EpiDeNet: An Energy-Efficient Approach to Seizure Detection for Embedded Systems

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PULP Platform

Open Source Hardware, the way it should be!

@pulp_platform

pulp-platform.org

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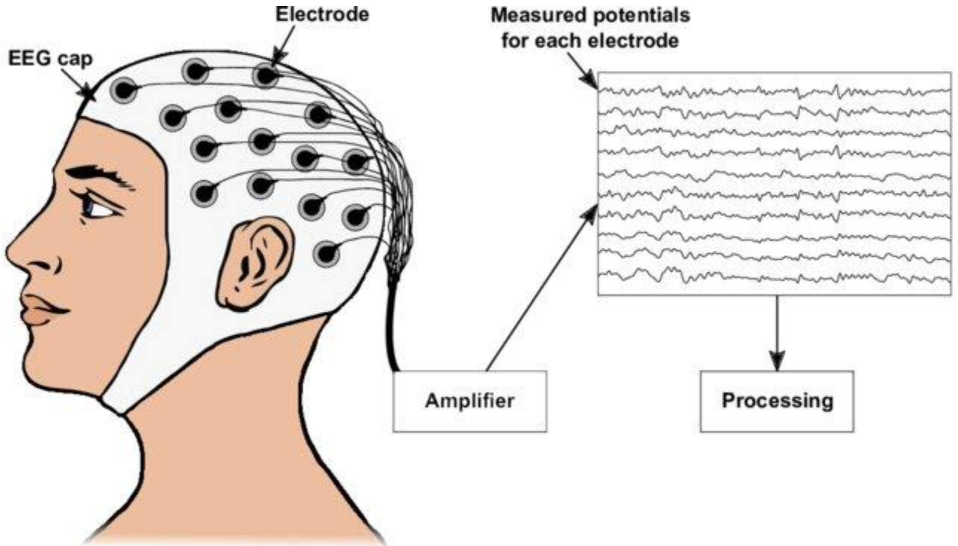
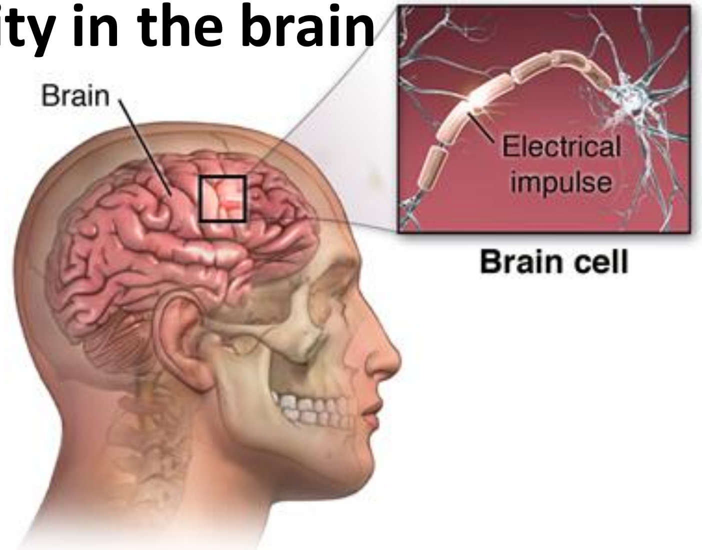
We are controlled by electrical activity

- **Seizures are sudden uncontrolled burst of electrical activity in the brain**
  - Interrupts normal brain signals



Source: Nagel, Sebastian. Towards a home-use BCI: fast asynchronous control and robust non-control state detection.

