# tinyML® EMEA

*Enabling Ultra-low Power Machine Learning at the Edge*

October 10-12, 2022
Limassol, Cyprus

TINY ML

www.tinyML.org

# In Sensor and On-device Tiny Learning for Next Generation of Smart Sensors

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TINY ML

# Introduction

- Internet of Things (IoT)
  - Variety of sensors
  - Connected to cloud (often wirelessly)
- Machine learning
  - Extract relevant information from data
  - High computational demand
- Data Processing and Learning
  - Mainly in the cloud

# Edge Vs Cloud

- Latency/reliability
- Data Protection
- No Wireless Communication Needed – Lower Bandwidth requirements
- Lower Power Consumption
- Lower Cost

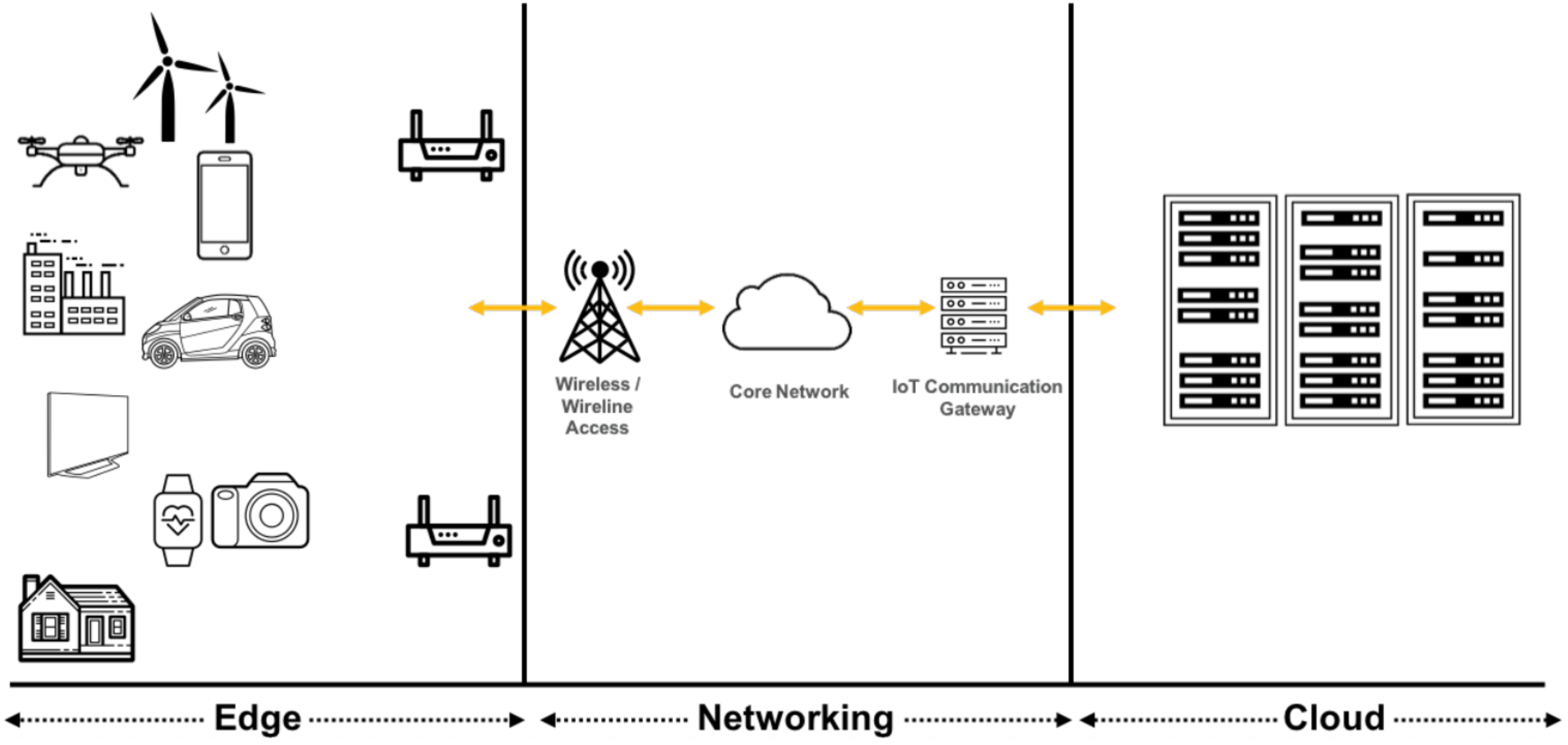
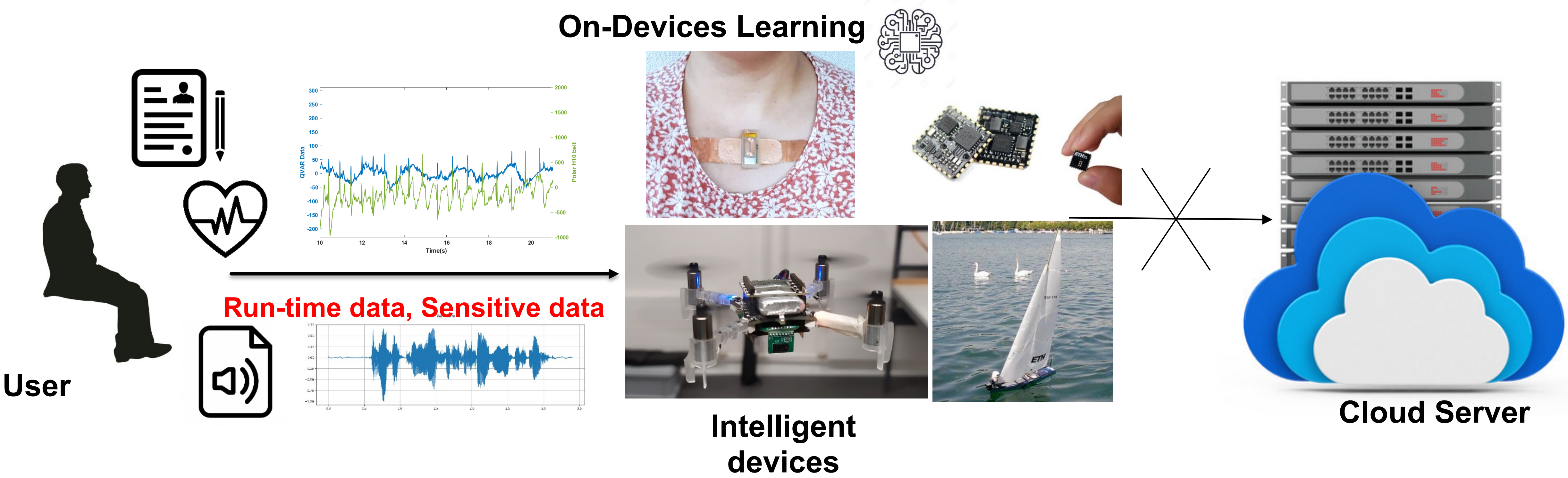



