# SYNtzulu: Low-Power FPGAs for SNN-Based Biosignal Near-Sensor Processing

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University of Sussex, United Kingdom, 12th June 2026

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# A (Very) Non-Exhaustive List of Global Problems

From World Health Organization

- **Cardiovascular diseases** are the **leading cause of death globally**. An estimated **19.8 million people died** from CVDs in **2022** (32% of all global deaths).

ECG

- Around **50 million people worldwide have epilepsy**, making it one of the most common neurological diseases globally.

EEG

- **Amputations** affect about **180 million people** worldwide.

EMG

- Globally, over **15 million people** are living with **spinal cord injury**.

EEG/iEEG

Wearable devices enable continuous monitoring, assistance, early detection, and personalized care

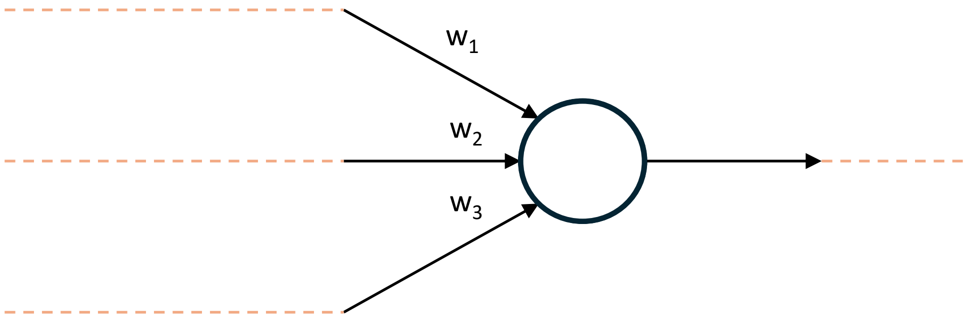
# Common Characteristics of ExG Applications

| | | HW design standpoint | Constraints |
|---|---|---|---|
| Recording sites | From 1 to +100 | From throughput-driven to energy-driven design | Bandwidth |
| Sampling frequency | From 200 Hz to 10 kHz → Fixed and constant rate | | |
| Signal preprocessing | Filtering, beat/spike detection, wavelet, etc.. | Feature extracion pre-processor | Preprocessing throughput |
| Task | Regression, classification, anomaly detection | Versatile algorithm Configurable accelerator | Memory |
| Inference or classification rate | From 1 to 1k per sec → inference rate != sampling rate | Power saving mode | Inference throughput |

All integrated into a low-power wearable device

# Spiking Neural Networks (SNNs)

- SNNs: spike-based version of NNs




- Input
  - Spikes are 0s and 1s
  - Sparse workload → event-based

- *LIF neuron dynamics*
  - $\mathrm{I}(t) = \sum s_i w_i$ *# not real multiplication*
  - $v(t) = \alpha v(t-1) + I(t)$ # MAC operation
  - $s(t) = v(t) > threshold$ # spike condition
  - $v(t) = v(t)(1 - s(t))$ # reset

# SNNs on FPGA

## FPGA as a target

- Flexible BRAMs: weights and potentials
- DSPs: LIFs/MACs
- LUTs:
  - Synaptic current
  - Sensor data processing
  - Sparsity exploitation
- Easy access and affordable cost

