ETH zürich — ALMA MATER STUDIORUM UNIVERSITÀ DI BOLOGNA

# Wearable TinyML Platforms for Biosignal Intelligence Across the Body


Integrated Systems Laboratory (ETH Zürich)

**Andrea Cossettini** cosandre@iis.ee.ethz.ch


**PULP Platform**
Open Source Hardware, the way it should be!

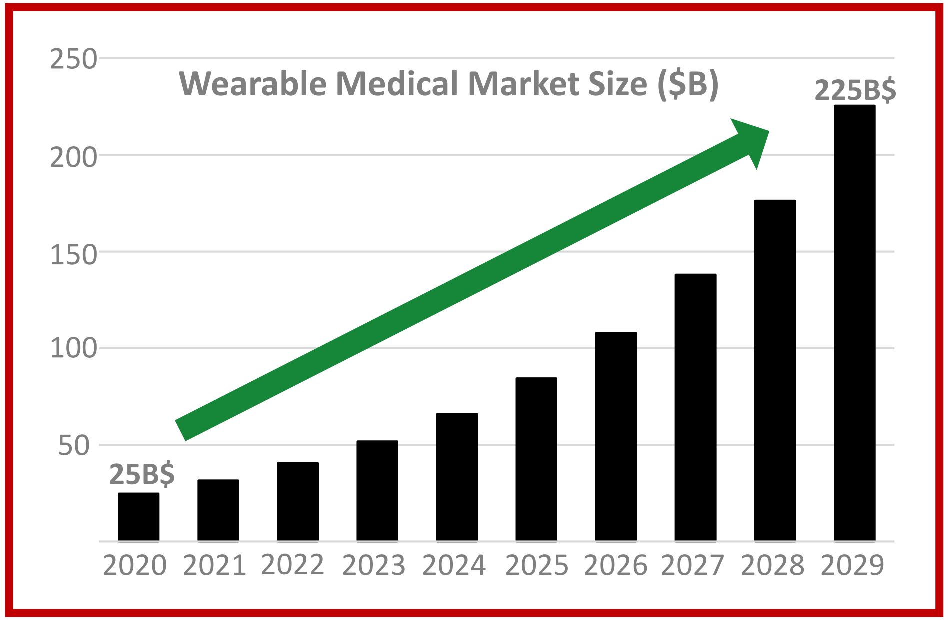
@pulp_platform
pulp-platform.org
youtube.com/pulp_platform

# We want smarter wearables

We all want technologies to enhance our wellbeing in daily life

## Health-monitoring

**Rapid Growth in Wearables Market**




**Limited on-device processing**

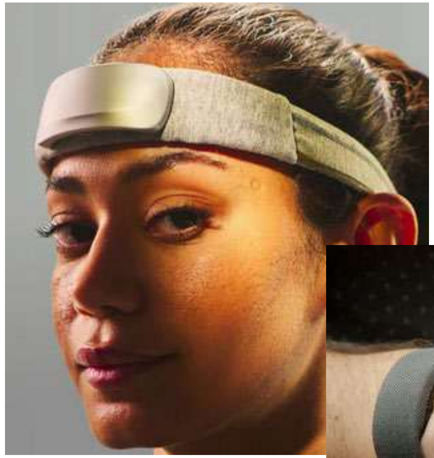
## New forms of interaction

*assisted speaking*
*controlling devices*

*Heart rate,*
*step count…*

A lot has been possible with these simple data (health metrics, …)

**Potential for more! biosignals**



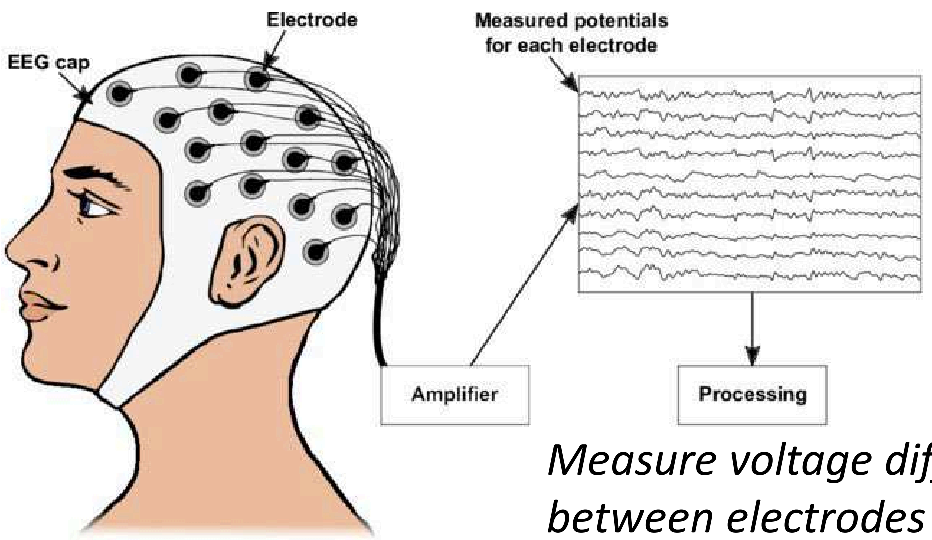
*Muse "Athena"*
*EEG headband*

*Meta "Orion"*
*EMG wristband*

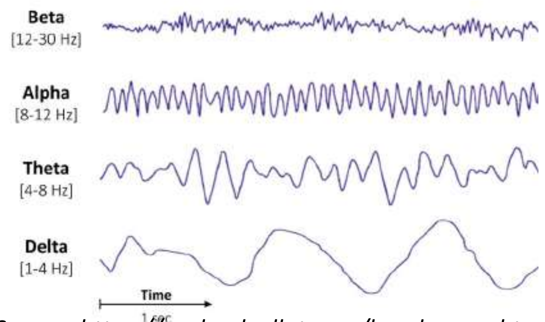
**Biosignals + edge intelligence for enhanced living**

# But what are biosignals? A window into the body

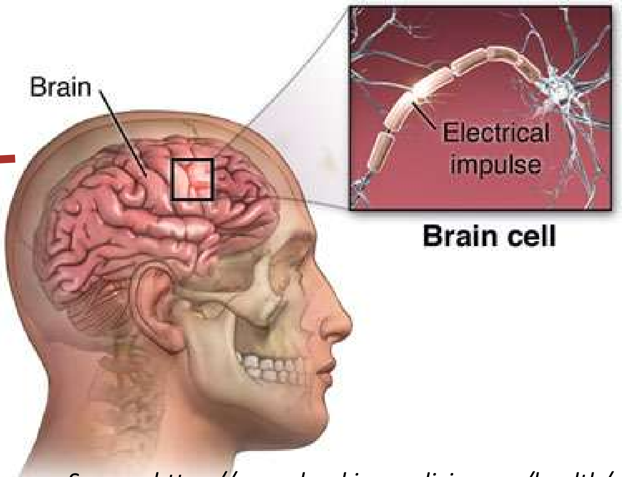
- **Electroencephalography (EEG)**




Scalp attenuates signals by almost 90%




Source: https://raphaelvallat.com/bandpower.html



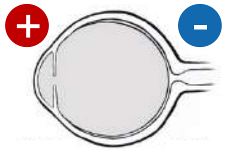

Source: https://www.hopkinsmedicine.org/health/conditions-and-diseases/epilepsy/evaluation-of-a-firsttime-seizure

*Measure voltage difference between electrodes on the scalp*

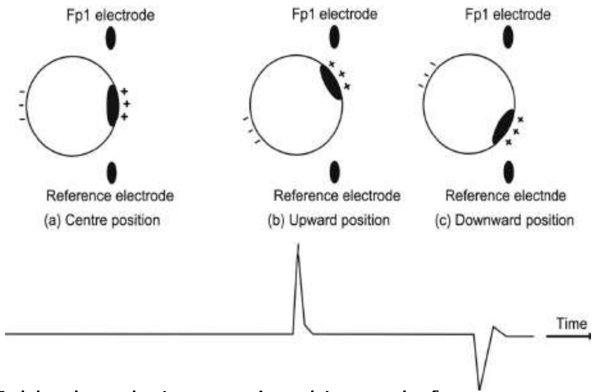
**Challenge**: signal range from 10 µV to 100 µV ← low SNR

- **Electrooculography (EOG)**

*Measure the corneo-retinal standing potential, between front and back of the eye*




Eyes are dipoles



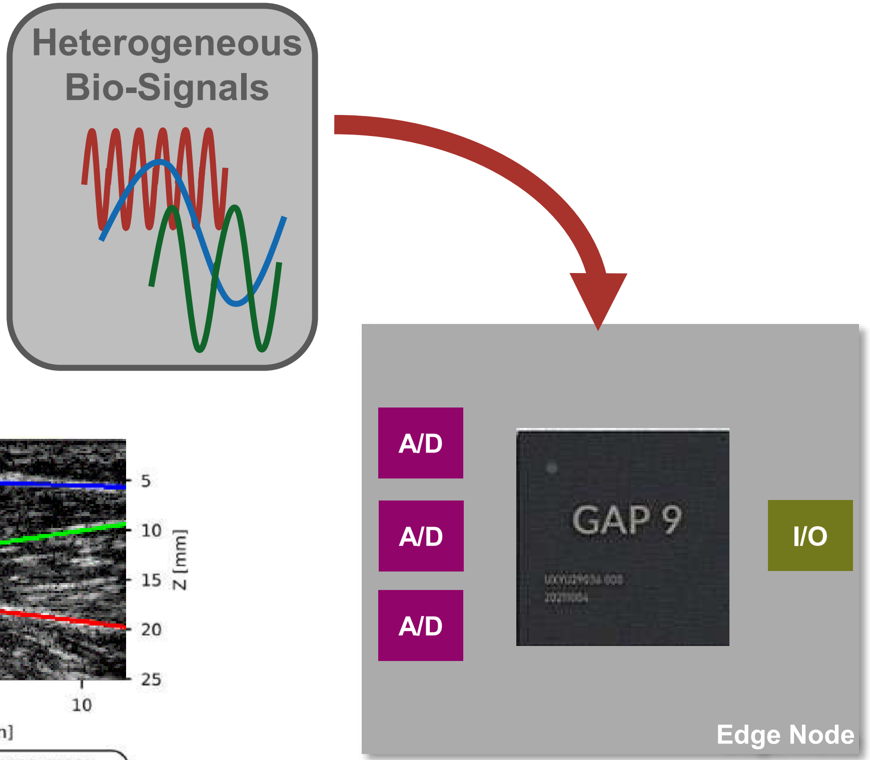

Source: Abo-Zahhad et al., *International Journal of Intelligent Systems and Applications, 2015*

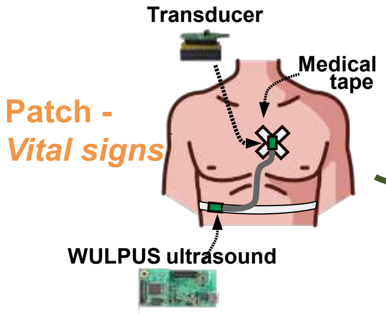
- **And others…**
  - EMG (muscles)
  - ECG (cardiac)
  - …

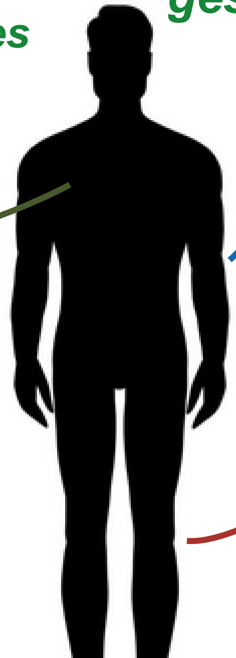
# Our research on smart biomedical wearables

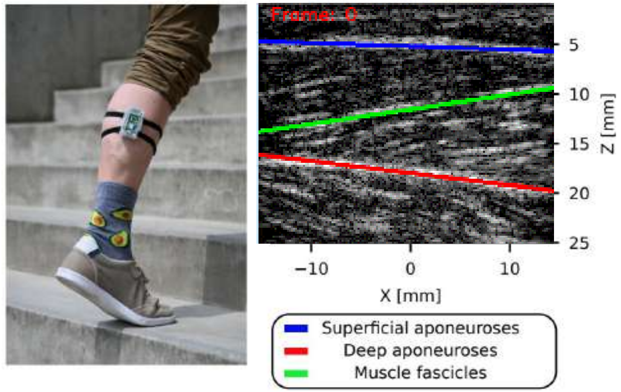

***[Smart Hearables and Glasses](#)*** ***for Epilepsy Monitoring and Human-Machine interfaces***

***Smart armbands* for gesture decoding for future prosthetics**






edgeAI on heterogeneous biosignals

***Wearable Ultrasound*** **in Smart Patches for cardiovascular sensing**

***Wearable Ultrasound*** **in Muscle Monitoring**

**At-Body AI: Low power edge-AI capable systems for biomedical applications**

# Use cases: Human-Machine Interfaces & Epilepsy

**Communicating with biosignals**

- Decoding imagined speech from the brain (EEG)
- Decoding ocular movements (EOG) to type on a keyboard

**Clinical application**

- EEG to detect seizures

**Let’s start from the hardware design**



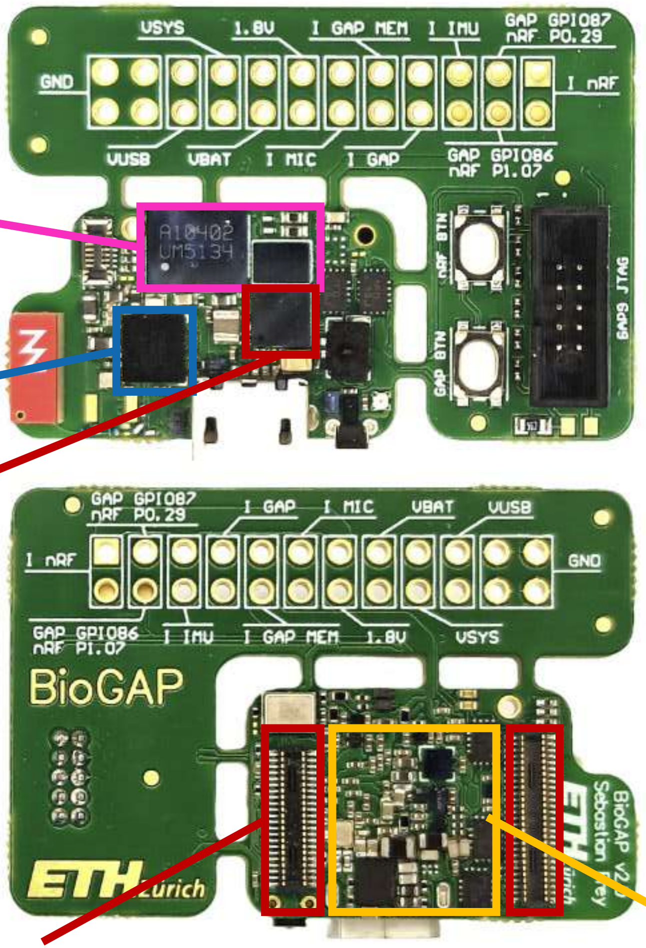
# What do we need for at-body biosignal intelligence?