Scalp attenuates signals by almost 90%



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

- **Electroencephalography (EEG) method of monitoring the electrical activity**
  - Signals typically range from 10 µV to 100 µV ← low signal to noise ratio

Wearable EEG Devices come at a price

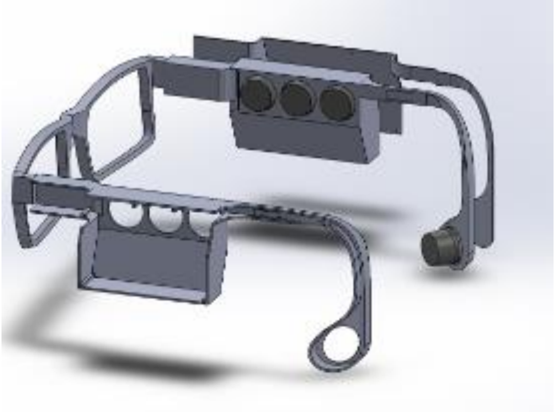
Source: https://www.flickr com/photos/tim_ uk/8135749317

Conventional EEG Caps

- Stigmatizing
- Power hungry
- Not intended for normal day use

Temporal region

Wearable solutions



Data acquisition more susceptible to artifacts

Seizure detection algorithms output false positives (FP)

Predicting a seizure when there is no seizure present.

> 1 FP/hour

< 1 FP/Day

- Non-stigmatizing
- Low-power
- Data processed locally
  - Privacy
  - Latency

Requirements for a Successful Wearable Device

What we target!

Safe

Privacy preserving

Accurate

Long battery life

Real-time response

Two goals:

Goal 1. How do we increase both the **Sensitivity** and **Specificity** at the **same time?**

Goal 2. Lightweight **end-to-end** approach w/o operating on **raw data for real-time response!**
(Also being wearable → Wearable on the temporal region)

A custom loss function enables concurrent improvement of sensitivity and specificity

Methods usually report a very high sensitivity
→ Comes down on the Specificity (FP/H) > 1 FP/hour

This is then magnified by the class imbalance
→ Need to inject domain specific knowledge into the network

Goal 1

- **Smoothing of output → Latency increase**
- **Weighting classes → Hard to get right weights**
- **Up/Down sample → Synthetic Data / Information Loss**
- **Use of different loss function → We introduce:**

Sensitivity Specificity Weighted Cross Entropy Loss (SSWCE)

Cross Entropy

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

Specificity and Sensitivity

EpiDeNet: A Highly Parallelizable and MCU-Deployable Neural Network Architecture

Mix of temporal and spatial filters

We present the novel *EpiDeNet*:

Block	Filters	Kernel	Output
Conv2D + MaxPool	4	(1,4) – (1,8)	(4,C,T//8)
Conv2D + MaxPool	16	(1,16) – (1,4)	(16,C,T//32)
Conv2D + MaxPool	16	(1,8) – (1,4)	(16,C,T//128)
Conv2D + MaxPool	16	(16,1) – (4,1)	(16,C//4,T//128)
Conv2D + AdAvgPool	16	(8,1)	(16,1,1)
Dense	-	-	2

Goal 2 ✓

***EpiDeNet* very efficient due to usage of parallelizable operations (Conv + Pool)**

***EpiDeNet* only utilizes 11k weights → fits on resource constrained devices**

Seizure Detection datasets

CHB-MIT

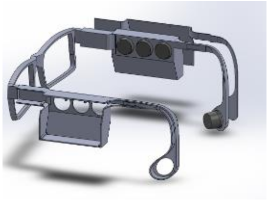
- 23 Pediatric Patients
- 256 Hz sampling rate
- 181 Seizures
- **Open-Source**

PEDESITE

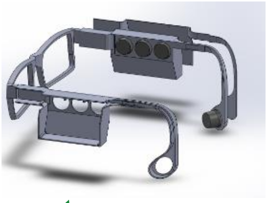
- 5 Adult Patients
- 1024 Hz sampling rate
- 25 Seizures
- **Private**

- **Over > 1000 hours of data!**

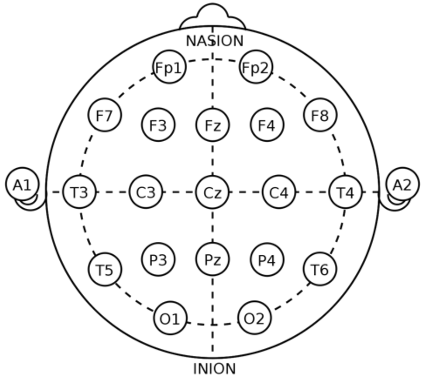
We limit ourselves to a mimicked wearable setup
→ 4 Channels near temporal region



