis-AI Inspector:

Check if model is supported by DPU

- Can't use adaptive pooling
- Can't use resizing
- Can't use cropping function or any other custom functions
- Can't use random sized kernels and strides

[VAIQ_NOTE]: All the operators are assigned to the DPU

Custom-Unet-256CH



Conv 2D
BatchNorm
ReLU

Conv 2D

Skip
connection

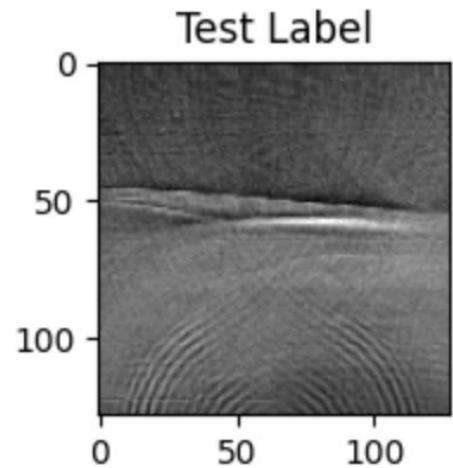
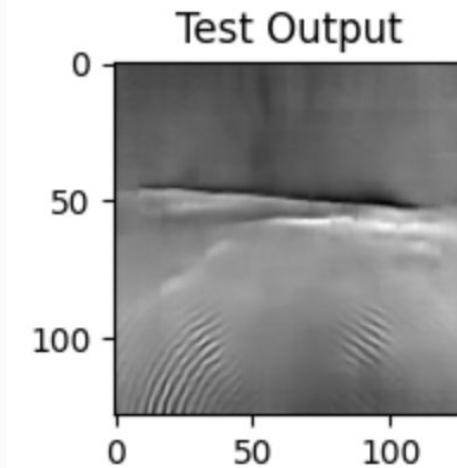
Max Pooling

Upsampling

Result

Custom-Unet-256CH

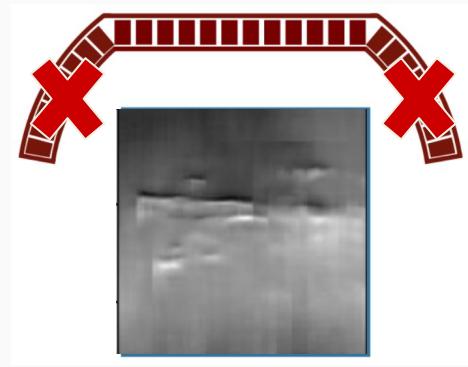
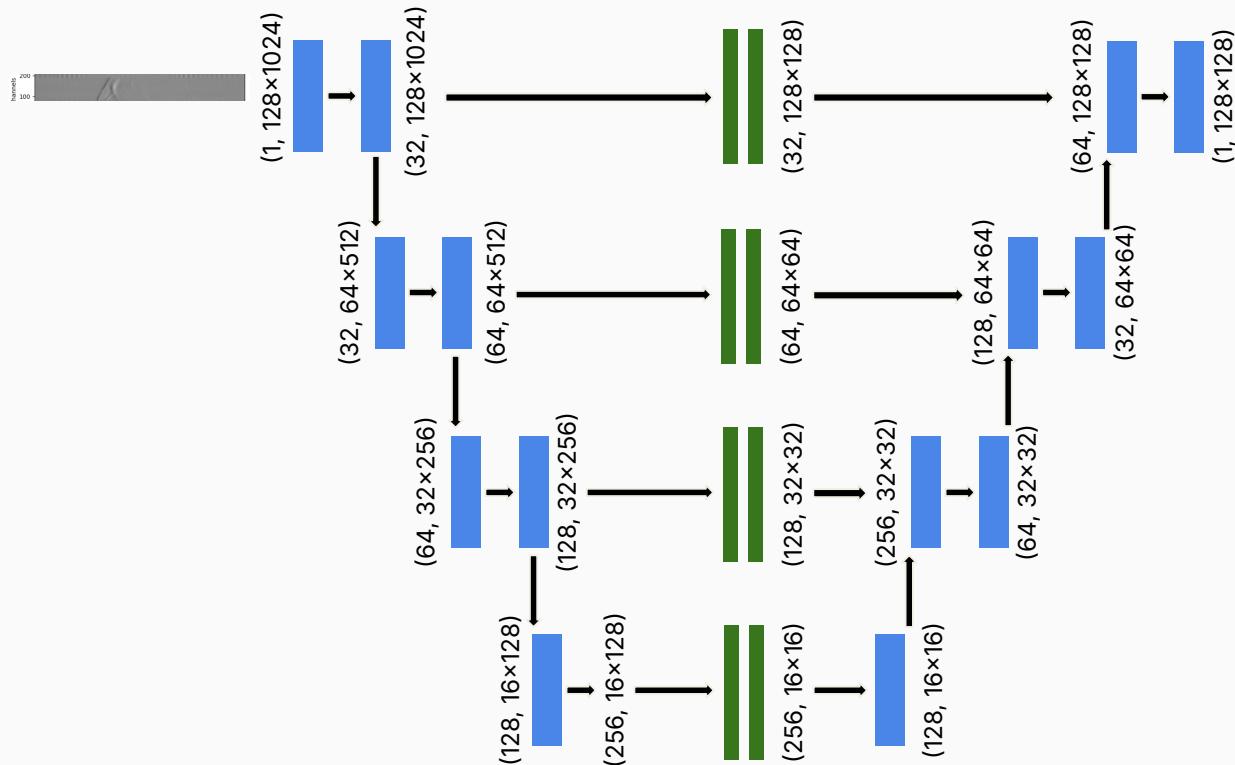
MSE on test set	0.5672
Parameter size	28.8 MB
Estimated Total size	617 MB
Inference time (on laptop)	166 ms → 6 fps