## A few key ingredients

| | |
|---|---|
| • Access to high-quality data (low-noise, especially EEG) | **Clinical-grade AFE** |
| • Continuous raw data access, multi-node sync (BAN) | **Bluetooth MCU** |
| • Long battery lifetime (full-day monitoring) | **Low-power design** |
| • Low latency (sub-100ms for EMG-HMIs), privacy, low-power inference | **edge-AI-capable** |
| • Scalability: support multiple biosignals, form-factors, future modalities | **modularity** |
| • Integration in non-stigmatizing devices | **compactness** |

# Designing the BioGAP platform: a modular approach

**Baseboard**




**Memories**
512Mb RAM
512Mb Flash

**BLE**
nRF5340

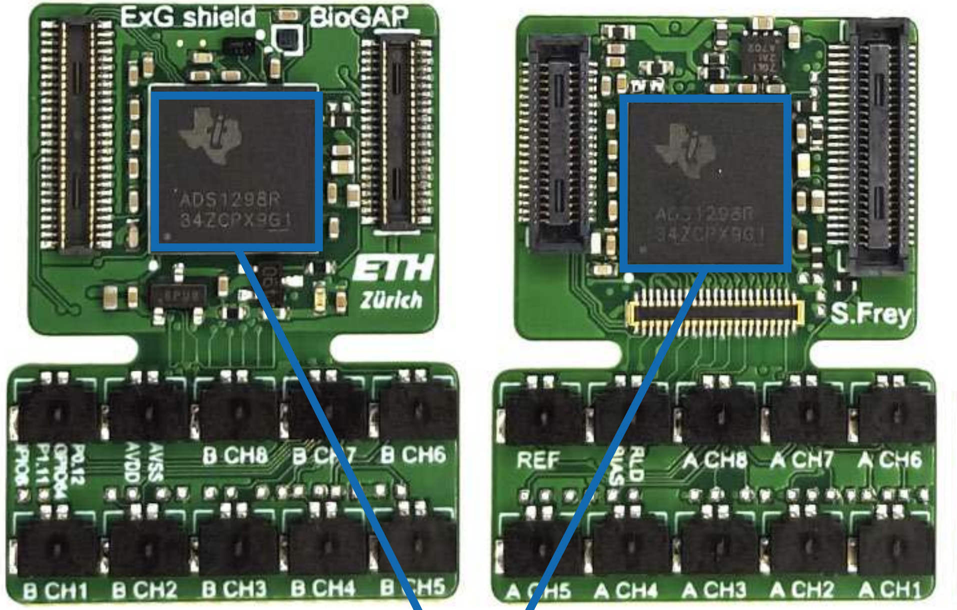
**edgeAI**
GAP9 SoC
(9 RV cores
cluster;
400 MHz;
L1: 128kB;
L2: 1.6 MB)

Connector for modules

power

**Biopotential PCB module**

*Top* *Bottom*




**Biopotential Analog Front End**
*2x* ADS1298 (16-ch.)
*[EEG, EMG, ECG]*

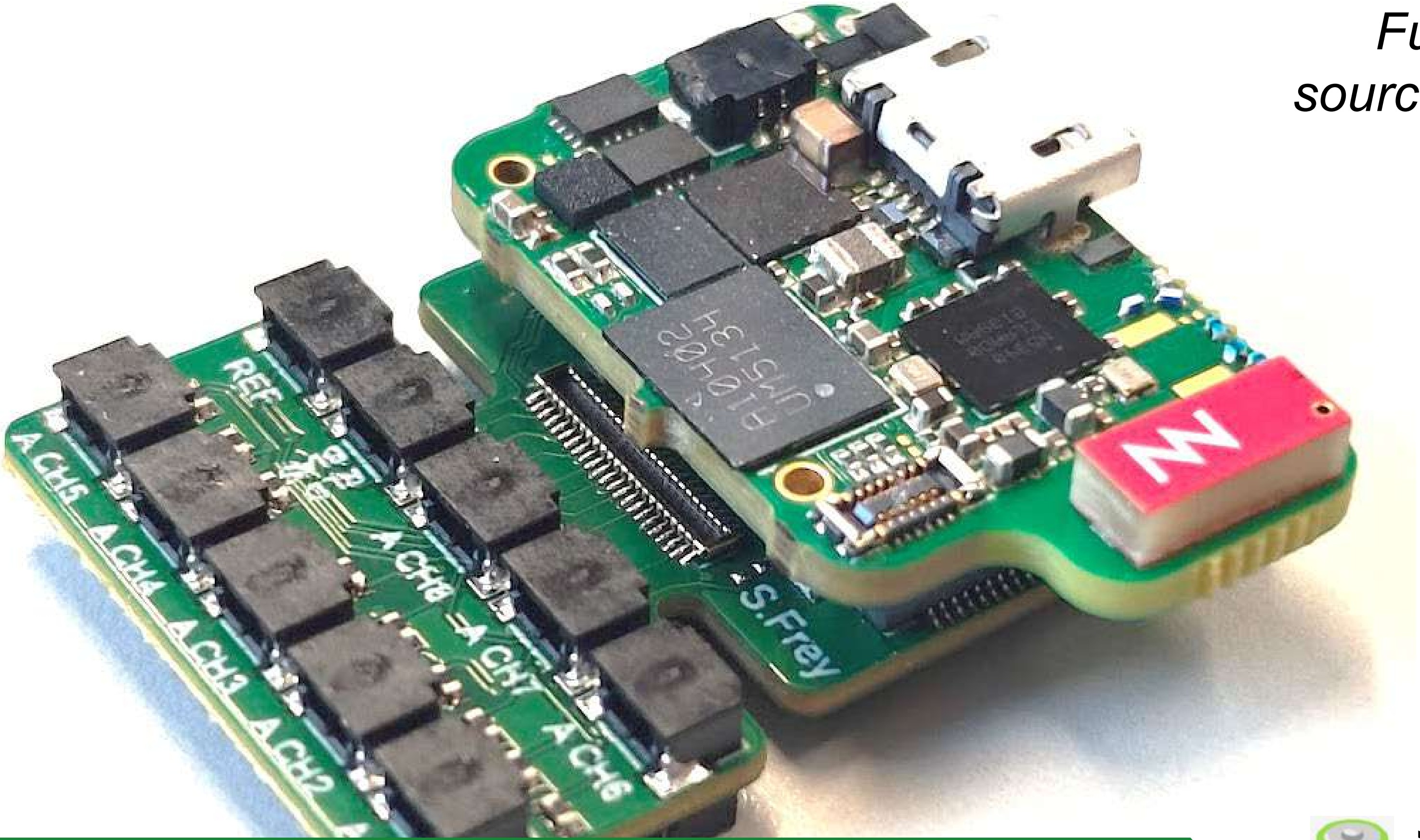
**PPG**

board-to-board connector for flexible placement

*S. Frey, 2025, https://arxiv.org/pdf/2508.13728*
*https://github.com/pulp-bio/BioGAP*

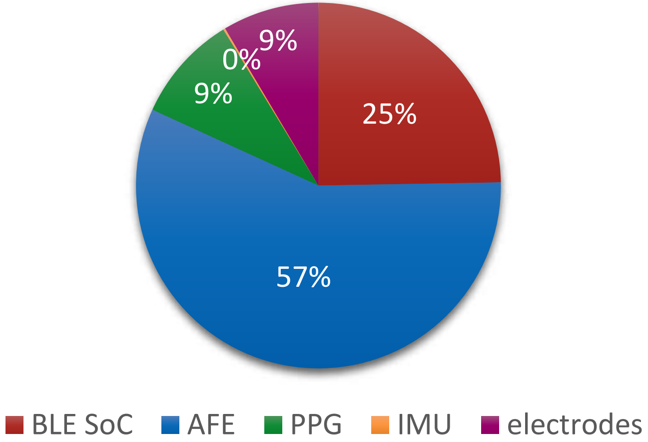


# BioGAP is our engine for biomedical applications



*Fully open source design*

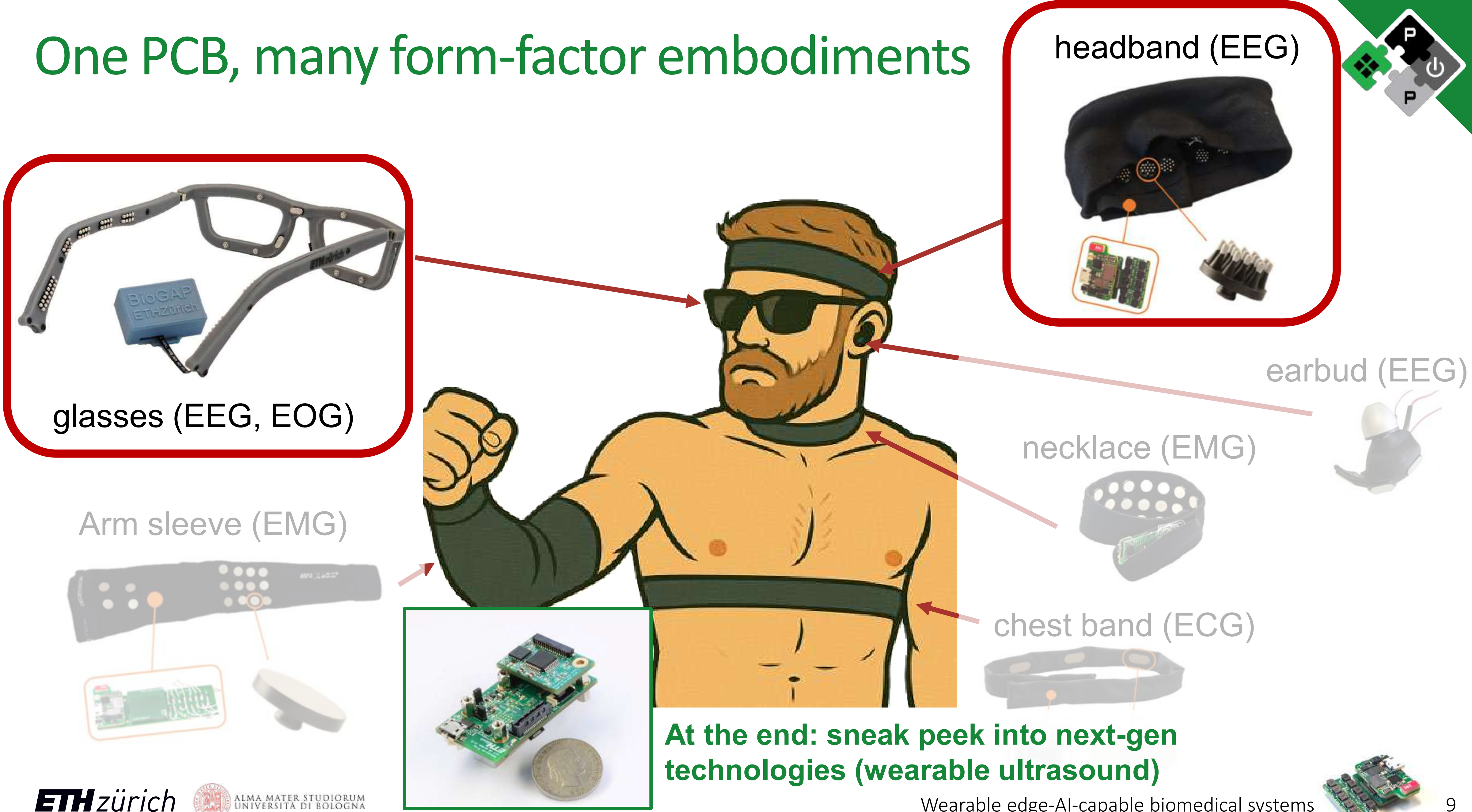
**Power consumption: 32.8 mW**




**Let’s bring it onto the body**

**>16h battery lifetime** *(150 mAh)* for continuous sampling and wireless raw data transfer

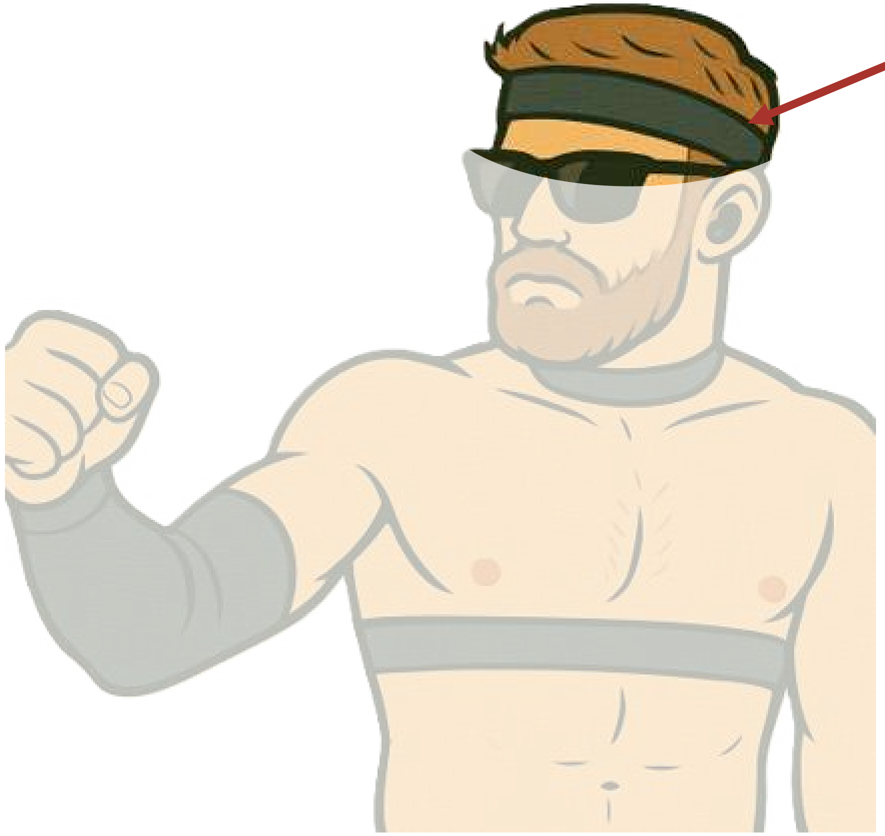
# One PCB, many form-factor embodiments




**At the end: sneak peek into next-gen technologies (wearable ultrasound)**

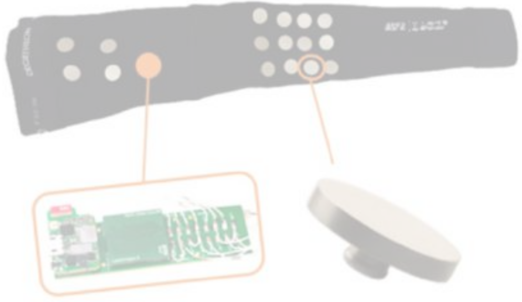
# One PCB, many form-factor embodiments

headband (EEG)



glasses (EEG, EOG)