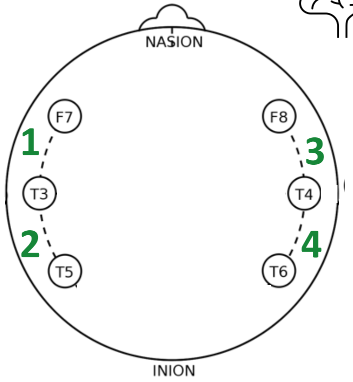
CHB-MIT Results



Going from a full channels (22) to a reduced montage (4)



Sensitivity 81.91%
Specificity 99.86%
FP/H 1.25
#Seizures 171/181



Sensitivity 68.73%
Specificity 99.75%
FP/H 2.24
#Seizures 165/181

Degradation in accuracy but still able to detect **majority of seizures**

Comparison to other **SoA** works with a **reduced electrode montage**

Random Forest [1] **(2 CH)**

Sensitivity 96.6%
Specificity 92.2%
FP/H 70.2

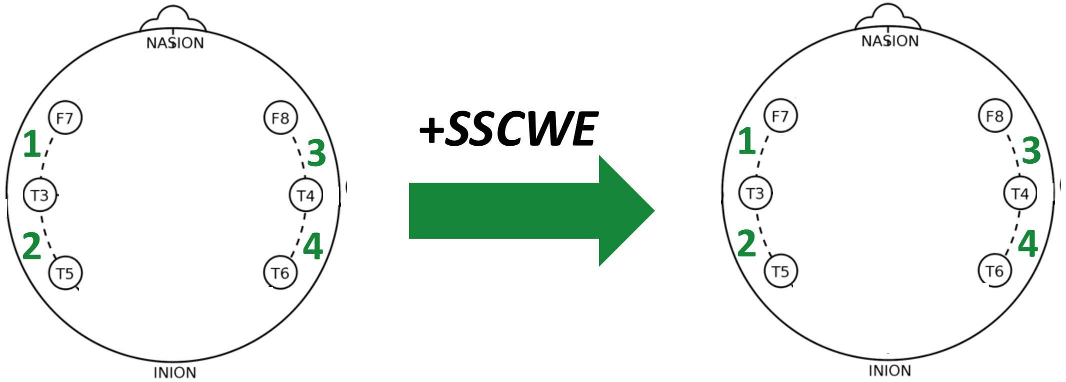
SVM [2] **(8 CH)**

Sensitivity 92.5%
Specificity 80.1%
FP/H >100

[1] Zanetti et al., Robust epileptic seizure detection on wearable systems with reduced false-alarm rate
[2] Zhan et al., A Resource-Optimized VLSI Implementation of a Patient-Specific Seizure Detection Algorithm on a Custom-Made 2.2 cm2 Wireless Device for Ambulatory Epilepsy Diagnostics

PEDESITE Results

Integration of the SSCWE increases the performance



Sensitivity	57.17%
Specificity	99.51%
FP/H	2.5
#Seizures	23/25

Sensitivity	**60.66%**
Specificity	**99.74%**
FP/H	**1.18**
#Seizures	**23/25**

Huge improvement in FP/H (2.12x)

Embedded Deployment of EpiDeNet

GAP8

- 8 Core RISC-V Cluster
- 100 MHz
- Memory:
  - L1: 80kB
  - RAM: 512 kB

GAP9

- 9 Core RISC-V Cluster
- 240 MHz
- Memory:
  - L1: 128kB
  - RAM: 1.5 MB
  - Non Volatile: 2 MB