**Figure reference: Accelerating Implementation of Low Power Artificial Intelligence at the Edge,** A Lattice Semiconductor White Paper, November 2018

# What about On-device Learning? Can we do at the edge?

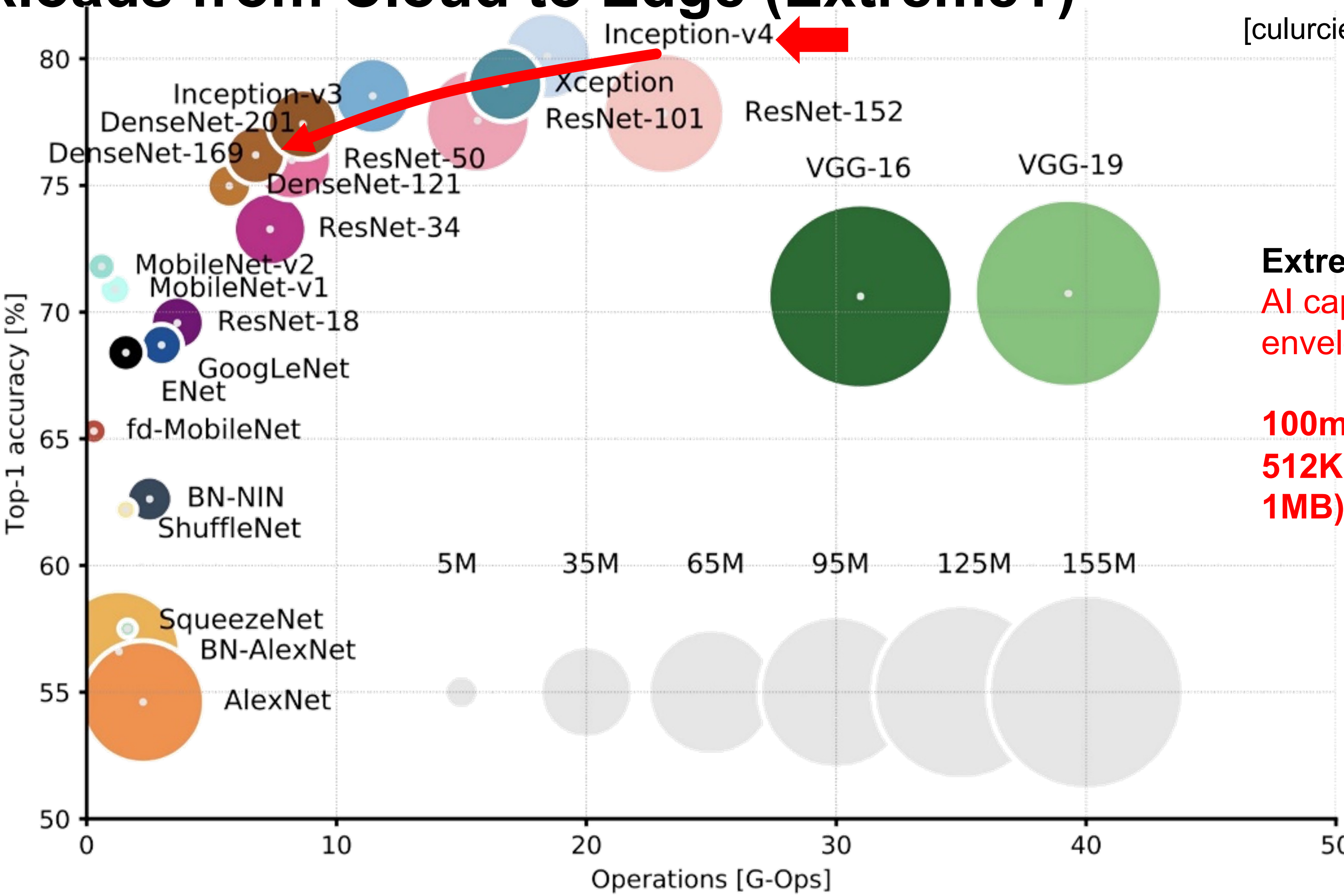



- Customization and Personalization: TinyML devices need to continually adapt to new data collected from the sensors.
- Security: Data cannot leave devices because of security and regularization.

# AI Workloads from Cloud to Edge (Extreme?)

[culurciello18]

