EPFL

EMBEDDED SYSTEMS LABORATORY

Bioinspired Edge AI Systems Co-Design for Internet of Things

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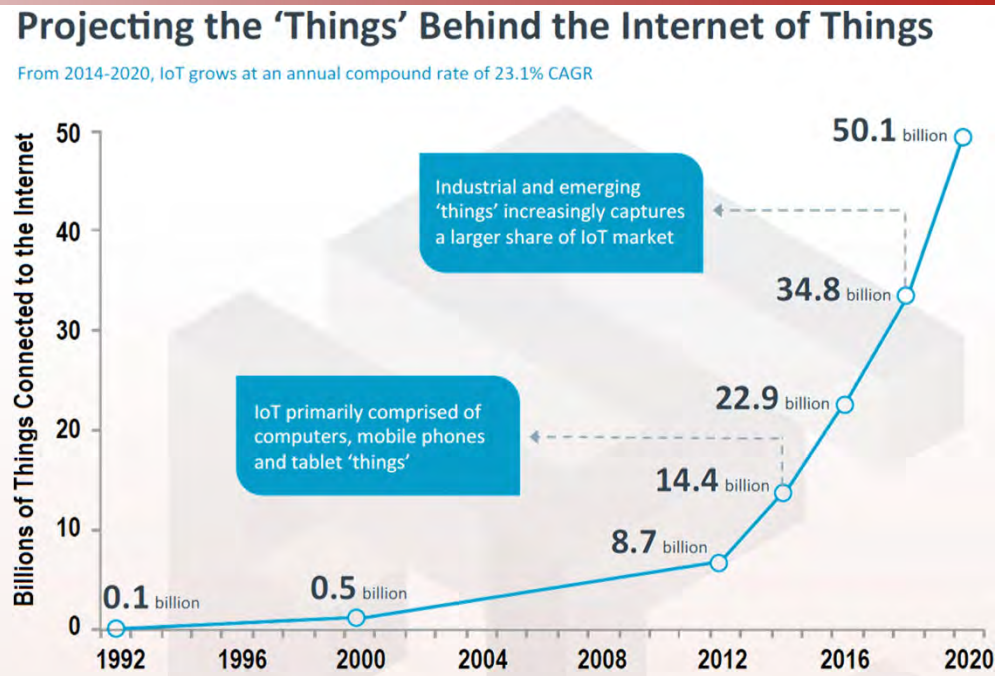
Internet of Things (IoT) and Sustainability

- IoT market constantly growing (20B devices by 2025)
- Artificial Intelligence (AI) and Machine Learning (ML) used for data analytics and classification
- Sustainable? Expected increase in energy consumption by 3x in 2040 in current trends [IDC'22]



How to increase IoT robustness andsustainability?

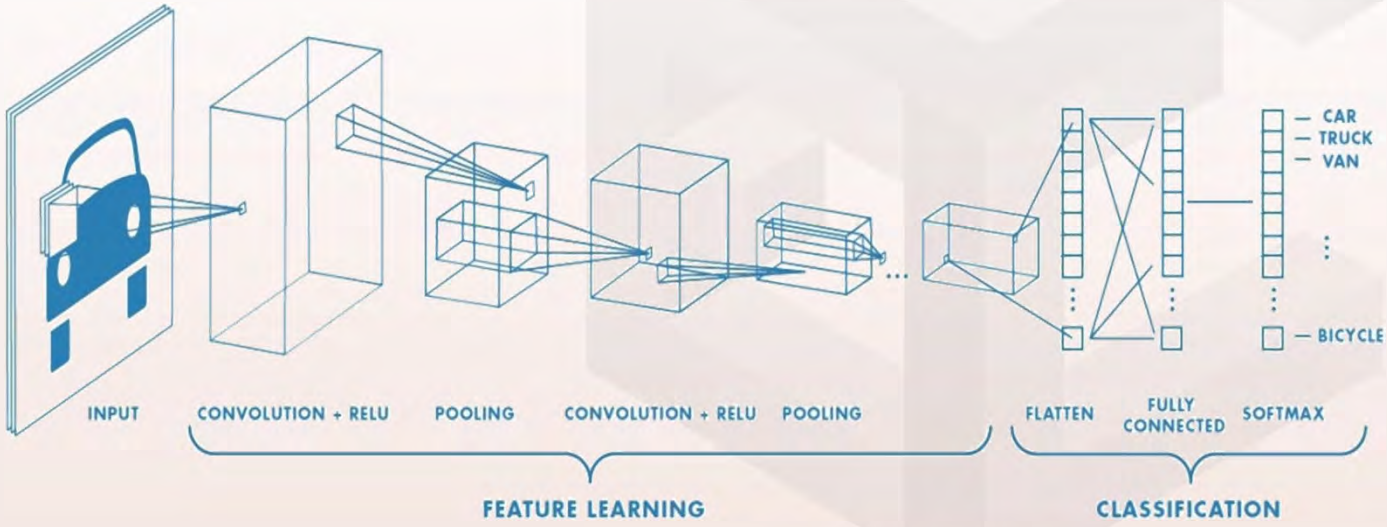
1) Less data transmitted over energy-hungry links
2) Faster response = Less latency (e.g., industrial systems)
3) Increased system knowledge (e.g., medical systems)

Most Popular AI/ML Today: Convolutional Neural Networks

Considered applications: CNN inference and training

- ML algorithms used for classification, detection, segmentation: Applicable to many domains
- Connection of arithmetic layers: Predefined control and data flow
- Extract features from input data to perform predictions: Energy-intense computation and storage

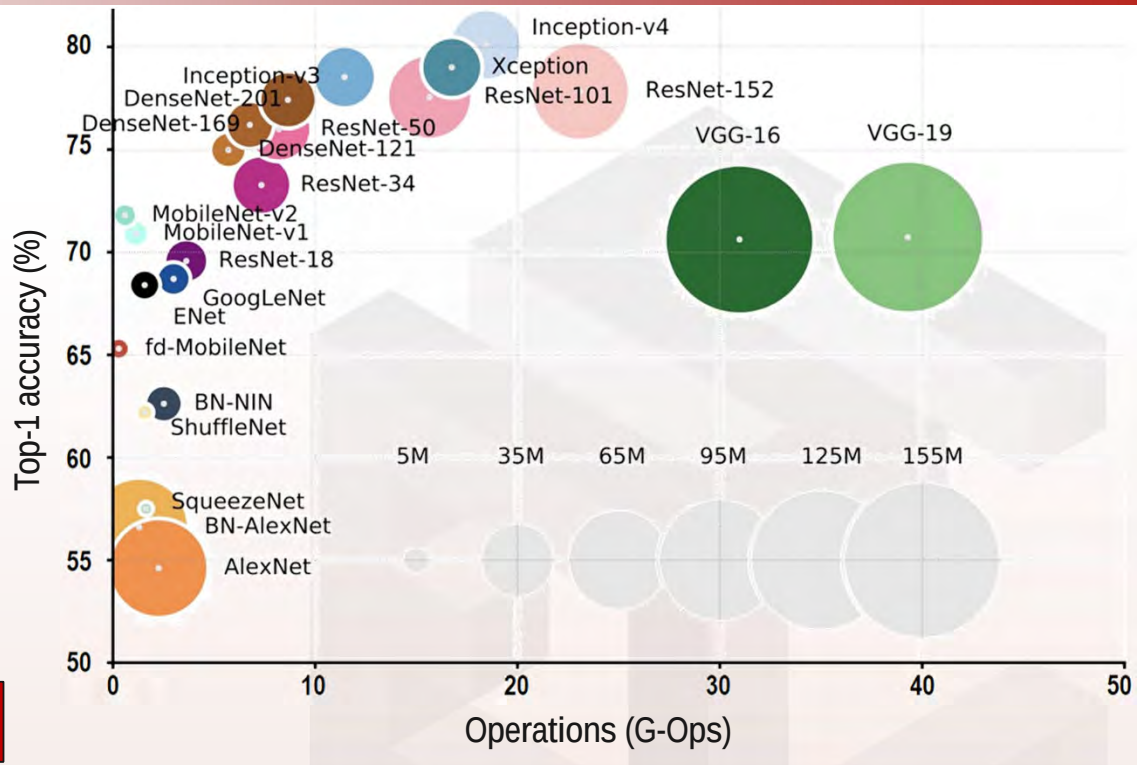
Originated from AI/ML community, and **still limited** connection with sustainable computing systems co-design



CNNs Getting Very Complex…

Use of Cloud and edge AI = Local computing near data sensing and acquisition

- High accuracy is achieved through:
  - Large models
  - Complex connections
  - Ensembles of CNN models



AI/ML on IoT (edge AI) systems

Software + Hardware Optimizations

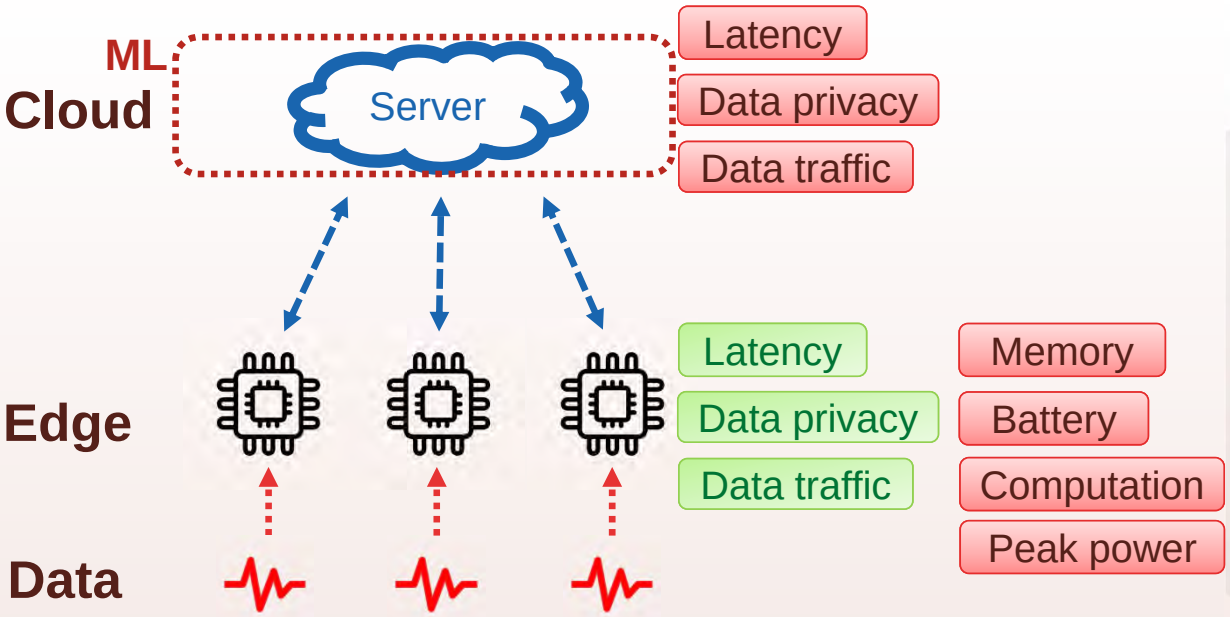
Pruning, Quantization,…

Voltage scaling, Approx. Computing

IoT applic. characteristics are key to choose the Edge AI architecture!

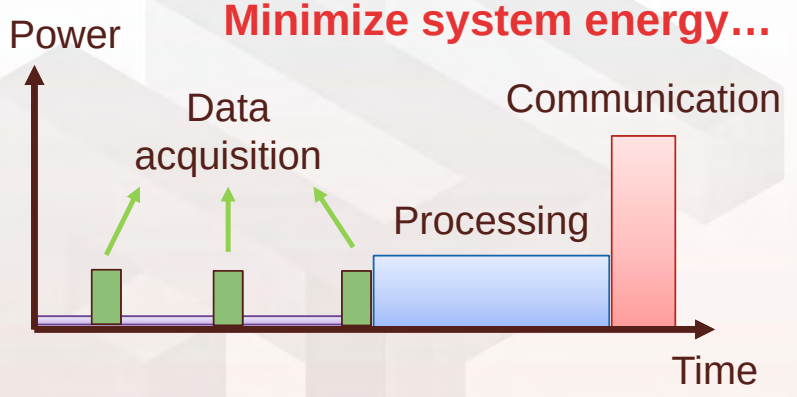
Why ML on IoT edge Devices?

State-of-the-art



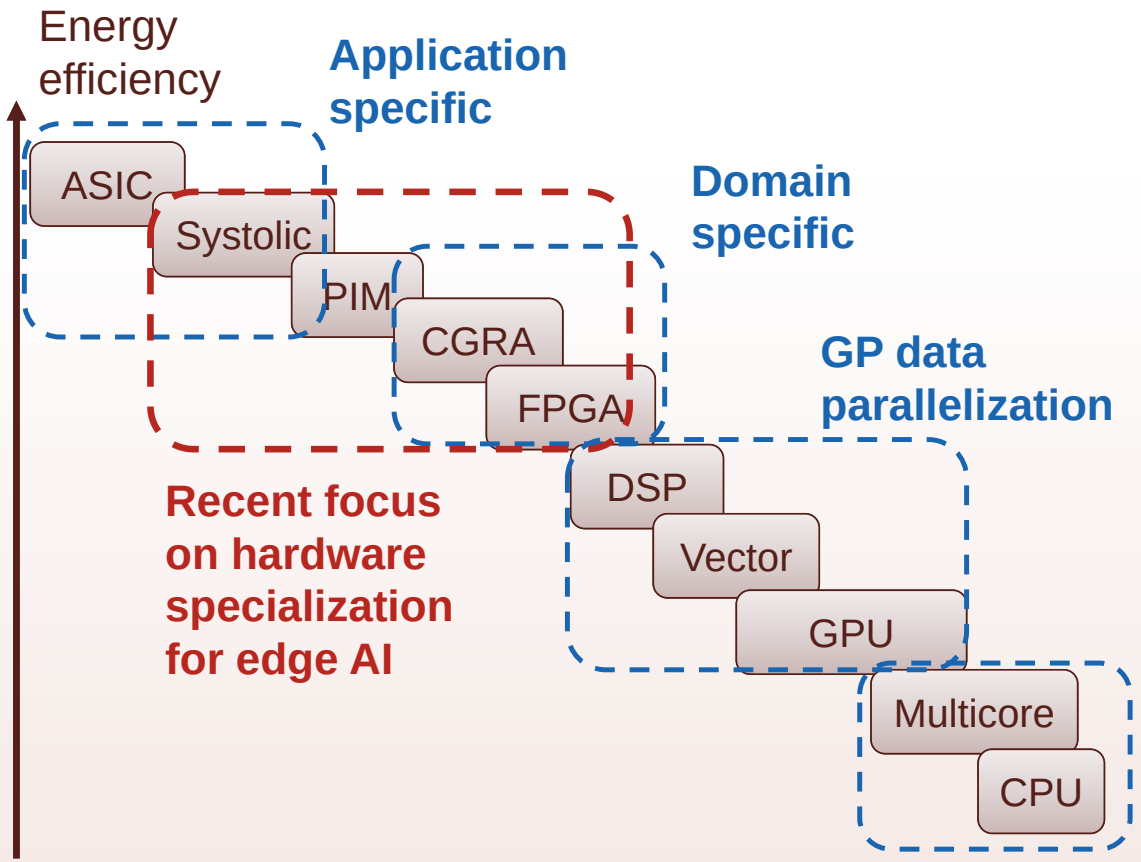
IoT applications drive system design options

Minimize system energy…



One edge AI architecture solution does not fit all!