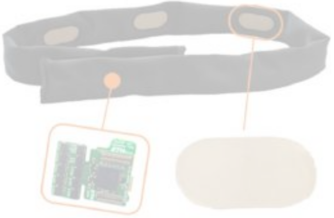

Arm sleeve (EMG)



earbud (EEG)

necklace (EMG)

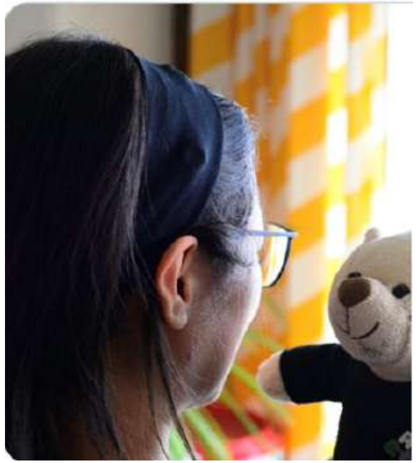
chest band (ECG)





# Designing a Headband for EEG

- **Goal**
  - Enable easy self-use by patients (seizures)
  - Comfortable monitoring during day and night (!)
  - Side goal: usability also as HMI interface

*X. Wang et al., IEEE BioCAS, 2023*

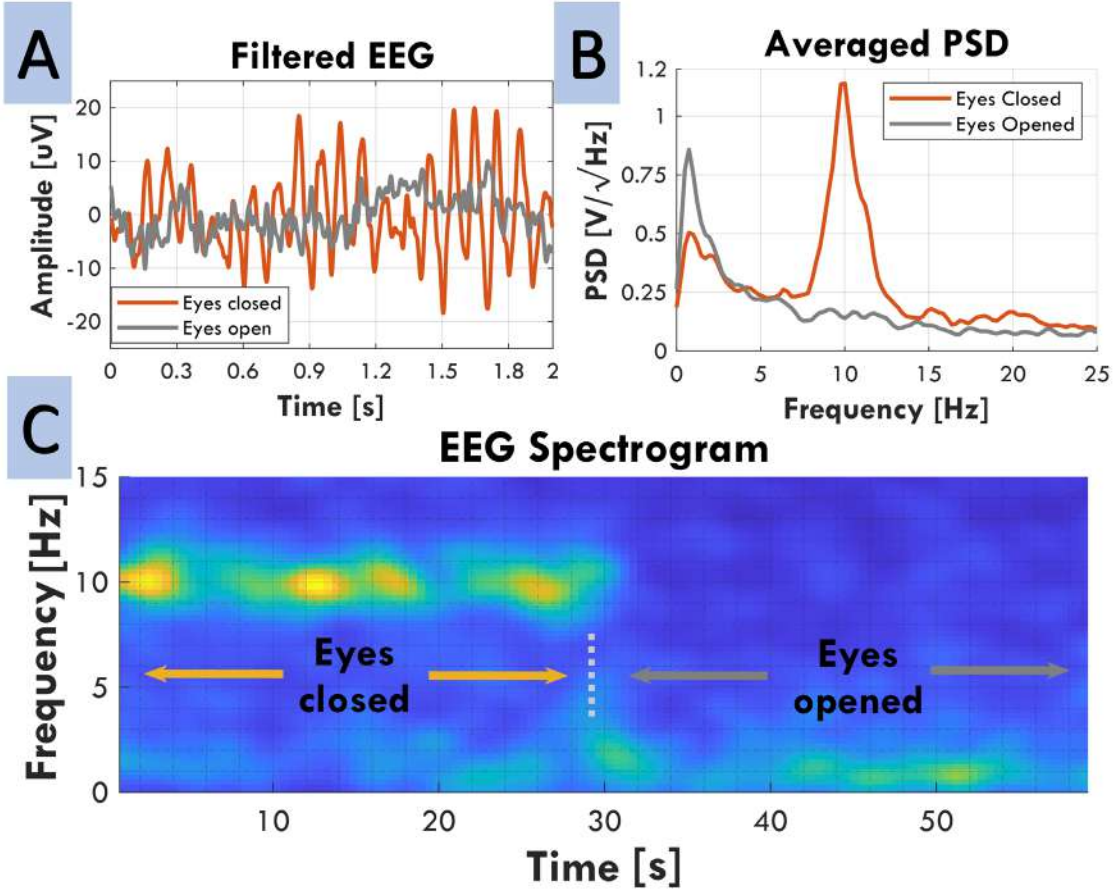
- **Features**
  - 8 channels (across temporal and occipital lobes), fully-dry
  - Easy to wear
  - All cables integrated in the textile
  - Powered by BioGAP for continuous data streaming and edgeAI

*4-channels in the temporal area: enough for seizure detection?* *ML on public datasets*

*Channel locations on temporal and occipital lobes: OK for HMI?* *ML across hw design iterations*

# EEG Headband: functional check validation

- **Measurement of alpha waves**
  - Typical EEG patterns appearing when the subject closes the eyes
  - RMS noise aligns with the IFCN standards for clinical recording of EEG signals (0.47 μV integrated RMS noise in 0.5 to 100 Hz)
  - Alpha waves correctly measured

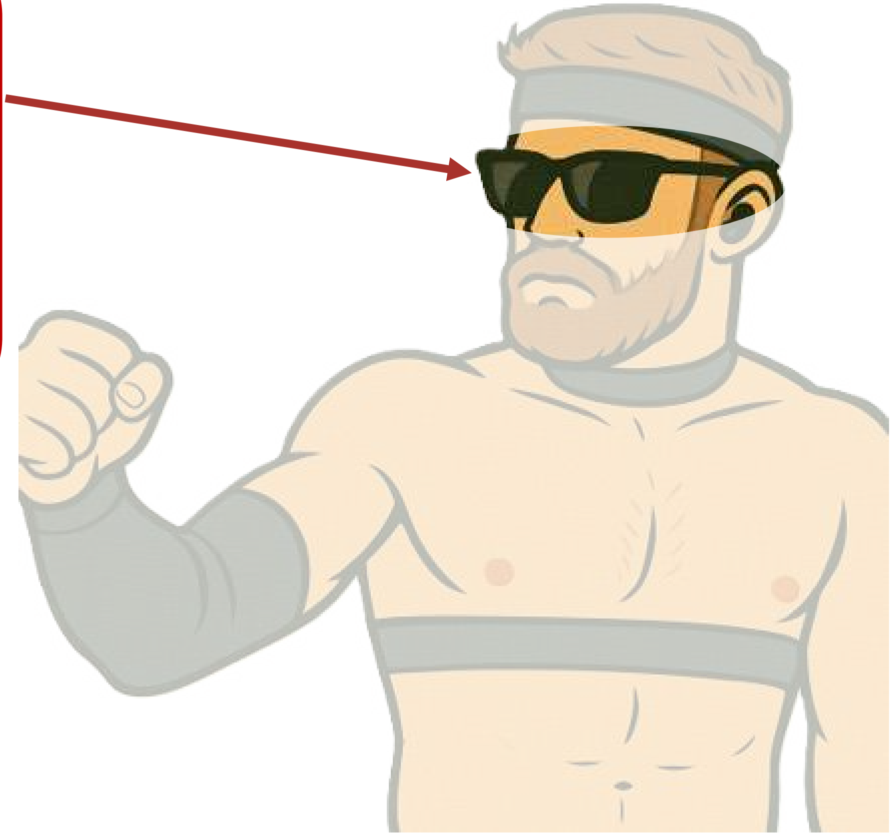



**Passed basic functionality check**

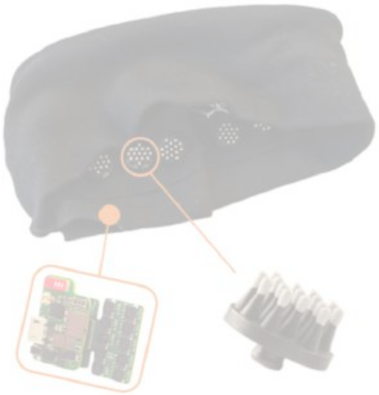
*S. Frey et al., IEEE COINS, 2023*

# One PCB, many form-factor embodiments


glasses (EEG, EOG)



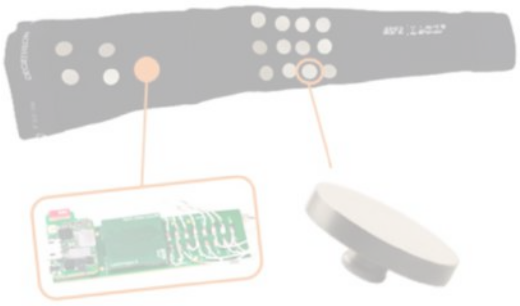
headband (EEG)



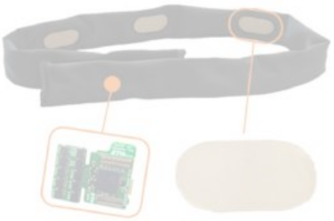
earbud (EEG)

necklace (EMG)

Arm sleeve (EMG)



chest band (ECG)

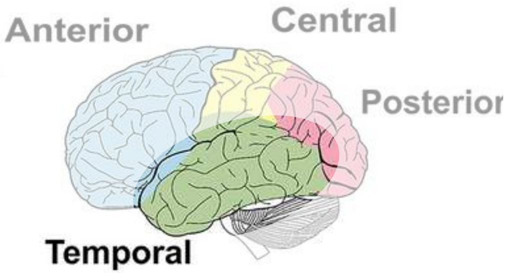


# Designing EEG/EOG smart-glasses

- **Goal**
  - Non-stigmatizing platform for daily monitoring of seizures (EEG)
  - Human-Machine Interface via eye movements

- **How to arrange EEG electrodes?**
  - Form-factor constraint
  - we know it works (headband, temporal region electrodes)

- **What about EOG?**
  - ML-based evaluation of glasses electrode placement vs conventional EOG electrode setups

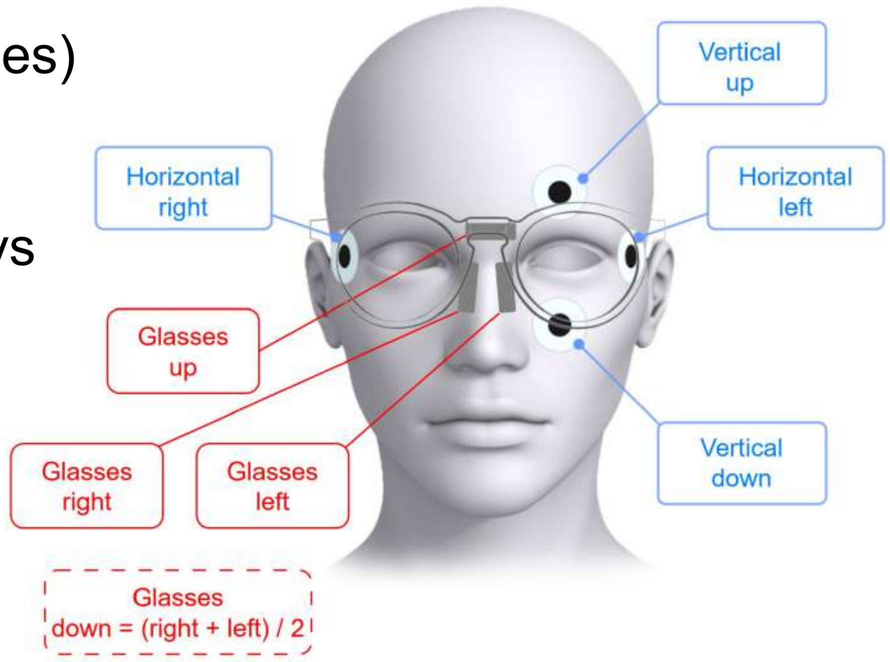



Traditional

- Wet sticky electrodes
- Active
- REF, Bias on mastoids

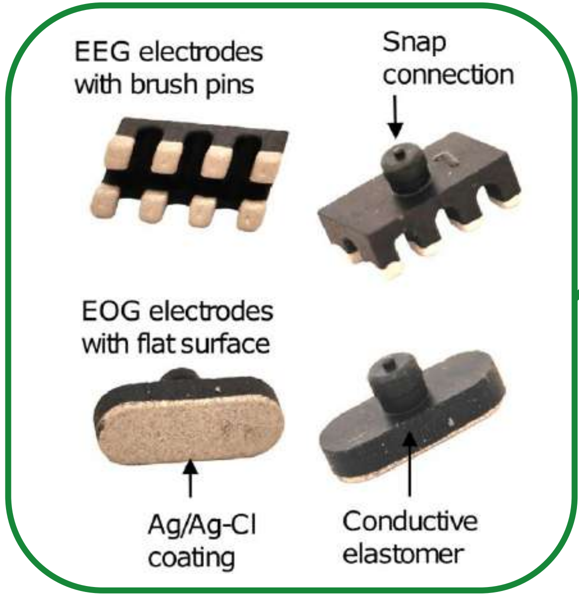
Glasses

- Dry sheet electrodes
- Active
- REF, Bias on matoids



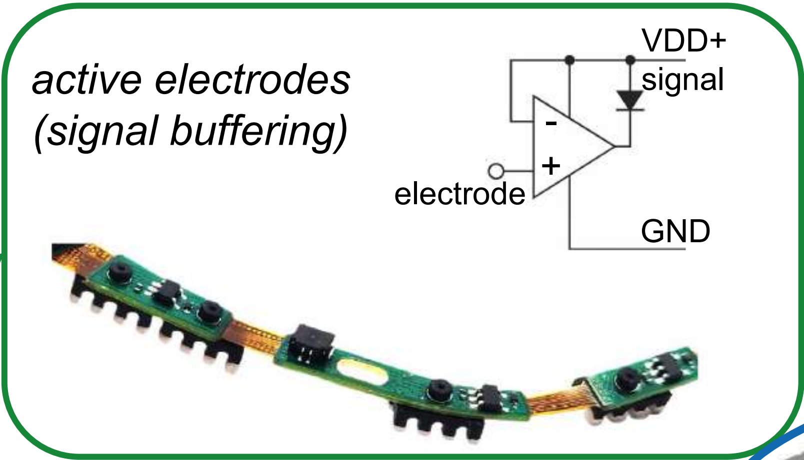
# GAPses: versatile smart-glasses for EEG/EOG