With DPU acceleration, very realistic to reach real-time imaging

Custom-Unet-128CH

Taking only linear segment



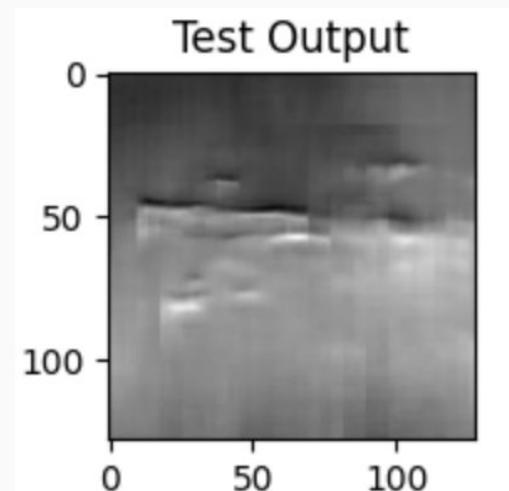
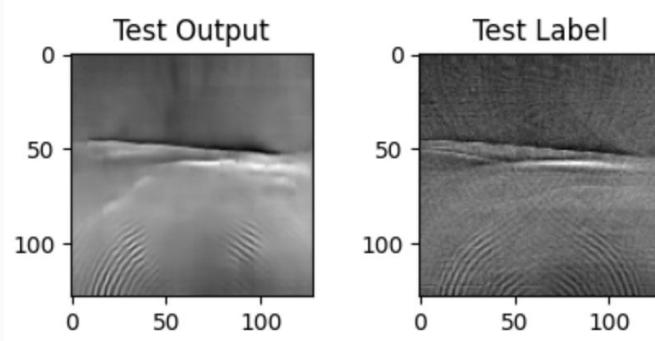
Result

Custom-Unet-256CH

MSE on test set	0.5672
Parameter size	28.8 MB
Estimated Total size	617 MB
Inference time (on laptop)	166 ms → 6 fps