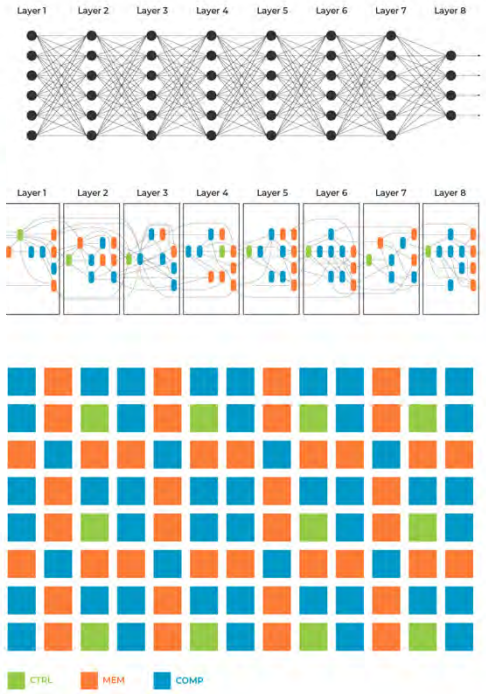
Hardware layer



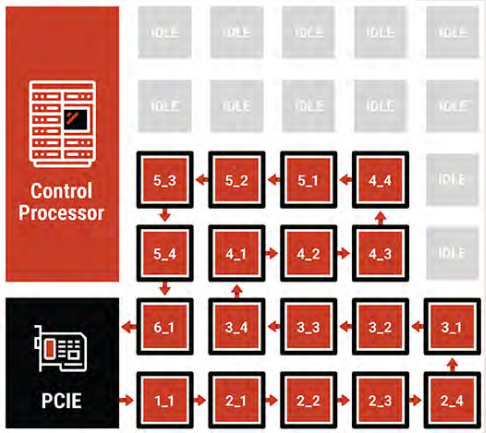
Hardware accelerators

- ASIC
- Spatial accelerator
  - Systolic array
  - FPGA
  - Coarse Grained Reconfig. Arrays (CGRA)
- Vector machine
- Manycore
  - GPU
- Process-in-memory (PIM)

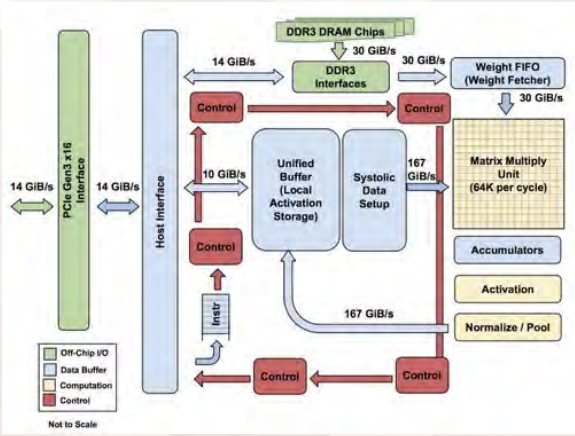
Application Specific Edge AI Accelerators



Hailo:
26 TOPS at 3 TOPS/W



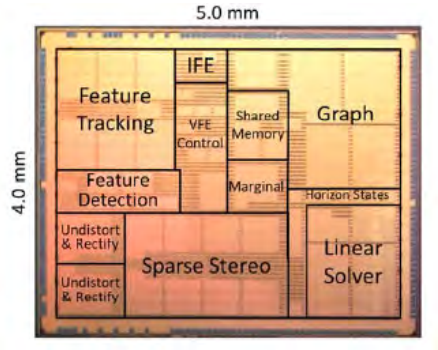
Mythic:
35 TOPS at 4 TOPS/W



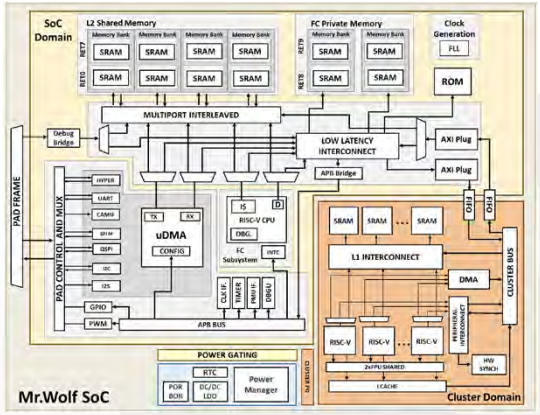
Edge TPU:
4 TOPS at 2 TOPS/W

Image Credit: Hailo, Mythic, Google

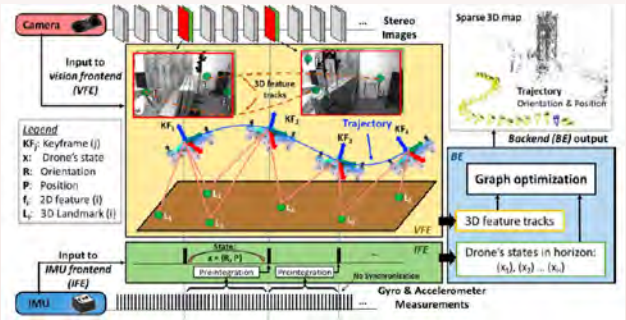
Applic.-Archi Edge AI Accelerators: Digital + Analog



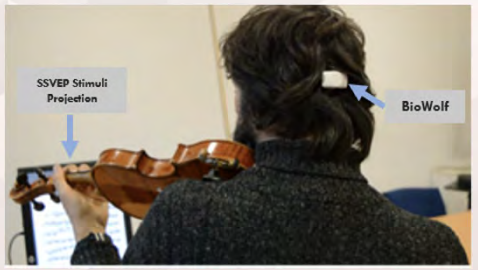
Navion: Visual-Inertial Odometry (VIO) Accelerator
24mW at 65nm



BioWolf: Brain-Computer Interface Platform
6.3mW providing 38hrs with 65 mAh battery

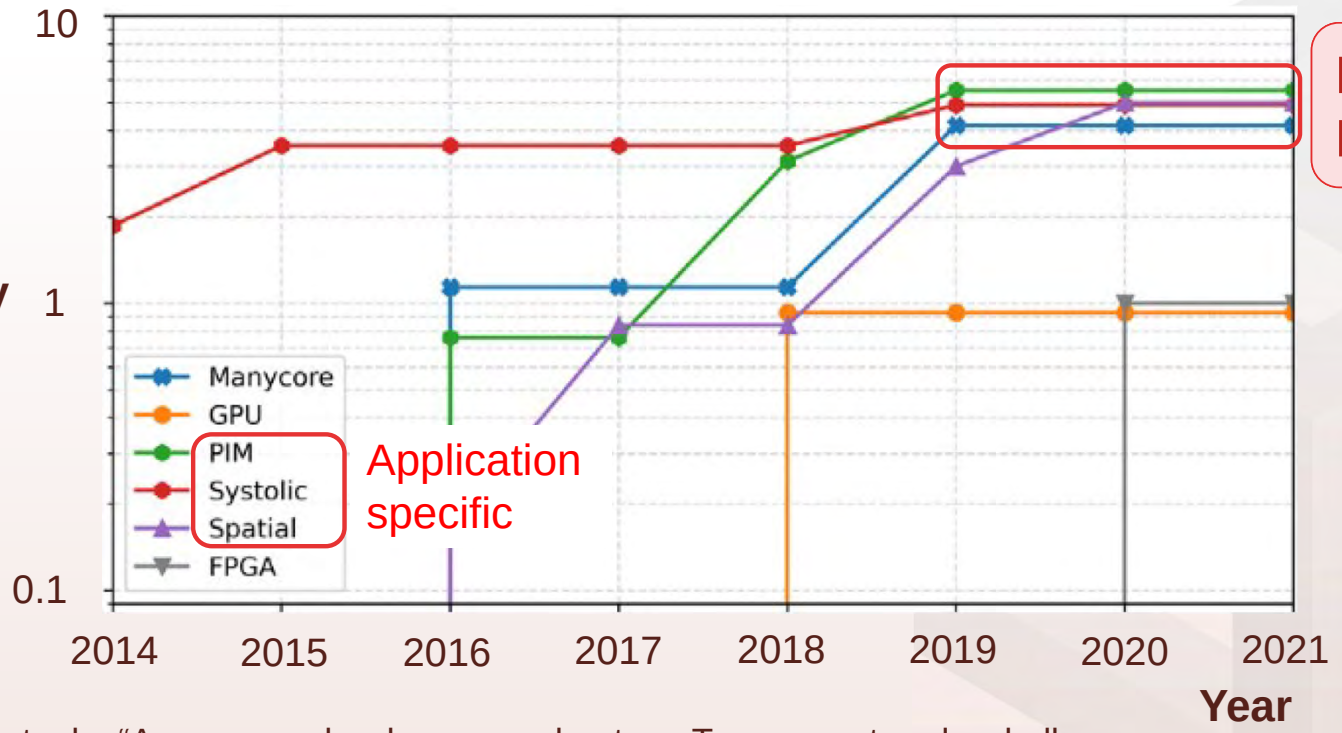


Amr Suleiman et al. JSSC'19



Victor Kartsch et al. TBioCAS'19

Application-Specific Edge AI are Reaching a Limit…

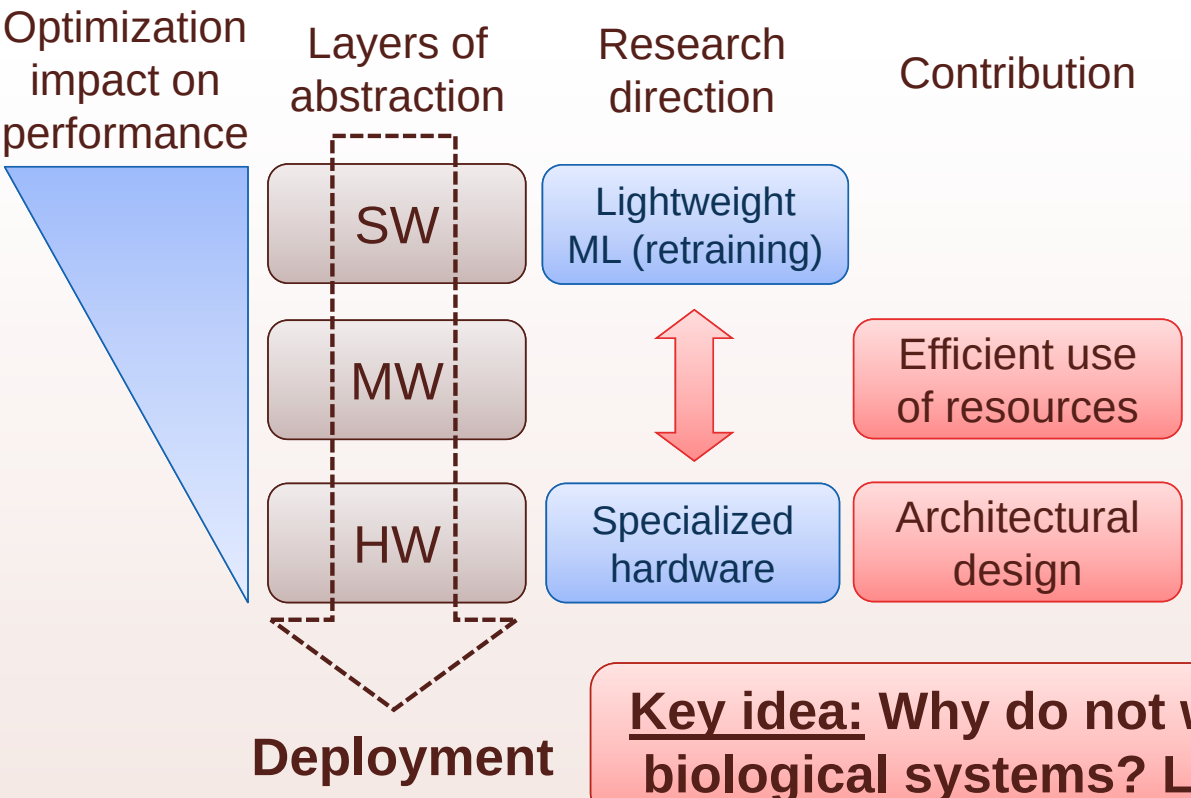


Efficiency Plateau

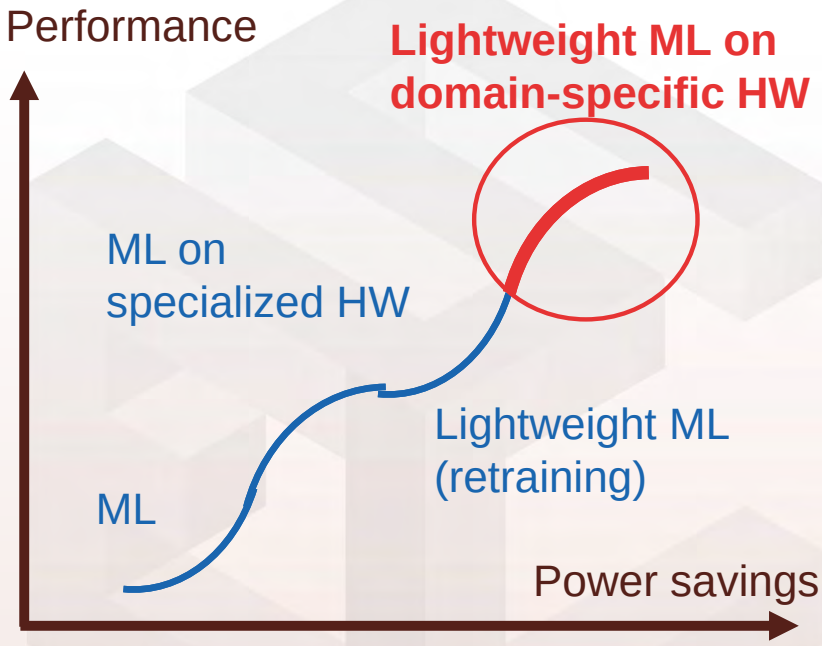
Architectures for conventional ML: DNN, CNN, RNN

B. Peccerillo, et. al. , “A survey on hardware accelerators: Taxonomy, trends, challenges, and perspectives,” Journal of Systems Architecture, vol. 129, p. 102561, 2022.