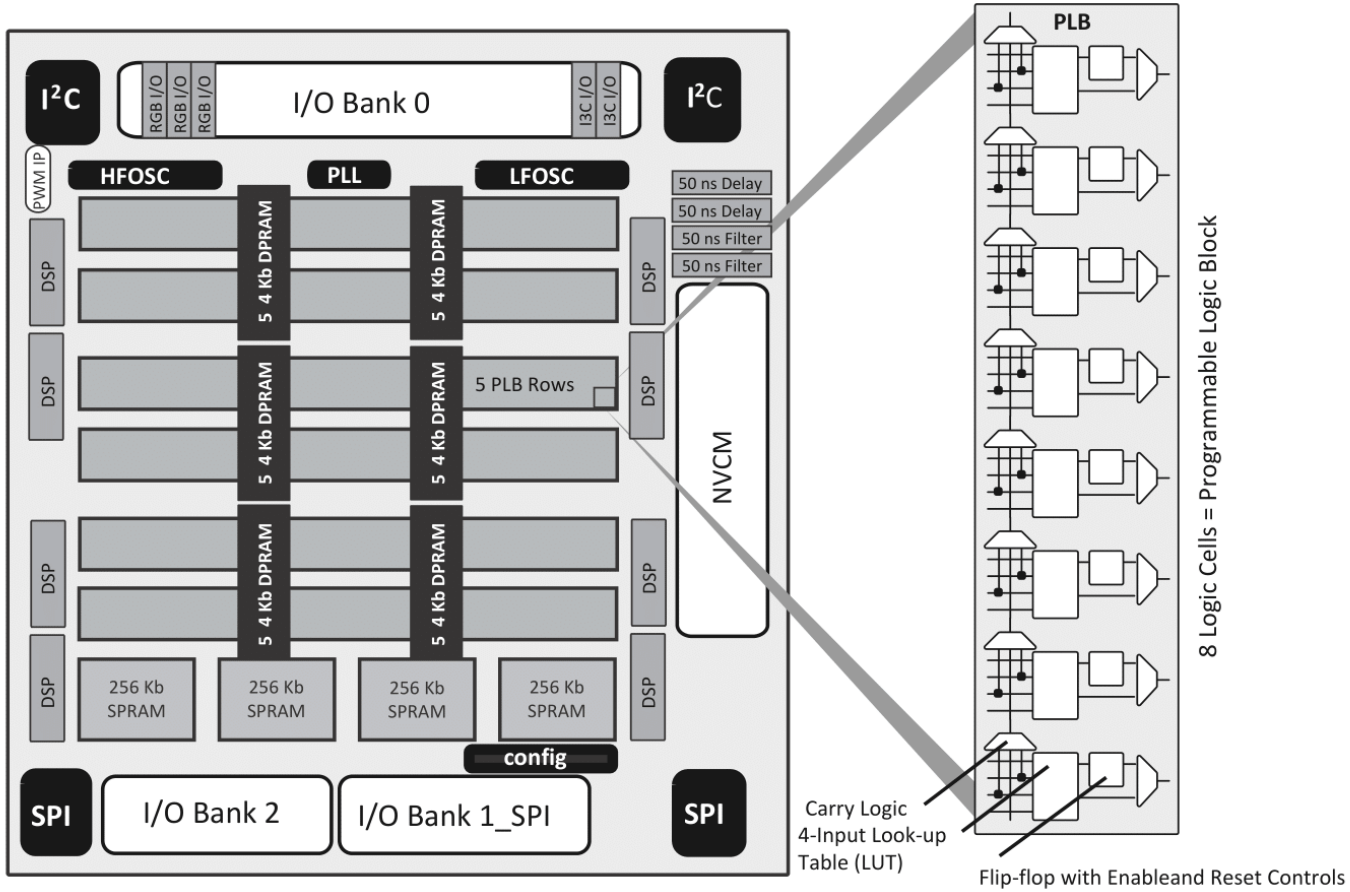
