

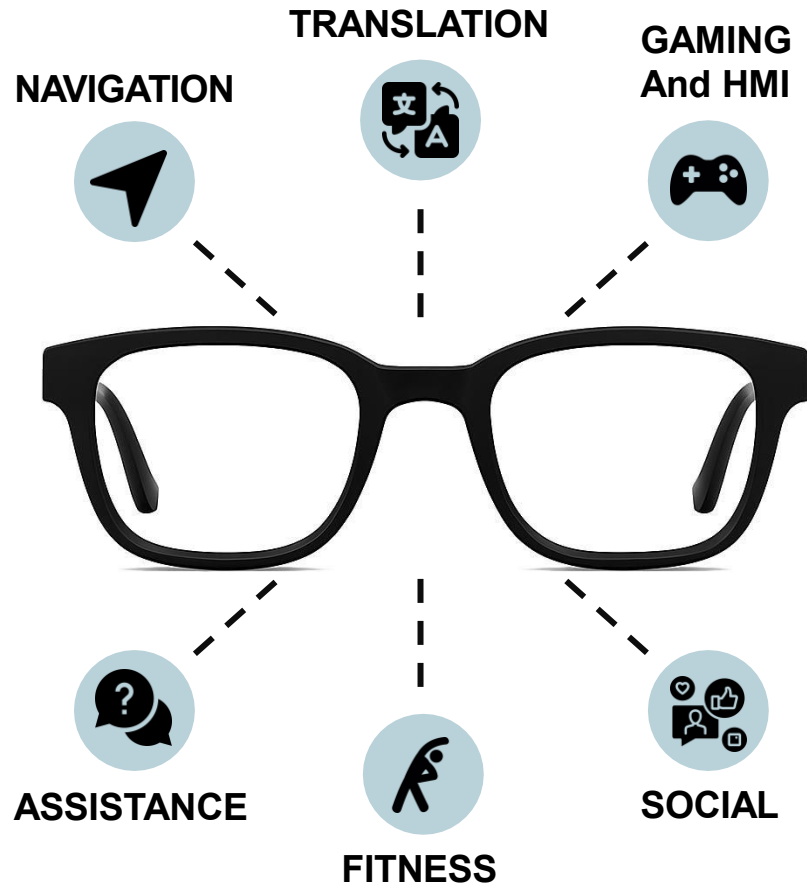
RVEdge-Vision: A Fully Open,
Ultra-Efficient On-Device AI
Platform for Smart Eyewear
Michele Magno

2026 – RISC-V Summit Bologna

Credits: Mayer, Muller, Bonazzi, Moosmann, Celik.



Smart Glasses as an Edge Platform



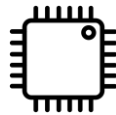
Wearables Are Going Mainstream

Growing demand for hands-free, context-aware computing



Battery Life Is a Bottleneck

Continuous sensing & vision require ultra-low power solutions



Edge AI Is the Future

Research is shifting towards local, efficient processing

Motivation – Background

Ray-Ban Meta



Rokid Glasses



Solos AirGo V



XREAL Air 2 Ultra



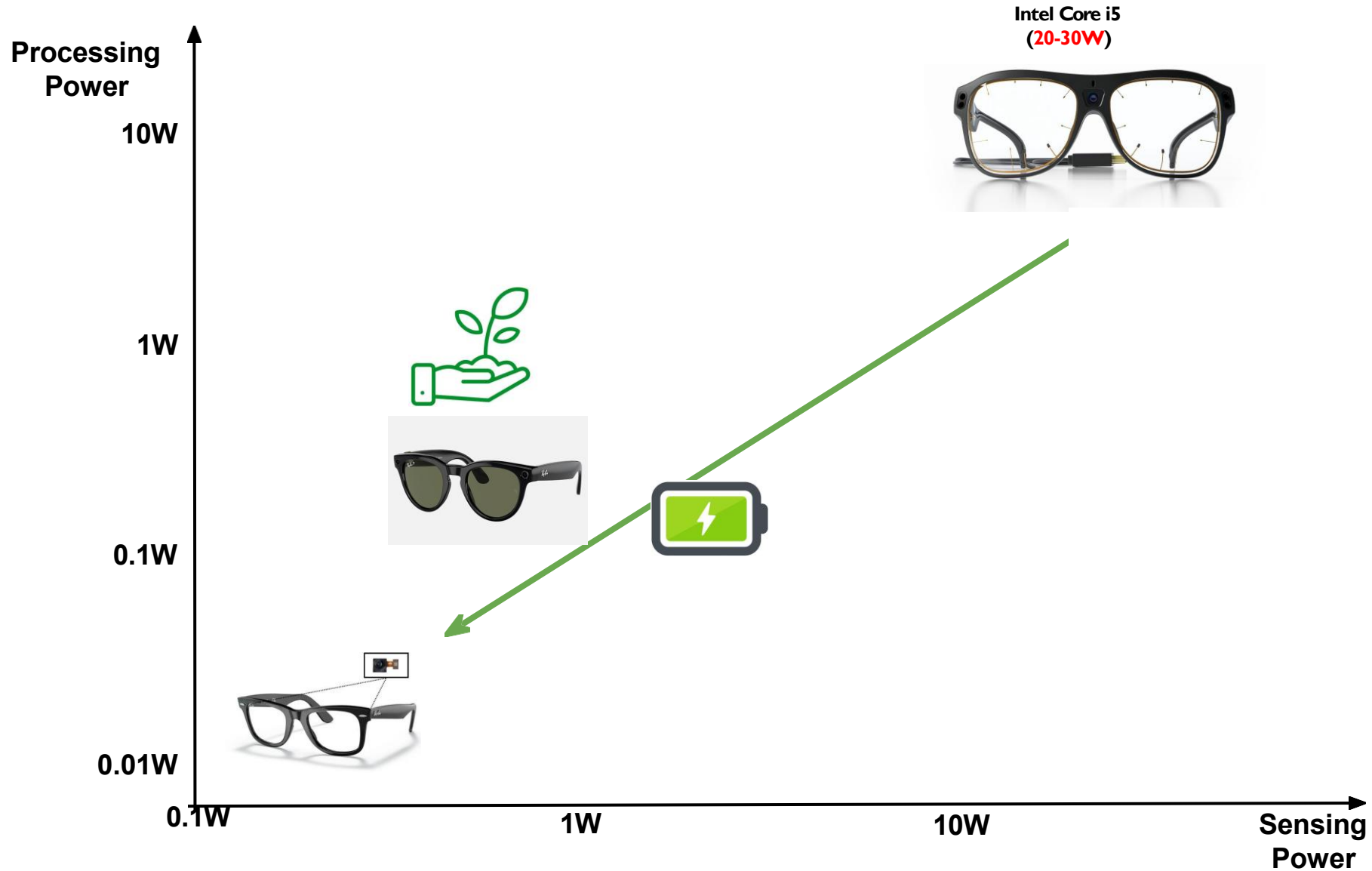
Recent Trends:

- Greater HW/SW complexity
- More functionality per area
- Better sensors

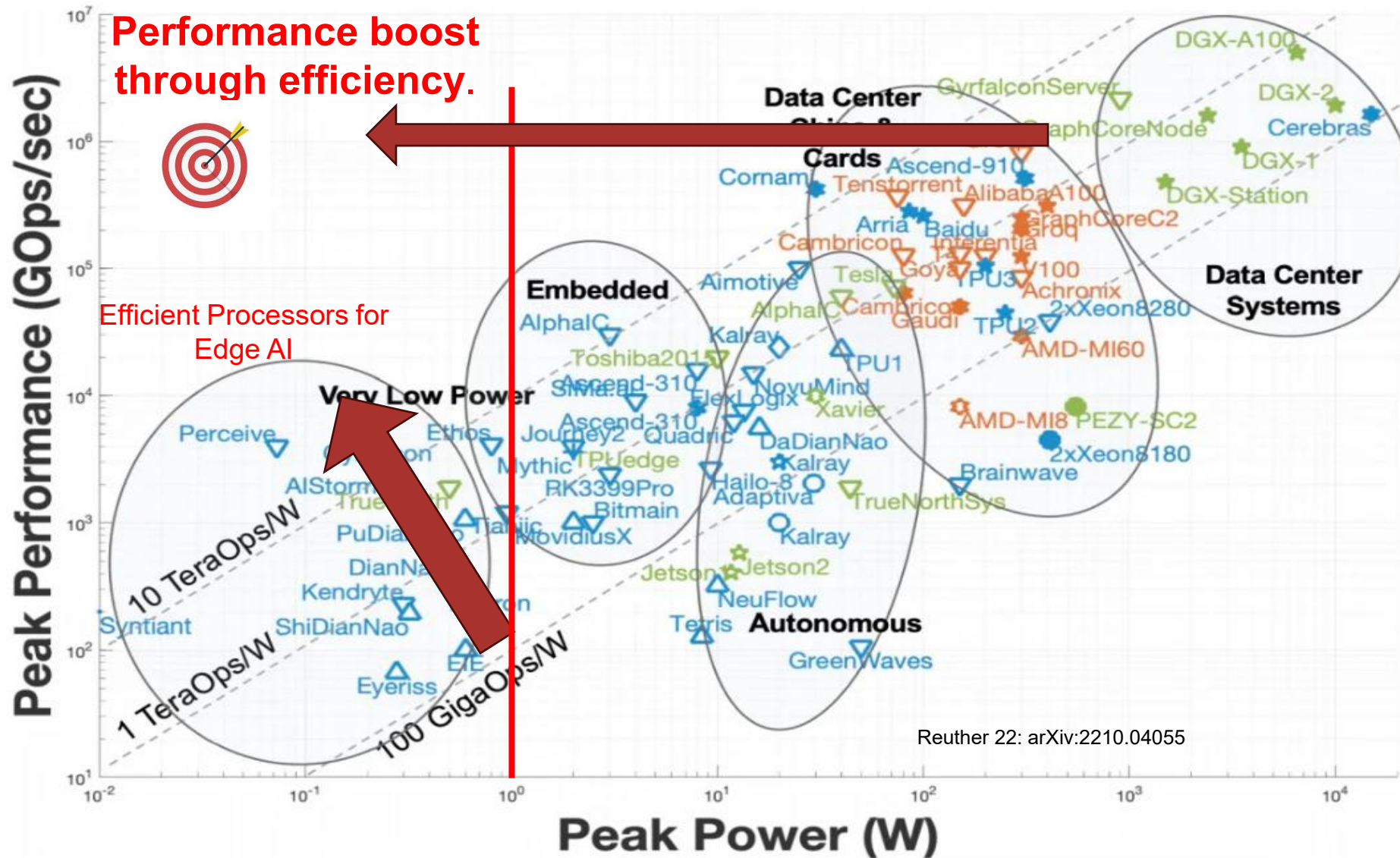
Biggest Challenges:

- Energy storage/consumption/source
- On Device processing

How to extend the lifetime?