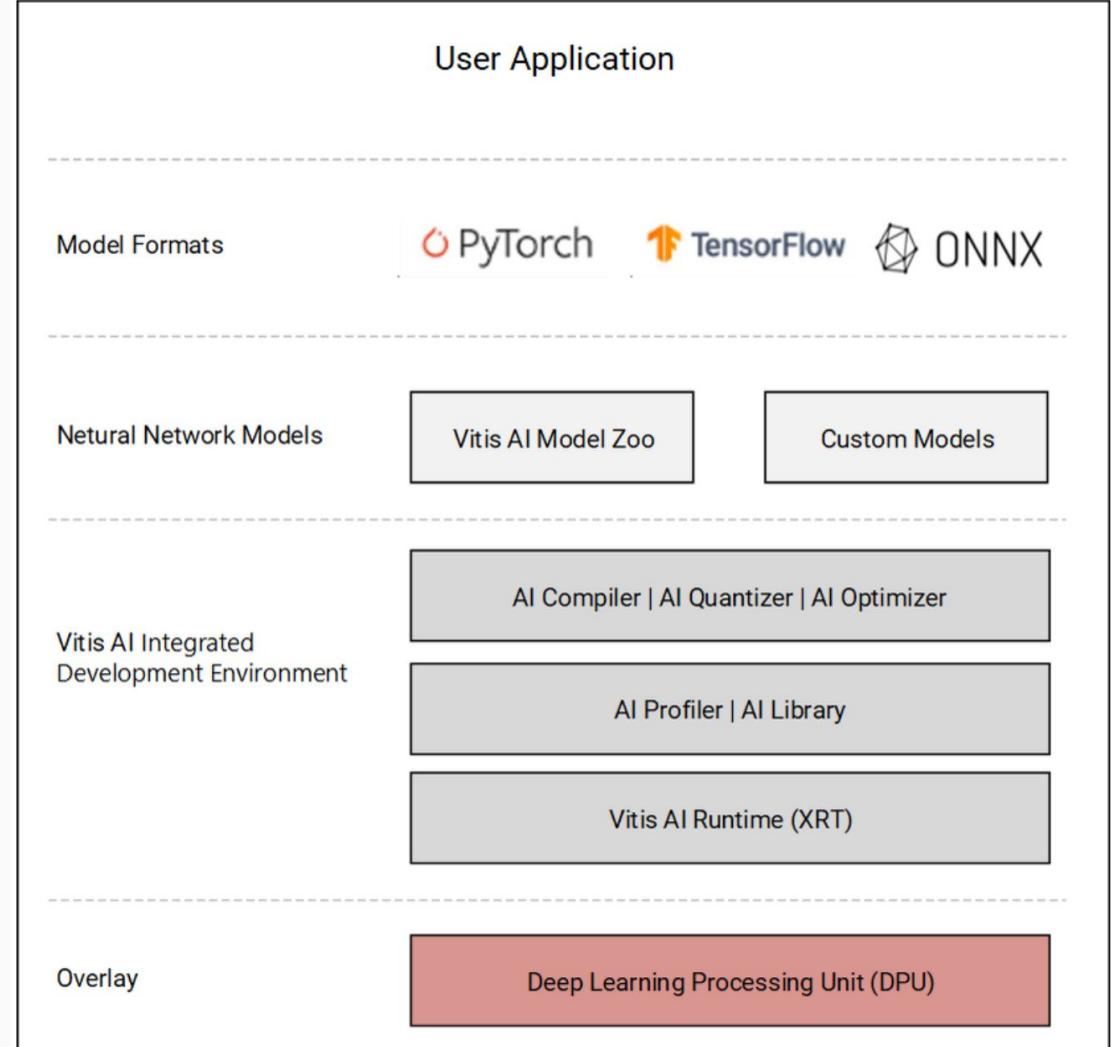
Custom-Unet-128CH

MSE on test set	0.7034
Parameter size	7.87 MB
Estimated Total size	301 MB
Inference time (on laptop)	87ms → 11.5fps