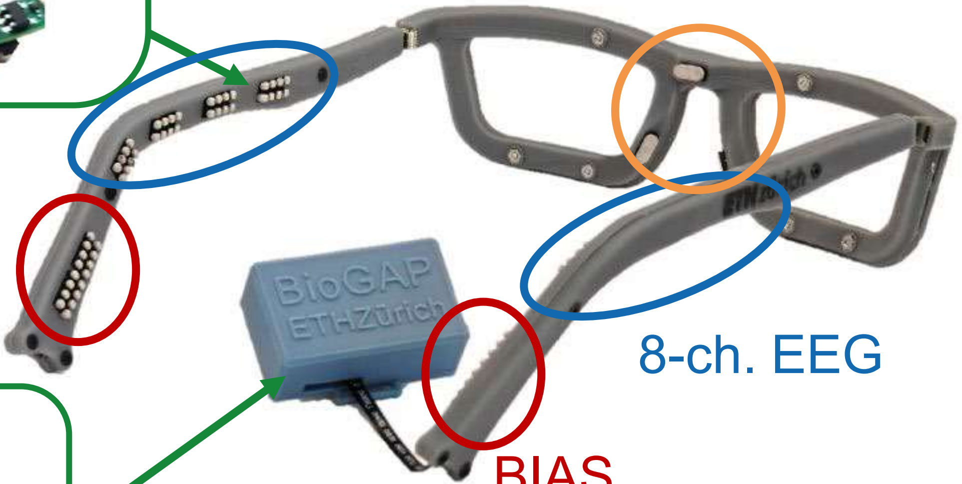
## ExG electrodes



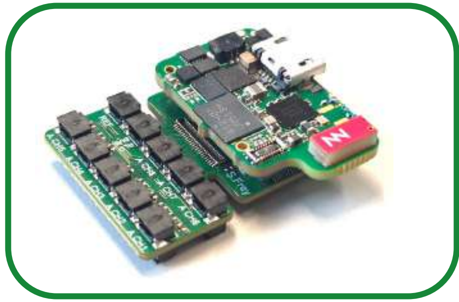

DATWYLER

## Electrode interface PCB




## BioGAP



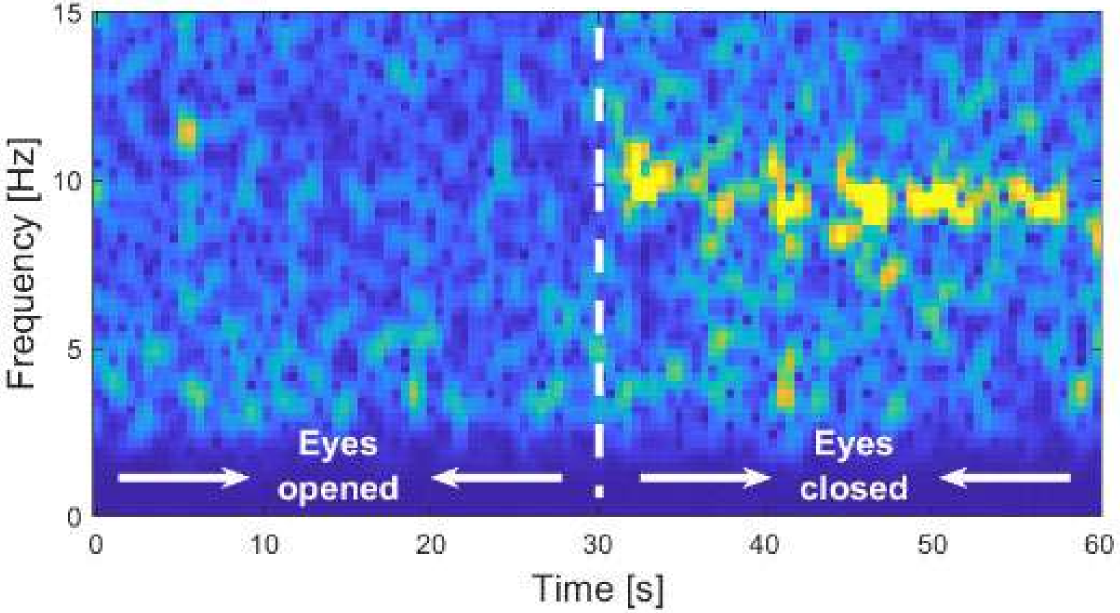
*Raw data streaming* **30mW**
*Online infer.* (3-ch.EOG) **16mW**

*S. Frey et al., IEEE T-BioCAS, 2024*

# EEG/EOG smart-glasses: functional check validation

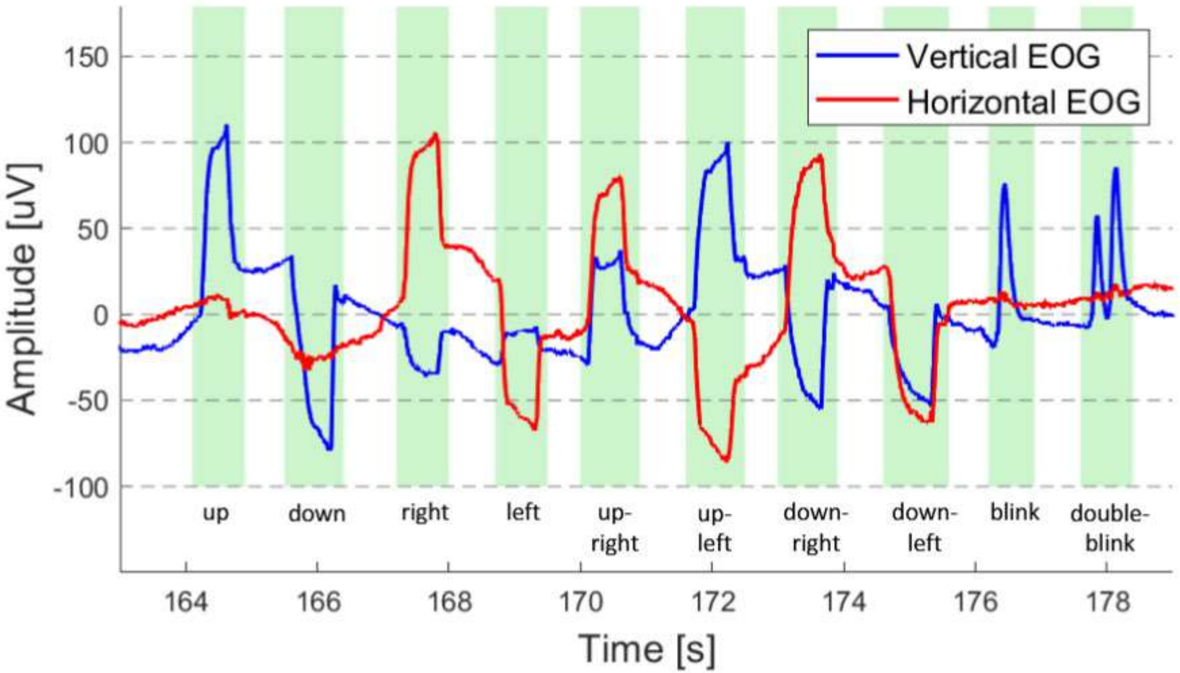
## Measurement of alpha waves

*EEG spectrogram*




## Measurement of eye movements

*EOG amplitude*



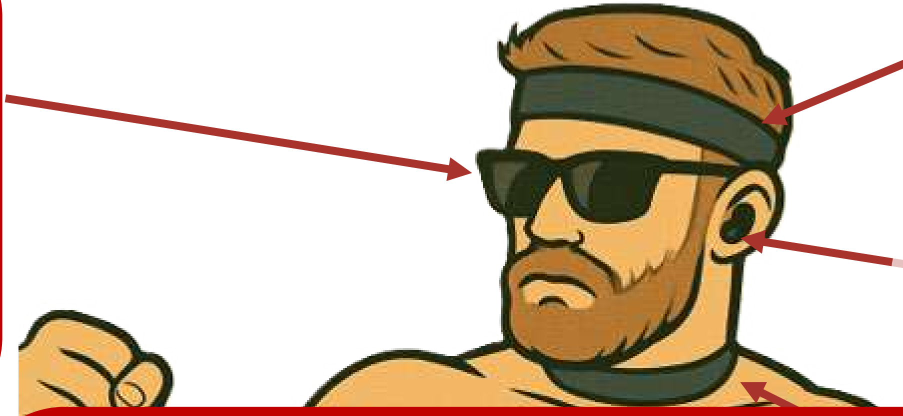

**Passed basic functionality check**

*S. Frey et al., IEEE T-BioCAS, 2024*

# One PCB, many form-factor embodiments

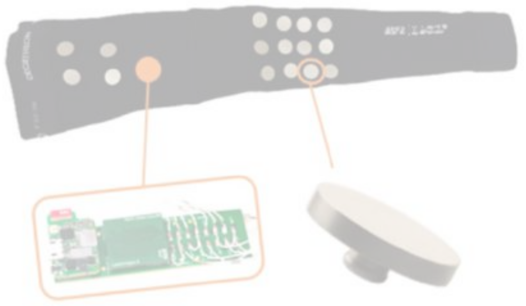
headband (EEG)


glasses (EEG, EOG)



earbud (EEG)

Arm sleeve (EMG)



**Let’s now bring the headband and glasses into use cases**

# We explored HMI and clinical use cases

**Hardware** ⟷ **TinyML**

HW makes biosignals accessible

ML makes biosignals useful

ML applications aid the design of the HW

HW enables on-device ML execution (privacy, latency, energy)

**Human-Machine Interfaces (HMI)**

**Seizure Detection**



# Headband for HMIs

**Human-Machine Interfaces (HMI)**

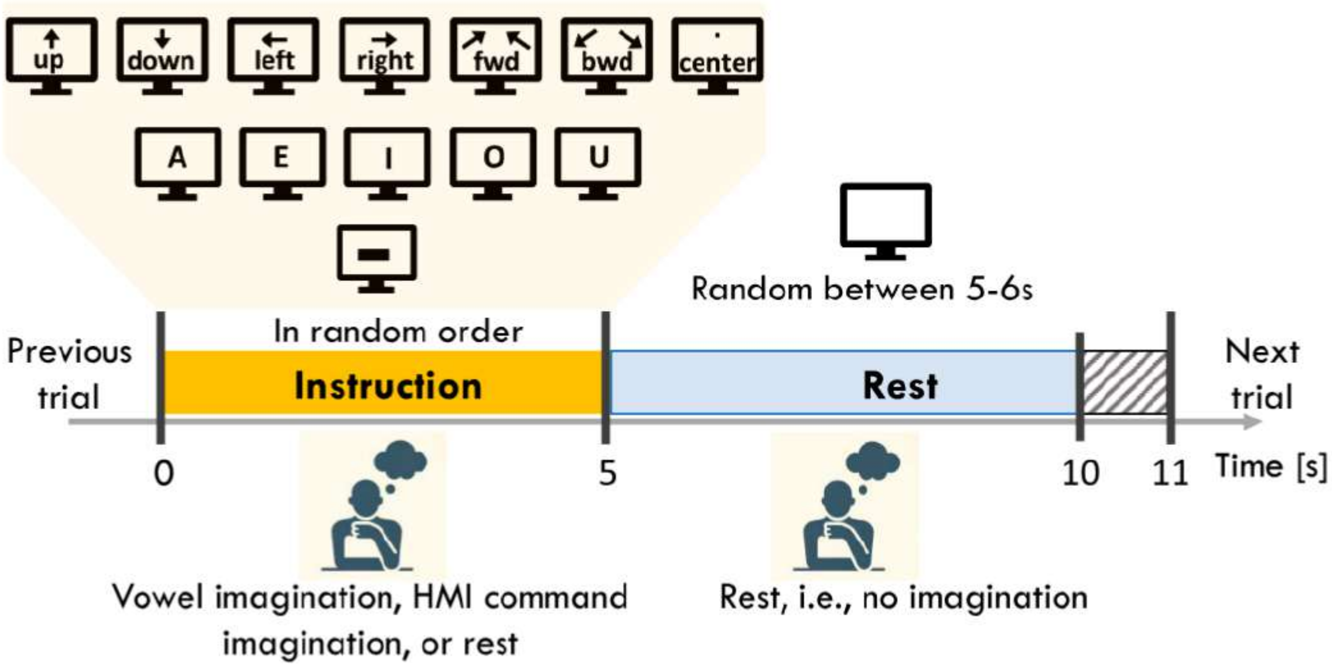
Seizure Detection

Using EEG signals to decode imagined letters/words

# Headband for EEG speech-imagery

- **What is speech imagery?**
  - A subject "imagines" to speak (letters, words)
- **The challenge**: is it doable with such a compact, minimal setup (low channel count)?

13 classes




VowelNet Architecture

| Layer (Type) | #Filters | Kernel Size | Output Shape |
|---|---|---|---|
| Temporal Conv | F1 | (1, 64) | (F1, C, T) |
| Batch Norm | - | - | (F1, C, T) |
| Depthwise Conv | D * F1 | (C, 1) | (D * F1, 1, T) |
| Activation | - | - | (D * F1, 1, T) |
| Pooling | - | (1, 4) | (D * F1, 1, T/4) |
| Dropout | - | - | (D * F1, 1, T/4) |
| Separable Conv | D * F1 | (1, 16) | (D * F1, 1, T/4) |
| Conv | F2 | (1, 1) | (F2, 1, T/4) |
| Batch Norm | - | - | (F2, 1, T/4) |
| Activation | - | - | (F2, 1, T/4) |
| Pooling | - | (1, 8) | (F2, 1, T/32) |
| Dropout | - | - | (F2, 1, T/32) |
| Flatten | - | - | (F2 * T/32) |
| Dense | N | - | (N) |

$F1 = 32$, $D = 2$, $F2 = 64$, $N =$ Number of classes, $C =$ Number of EEG channels, $T =$ Number of time samples.