Challenges of Bringing AI to the Edge



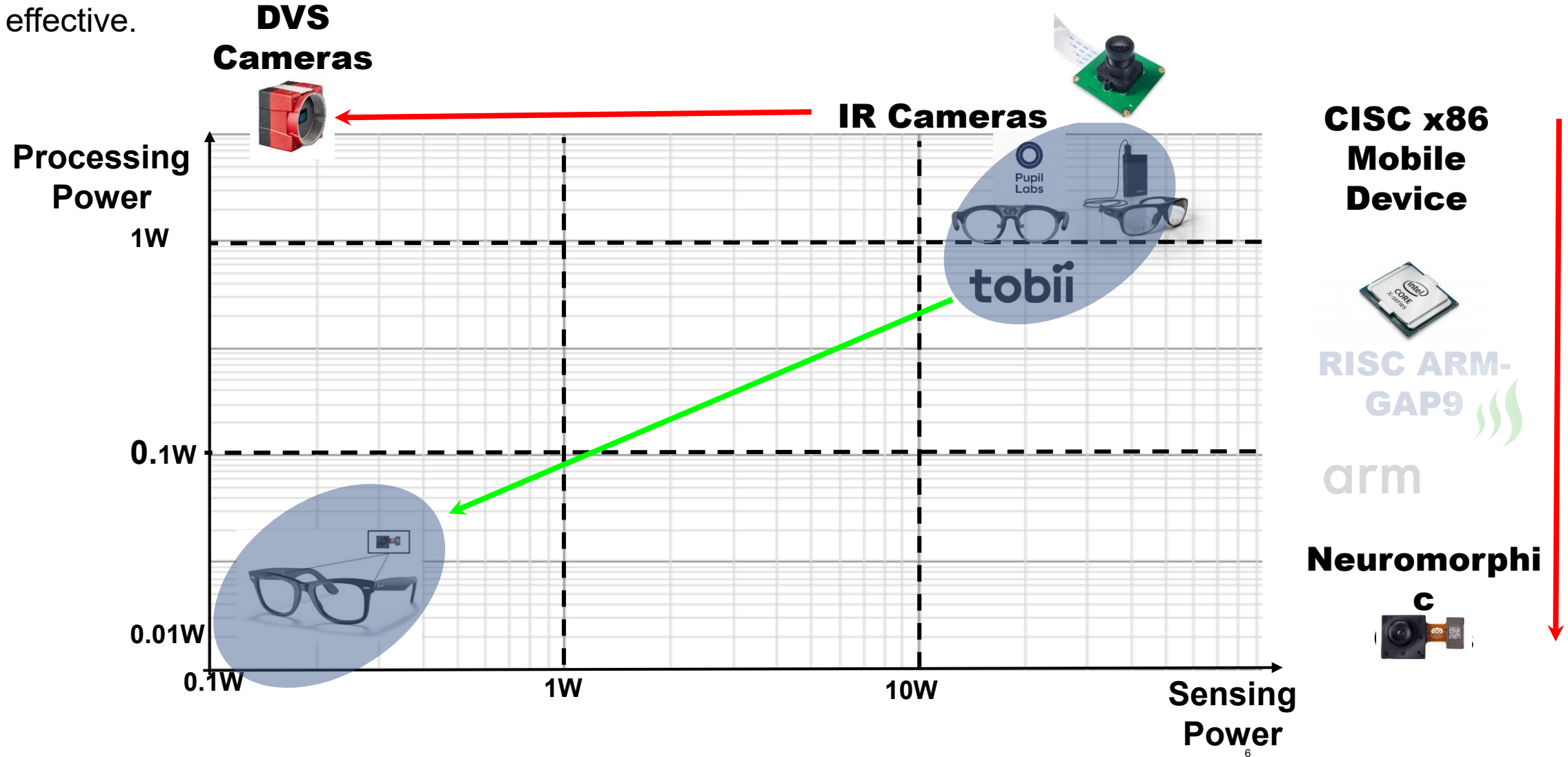
Nvidia GPUs

Advanced AI

Hardware alone is not enough— efficient systems, model compression and software optimization can reduce memory and compute needs by up to 90%, enabling real-time AI even on sub-Watt devices.

Application-Specific Sensors Reduce Data Load

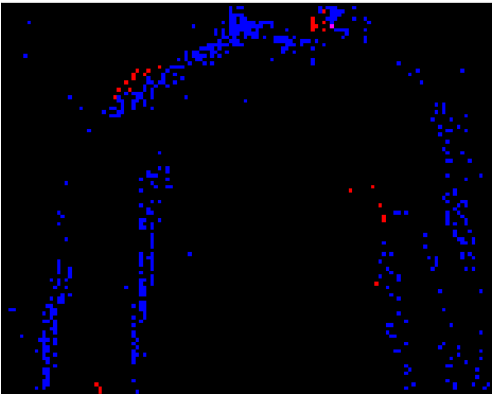
- Instead of using high-bandwidth cameras for every application, **specialized sensors** can be more effective.



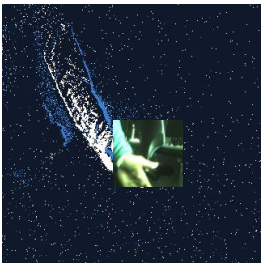
Energy Efficient and Low Latency Smart Sensors

Edge AI & Sensor Fusion Efficient processing and AI-driven adaptation

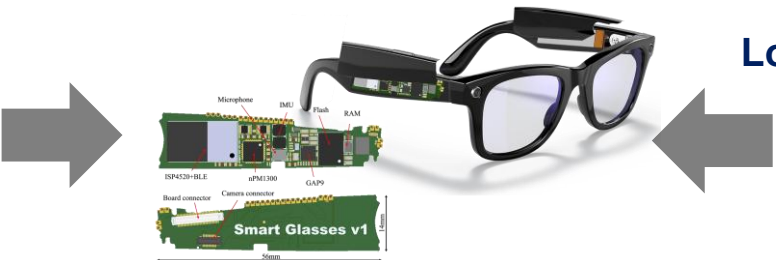
10-1000x more intelligence
10-100x Less Latency



1000-10000x Less data
1-100x Lower Power

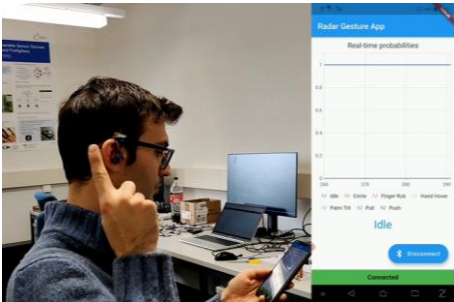


Applications Specific: Intelligent
Smart glasses



Low Power Sensors & Efficient Hardware Design

100-10000x Efficiency



Eff. Wireless Communication
(Optimized data transfer, seamless interaction).