**GOP+**
**MB+**

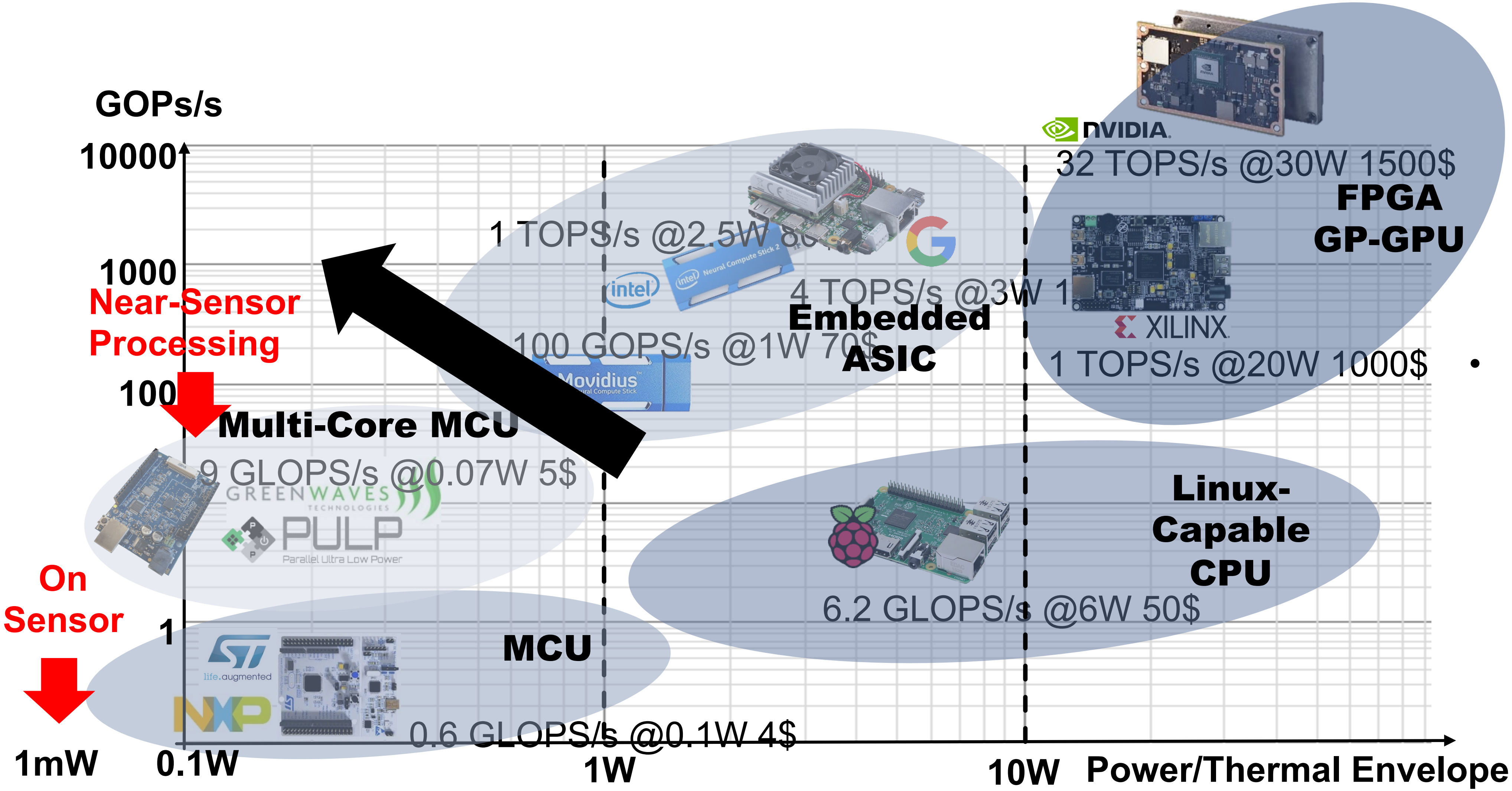



**Extreme edge AI challenge**

AI capabilities in the power envelope of an little cores:

**100mW peak (1mW avg)**
**512KB RAM (best case 1MB)**

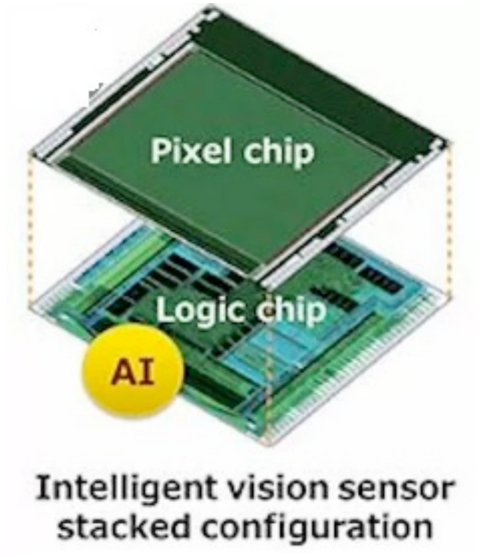
# New platform for edge computing every year. Edge-AI Platforms




- **Trends:**
  - Optmized accellerator for NN
  - Parallel Solutions
  - Custom Architectures