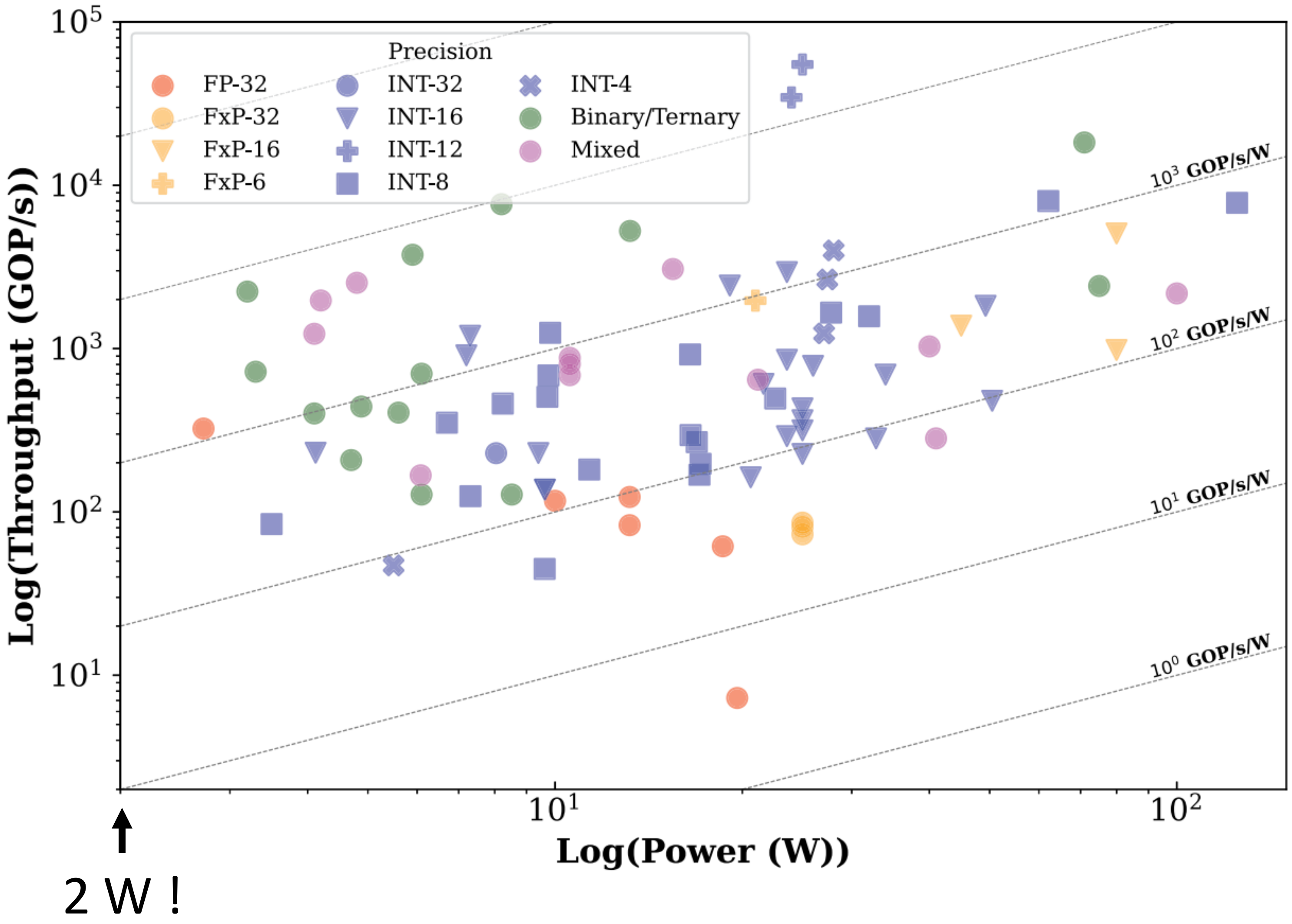