Open Smart Glasses Platform



Development Platform

Visually Appealing

On-device AI execution

Privacy Conscious

Ultra-low Power

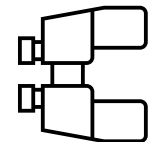
Multi-day Battery runtime



Wake-up Sensors



On-Board Inference



Vision Sensors



Spatial Sensors



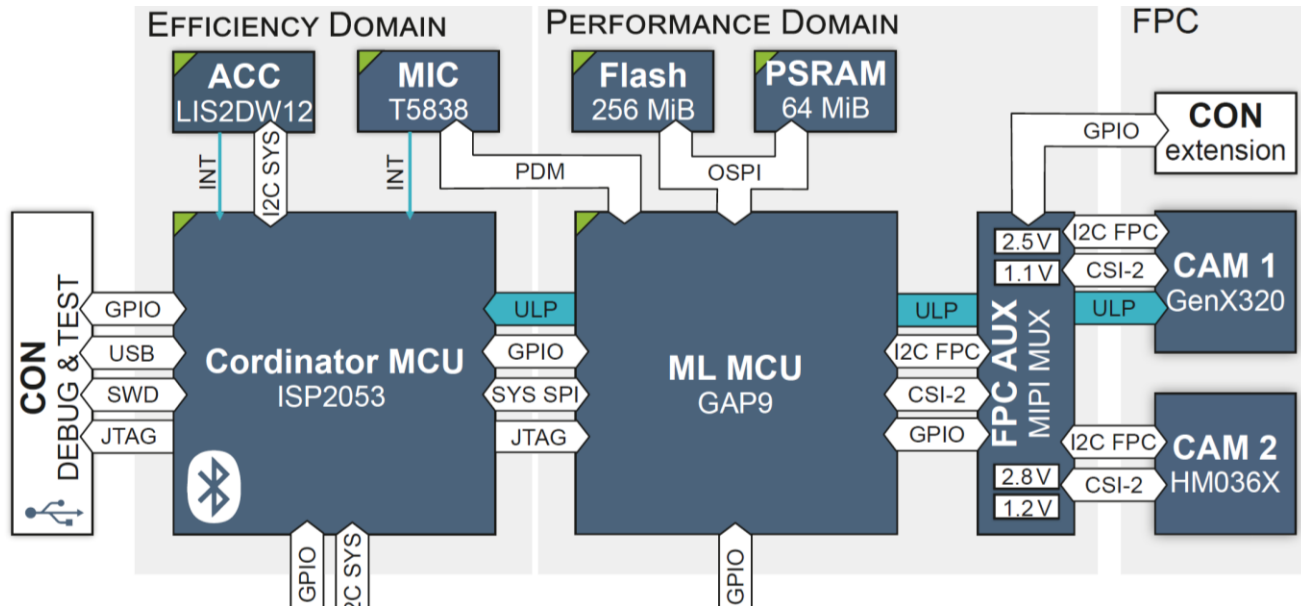
Battery Operated



BLE

Hardware Architecture and Sensors

Open Smart Glasses



Processing

- GAP9 – 9 RISC-V core compute cluster with AI accelerator - L3: 256 MB RAM & 256 MB Flash
- nRF5340 – Cortex-M33

Connectivity

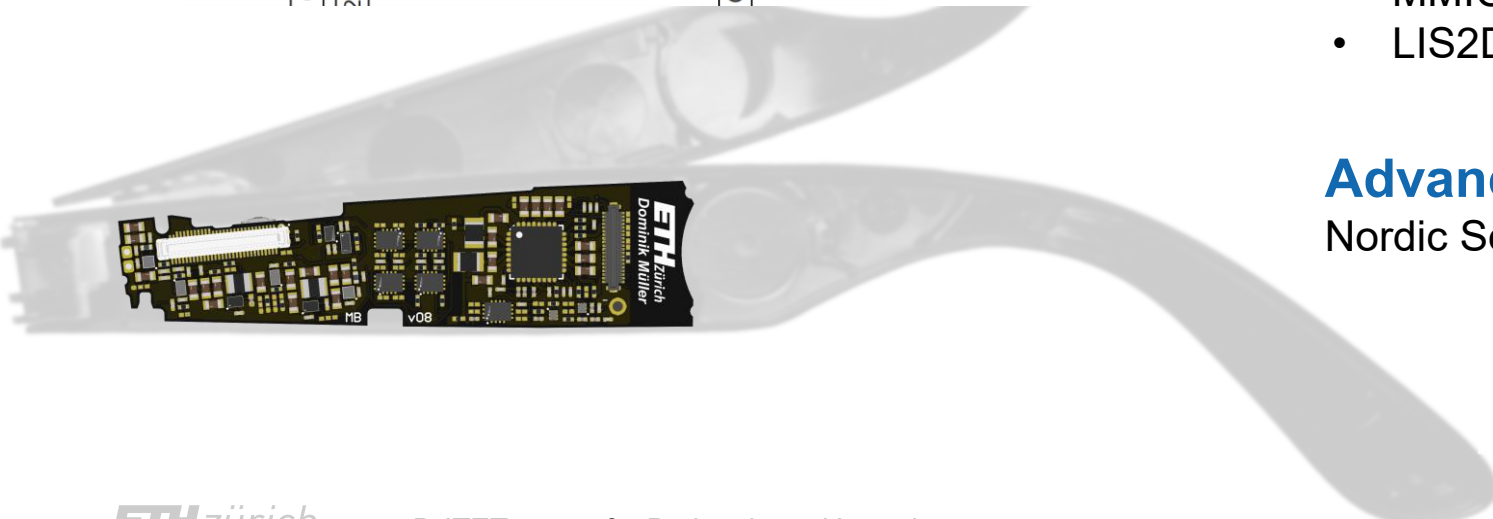
Bluetooth 5.4, BLE, BT Mesh, Thread, Zigbee, Matter, ANT