ML Deployment

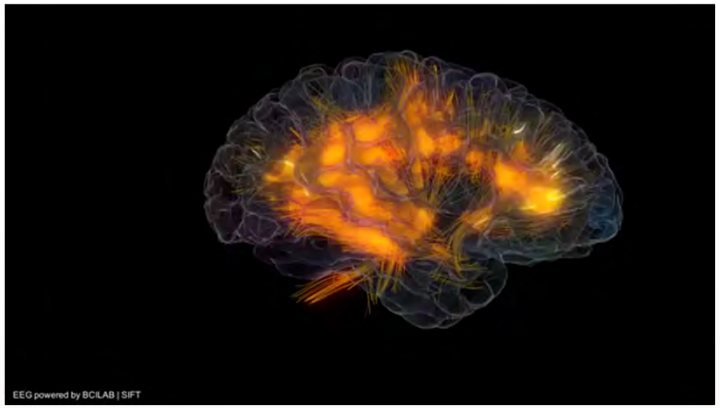


Domain-Specific Exploration

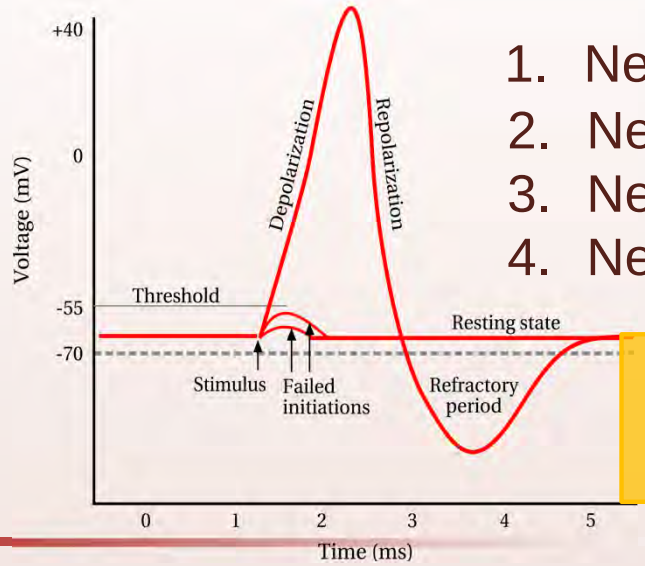


<u>Key idea:</u> Why do not we follow the design concepts of biological systems? Let's use medical IoT as example

How Does our Brain "Work"?



- Brain "embedded" computing features:
  - Size: 4-100 μm neurons, 1.3-1.5 dm^3
  - Approx. 80B Neurons, 100 Trillion Synapses
  - **20W average** (>10,000 TFLOPS)

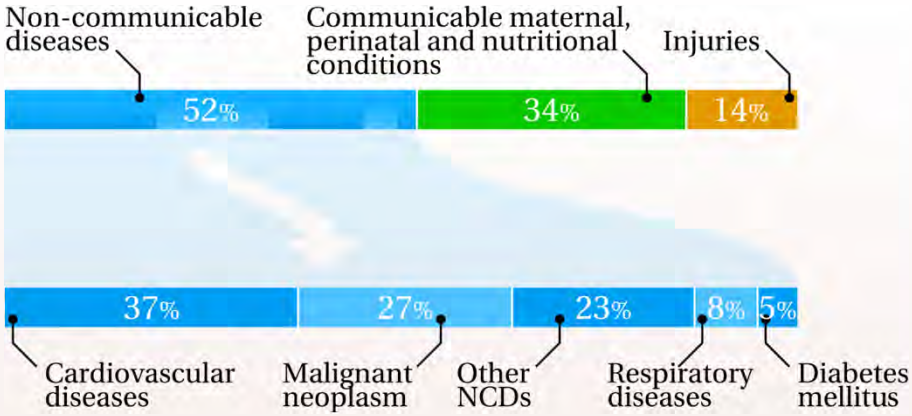


1. Neurons are idle most of the time (**no power** consumed)
2. Neurons react only to significant stimulations (**events**)
3. Neurons **integrate** storage with processing
4. Neurons are **reconfigurable**

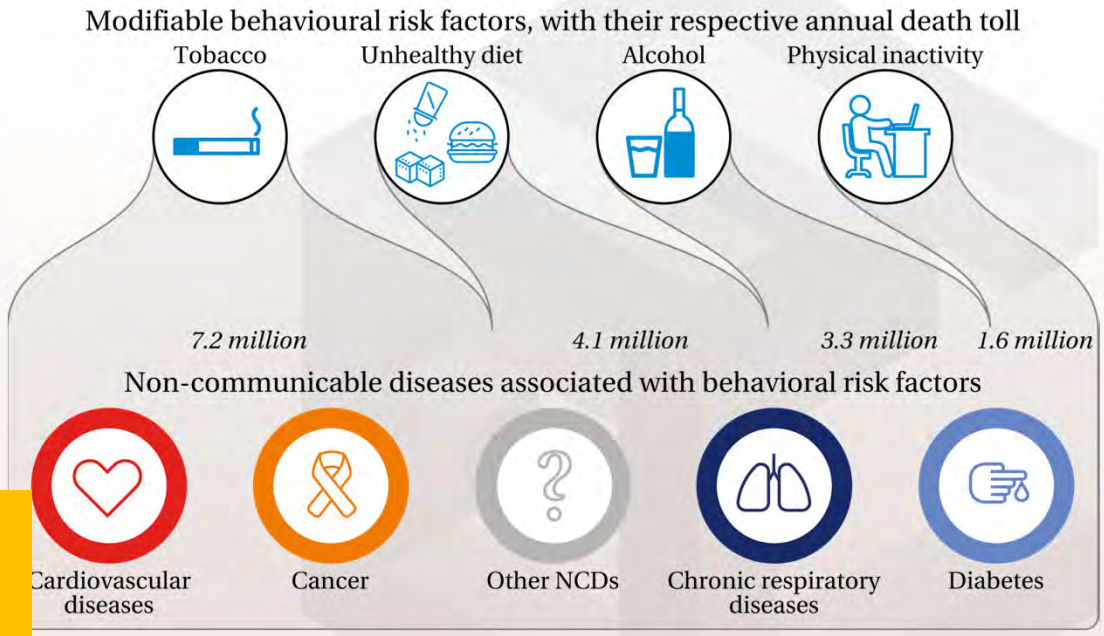
Design of event-driven edge AI architectures based on domain-specific properties and adapt computing

Current Situation of Healthcare

Causes of death worldwide [3]



Behavioural risk factors [4]

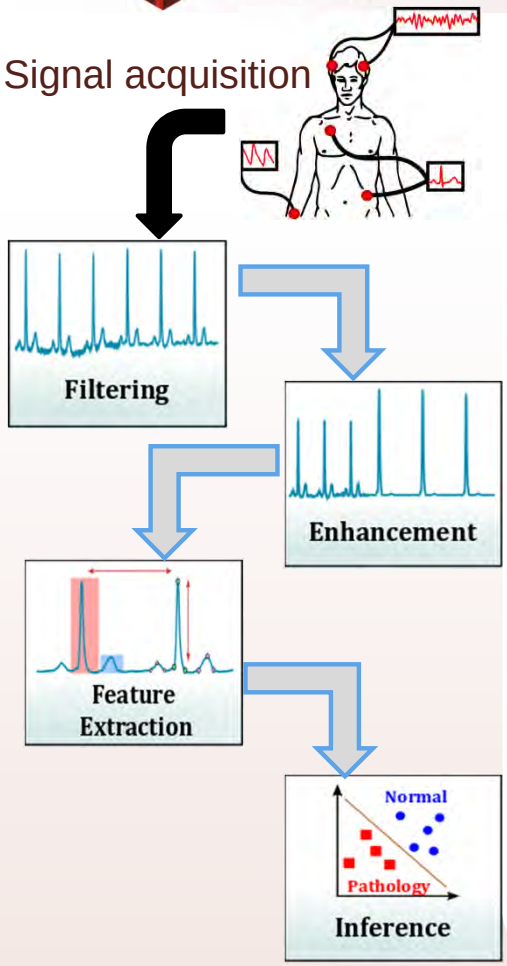


Sustainable long-term monitoring of lifestyle habits with edge AI wearables is key!

But each person is different!

- [3] World Health Organization. Noncommunicable diseases, 2018
- [4] World Health Organization. Noncommunicable diseases and mental health: challenges and solutions, 2014

Biosignal-Taylored Edge AI Co-Design



- Configurable signal-specific signal acquisition
- Modular processing structure for each biosignal

Modular phase-based process structure (with approx. computing in different levels)

- Computation phases
  - Adjust accuracy to resource needs
  - Memory power management
- Optimization techniques
  - Parallelization
  - Efficient synchronization
- Application-specific accelerators
  - Heterogeneous computing
  - Exploit patterns between phases

- Activate partial resolution units
- Multiple banks
- Independent power
- Per lead, per window, pipelining, etc.
- HW event managers
- Avoid context-switches with dedicated cores

Valid for Complex IoT Signals? ECG Spectrogram

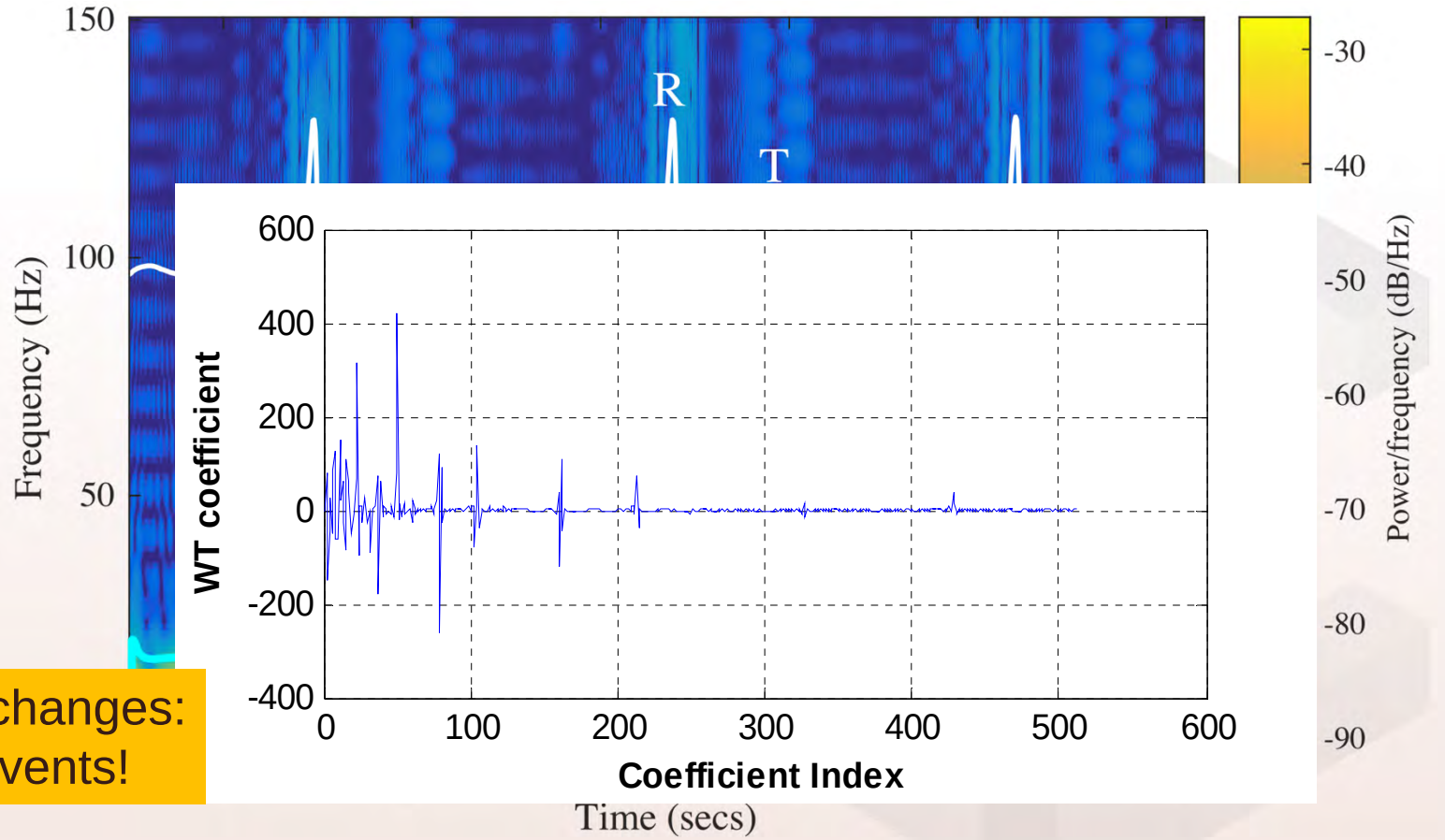
ECG temporal properties:

- High frequencies
- Low frequencies
- Changing in time

Different frequencies localized in time

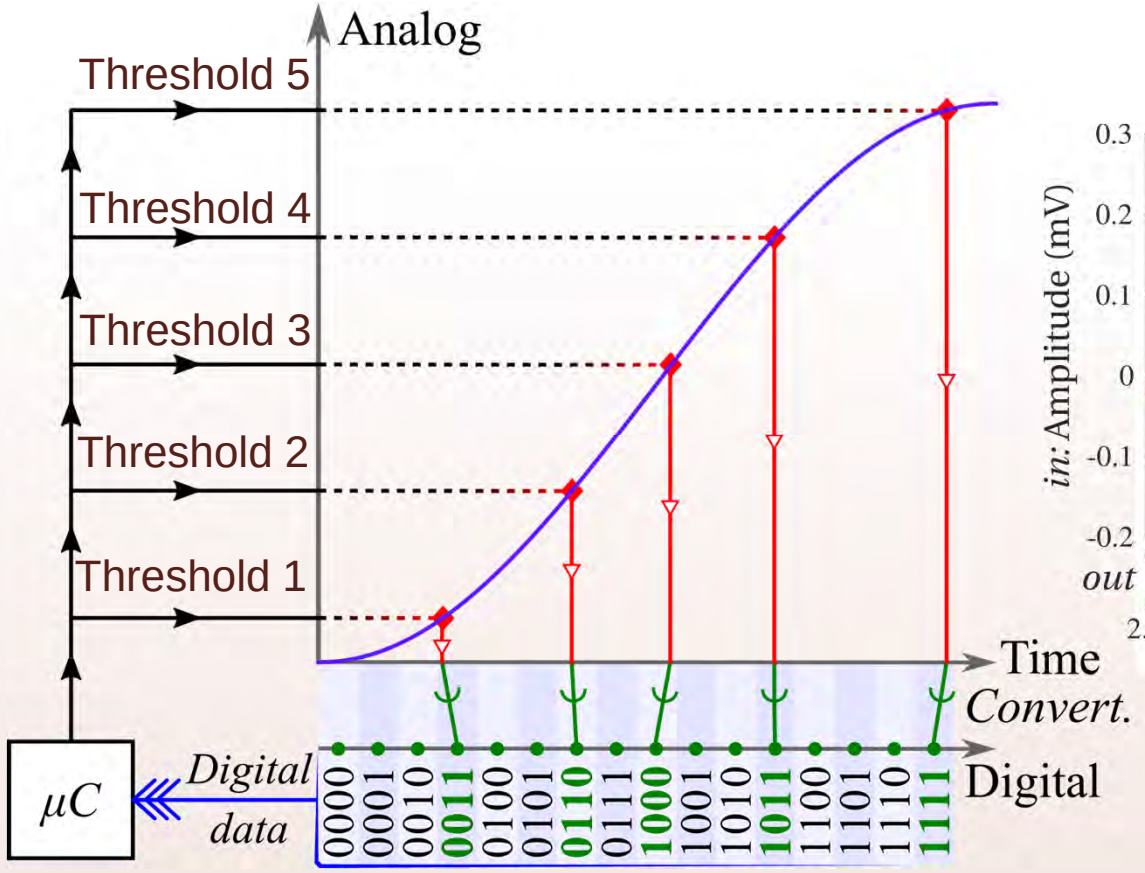
Uniform sampling is sub-optimal

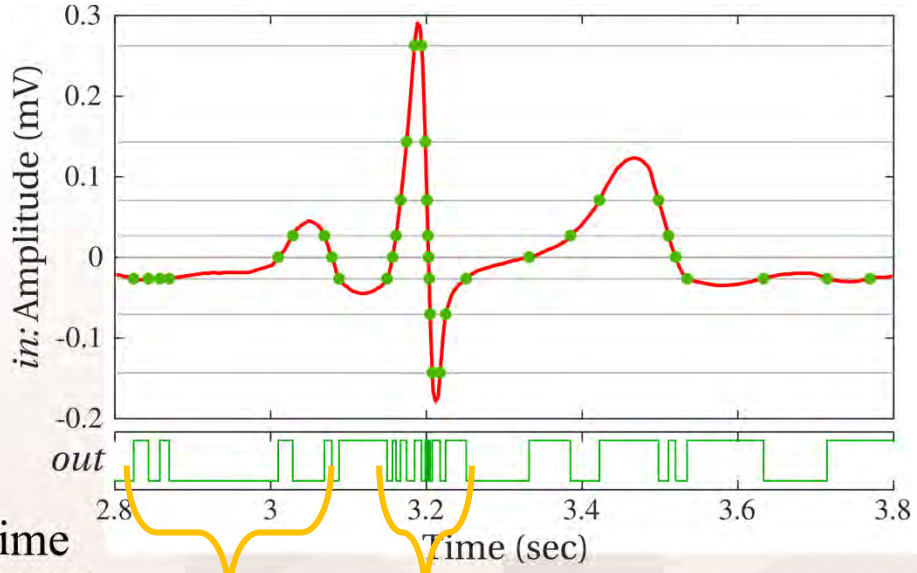
And if representation changes: sparse signal = Few events!



G. Surrel, et al., “Online Obstructive Sleep Apnea Detection on Wearable Sensors”, IEEE Transactions on Biomedical Circuits and Systems (TBioCAS), May 2018.

Event-Based Sampling in Edge AI Wearables

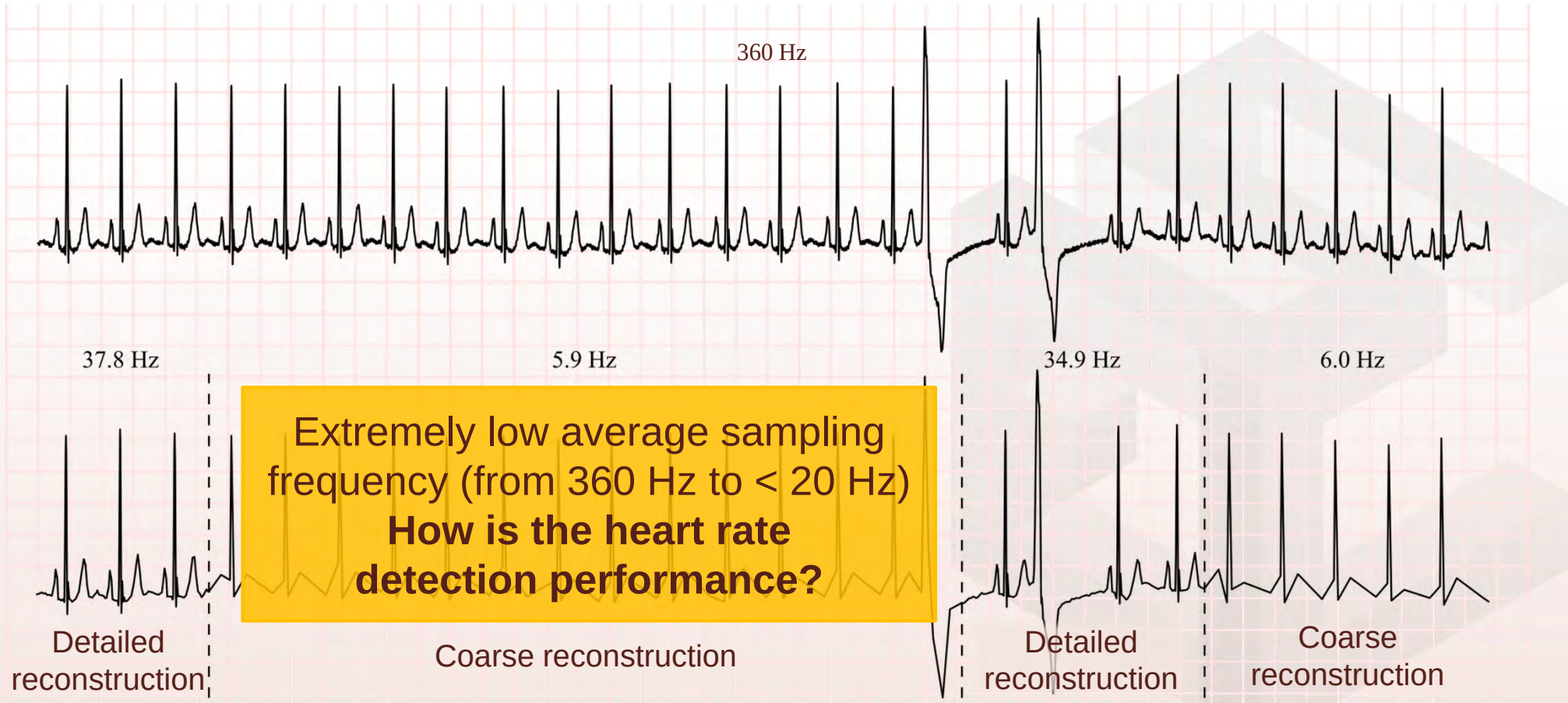




Sampling driven by **biosignal's properties, it can be dynamically tuned**

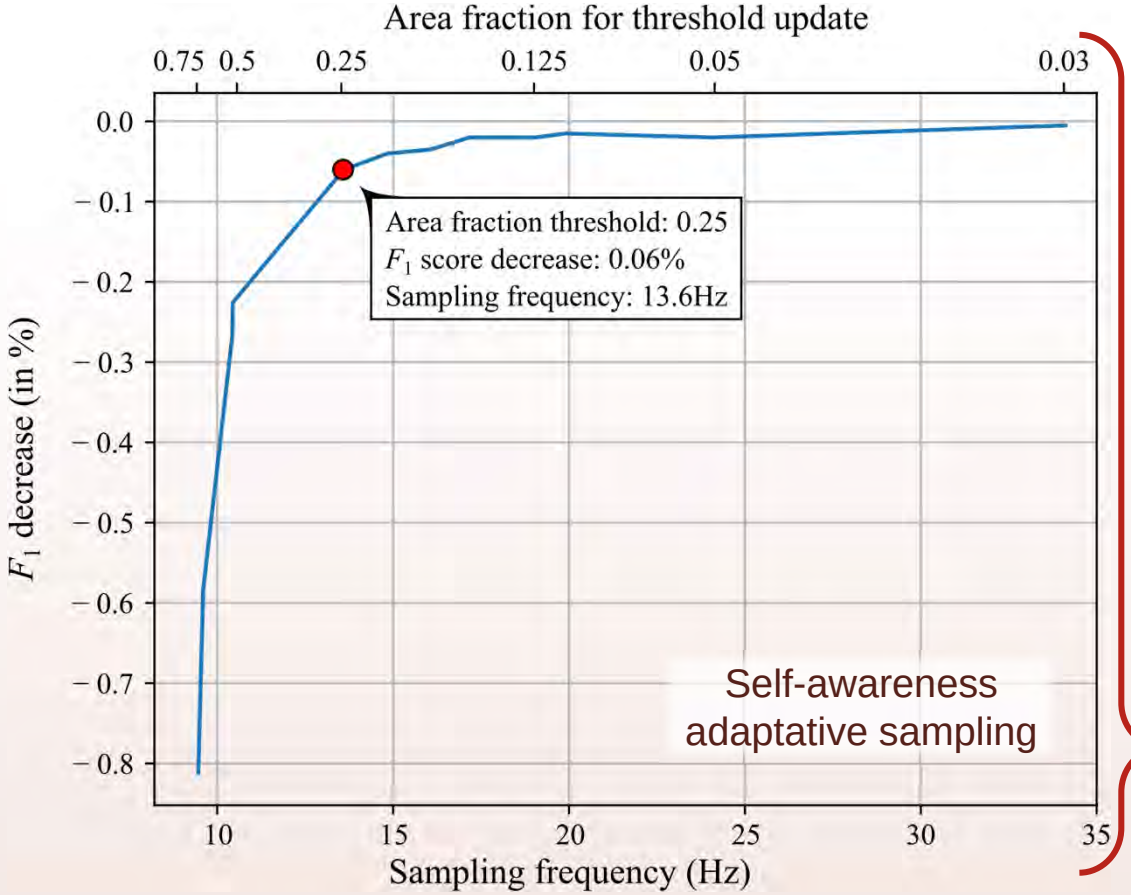
G. Surrel *et al.*, "Event-Triggered Sensing for High-Quality and Low-Power Cardiovascular Monitoring Systems", IEEE D&T 2019

Brain-Inspired Self-Aware Adaptive Sampling



S. Zanoli, Flavio Ponzina, Tomas Teijeiro, Alexandre Levisse, David Atienza, “An Error-Based Approximation Sensing Circuit for Event-Triggered Low-Power Wearable Sensors”, IEEE JETCAS, June 2023.

Performance vs Sampling Frequency



Performance: *American National Standard for Ambulatory ECGs*
Database: PhysioNet MIT-BIH Arrhythmia Database (110k beats)

Strategy	F1 score	Samp. freq.

Similar performance, different sampling rates

H. Mamaghanian, *et al.*, "Design and Exploration of Low-Power Analog to Information Conversion Based on Compressed Sensing", IEEE JETCAS, 2012
G. Surrel *et al.*, "Event-Triggered Sensing for High-Quality and Low-Power Cardiovascular Monitoring Systems", IEEE D&T 2019
S. Zanoli, *et al.*, "An Event-Based System for Low-Power ECG QRS Detection", Proc. of DATE 2020

Healthcare in IoT ecosystem of brain disorders monitoring

Continuous and reliable health surveillance

- Early alert detection
- Personalized treatment

Challenges in edge AI for brain disorders monitoring

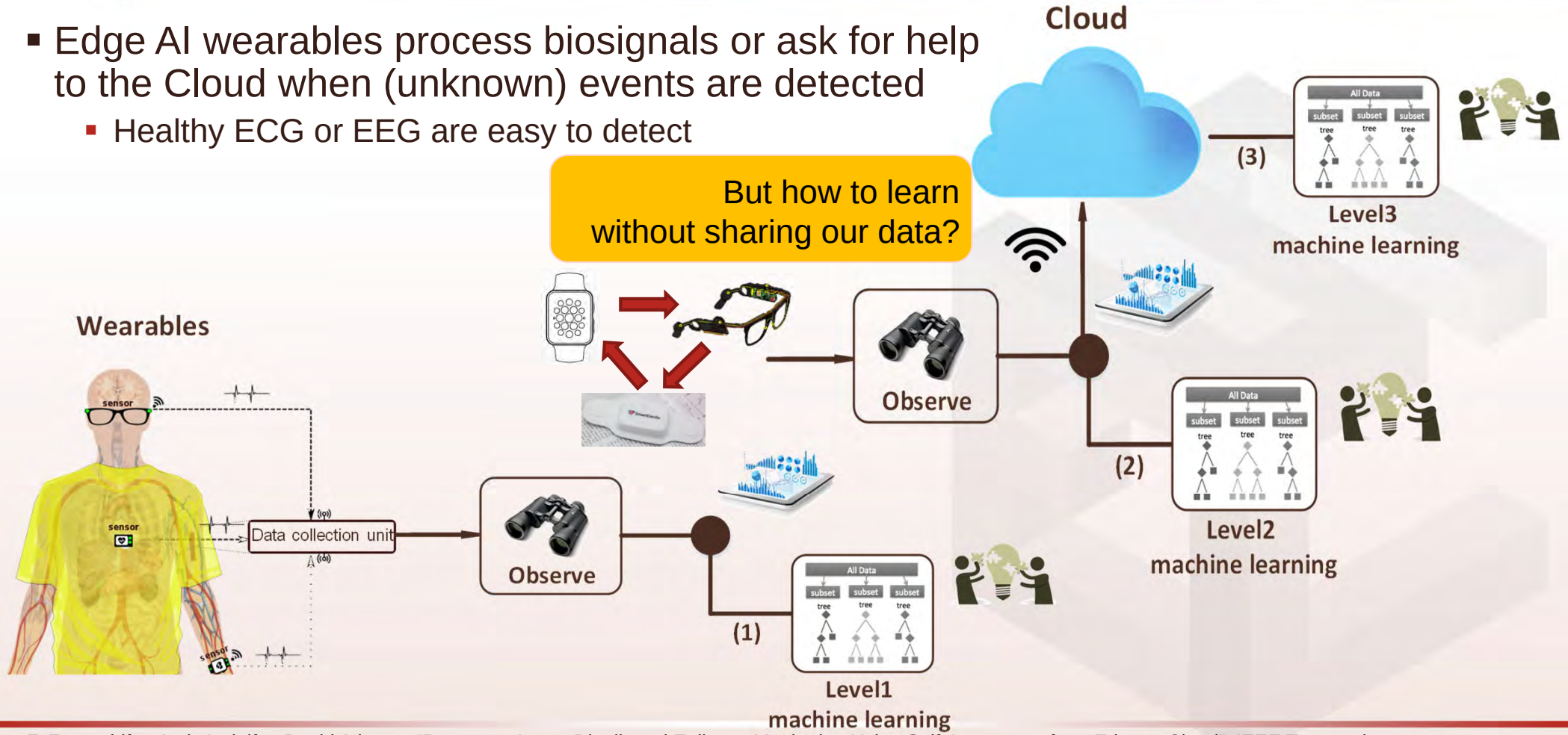
1. **Long-term and accurate monitoring**
2. **Real-time and personalized**
3. **User experience**

Social stigma: Patients refuse to wear EEG caps

Need for high accuracy with sensors in suboptimal positions in edge AI systems!