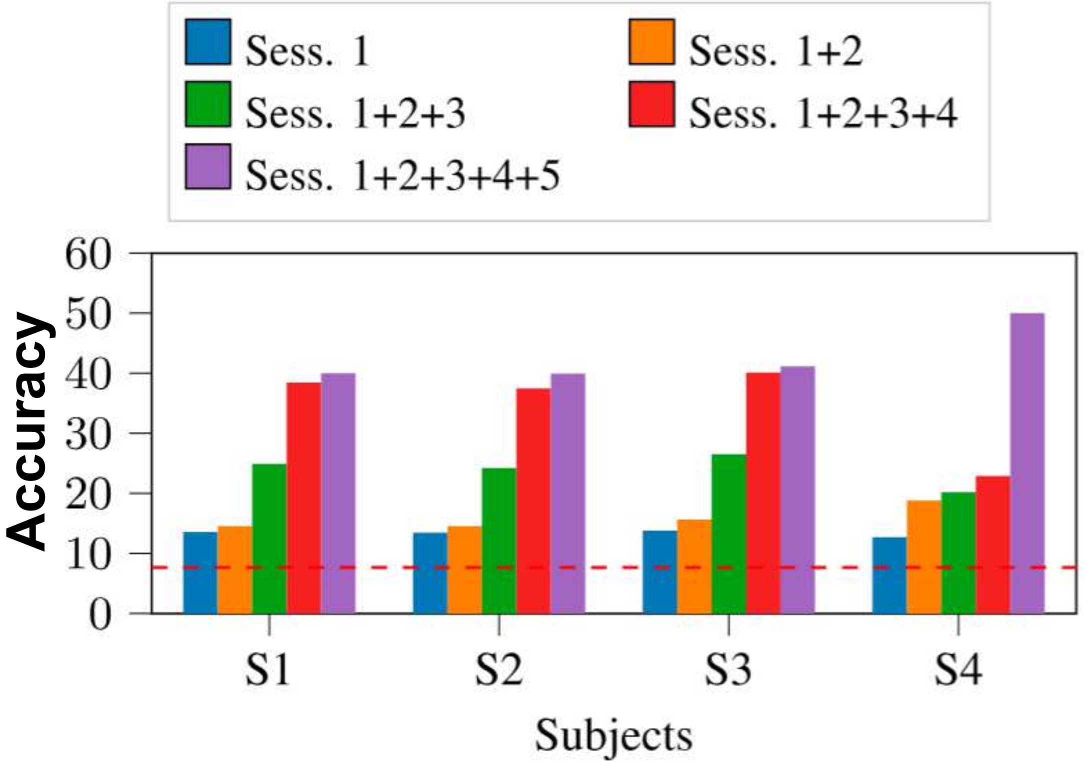
34k parameters, operating on 5s windows

**Signal filtering**: 50 Hz notch,0.5-100 Hz bandpass, 0.5s moving average

*T. Ingolfsson et al., IEEE T-BioCAS, 2025*

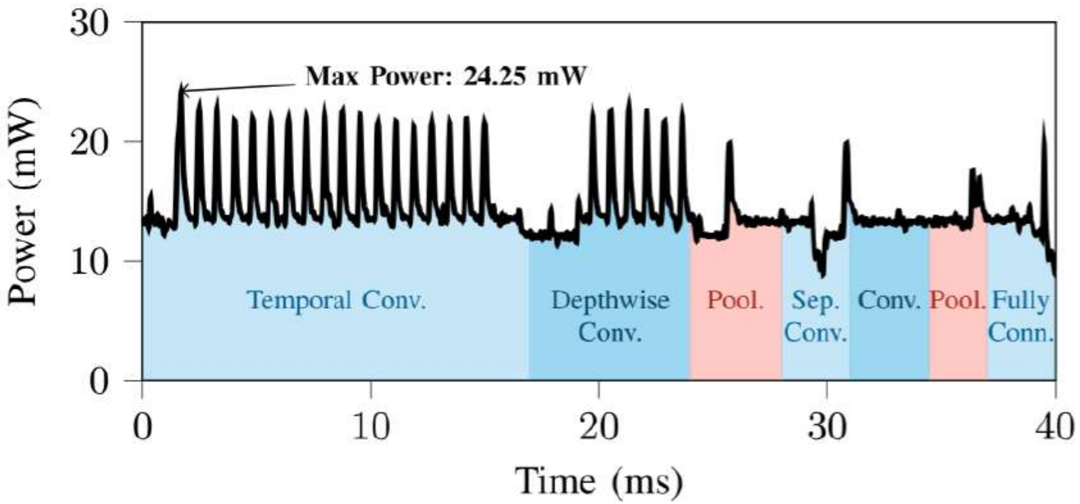


# EEG speech-imagery on the edge




Subject-specific CV results (13-classes)


**Efficient edge deployment (GAP9)**
40.9 ms/inference, 0.71 mJ/inference




**Wearable EEG can be used for words imagery on the edge (but long windows, 5s)**

*T. Ingolfsson et al., IEEE T-BioCAS, 2025*

# EEG speech-imagery on the edge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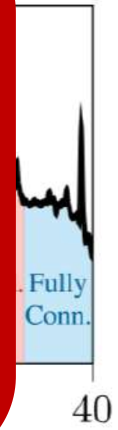



**Can we communicate faster with a different biosignal?**

**Wearable EEG can be used for words imagery on the edge (but long windows, 5s)**

*T. Ingolfsson et al., IEEE T-BioCAS, 2025*

# Glasses for HMIs


**Human-Machine Interfaces (HMI)**

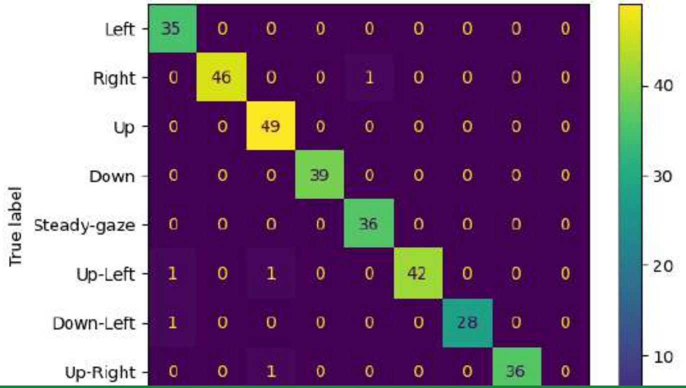
Seizure Detection

Using EOG signals to type on a keyboard

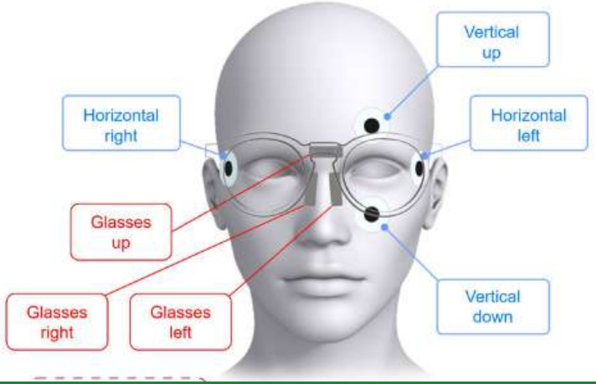
# But first: EOG on glasses, sufficient accuracy?

- **Goal:** evaluation of the EOG electrode setup choice
- **Protocol:** single-subject looking in different directions, 9-classes (up, down, left, right, diagonals, center: 9-classes)
- **Data processing**: filtering, handcrafted feature extraction, kNN classifier

❖ **Accuracy:** 97.3%
❖ **F1 score:** 96.6%

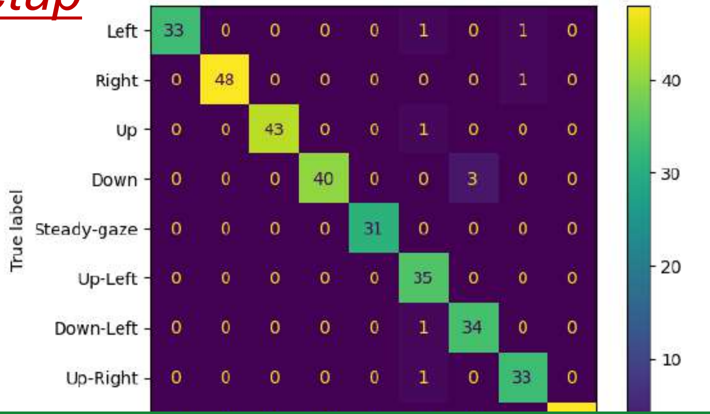



*Traditional electrode setup*




*Glasses electrode setup*

❖ **Accuracy:** 96.1%
❖ **F1 score:** 95.0%

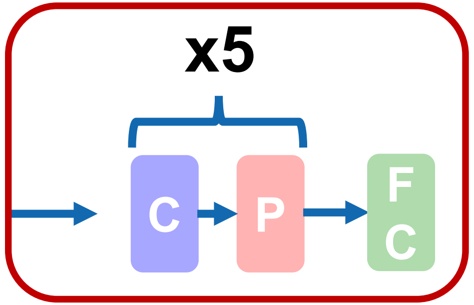


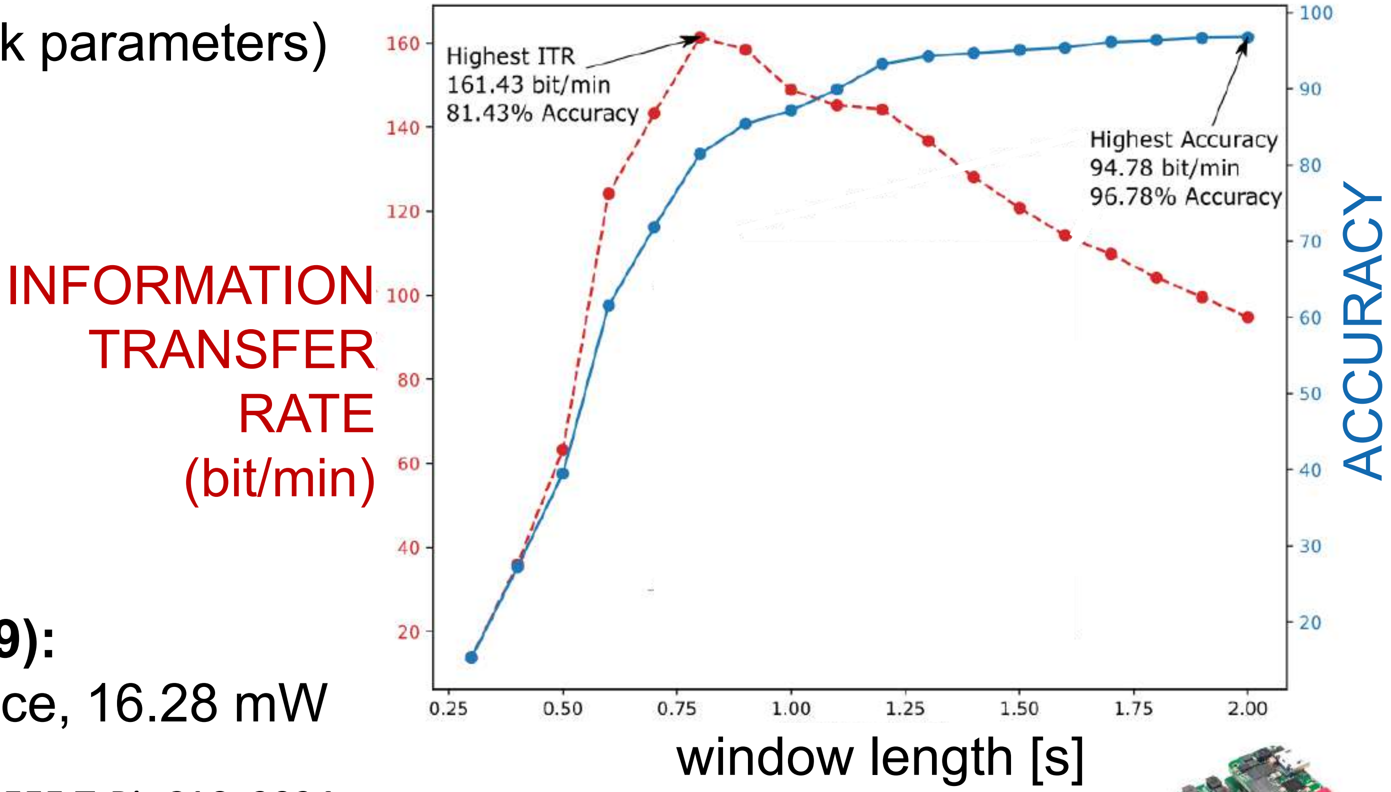

**EOG (dry) setup offers comparable accuracy to traditional (wet) electrode placement**

*A. Bernardi, ETHZ sem. thesis, 2023*

# EOG on smart-glasses in action


- **Protocol:** 5-subjects performing eye movements: 11 classes (looking up/down/left/right, diagonals, rest, blink, double-blink)
- **Data processing**: band-pass filtering (0.5-40 Hz), 2s moving average filter
- **Classification**: compact CNN (<10k parameters)

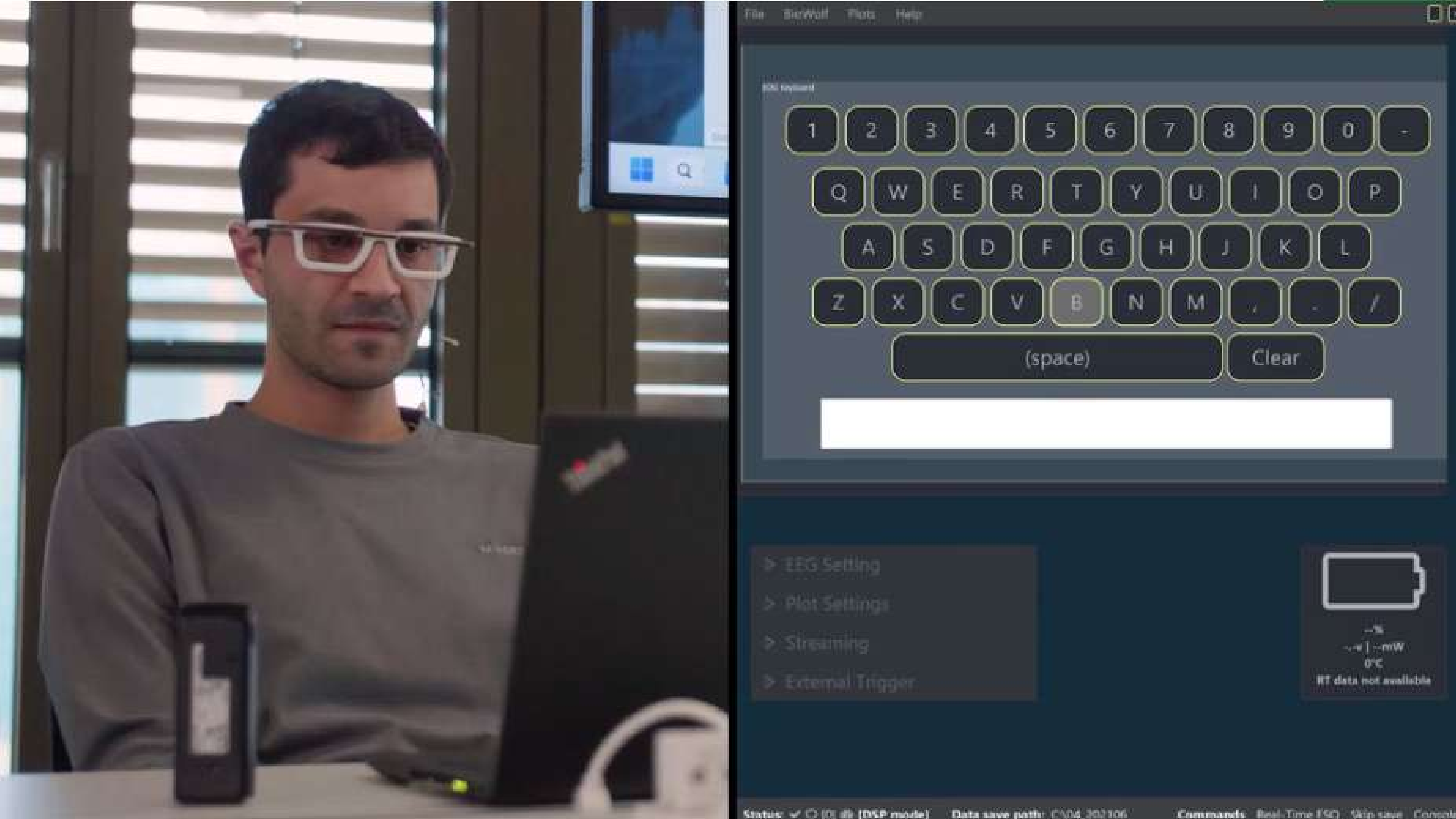




**Efficient edge deployment (GAP9):**
1.5 ms/inference, 0.024 mJ/inference, 16.28 mW

*S. Frey et al., IEEE T-BioCAS, 2024*


File
BioWolf
Plots
Help
1 2 3 4 5 6 7 8 9 0 -
Q W E R T Y U I O P
A S D F G H J K L
Z X C V B N M , . /
(space)
Clear
EEG Setting
Plot Settings
Streaming
External Trigger
RT data not available