Sensing

- MMICT5838 – Microphone
- LIS2DW12 – Accelerometer

Advanced Power Management & Monitoring

Nordic Semiconductor nPM1300 – fine-grain power gating



New Platforms for Edge Computing: Importance of Hardware Awareness

Near-Sensor Processing



GOPs/s

10000

1000

100

10

1

Trends:

- Optimized Accelerators
- Parallel Architectures
- Custom Sensing SiP



MCU with Accelerators



150 GOPS/s @0.05W 10\$

Neuromorphic SoC

1 GOPS/s
@5mW 7\$



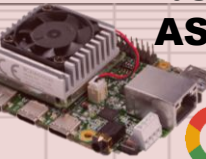
MCU

0.6 GOPS/s
@0.1W 4\$

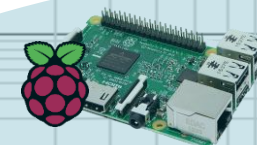


Embedded ASIC

1 TOPS/s
@2.5W 80\$



4 TOPS/s @3W 150\$



6.2 GOPS/s @6W 50\$

Linux-Capable CPU

FPGA GP-GPU

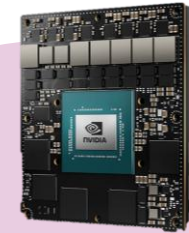
NVIDIA

275 TOPS/s @15-60W 2000\$



XILINX

1 TOPS/s @20W 1000\$



0.01W

0.1W

1W

10W

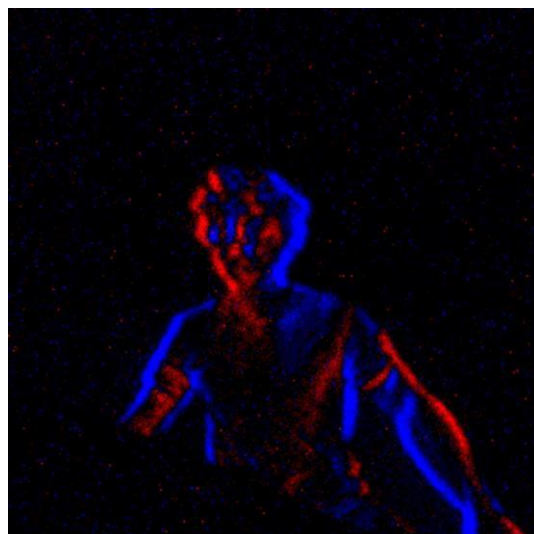
Power/Thermal Envelope

Smart Glasses – Frame Flex



GenX320 [2]

Event-based Vision Sensor



320 x 320 px
>140 dB



6.7 x 4.7 x 1.58 mm

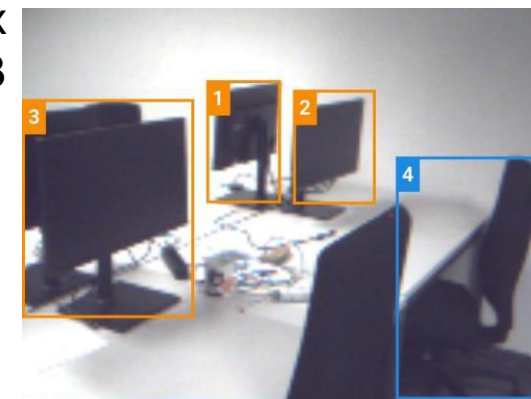
ADAP UT-P2023 [4]

MEMS Speaker

HM0360 [3]