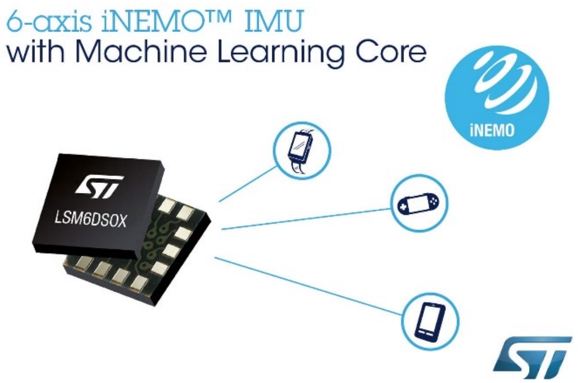
# New trend on-sensors capabilities

## Sony IMX 501




## IniVation Foveator DVS-Sensor plus AI cores


## ST LMS6DSOX and new ISM330




## Bosch BHI260AP

# Next generation of IoT devices: Always-on Smart Sensors.

**1. ) Edge Signal Processing and AI**

Smart devices
for perpetual operation

**3. ) Low power system design**

**2. ) Energy harvesting**

**4. ) Low Power and long range communication**

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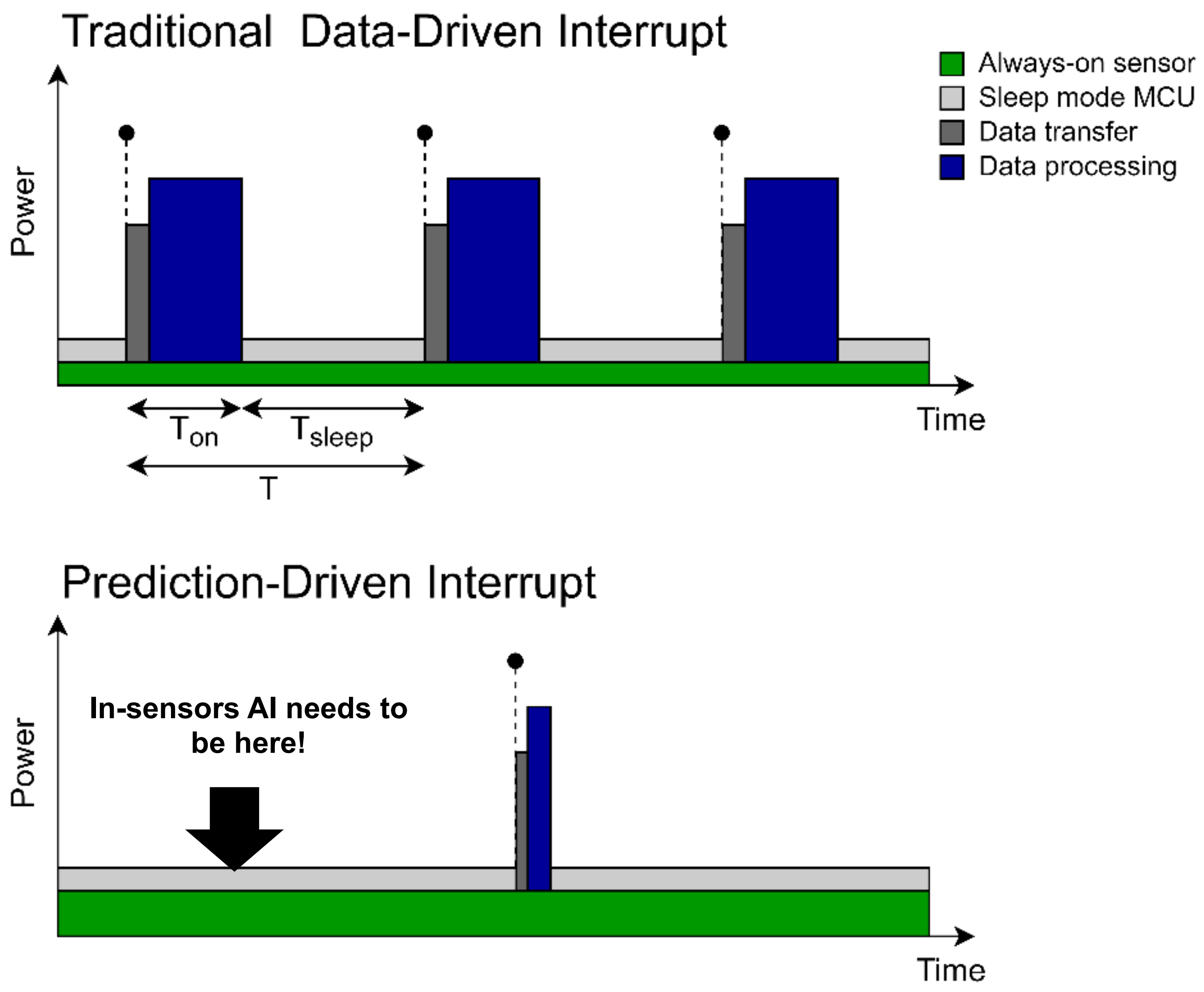
# On-Sensors ML and ODL

- Typical "Smart" Sensor
  - Traditional Sensors
  - MCU or other Edge processor for data collection and analysis
  - Wired/wireless interface to transmit findings (optional)

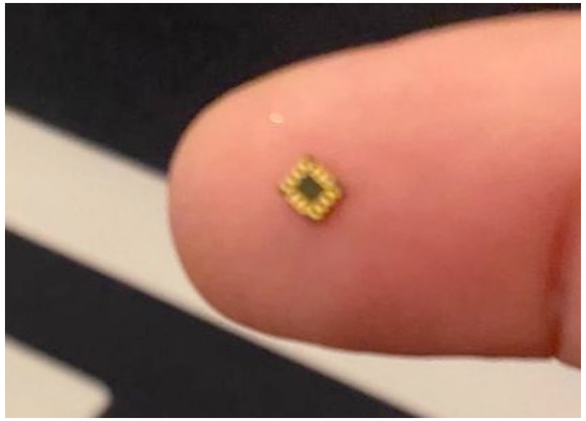
- In-sensor approach
  - Intelligence embedded in the sensor IC
  - Always-on **analysis** and **learning**
  - "Zero" latency



# On-Sensor Learning

- Project Goal: anomaly detection based on Neural Network (encoder-decoder), parameters learned on the device.

- Advantages:
  - Plug-and-Play anomaly detection: no data acquisition, no training/deployment. Place-and-forget device.
  - Always on monitoring with low power consumption