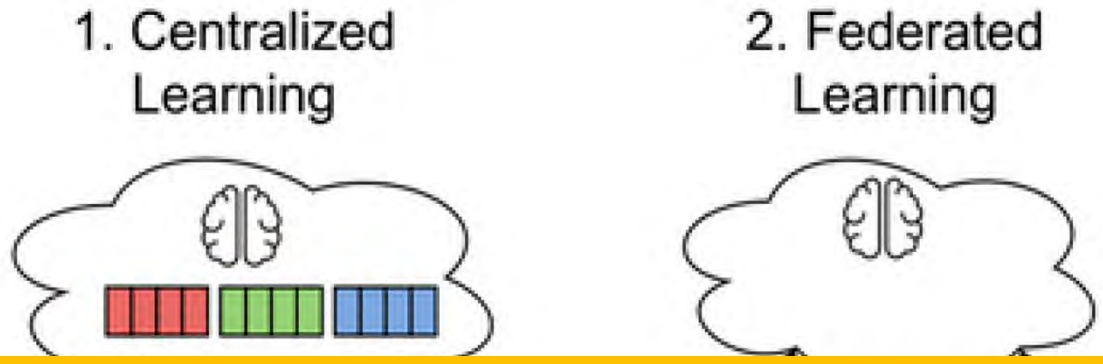
Multi-Level AI for Healthcare: Edge AI + Cloud Big Data

- Edge AI wearables process biosignals or ask for help to the Cloud when (unknown) events are detected
  - Healthy ECG or EEG are easy to detect

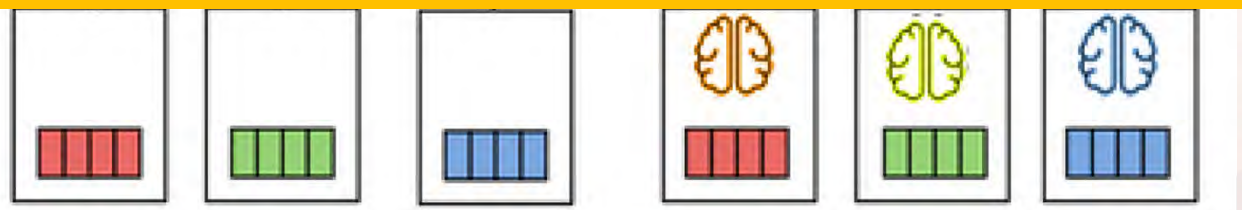


F. Forooghifar, Amir Aminifar, David Atienza, "Resource-Aware Distributed Epilepsy Monitoring Using Self-Awareness from Edge to Cloud", IEEE Transactions on Biomedical Circuits and Systems (TBioCAS), December 2019

- Components
  - ML model:
  - Data:



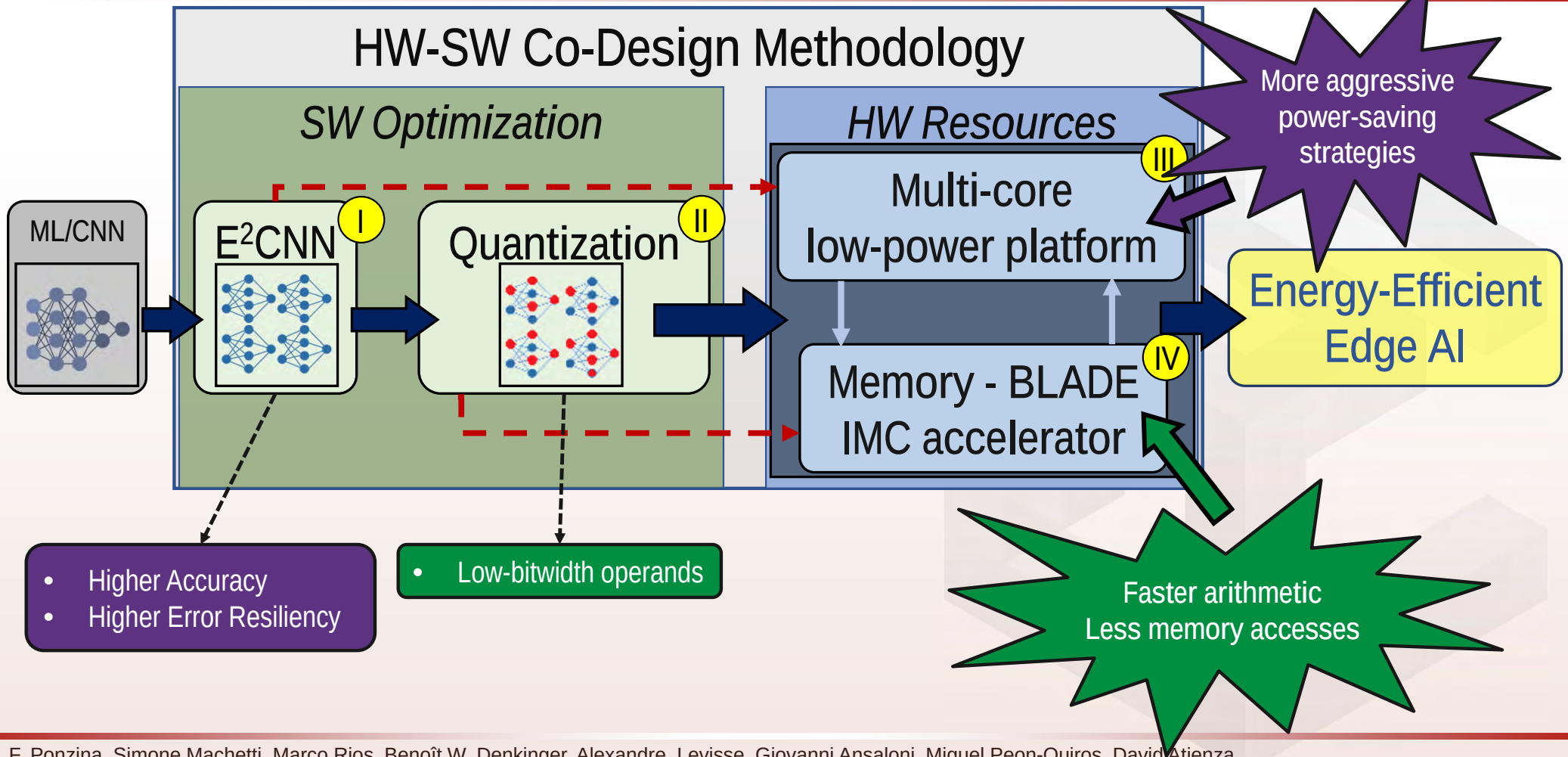
Training in Edge AI systems is key:
Particularly in medical devices as data is very sensitive!



Status Quo
(data sharing)

Privacy preserving
(NO original data shared)

System Co-Design Methodology for Medical Edge AI on FL Era

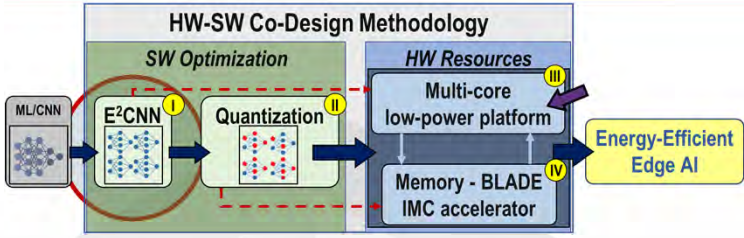


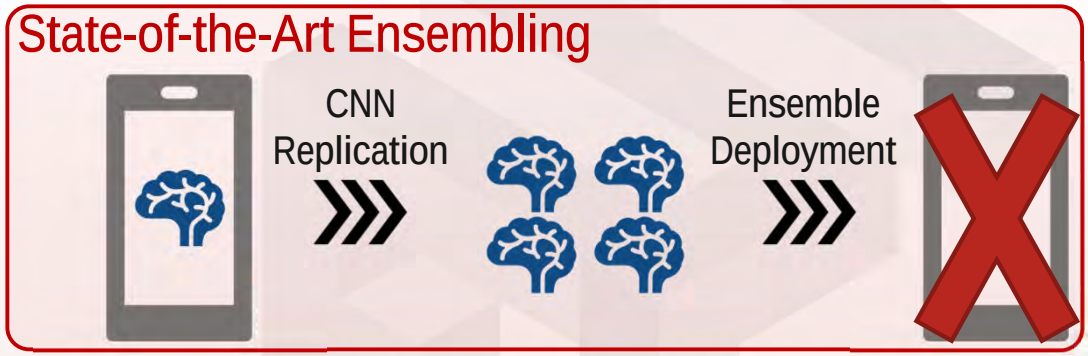
F. Ponzina, Simone Machetti, Marco Rios, Benoît W. Denkinger, Alexandre. Levisse, Giovanni Ansaloni, Miguel Peon-Quiros, David Atienza, "A hardware/software co-design vision for deep learning at the edge", IEEE Micro Magazine, November 2022

E²CNN: Embedded Ensembles of ML/CNNs

- Designed to be deployed in EdgeAI systems
  - SoA ensembles significantly increase workload and memory requirements
- How to build E²CNN
  - Be *N* the desired number of instances forming the ensemble (*N*=4 in the example)
  - First, before training, compress the initial CNN via filter pruning by a factor *N*
  - Replicate the obtained structure *N* times
  - Train each CNN independently
  - Average instances' predictions at run-time

No memory overhead
No computational overhead

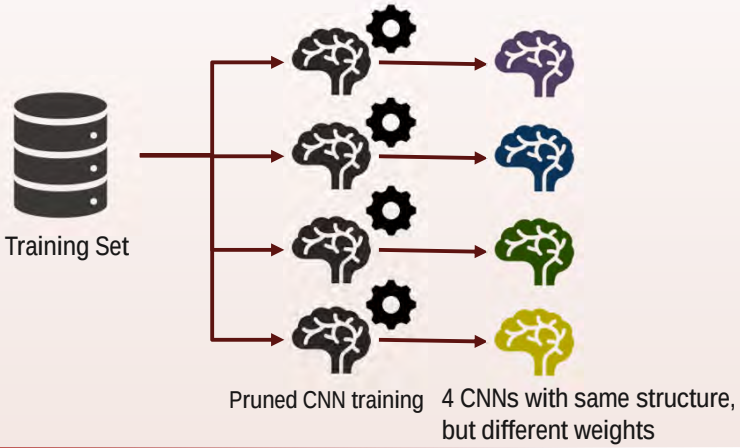




E²CNN – Use in Edge AI systems with FL

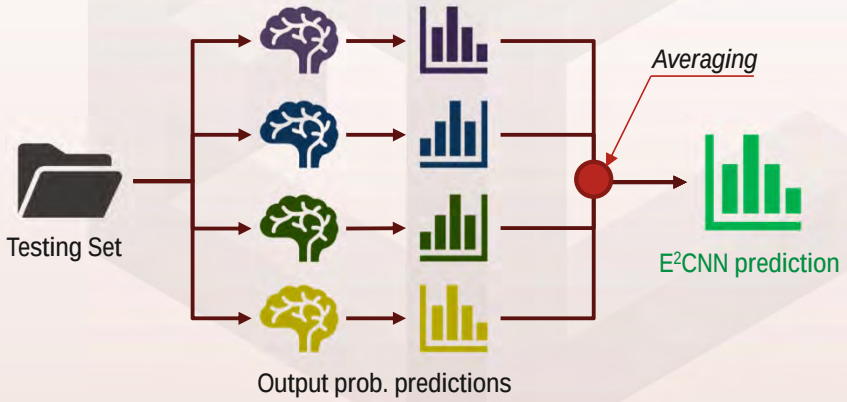
How to train the E²CNN design

- Train each CNN structure independently on the target dataset
- Use a (different) random weights initialization for each CNN structure



How to run inference with E²CNN

- Feed each instance with the target input data to be classified
- Average the individual output predictions to get E²CNN output



Quantization (Epilepsy Monitoring as Case Study)

a) **Uniform Quantization**
- Multipliers: 8 bits
- Multiplicands: 16 bits

CNN STRUCTURE		
Layer	Weights	Activations
Conv	8	16
Conv	8	16
FC	16	8

b) **Multipliers Optimization**
- Layer-based quantization
- Target: multipliers
- $2 \leq N \leq 8$ quant. bits

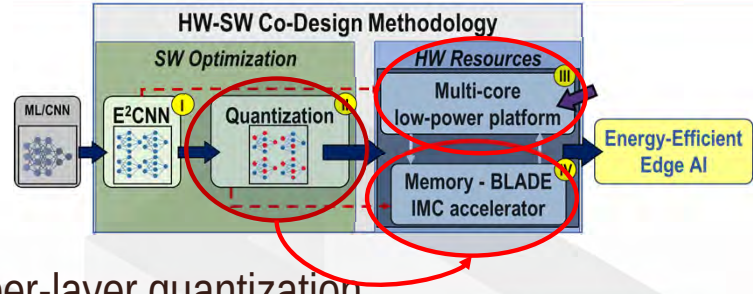
CNN STRUCTURE		
Layer	Weights	Activations
Conv	4	16
Conv	5	16
FC	16	3

c) **Filter-level Optimization**
- Filter-based Optimization
- Redundant bits removal