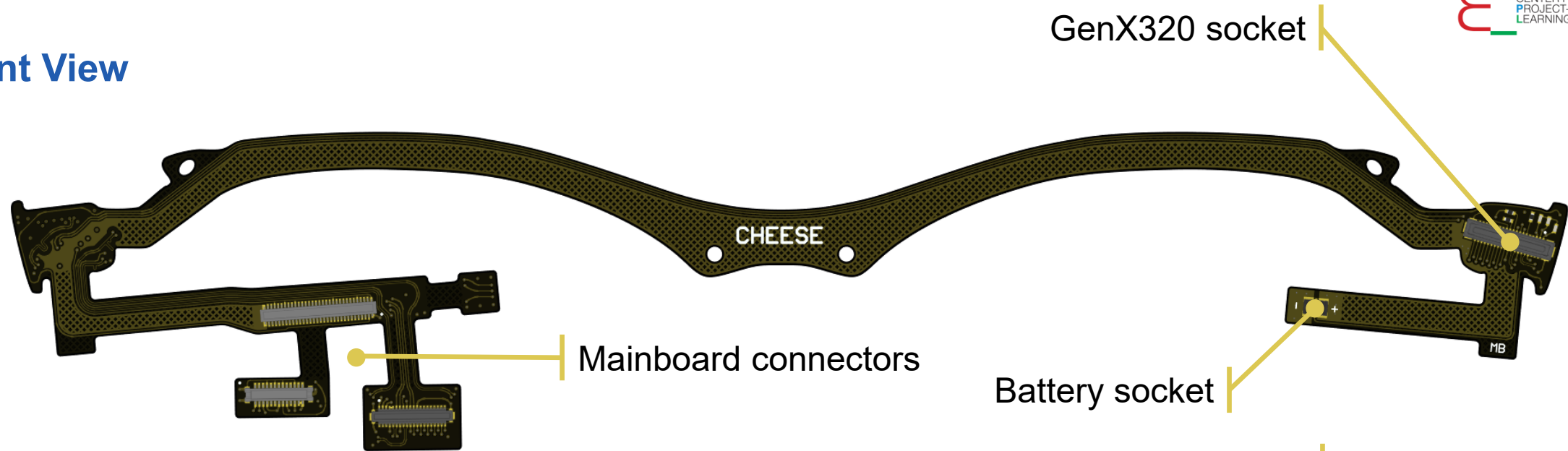
ULP CMOS Image Sensor

640 x 480 px
85 dB



Frame FPC

Front View

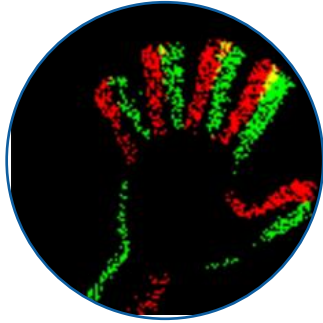


Back View

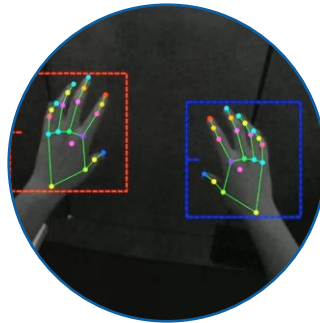


Use-Case Gesture Recognition

Event-based Gesture Recognition



Event-based
dataset for
robust gesture
recognition



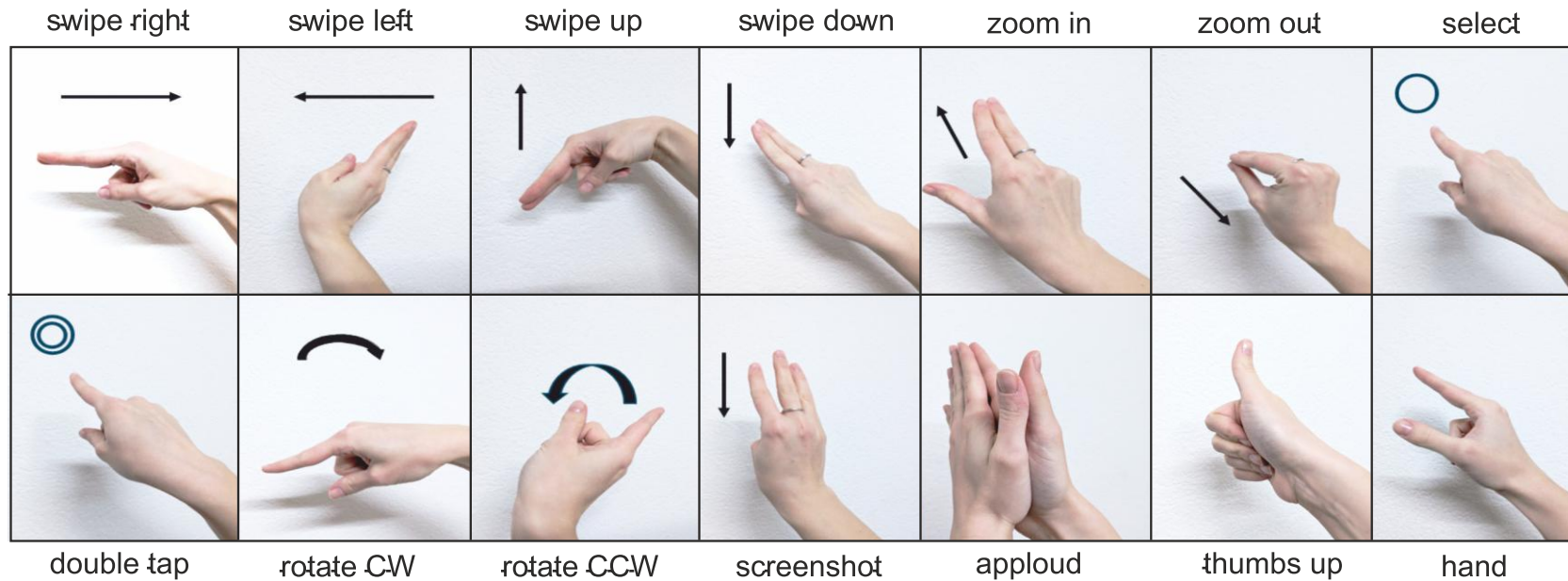
Simultaneous
gesture
recognition and
hand tracking