ARM M4F

- ARM Cortex M4F Core
- 80 MHz
- Memory:
  - SRAM: 128kB
  - Flash: 1 MB

ARM M7

- ARM Cortex M7 Core
- 216 MHz
- Memory:
  - SRAM: 320kB
  - Flash: 1 MB

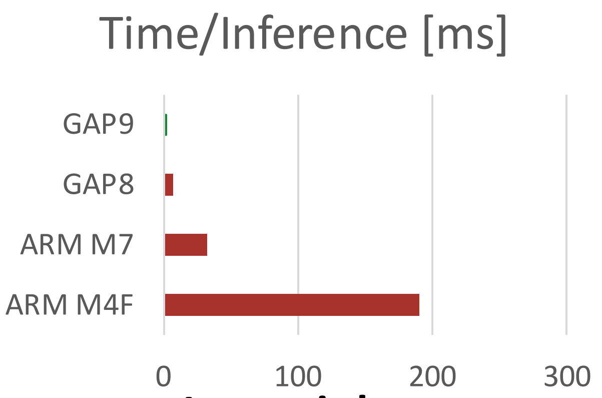
Quantized to 8bit

Quantlab → **DORY**

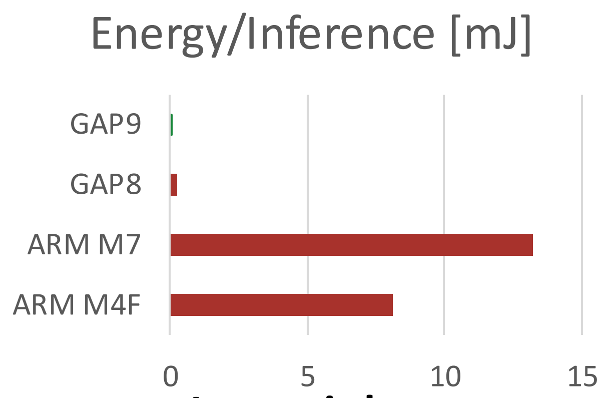
Deployment

TFLite → **CUBE.AI**

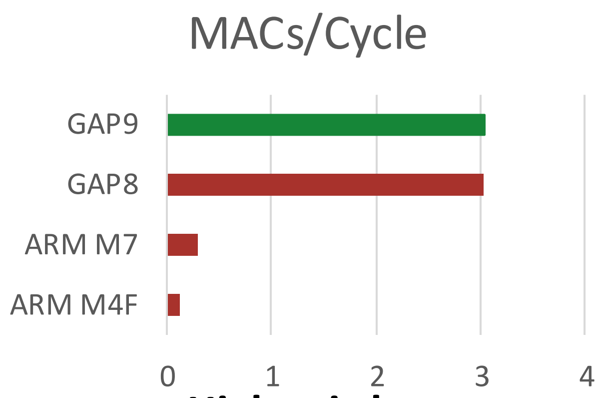
Deployment results



Lower is better

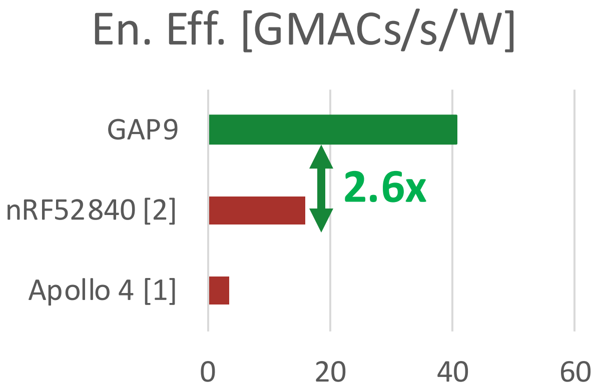


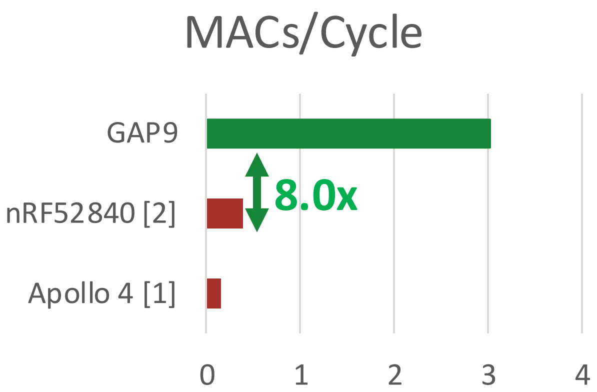
Lower is better



Higher is better

Implementation of **EpiDeNet** is around **160x more energy-efficient** on **GAP9** then on ARM