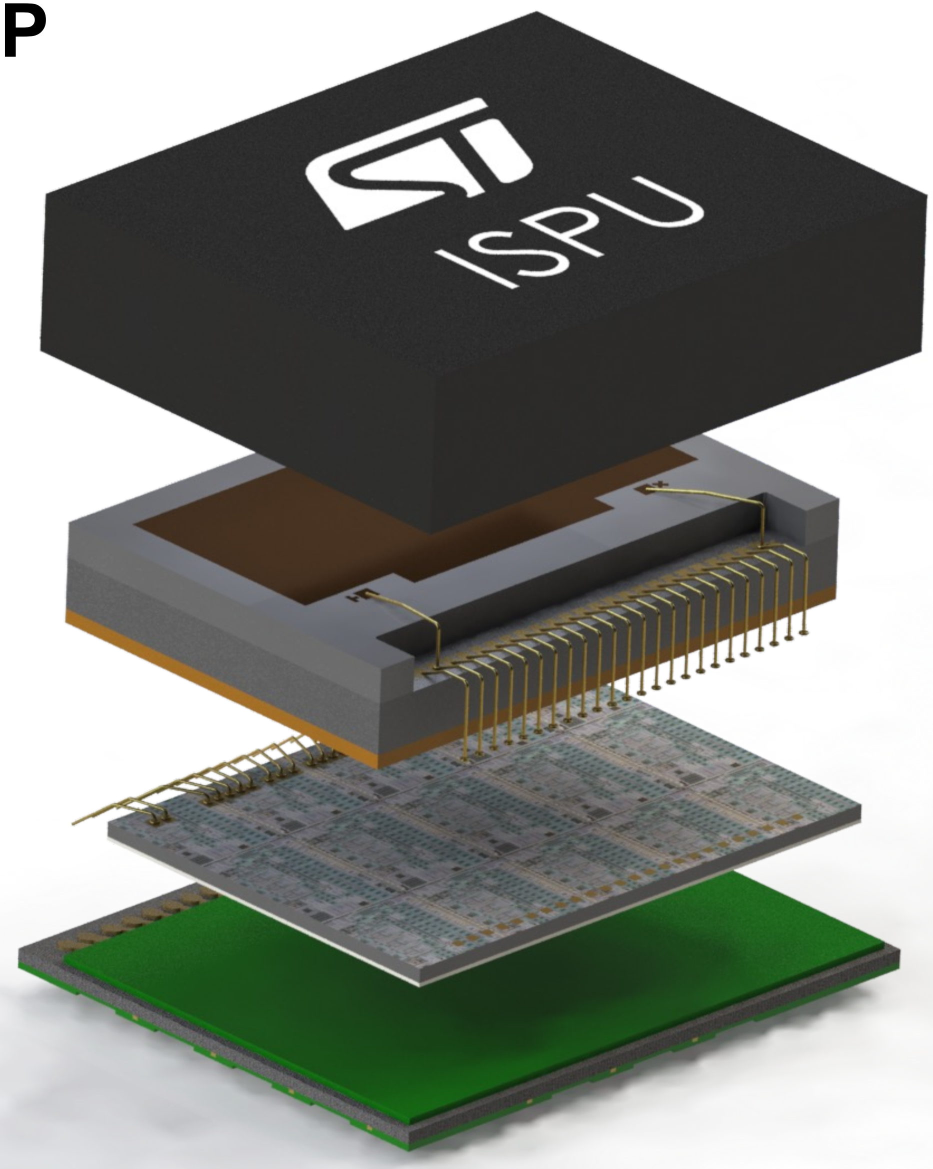



# In-Sensor Hardware: ST ISM330AILP

ST's sensor puts together Sensor and Processing

- Established ST's MEMS technology + proprietary ISPU (intelligent sensor processing unit)
- NN Core = small MCU with proprietary RISC architecture, FPU, BNN accelerator
- 40KB of memory (RAM+program)
- 4 cycle wake-up

- Previous work shows the performance use with supervised learning!
  - Will be presented at IEEE Sensors 2023.



# Challenges

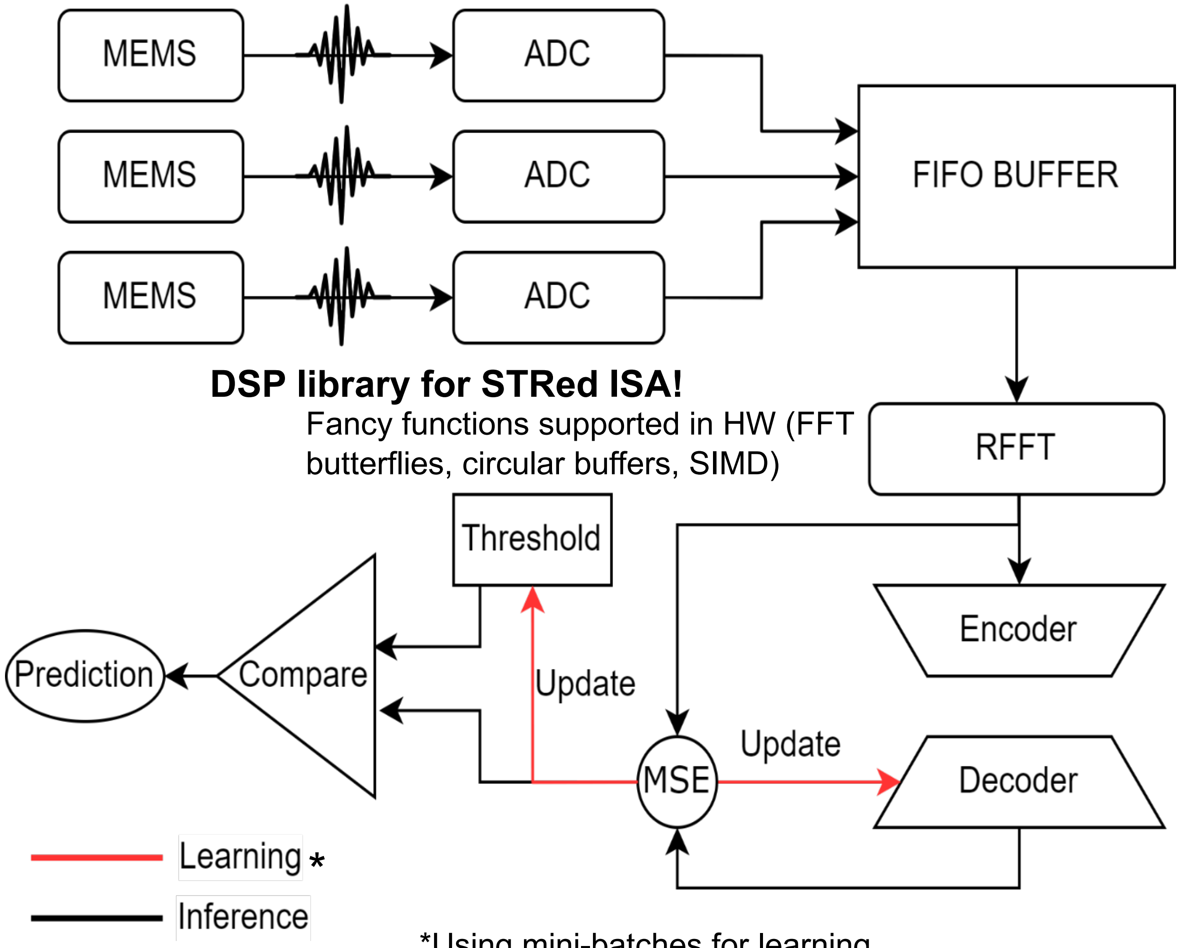
- **Memory: 8+32KB of memory** for both .text and RAM
- **Computation resources**
  - Max 10MHz, but ideally only 5MHz
  - DSP instructions
- **Learning is memory intensive**
  - Only small models allowed as well as encoder/decoder
  - Partial learning (last layer, bias only update)