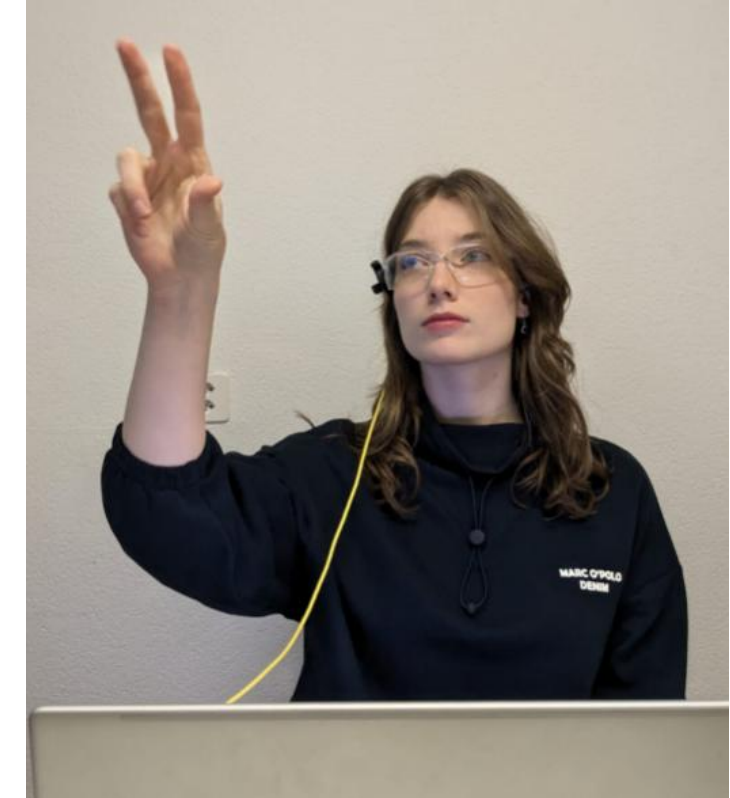
Deployment on
custom
ULP HW



Event-based Gesture Recognition Dataset



#Subjects	# Gestures	# Sequences	Avg. Sequence length (s)	# Frames
19	14	988	18	375,440



Event-based Gesture Recognition Dataset

swipe right

swipe left

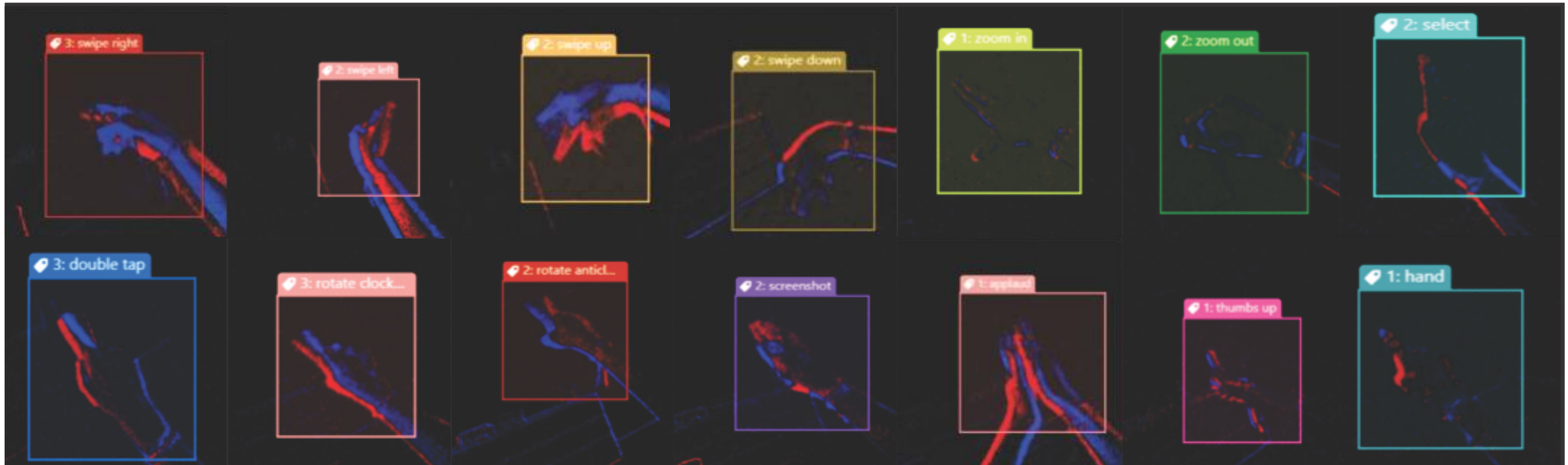
swipe up

swipe down

zoom in

zoom out

select



double tap

rotate CW

rotate CCW

screenshot

apploud

thumbs up

hand

Event-based Gesture Recognition

Evaluation of Gesture & Bounding Box Prediction

BEST TEST RESULTS PER ARCHITECTURE (STRICT SUBJECT HOLD-OUT, $T=10$, STRIDE 5). PER-CLASS RESULTS FOR THE BEST MODEL (R(2+1)D, DROP G12/13, AUG, BUNDLED; TEST ACCURACY 83.94%).

Architecture	#Params	Test Acc.	Macro F1	Wtd. F1
MobileNet	3 776 855	61.79%	0.486	0.609
DD-TCN	526 545	63.79%	0.486	0.638
TCN	493 137	69.06%	0.551	0.690
TSM	589 887	79.62%	0.731	0.795
R(2+1)D	627 407	83.94%	0.781	0.840