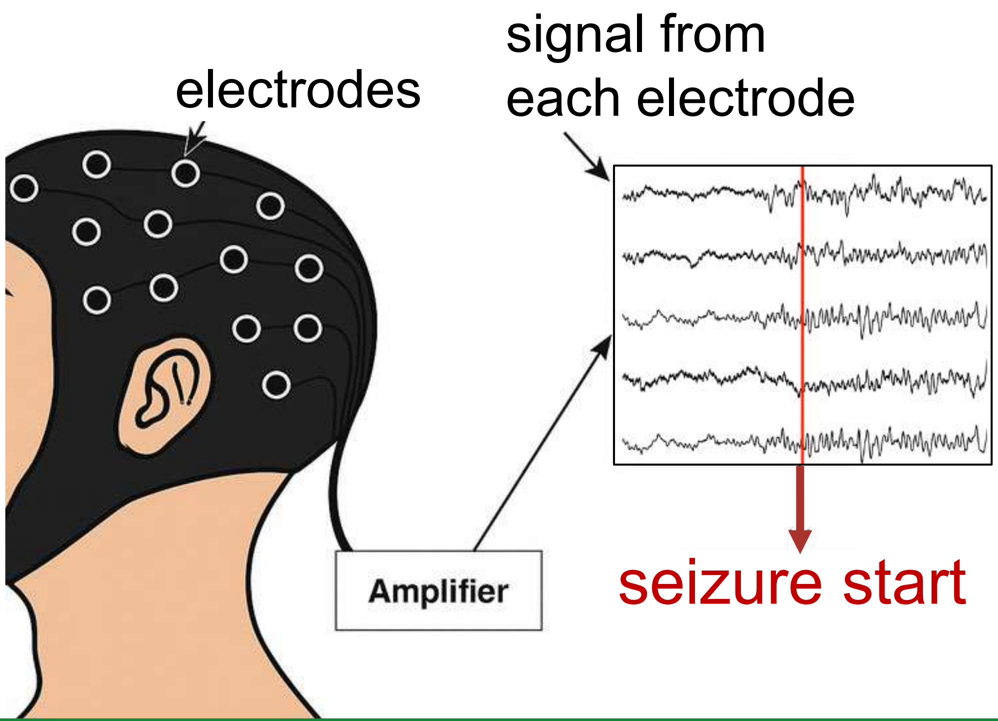
# Clinical application: seizure detection

Human-Machine Interfaces (HMI)

**Seizure Detection**

# Epilepsy

- Neurological disorder affecting >50M people globally
  - recurrent seizures that temporarily impair brain function




- Need for wearable seizure detection
  - Long-term recording in ambulatory patients
  - Aiding assessment of seizure type/frequency
  - Enabling seizure-triggered alarms
- Key requirements
  - Non-stigmatizing EEG devices
    - Full EEG-caps are not OK!
    - headband, smart-glasses, …
  - Algorithms
    - Maximize sensitivity
    - Minimize False Alarms (!!!), <1 FP/day

**Our key starting points for developments in wearable EEG**

# Already existing seizure datasets as our first step

- Validation before HW design
  - *seizure detection possible with few temporal channels?*
- Design and stress-test ML algorithms with HW constraints (*e.g. on-chip memory)*
  - Validate edge deployment of the whole pipelines

**CHB-MIT**

- 23 Pediatric Patients with 181 Seizures
- 256 Hz sampling rate
- **Open-Source**

**PEDESITE**

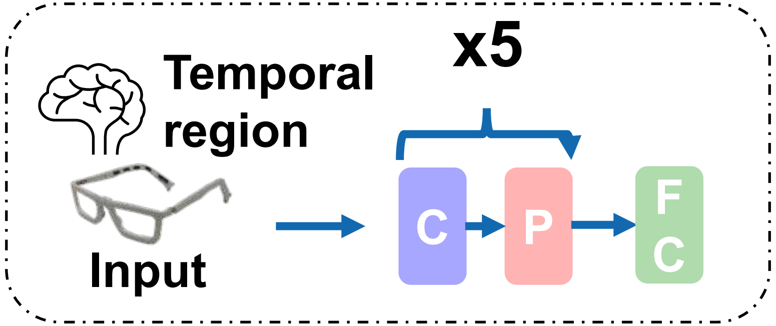
CHUV

Swiss National Science Foundation

- 5 Adult Patients with 25 Seizures *(more available, not used here)*
- 1024 Hz sampling rate
- EEG + synchronized PPG/IMU
- **Private**



# EpiDeNet: efficient network for seizure detection




**EpiDeNet**

- Operates on ~~23~~ only **4 temporal channels**
- Hardware and algorithmic co-design
- Compact and Efficient, 11K parameters

**91%** Seizures detected **2.24** FP/h

*CHB-MIT*

**Demonstrated good results with 4 channels. Can we do better?**

A custom loss function

**Sens.** ↑

**Spec.** ↑

Sensitivity Specificity Weighted Cross Entropy Loss (**SSWCE**)

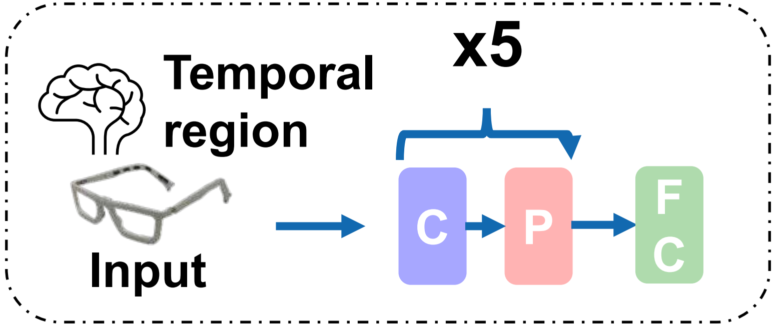
$$\mathbf{SSWCE}(y, p) = \mathbf{CE}(y, p) + \alpha(1 - \mathbf{SP}) + \beta(1 - \mathbf{SN})$$

**92%** Seizures detected
**1.18** FP/h

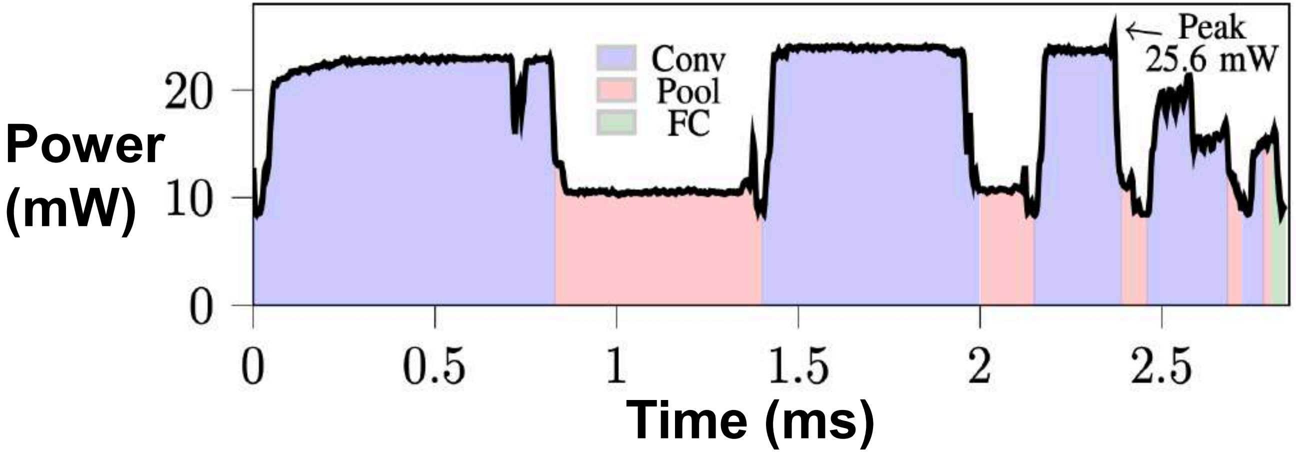
**Let's now deploy it on the edge**

*T. M. Ingolfsson et al., IEEE BioCAS, 2023*
*T. M. Ingolfsson, ETHZ PhD* Diss.-No. 31324

# EpiDeNet can run on the edge for >300 hours








**< 26mW** Power Envelope

**0.051 mJ** per inference

300mah battery

**→ 300 hours**

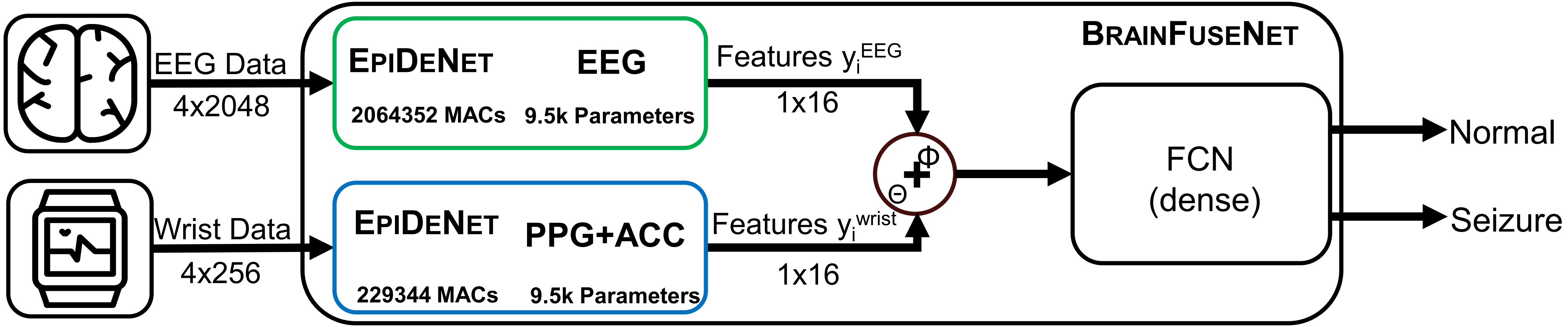
**We now have a good baseline seizure detector for edge devices**

*T. M. Ingolfsson et al., IEEE BioCAS, 2023*

*T. M. Ingolfsson, ETHZ PhD* Diss.-No. 31324

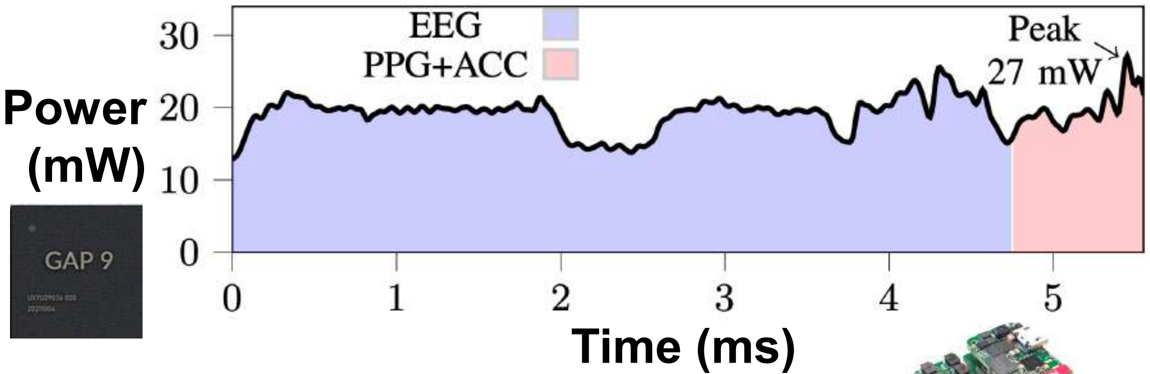
# Sensor fusion further reduces false positives

*PEDESITE dataset (EEG + PPG/ACC)*



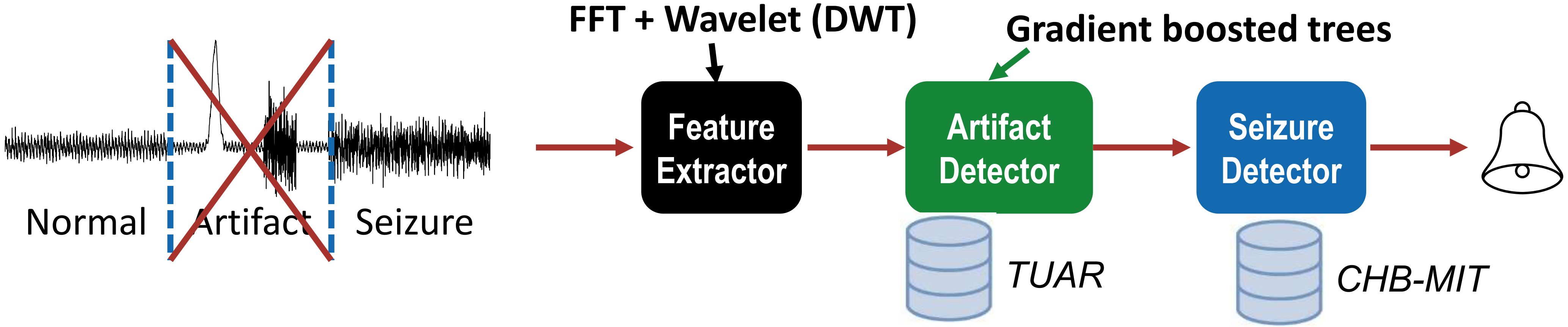

|  | Data | Sens. | FP/h |
|---|---|---|---|
| **EpiDeNet** | EEG | 60.7 | 1.18 |
| **BrainFuseNet** | EEG+ PPG+ACC | 64.28 | **0.21** |