Current work

- ODL options
  - Full training (very memory intensive, some optimizations possible, discouraged) [1]
  - Update bias only (probably negligible effect in small networks) [2]
  - Output layer only (seems the best option) [3]

[1] https://arxiv.org/abs/2206.15472
[2] https://arxiv.org/abs/2007.11622
[3] https://arxiv.org/abs/2103.08295

# ODL Pipeline

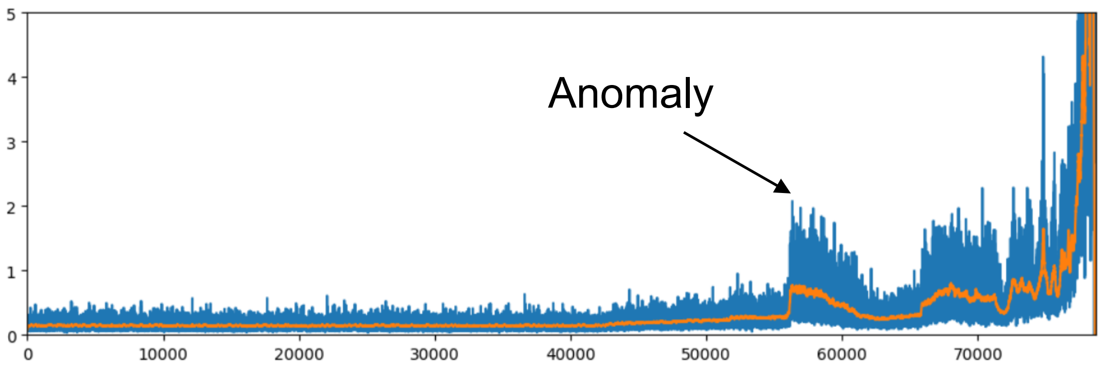



**DSP library for STRed ISA!**
Fancy functions supported in HW (FFT butterflies, circular buffers, SIMD)

*Using mini-batches for learning

On the Airbus [1] dataset.

Example of Dataset: frame error (blue) + smoothed (orange)




[1] https://www.research-collection.ethz.ch/handle/20.500.11850/415151

# Evaluation

## On Airbus anomaly Detection Dataset [ETH]

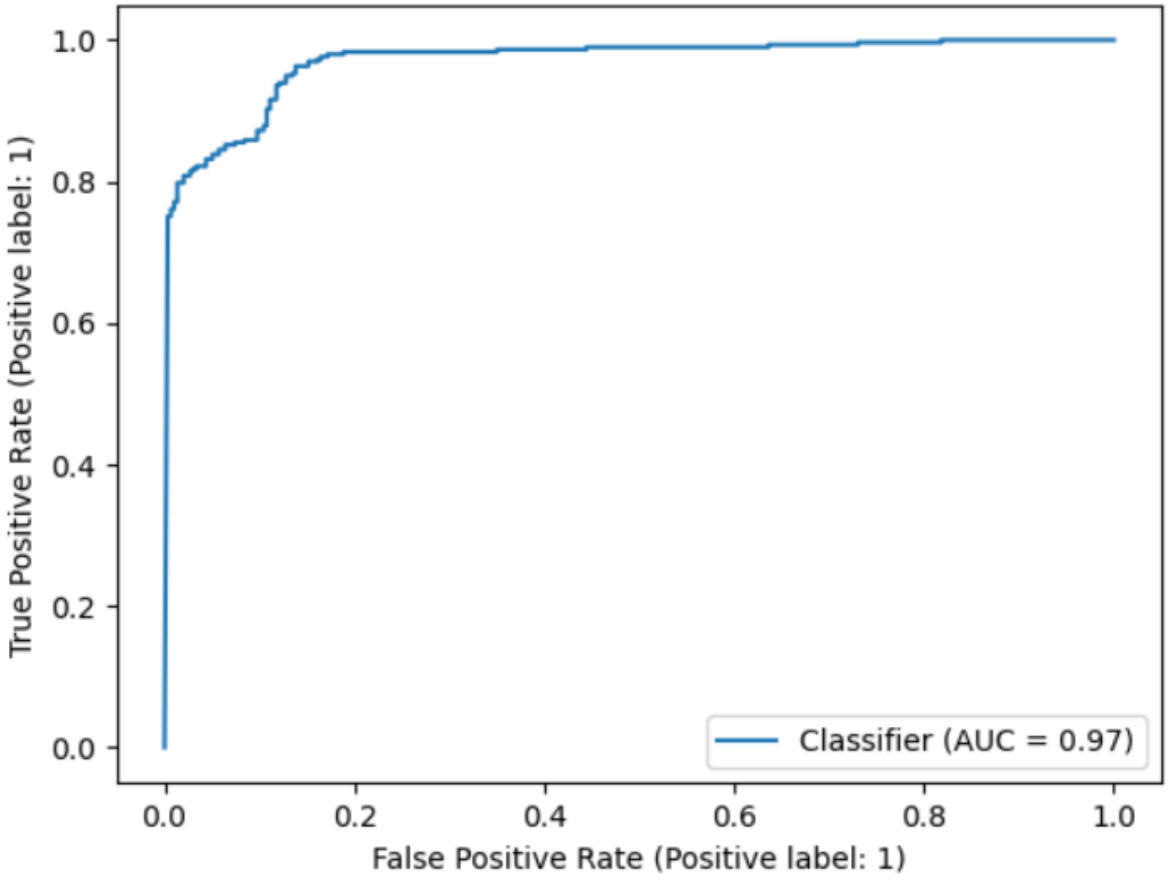
- **Evaluating on Anomaly Detection Task**
  - Pipeline: RFFT → Accumulate/Avg → Autoencoder → MSE

- **Evaluation of Feasibility:**
  - Memory requirements
  - Network Inference/Training complexity (FLOPs)
  - Training latency considering real-time data

- **Hyper Parameters:**
  - FFT size
  - Network size
  - STFT length
  - Regularizations
  - Training time
  - Batch Size
  - …