CNN STRUCTURE		
Layer	Weights	Activations
Conv	Mixed	16
Conv	Mixed	16
FC	16	3

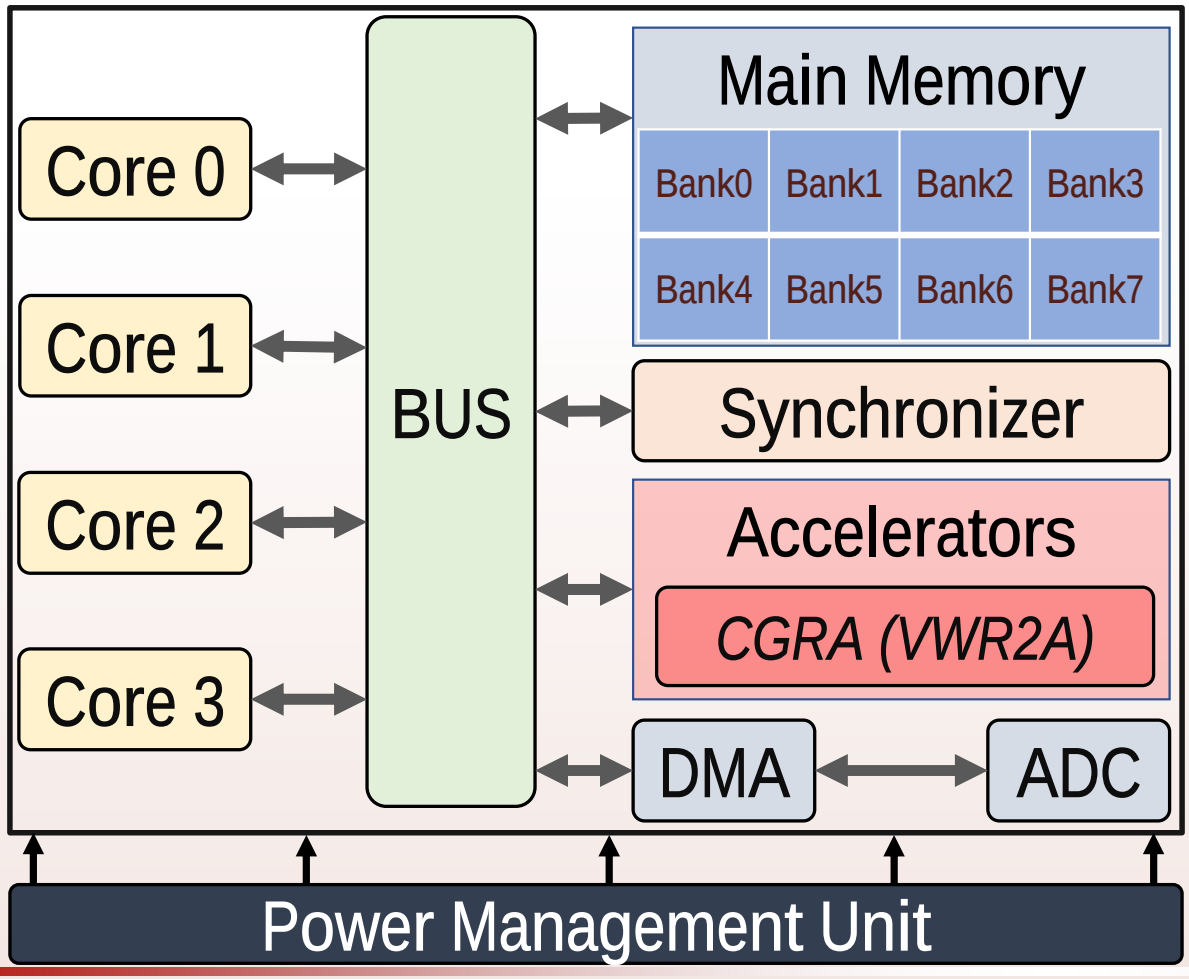
d) **Multiplicands Optimization**
- Layer-based quantization
- Target: multiplicands
- N=8 or N=16 quant. bits

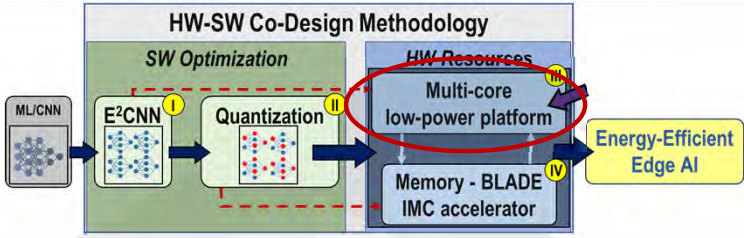
CNN STRUCTURE		
Layer	Weights	Activations
Conv	Mixed	8
Conv	Mixed	16
FC	8	3



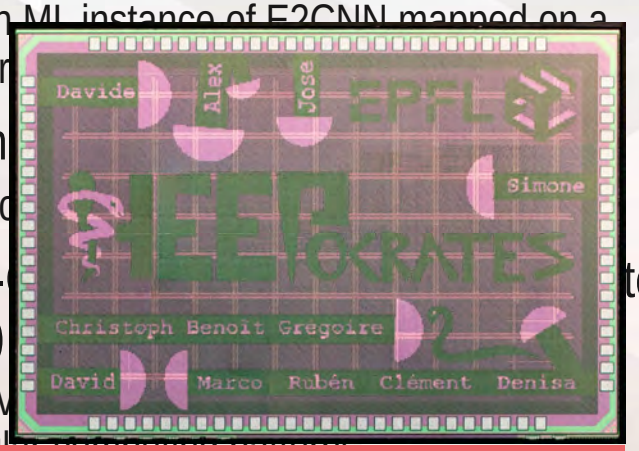
- Heterogeneous per-layer quantization
  - Applied on top of a uniformly quantized baseline (a)
- Accuracy-driven
  - Quantization in steps (b) and (d) constrained by a user-defined accuracy level (e.g., medical application)
- Custom bitwidths
- Filter-level optimization
  - Remove entire convolutional filters if containing only 0s weights
  - No impact on accuracy, but significant MACs reduction
- Resource-aware quantization
  - Multiplicands and multipliers optimized to maximize data reuse in accelerators and performance on in-memory computing

Multi-core low-power platform: HEEPocrates





- Multi-core architecture
  - Each ML instance of E2CNN mapped on a differ
- Indepen
  - Switc
- Coarse- tor (CGRA)
  - Conv
- Powe
  - V

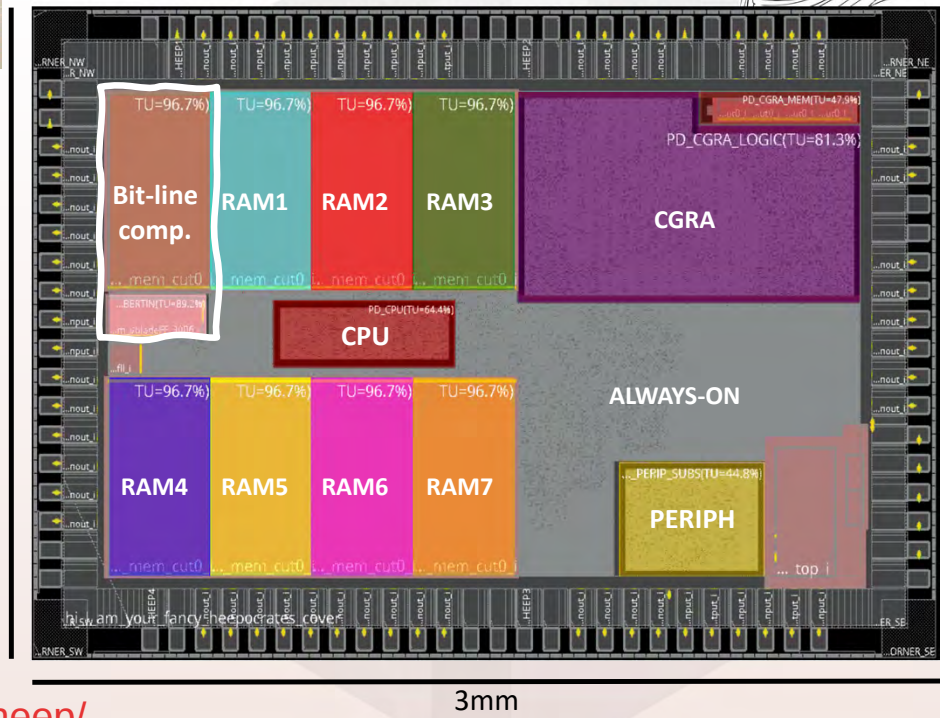


Specialized MPSoC wearable architectures fulfils workloads with 40% lower power than current wearable systems

https://www.epfl.ch/labs/esl/research/2d-3d-system-on-chip/x-heep/

HEEPocrates: first Open-Source Brain-Inspired Edge AI Architecture

- CPU: Core-V RISC-V [1]
  - Ibex
- Bus: Contiguous
- Memory: 8 banks, 256KB each
- ASIC implementation, 28nm TSMC
  - Area: 6mm^2
  - Max frequency: 250MHz
  - Power consumption: 28uW/MHz
- Extensions enable ACCELERATORS:
  1. **Coarse-Grained Reconfig. Array (CGRA)**
  2. **In-memory (bit-line) computing**

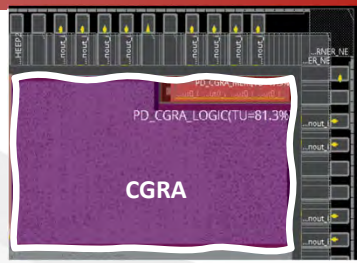


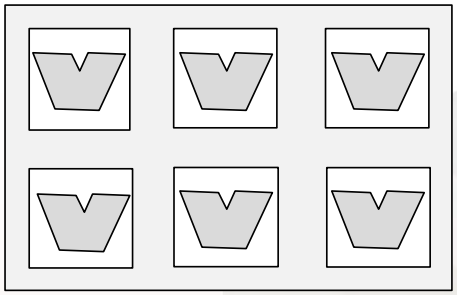
https://www.epfl.ch/labs/esl/research/2d-3d-system-on-chip/x-heep/

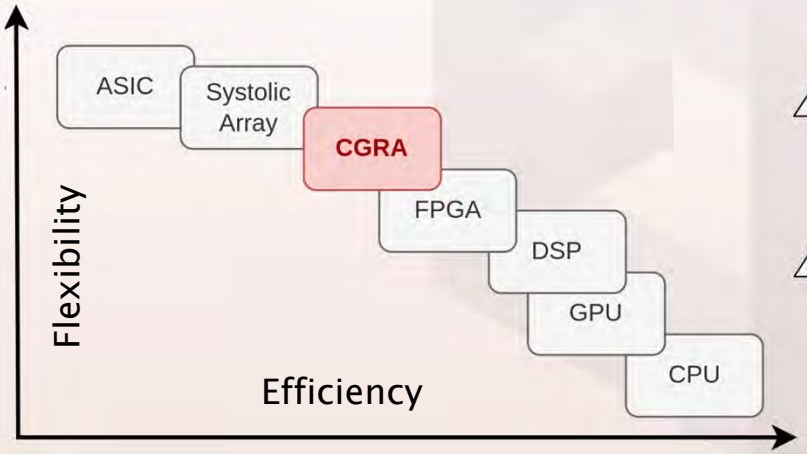
[1] OpenHW group github: https://github.com/openhwgroup

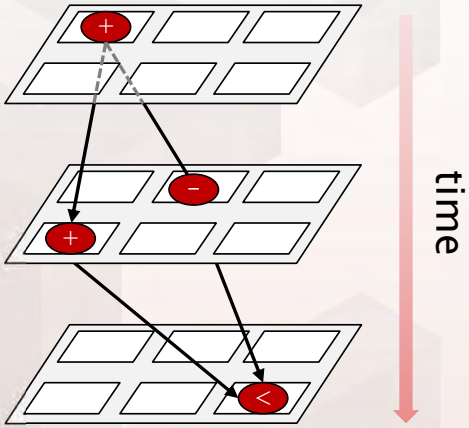
CGRA accelerator: Fundamentals

- Coarse Grained Reconfigurable Arrays
  - 2-D meshes of ALUs
  - Typically:
    - nearest-neighbor connections
    - local register files
    - multi-ported links to memory
    - space/time configurable
      → arithmetic operations mapped on ALUs
  - fast re-configuration
  - high parallelism



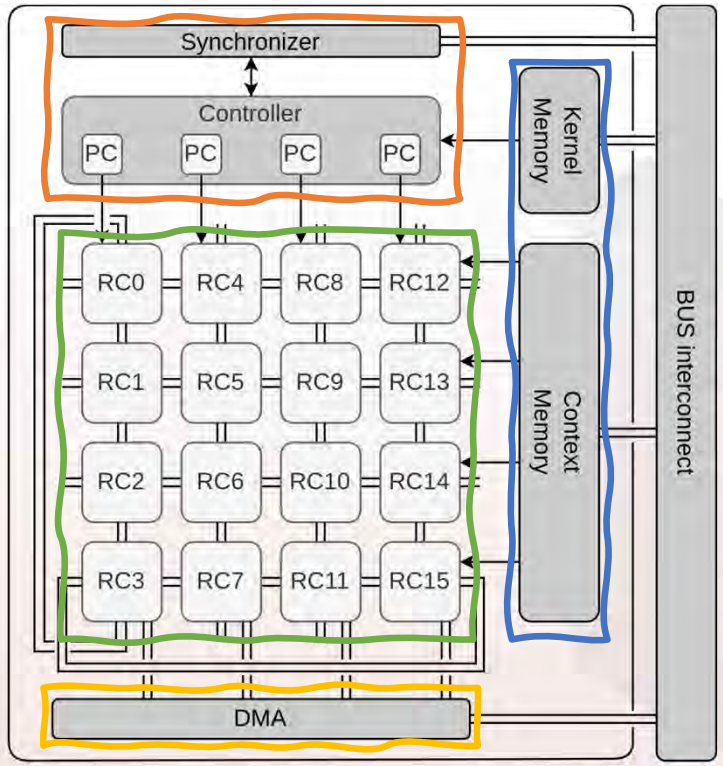


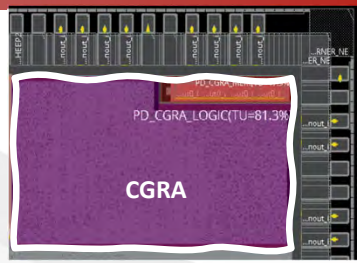


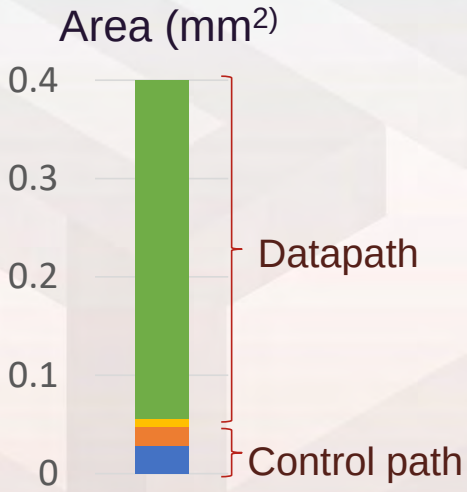


CGRA implementation

- Synchronizer and Controller
  - orchestrates execution
- Datapath
  - ALUs and register files
- DMA
  - input/output to/from memory
- Context/Kernel memory
  - stores CGRA configurations





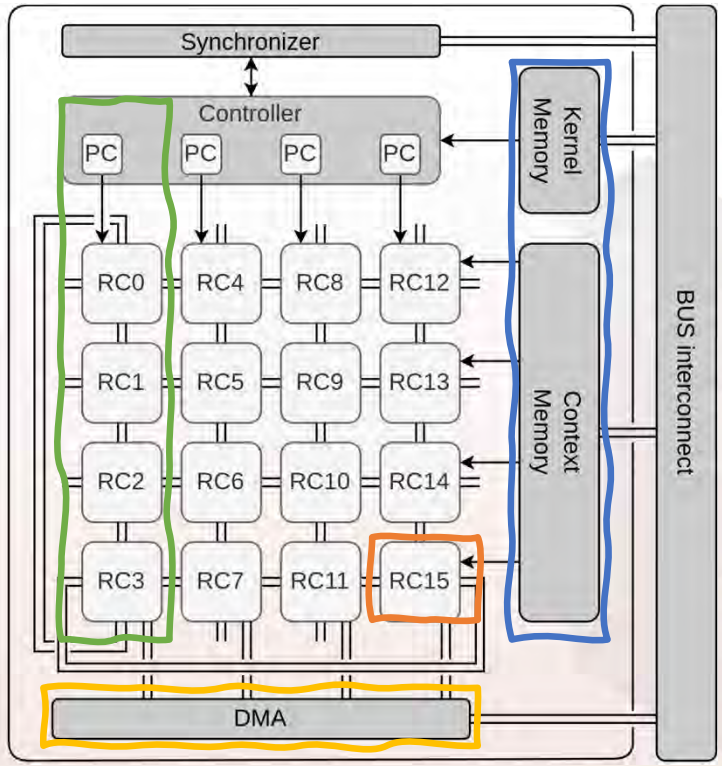


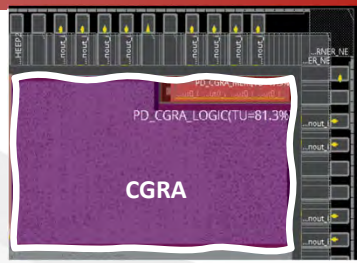
- Datapath occupies >80% of area

Loris Duch, Soumya Basu, Rubén Braojos, Giovanni Ansaloni, Laura Pozzi, David Atienza, "HEAL-WEAR: An Ultra-Low Power Heterogeneous System for Bio-Signal Analysis" IEEE Transactions on Circuits and Systems: Part I (TCAS-I), September 2017.