**0.11 mJ** per inference, **19.25 mW** avg.



# A seizure detector alone is not enough for wearables

- Most public datasets have clean, artifact-free data
  - But most of wearable data will be **artifact** rich
  - Artifacts are the main source of false alarms



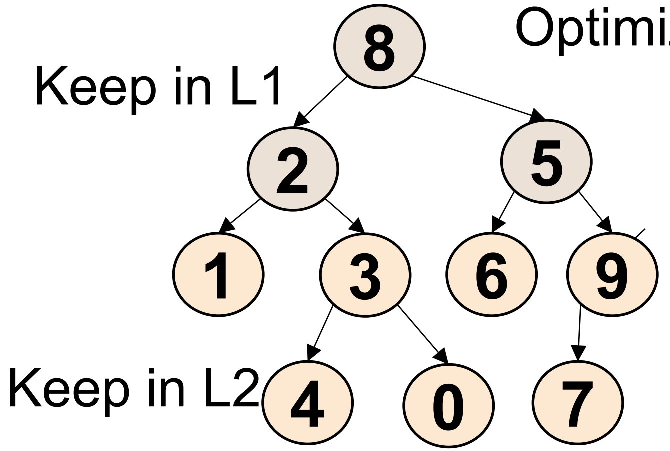

- **Problem**: no dataset labelled for both artifacts and seizures
  - use separate datasets to prepare pipelines for future wearables

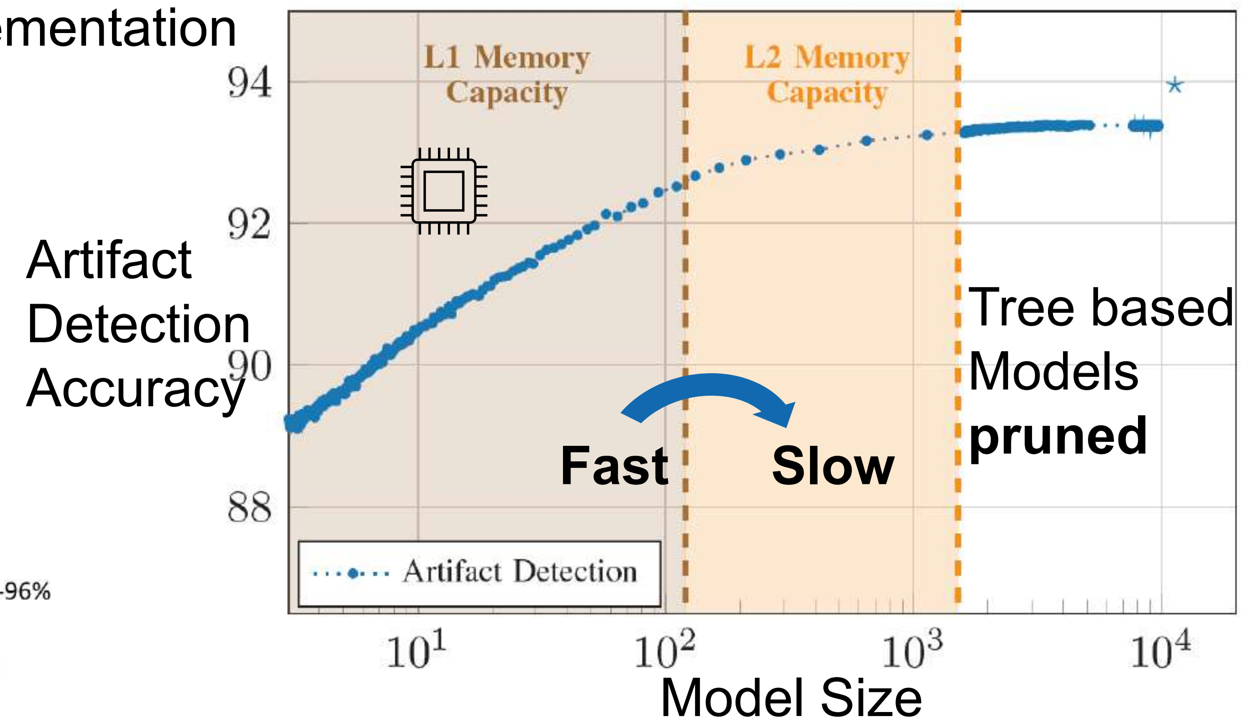
**Let's make the artifact detector**

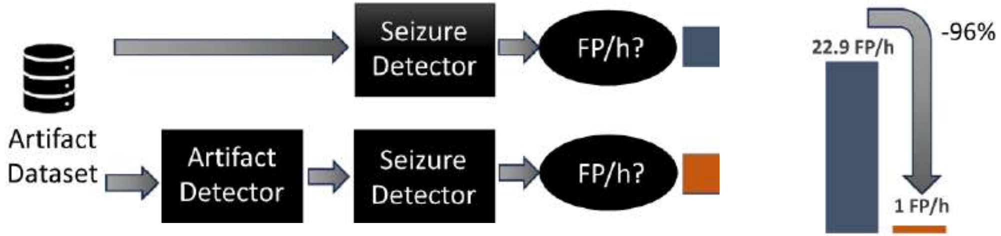
# Optimizing a tree-based artifact detector for the edge


*on **4 temporal channels***

Optimized implementation

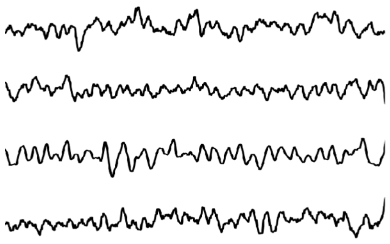


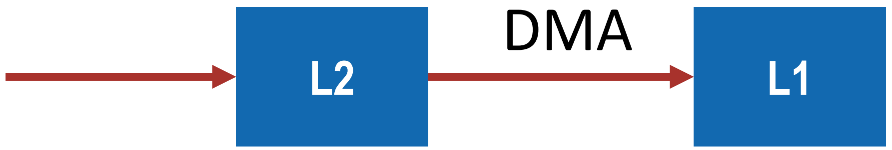

*T. M. Ingolfsson et al., Sci. Rep., 2024*
*T. M. Ingolfsson, ETHZ PhD* Diss.-No. 31324

# Edge deployment of EEG artifact + seizure detector



**Data streaming in at 250-500 Hz**

16/32 kB per 4s window (4 channels)




**Feature extraction**

4 Cores FFT Features

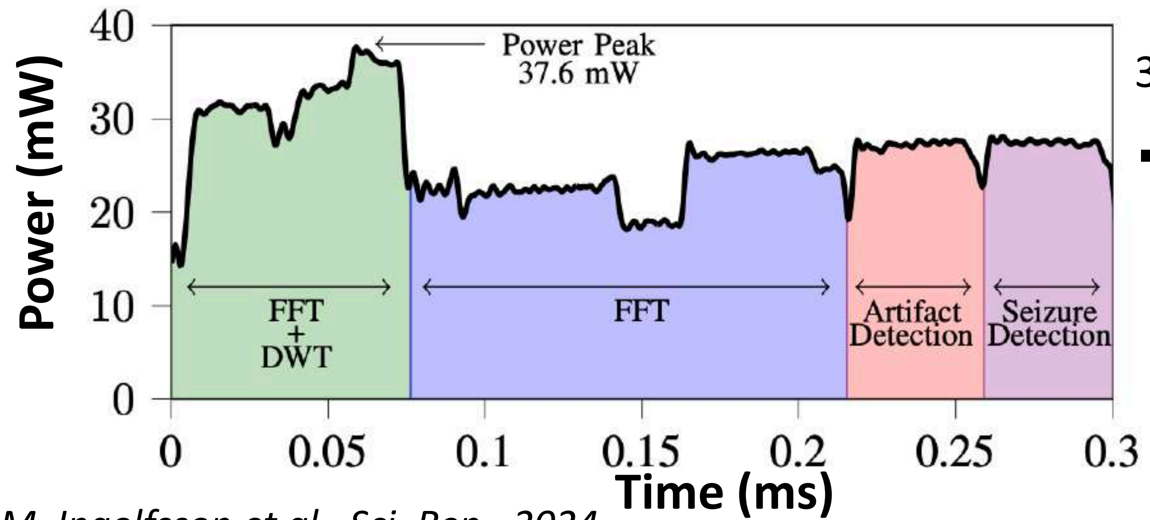
4 Cores DWT Features

1 Core for memory transfers

**Artifact/Seizure Detection**

# of trees Divisible by number of Cores

**7.93 µJ** energy per 4 s window




300mah battery → **12.5 days**


*T. M. Ingolfsson et al., Sci. Rep., 2024*

*T. M. Ingolfsson, ETHZ PhD* Diss.-No. 31324

# These ML works progressed while developing the HW

17 adult patients, >150h of recordings, 3 seizures
*study still in progress*

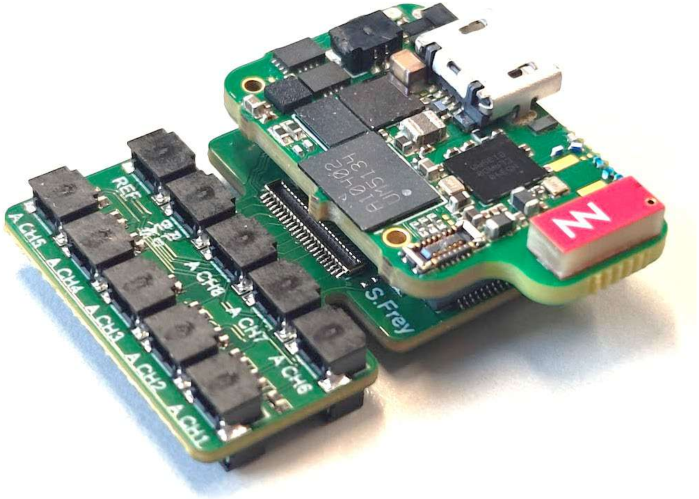
**BioGAP headband and smart-glasses are in use in clinical studies**

**Our next step will be closing the loop**

online execution of the proposed algorithms on our data & our devices,
for real-time feedback to patients and caregivers

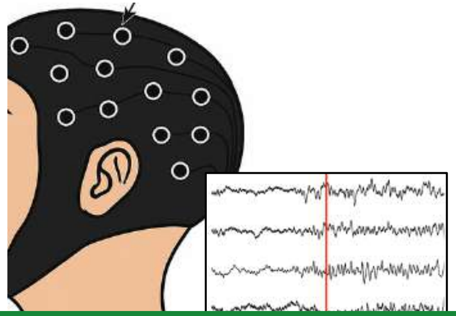
# Recap of form factors and applications

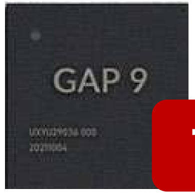
From one hardware platform...



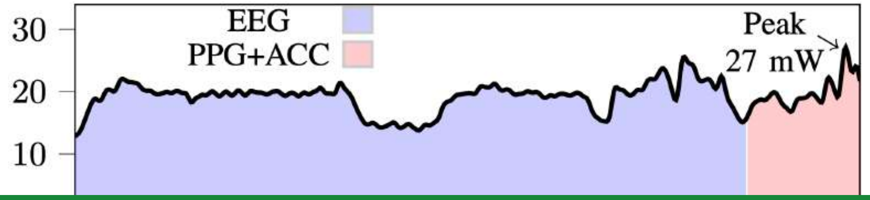
To many wearable form factors

**Clinical applications**

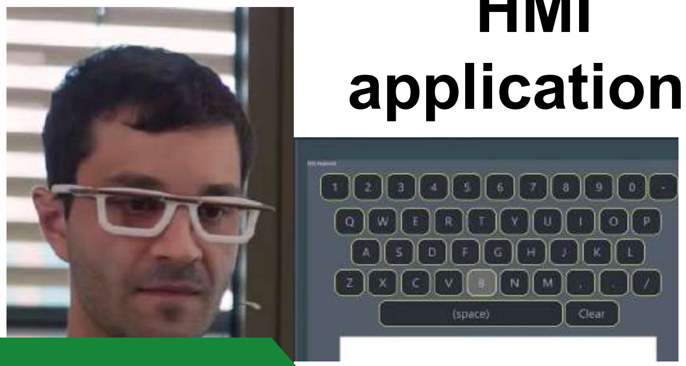





**TinyML on the edge**




**HMI applications**

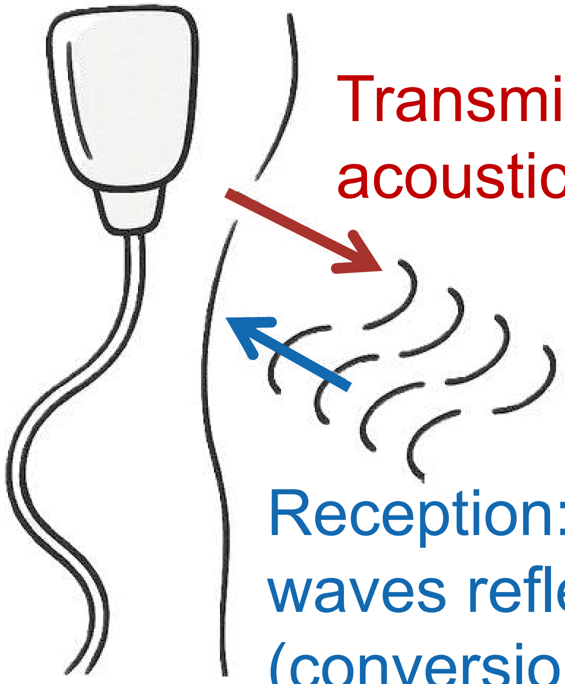


**So far we discussed only signals on the body surface: going deep?**

# Don’t stop at the skin: a glimpse into ultrasound

- **Emission of acoustic waves and detection of the reflected signals**

Ultrasound probe
(piezoelectric)