Evaluation metric: ROC AUC

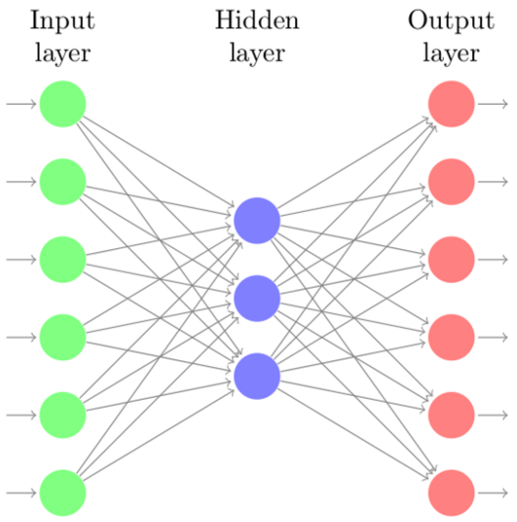
- Training time of 2 seconds



# Experimental results and evaluation

## Training vs Inference vs Sampling rate.

- High AUC/Accuracy can be achieved with
  - FFT preprocessing 672 flops
  - RAM usage: 4-15 KB + program (usually around 8KB with DPS functions) → should fit
  - FLOPS for training 232k
    - 1.6 mJ/training!
    - 0.23s of compute time at 5MHz with 5 cycles/FLOP
  - FLOPS per inference 1097
- We measured in ISPU ~5cycles/FLOP → training latency ~20s due to data to learn, of which ~0.25s of computation
  - Mostly dominated by data sampling rate, not by training
    - Sampling 1024Hz → 20s to acquire enough data for entire training
    - Energy for Sampling 1.8uJ/sample,
- **Next steps: try with autoencoder in time domain (justifies the NN better, no need for FFT code (saves memory)**

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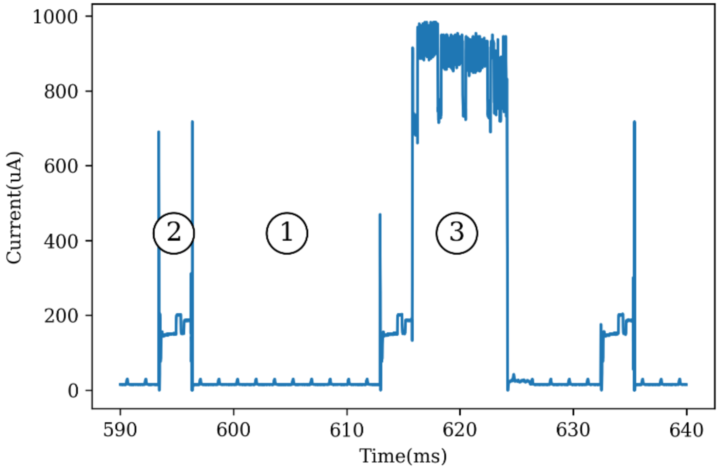