CGRA implementation

- 4 independent columns
  - Each can execute a different kernel
  - Kernels can use more than one column
  - Kernels-to-column mapping at run-time
- 2KB context memory
  - ”configurations cache”
- One DMA port per column





- 16 Reconfigurable cells
  - 32-bit ALUs
  - 4-words register file
  - 32x32bits instructions

CGRA compiler support

CGRA Kernel (.c)

```
void sha_transform(int w[]){
   for(int i = 16; I < 80; ++i)
      w[i]= w[i-3]  ^ w[i – 8] ^
            w[i–14] ^ w[i – 16];
}
```

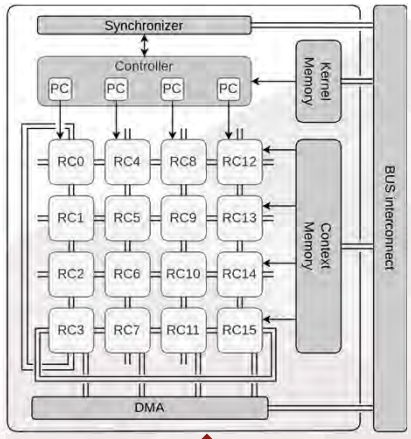
SAT- MAPit Assembler [1] (USI-Lugano)

CGRA Assembly

```
NOP
SADD R0, R1, RCT
LXOR ROUT, RCT, RCR
LWI ROUT, RCR
NOP
SADD ROUT, RCB, -16
SMUL ROUT, RCL, 4
NOP
NOP
SADD ROUT, ZERO, RCR
SADD ROUT, R0, RCT
SADD ROUT, R0, ROUT
NOP
...
```

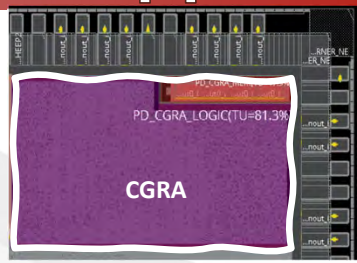
CGRA Configuration

```
0x00010001,
0xf3f6c200,
0x12358a22,
.........
```



CGRA Configuration

```
void main(){
   ...
   memcopy(CGRA_Configuration, CGRA_ADDR, N);
   ...
}
```



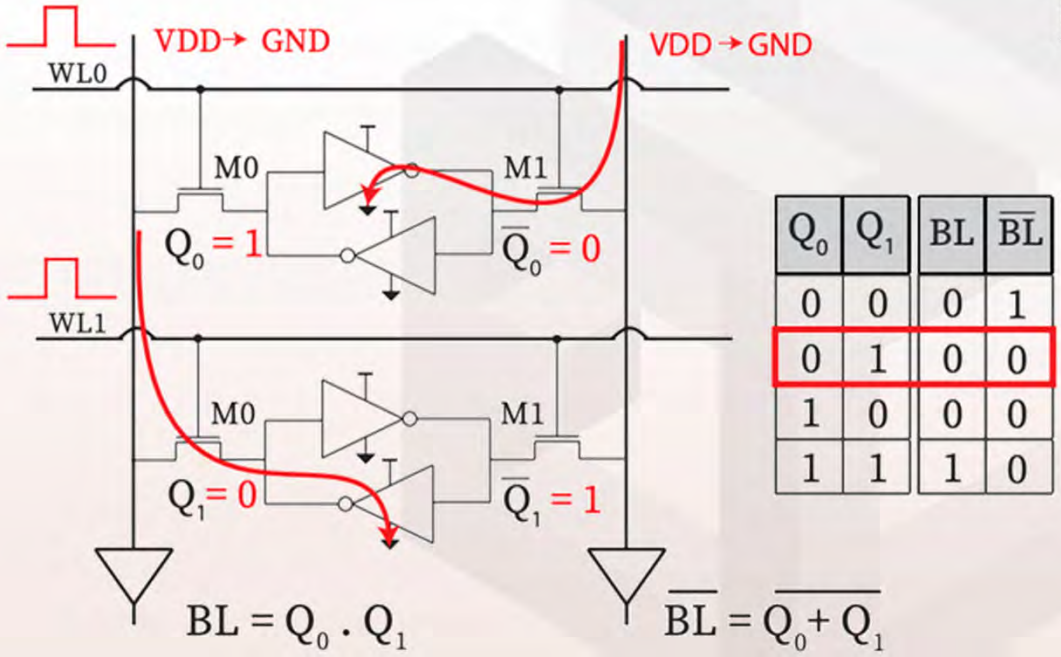
[1] Tirelli, Cristian, Lorenzo Ferretti, and Laura Pozzi. "SAT-MapIt: A SAT-based Modulo Scheduling Mapper for Coarse Grain Reconfigurable Architectures." *Design, Automation and Test in Europe Conference Exhibition (DATE)*. 2023.

In-Memory Computing - BLADE: Bit-line computing at the Edge

- Computation performed on SRAM array
  - parallelism
  - minimal cost for data movements

- one main ”Trick”
  → two rows activated at the same time

- AND and NOR on the bit-lines

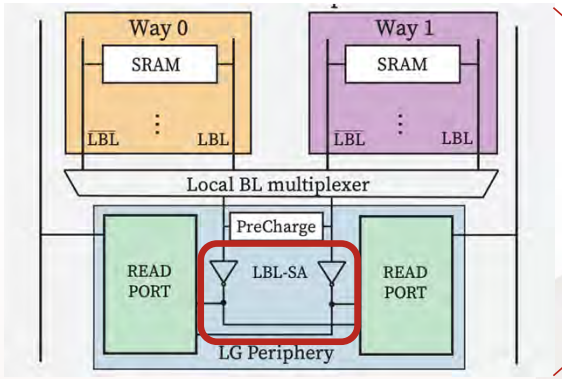


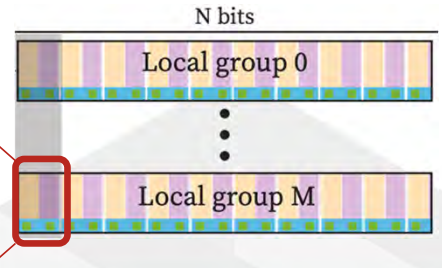
Q_0	Q_1	BL	$\overline{BL}$
0	0	0	1
0	1	0	0
1	0	0	0
1	1	1	0

Rios, Marco, et al. "Bit-Line Computing for CNN Accelerators Co-Design in Edge AI Inference." *IEEE Transactions on Emerging Topics in Computing* (2023).

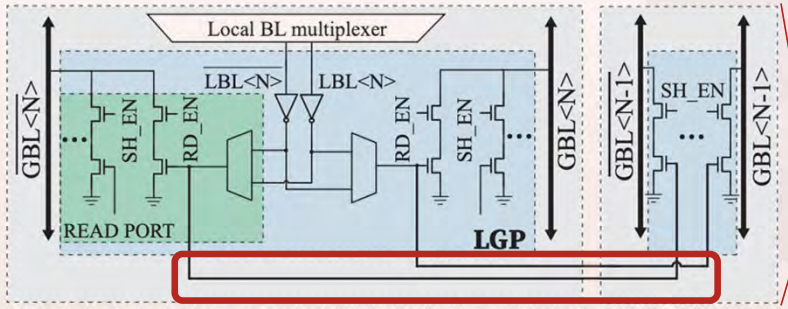
BLADE Bit-line array architecture

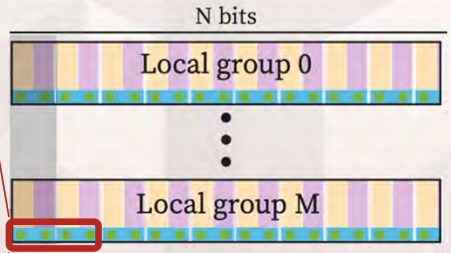
1. Each bit can be negated
   1. inverter after the sense amplifier





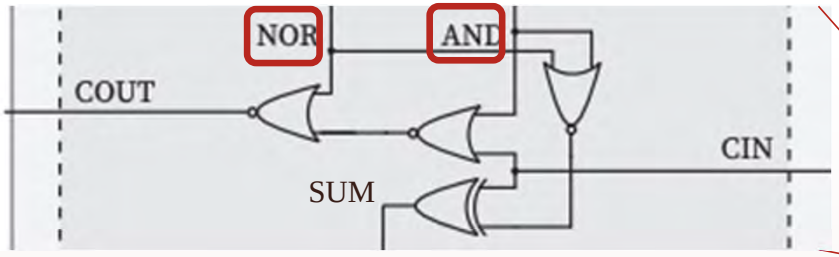
2. Operands can be shifted





BLADE Bit-line array architecture

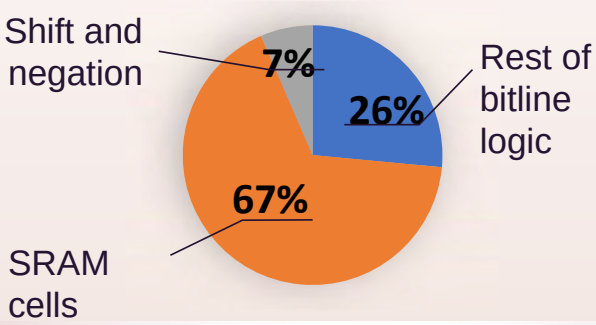
3. Ripple-carry adder at the SRAM periphery



→ Shift, add, negation implement MAC

- 2.2GHz
- 640B SRAM
- 28nm TSMC

Area: 1240 μm²



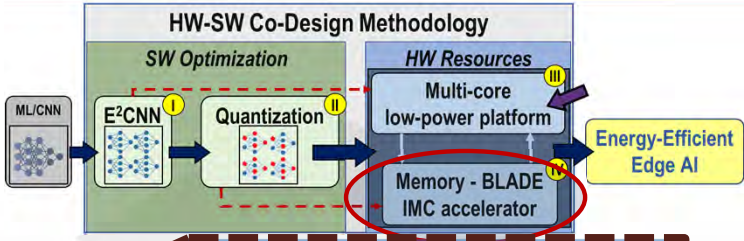
Energy

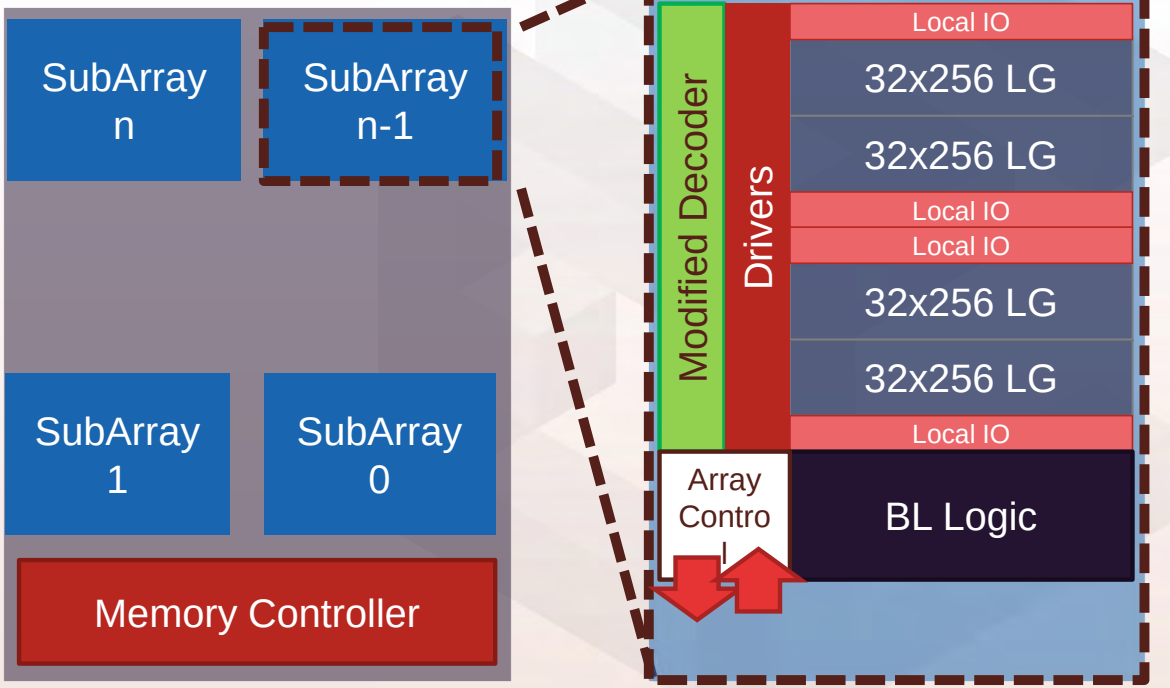
16-bits word		
Read	Write	IMC
376pJ	414pJ	381pJ

BLADE: Results

- New bit-line (BL) computing accelerator for Edge AI
  - in-SRAM computing
  - CMOS compatibility
- Memory array divided in subarrays
  - Higher reliability of in-memory operations
  - Higher performance
- MACs implement convolutional and fully connected layers
  - ultra-low power
  - on each SRAM array in parallel
- Lower energy than 2-bits computation
  - **1% accuracy accuracy degradation wrt 8-bit quantization**

3x performance gain for convolutional layers!





e-Glass[1]: A system for real-time seizure monitoring

Comparison: 24 vs 4 electrodes

e-Glass first prototype.