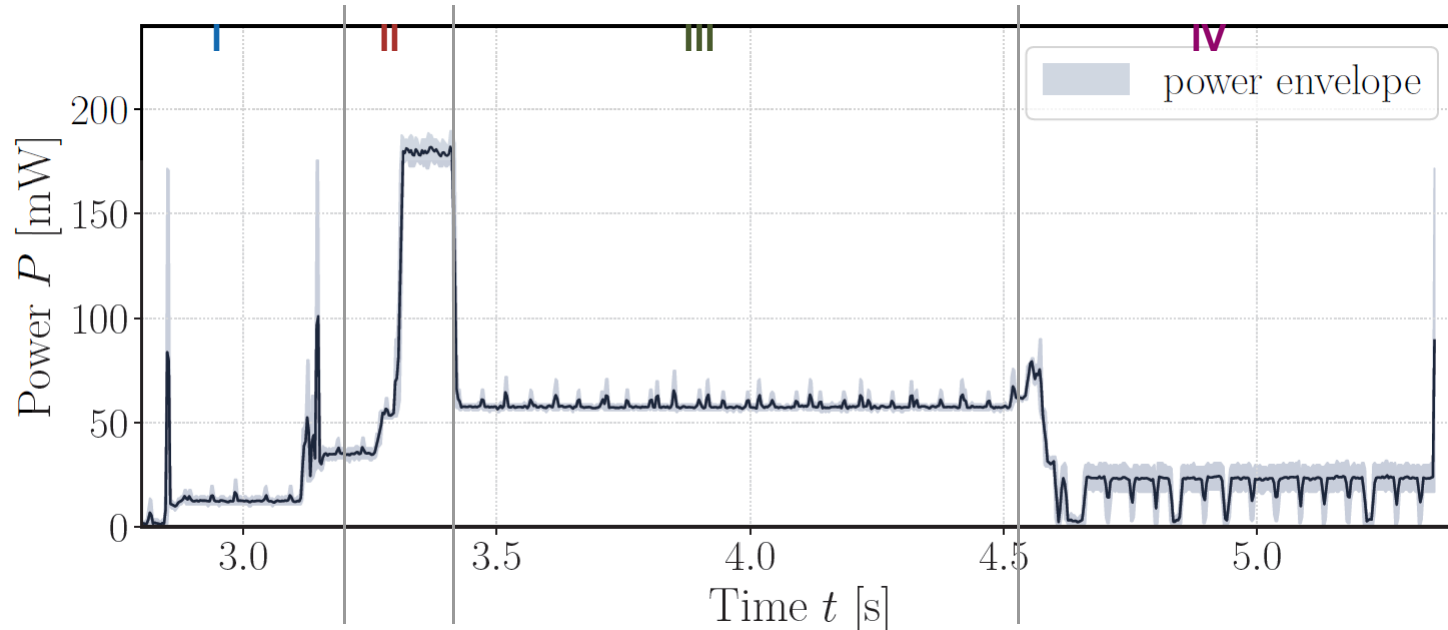
R(2+1)D wins: 83.94% accuracy at ~6× fewer params than MobileNet

- Best accuracy and smallest viable footprint (627K params, 0.840 wtd. F1)
- Strict subject hold-out confirms generalization to unseen users
- Distinct gestures reach $F1 \geq 0.90$; ambiguous ones (Select, Zoom In) lag

Gesture	Precision	Recall	F1	Support
Swipe Left	0.806	0.844	0.824	64
Swipe Right	0.970	0.955	0.962	67
Swipe Up	0.821	0.622	0.708	37
Swipe Down	0.870	0.944	0.905	71
Zoom In	0.561	0.649	0.602	57
Zoom Out	0.630	0.741	0.681	85
Select	0.400	0.286	0.333	28
Double Tap	0.833	0.938	0.882	160
Rotate CW	0.987	0.854	0.916	178
Rotate CCW	0.918	0.855	0.885	221
Screenshot	0.868	0.917	0.892	72
Weighted avg			0.840	1040
Macro avg			0.781	1040

P. Bonazzi, J. Moosmann, A. Celik, P. Mayer and M. Magno, *OpenGlass: Open-Source Smart Glasses Platform for Event-Driven Gesture Interaction*, ETH Zurich, 2026.

Power Measurements



Full end-to-end cycle resolves into four power phases:

- **I Cold start / GAP9 init** – ≈ 22.9 mW avg, transient spikes during peripheral bring-up
- **II Camera power-up** – ≈ 180 mW plateau during GENX320 cold-start
- **III Vision pipeline** – ≈ 65.6 mW avg; one inference every 75.4 ms (Model Inference = 7.63 J, the cycle's dominant cost)
- **IV BLE TX & deinit** – ≈ 27.7 mW avg, duty-cycled pulses (nRF5340 advertise / connect / transfer)

OVERVIEW OF EXECUTION TIME AND ENERGY CONSUMPTION ACROSS THE STAGES OF THE IMAGE PROCESSING PIPELINE EXECUTED ON THE GAP9 MICROCONTROLLER (MCU).

		t [ms]	$\bar{P}$ [mW]	E [J]
	Initialization	505.180	22.942	11.590
Vision Pipeline	Image Acquisition	20.251	45.903	0.930
	Pre-Processing	0.532	80.527	0.043
	Model Inference	75.400	96.061	7.627
	Post-Processing	0.222	56.357	0.012
	Pipeline	33.920	65.612	8.613
	Deinitialization	31.070	27.736	0.862

Battery Lifetime — 300 mAh @ 3.7 V

Always-on

continuous vision pipeline, 65.6 mW

≈ 17 h

1 inference / day

5 s wake cycle, 50 μ W deep sleep

≈ 324 days

Inference (7.63 J) dominates the active-cycle budget.

Conclusion



- Efficiency is the Key Enabler** – Power constraints demand ultra-low-power AI, requiring optimized hardware-software co-design.

- Open Architectures Drive Innovation** – RISC-V and modular platforms enable scalable, customizable, and efficient AI processing for wearables.

- Sensor Fusion Enhances AI Efficiency** – Event-based vision (DVS), radar, and novel sensing (e.g., electrostatic charge) significantly reduce energy consumption.

- Application-Specific AI is the Future** – Tailored, domain-specific AI models like TinySSIMO YOLO maximize performance while keeping power usage minimal.

- Future Outlook: Smarter, More Efficient Wearables** – Advancements in edge AI, energy-efficient sensors, and hardware accelerators will drive the next generation of intelligent eyewear.

Thank you for your attention!

Q&A