Vertical resolution lost

Development flow



Quantization & Deployment

Before Quantization

MSE: 0.5672

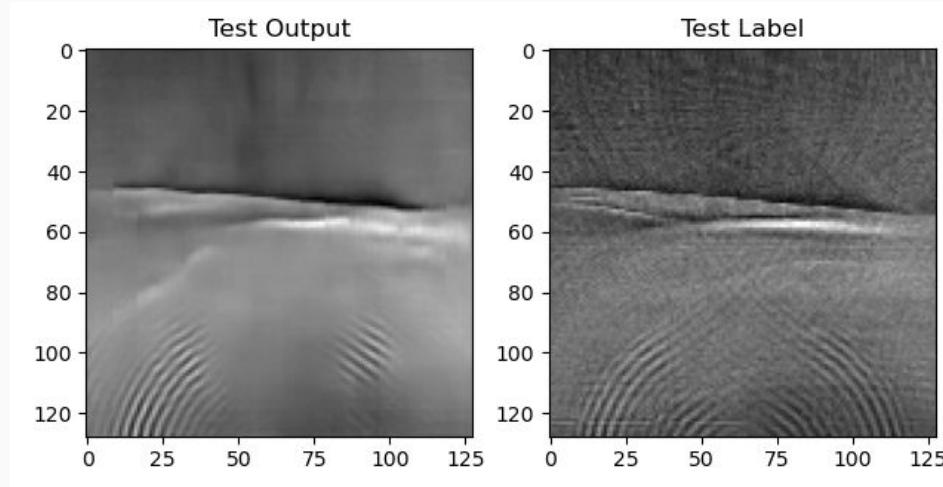
Params size: 28.8 MB

Post training quantization (Float32 → Int8)

MSE: 0.5706

Params size: 7.5 MB

- Smaller than 4Gb DDR4



→ Generated .xmodel file deployable on FPGA

Conclusion

Main tasks:

1. Generated dataset
2. Optimized model for DPU while preserving accuracy
3. Explored subchannel sampling
4. Quantized the model using Vitis-AI tool and generated deployable model

→ Proof of concept: **can implement “real-time” optoacoustic imaging on Kria FPGA using deep learning**

Limitation: Generalization

Thank you!

Q&A

Remarks or less useful

- Don't have display connector nor ethernet port or router
- ROS on KR260: <https://github.com/amd/Kria-RoboticsAI>
- Youtuber 1, getting started: <https://www.youtube.com/watch?v=N6UBuat8f2U>
- Youtuber 1 ai kv26: https://www.youtube.com/watch?v=L_Zd9R4Zeil
- Mnist github:
https://github.com/Xilinx/Vitis-AI-Tutorials/tree/1.4/Design_Tutorials/09-mnist_pyt
- Resnet github:
https://github.com/Xilinx/Vitis-AI/blob/3.0/src/vai_quantizer/vai_q_pytorch/example/resnet18_quant.py
-

Useful

- Vitis AI compression flow:
<https://docs.amd.com/r/en-US/ug1414-vitis-ai/Vitis-AI-Quantizer>
- KR260 AMD user guide:
<https://docs.amd.com/r/en-US/ug1092-kr260-starter-kit/Summary>
- Youtube video Useful for presentation:
<https://www.youtube.com/watch?v=7JmM94AJda0&pp=ygUZdHJhaW4gbW9kZWwgd2l0aCB2aXRpcyBhaQ%3D%3D>
- Kr26 doc page:
https://xilinx.github.io/kria-apps-docs/kr260/build/html/docs/10gige_vision_camera/10gige_vision_camera_landing.html#tutorials
-

Useful

- Pytorch pruning: https://docs.pytorch.org/tutorials/intermediate/pruning_tutorial.html
- Mouser good doc kr26:
<https://www.mouser.com/pdfDocs/wp529-som-benchmarks.pdf>

Exam structure:

- **Suggested Structure:**
 - Goal of the project
 - Methodology used
 - Results achieved
 - Comparison to state-of-the-art
- **Be Prepared** to answer detailed follow-up questions.

Quantization vitis-ai:

<https://docs.amd.com/r/en-US/ug1414-vitis-ai/Running-Quantization-and-Getting-the-Result>