Higher is better

Comparing the best implementation (**GAP9**) of **EpiDeNet** with SoA implementations in Seizure detection shows:

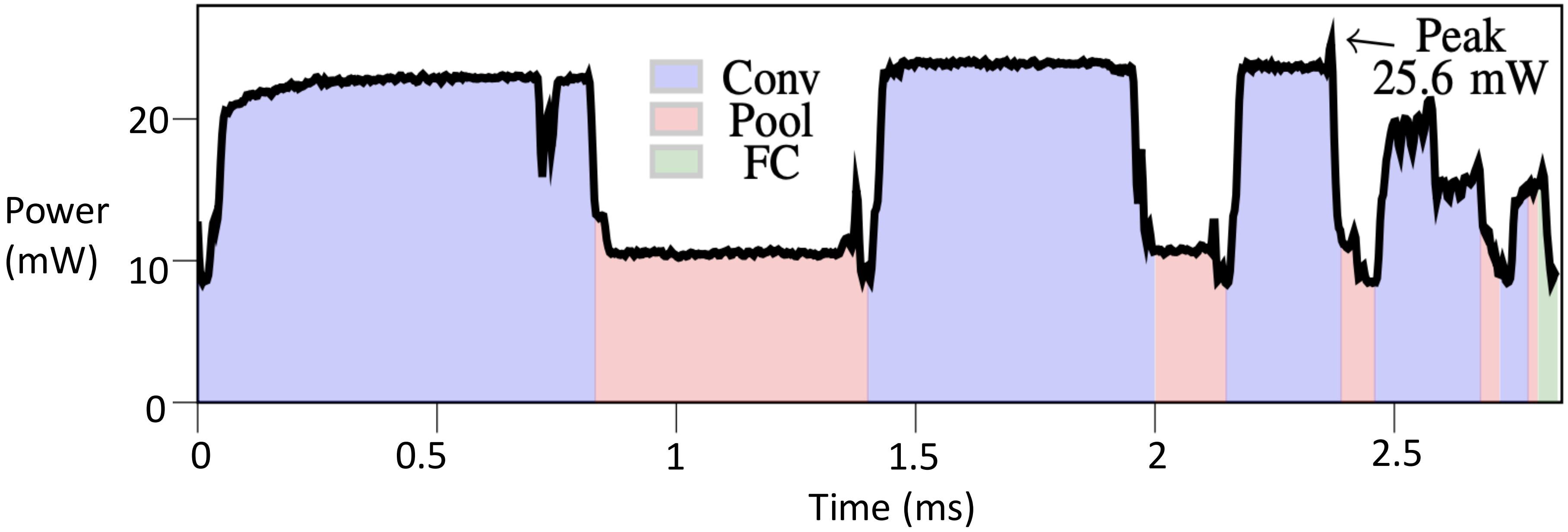
- **11.6x and 2.6x** more energy efficient
- **18.9x and 8.0x** more MACs/Cycle

[1] Busia et al., EEGformer: Transformer-Based Epilepsy Detection on Raw EEG Traces for Low Channel Count Wearable Continuous Monitoring Devices
[2] Liu et al., Edge deep learning for neural implants: a case study of seizure detection and prediction

Low power implementation allows for **multiday use**

- **Detection of 92%** of all seizure events with **SSWCE**
- **3x reduction** in false positives using **SSWCE**

51 µJ energy per 4 s window



GAP9 Implementation

300mah battery

→ **300 hours**

Contact info