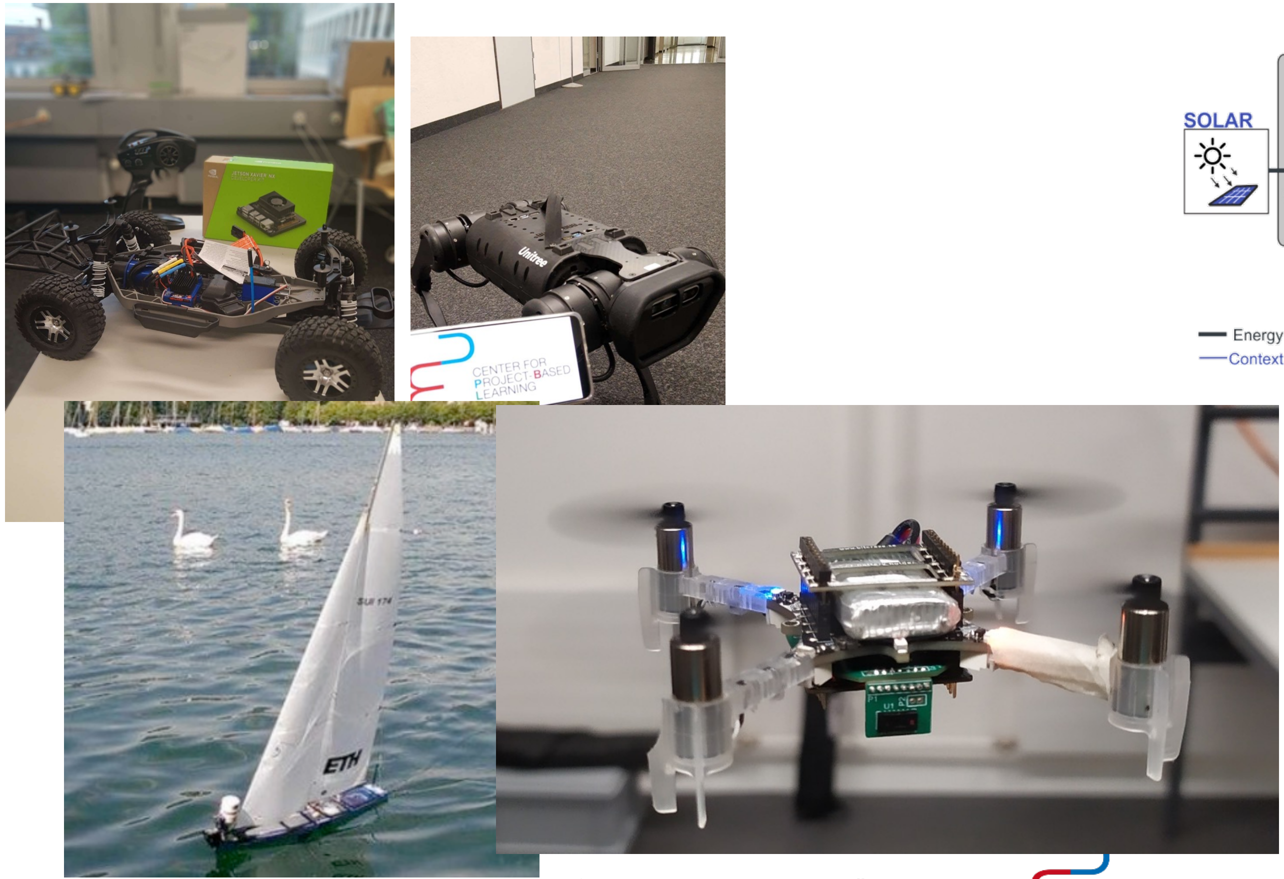

1) idle
2) sampling
3) ISPU processing power

# Conclusion and take away

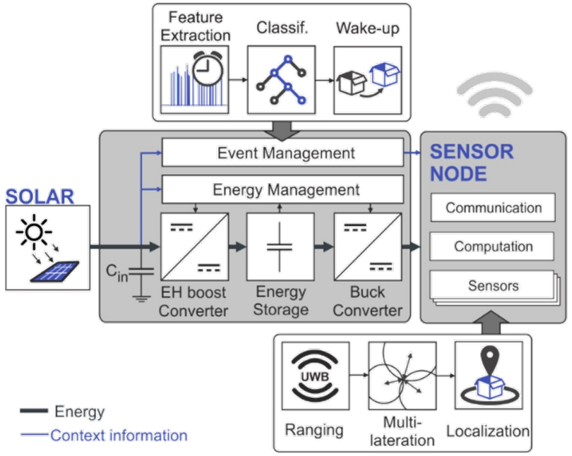
- TinyML come become very tiny with in-sensors device
- ODL is an hot emerging top but even more challenging
- Anyway new technology are enabling both in sensors and ODL
- With a lot of limitation! :D

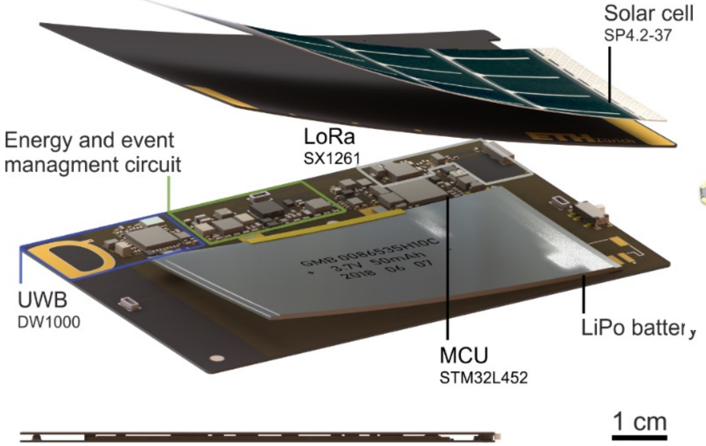
# Thank you for your attention!

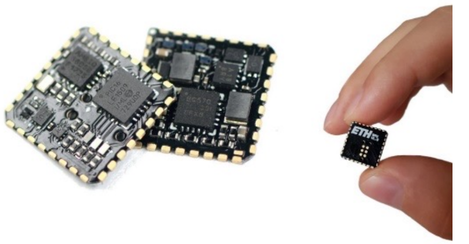
- TinyML and Embedded Control on Robots




- Self Sustaining Smart-Sensors for Indoor and outdoor Applications and Industrial Applications



# Thank you
# pbl.ee.ehtz.ch

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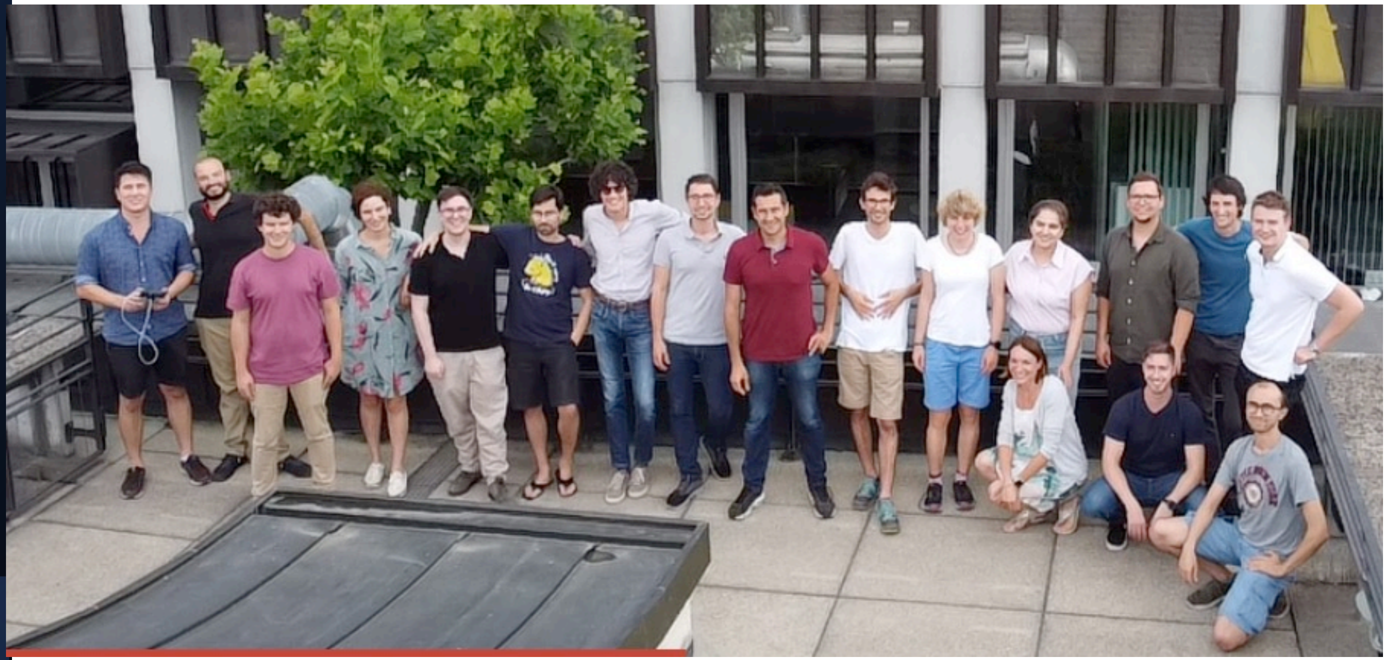

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