Glasses embodiment to reduce social stigma!

Sensors:

- EEG:
  - 24-bits
  - 3 channels
  - Soft-dry electrodes
- Accelerometer (3-axial) /Gyroscope

Interfaces:

- Bluetooth 4.2
- USB 2.0

Processing:

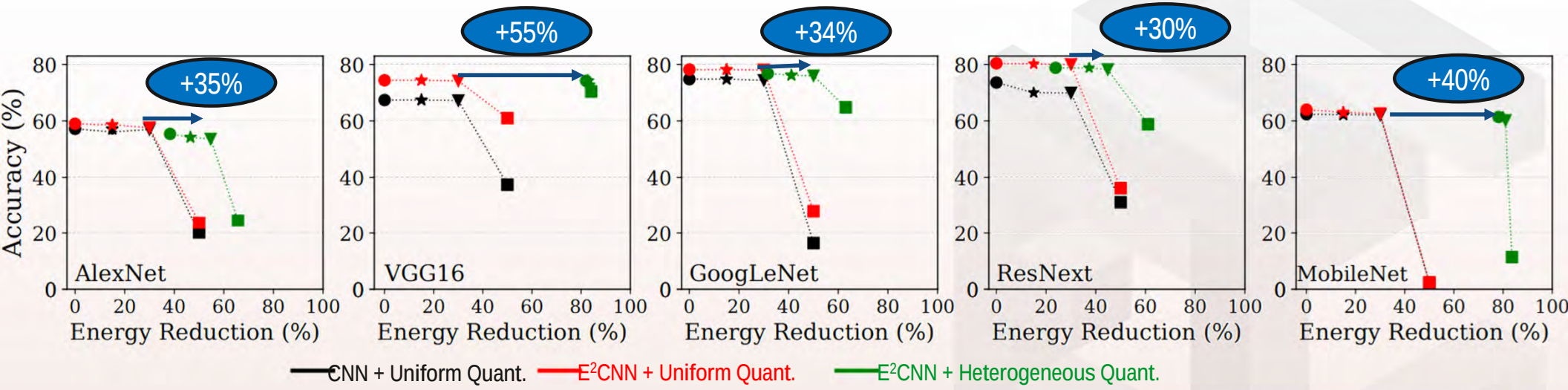
- HEEPocrates – Ultra-low power edge AI
- Onboard memory: 64 MB (up to 8,2 hours)

Battery powered: up to 24h monitoring.

D. Sopic, A. Aminifar, and D. Atienza, “e-Glass: A Wearable System for Real-Time Detection of Epileptic Seizures,” in 2018 IEEE International Symposium on Circuits and Systems (ISCAS). Florence, Italy: IEEE, may 2018, pp. 1–5.

Experimental Results: Heterogeneous Quantization with Edge AI Co-Design

- Co-design enables heterogeneous quantization at different levels without quality reduction
  - Energy savings up to *55%* at system level, *without any accuracy drop*

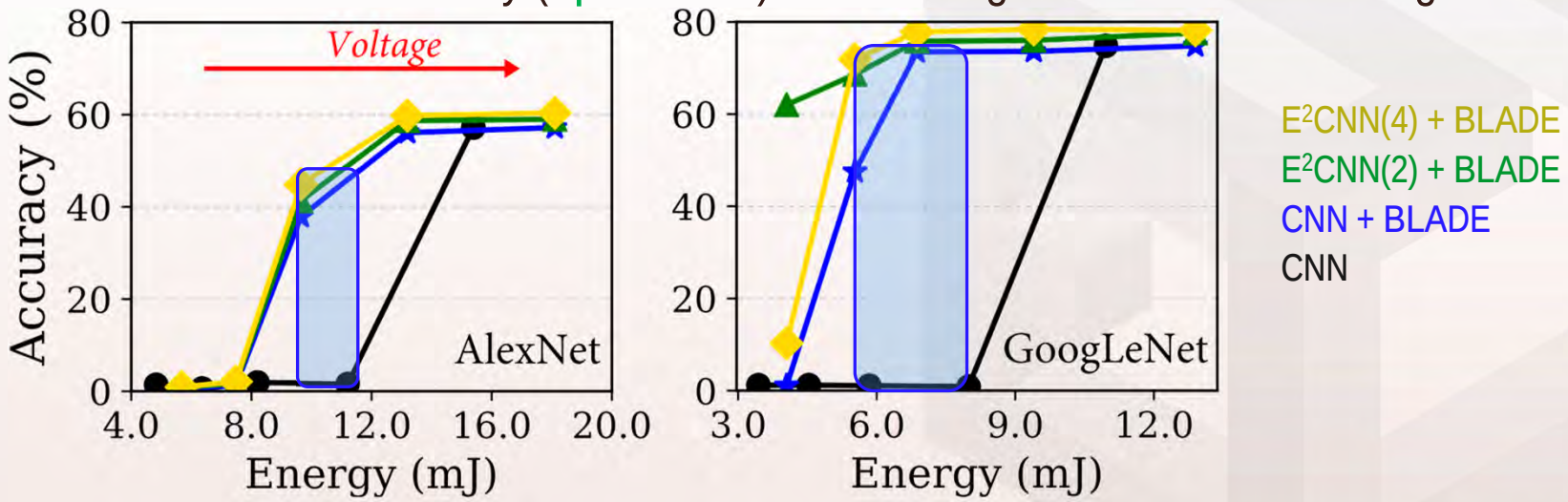


Markers correspond to different approx. layers used to improve energy efficiency

Can in-memory computing (IMC) and HW/SW co-design support each other?

Experimental Results (2): E²CNN and BLADE

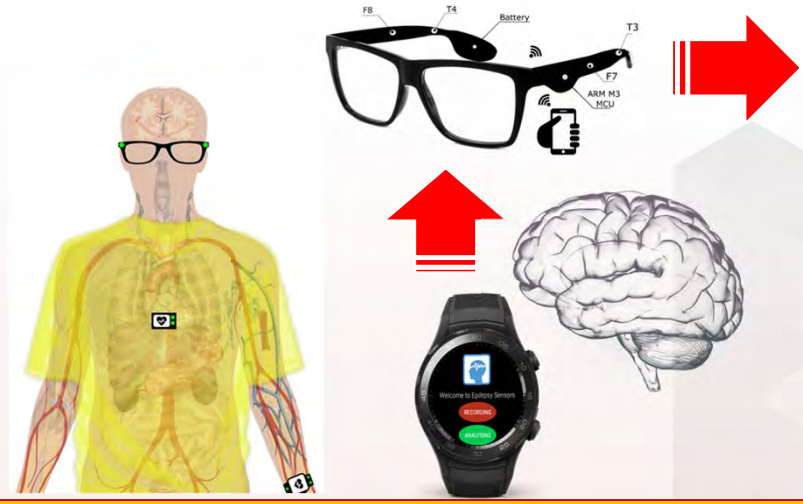
- Expand the benefits of BLADE IMC with HW/SW co-design methodology
  1. Apply voltage scaling to save energy
  2. Introduce BLADE to operate custom operations and prevent possible errors
  3. Replace single-instance CNN with our E2CNN methodology
- E²CNN further increases accuracy (up to 70%!) at wide range of sub-nominal voltages

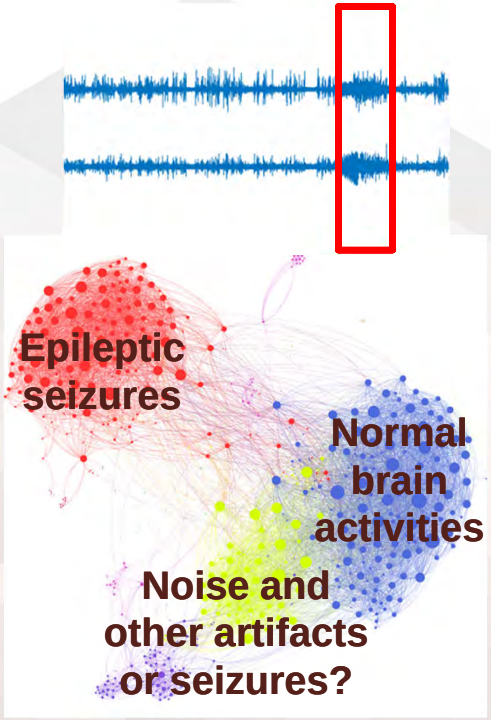


Accuracy of edge AI is low for medical devices: All need to work (train) together!

Extension of Edge AI: ML Adapts with User Feedback

- And if we know that there is a seizure in the past hour?
  - User informs with watch





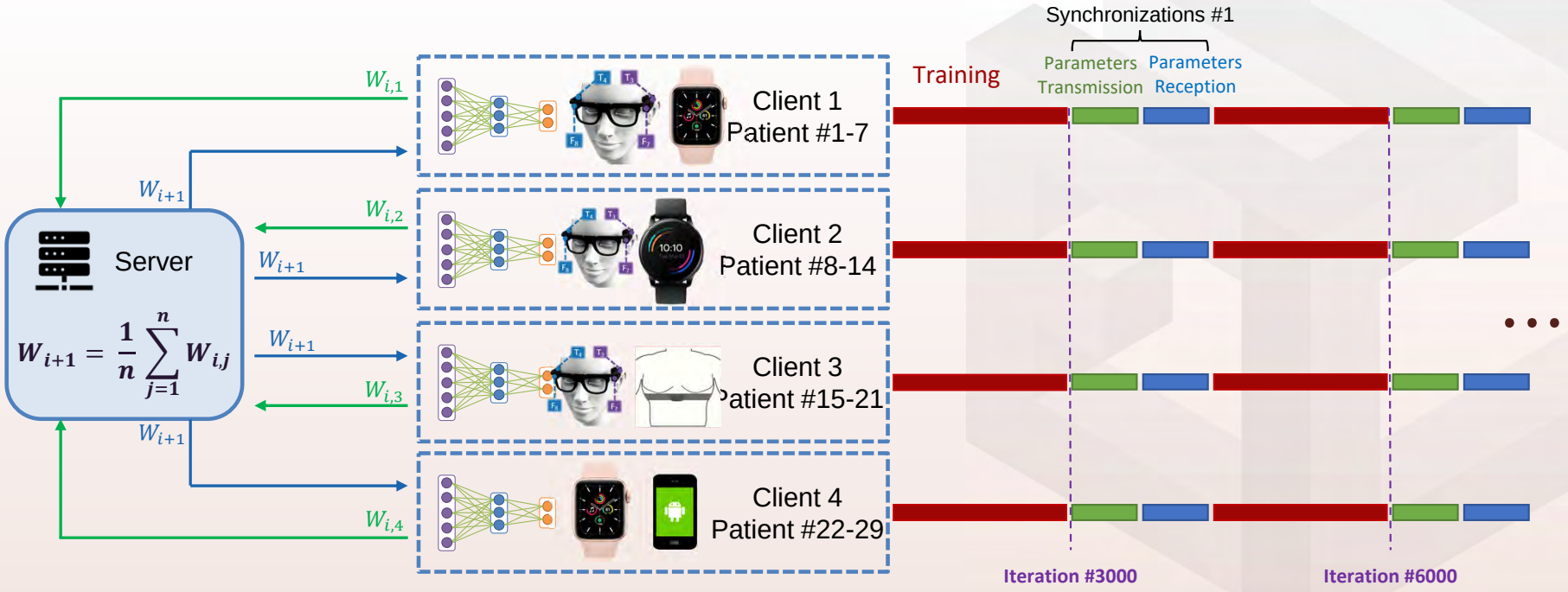
In our minimally-supervised seizure detection, 90% of identified ML segments overlap with actual seizures

But we have not really used the power of FL yet!

[Pascual at al., DATE 2019]

FL to the Rescue of Medical Edge AI: Global Epilepsy Monitoring

- Weights of ML/CNN models of each edge AI instance (client) shared after a certain number of local training iterations
  - Explore trade-offs in transmission power vs. central coordination
  - Use of common vs personalized model at client



Results (4): FL in Edge AI Wearables for Epilepsy Use Case

- FL improves edge AI results with reduced synchronization checks
  - Very limited decrease in geometric mean, and significant energy consumption reduction

Single edge AI machine use		Federated training (sync every 30 iterations)		Federated training (sync every 3000 iterats.)		Federated training (sync every 10000 iterats.)	
Sensitivity	81.5%	Sensitivity	81.25%	Sensitivity	81.25%	Sensitivity	79.6%
Specificity	86.75%	Specificity	89.5%	Specificity	87.5%	Specificity	74%
Geometric mean	84.08%	Geometric mean	93.36%	Geometric mean	91.62%	Geometric mean	76.74%
Required battery	755 mAh	Required battery	1111 mAh	Required battery	344 mAh	Required battery	338 mAh

Training + Transmission + Reception

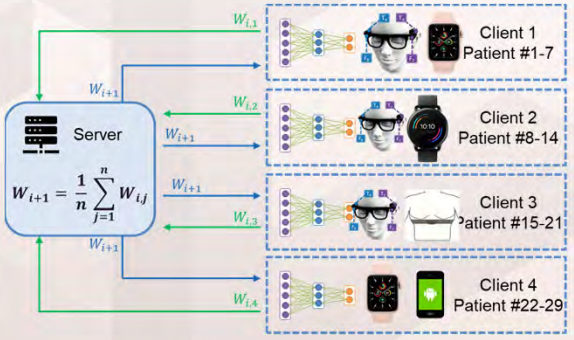
Bluetooth low energy (nRF52840)

Use of FL with edge AI for epilepsy monitoring enables 95% data transmission reduction with personalization, and 2x energy improvement!

Conclusion

- IoT age can provide a great new world in many fields
  - We need to effectively combine: Edge computing with low-power AI/ML
- Sustainable IoT = Edge AI needs to be reliable and low-power
  - New system-level flows: combining ensembles in CNNs and MPSoCs
  - Improve of edge AI through Federated Learning (FL)

- System co-design for next-generation edge AI systems
  - Methodological heterogeneous optimization on edge AI systems
  - Trade-offs in edge AI systems: 37.2% less energy with 1% accur. drop
    - Extra 70% less SRAM energy if in-memory computing is applied!
  - Enables efficient use of FL for efficient edge AI training: results competitive with respect up to Cloud-based training!



Thanks for Your Attention!

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