Transmission:
acoustic waves emitted into the body

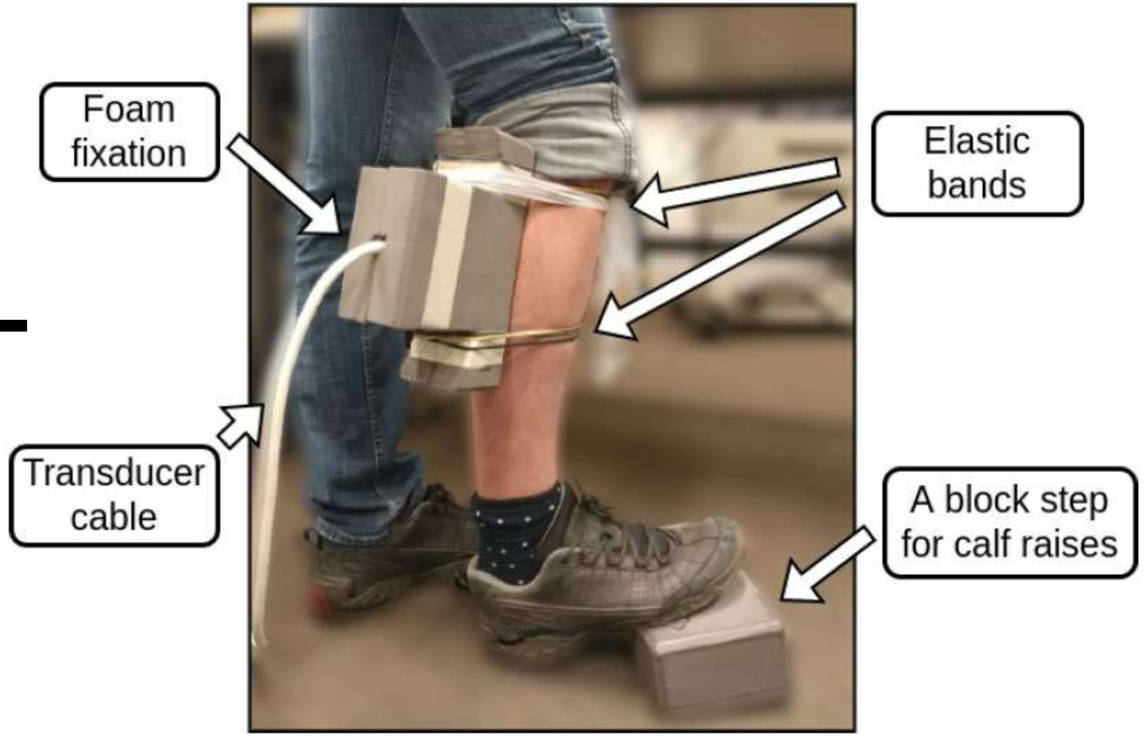
Reception:
waves reflected back to the probe
(conversion to electrical signals)


Standard tool in clinical practice
(safe, real-time, low cost)

# Research ultrasound is evolving from bulky systems…


https://verasonics.com/vantage-systems/

+




Vostrikov *et al*, EMBC 2022.

Innovations in digital electronics enabled to bring computing <u>at</u> the transducer

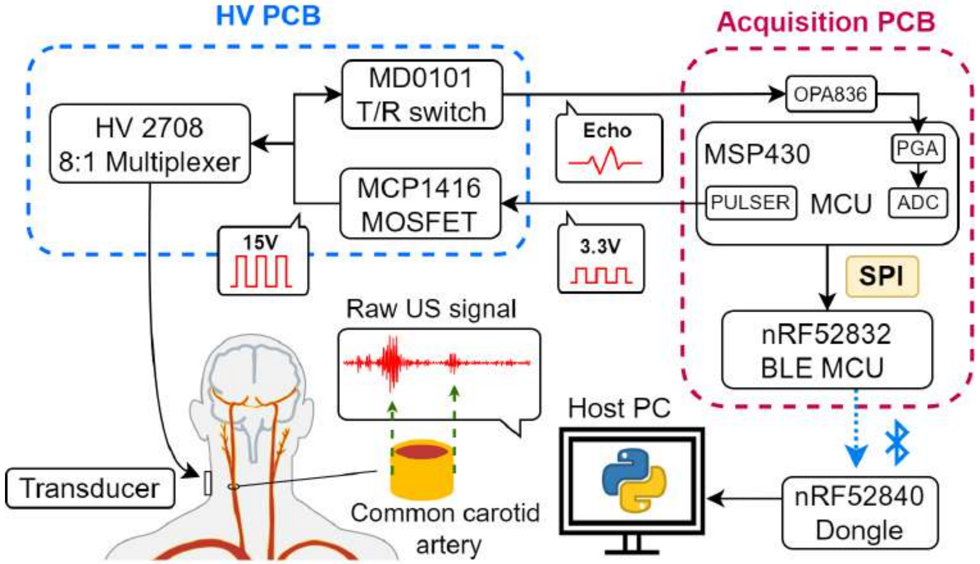
# … to truly wearable ultrasound probes

*Frey et al. IEEE IUS, 2022*

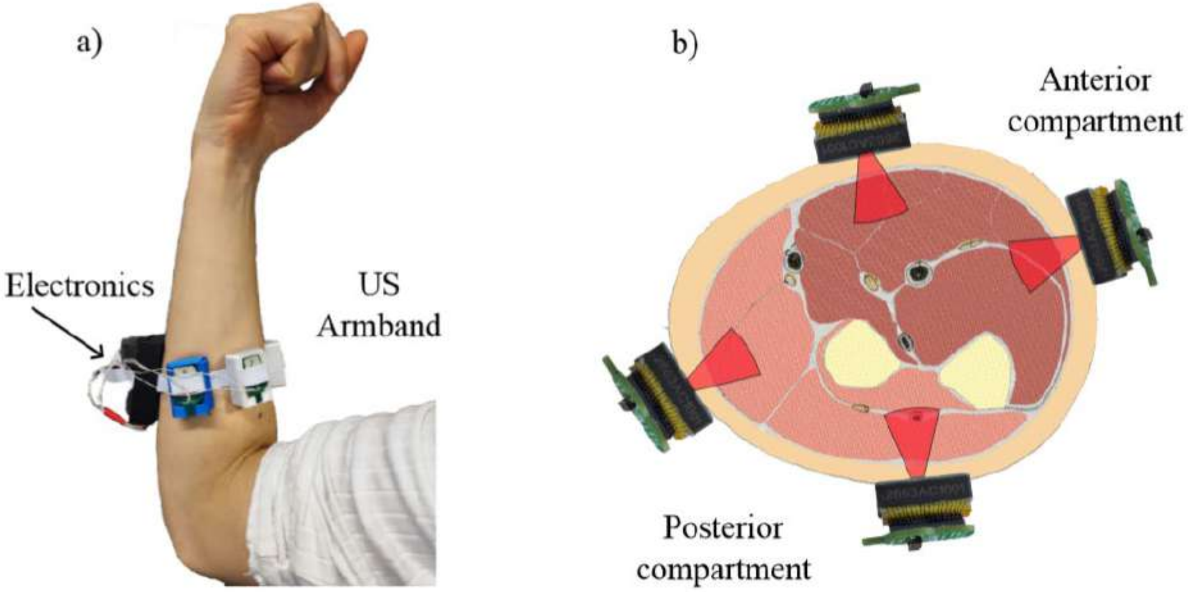
Vostrikov *et al.*, IEEE T-UFFC, 2024

# WULPUS: wearable ultra-low-power ultrasound

***OPEN-SOURCE DESIGN** (hw, fw, sw):*
https://github.com/pulp-bio/wulpus



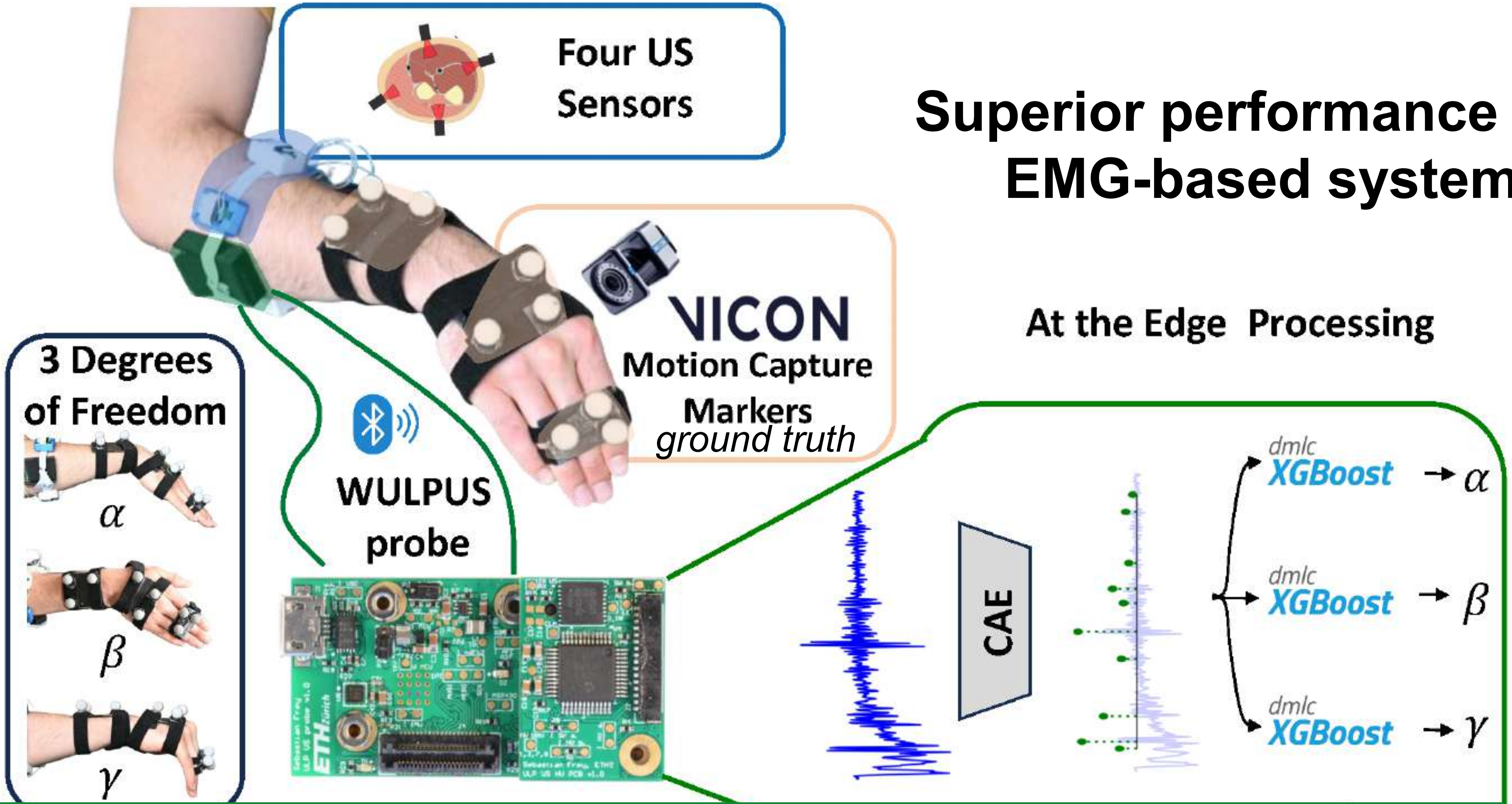

*Frey et al. IEEE IUS, 2022*




*Vostrikov et al. IEEE IUS, 2023*

# Example application: hand-movements recognition

**Superior performance w.r.t. EMG-based systems**




**Results**

**Baseline:**
RMSE: 7.3°± 2.0°
Performance comparable to high-end, 256-channels, B-mode

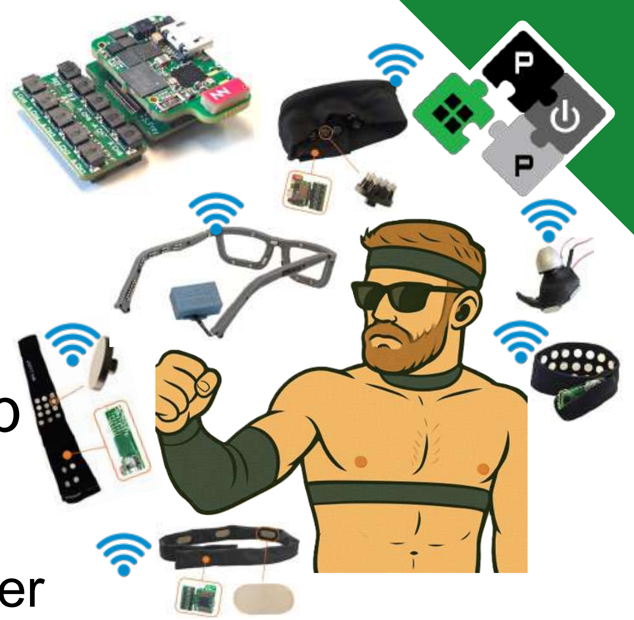
**With Armband Repositioning:**
RMSE: 11.1°± 4.1
High accuracy in real-life conditions

**On Device:**
80ms/inference
<30mW

**Ultrasound is becoming a key technology for wearable sensing**

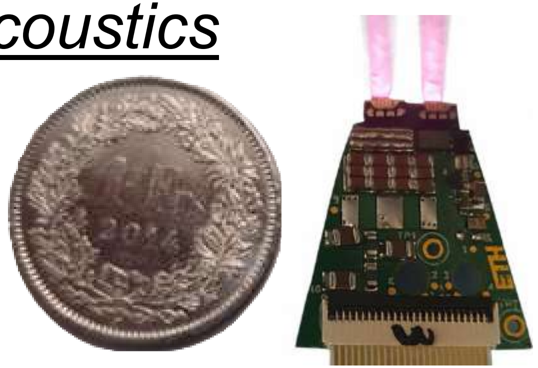
*Spacone et al. IEEE T-BioCAS, 2024*

# The Future



- **Body area networks** for distributed sensing
- **Open-platforms** enable rapid innovation
- **EdgeAI** for privacy, energy-efficiency, real-time closed-loop
- **Foundation Models on wearables**
  - aggressive **HW-SW co-optimization** for fast inference at low power
- **On-device customization** (zero-shot, few-shot)
- **Multimodality**: exploit signal heterogeneity (sensor fusion) and next-gen wearable technologies
  - *fNIRS, mm-Wave sensing, optoacoustics*

[Bahmani et al., arxiv 2505.13663, 2025]



[Liu et al., Laser & Photonics Reviews, 2025]

# Acknowledgment: work by the PULP team

**Led by Luca Benini**


A. Cossettini


V. Kartsch


C. Leitner


X. Wang


S. Benatti


T. Ingolfsson


S. Frey


S. Vostrikov


F. Villani


G. Spacone


A.H. Bernardi

*and many more…*

PULP

https://pulp-platform.org/

*funding and partners*

Swiss National Science Foundation

*project PEDESITE*

ETH zürich

*project Listen-to-Light*

Future Computing Laboratory

CHUV

DATWYLER

ETH zürich

ALMA MATER STUDIORUM UNIVERSITÀ DI BOLOGNA