Figure 3.1. iCE40UP5K Device, Top View

From Lattice datasheet

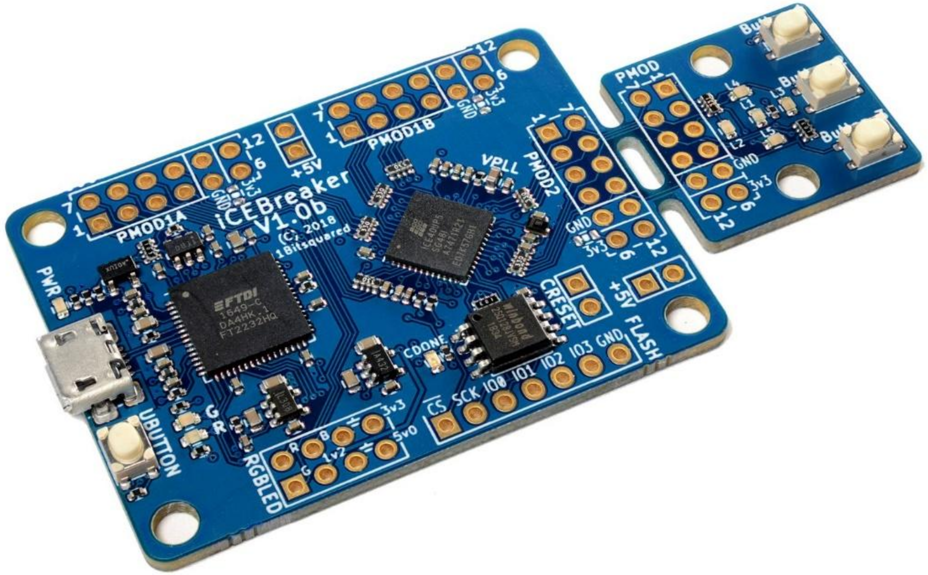
# FPGA-based NN Accelerators



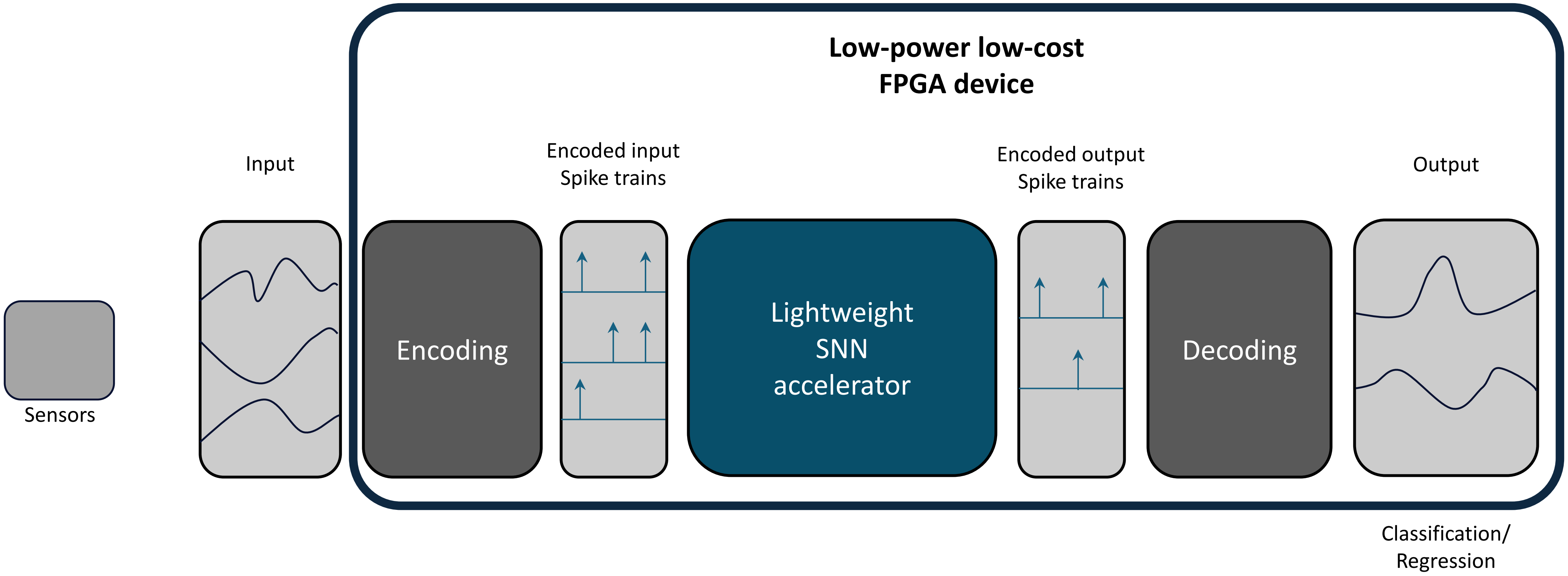
# Target FPGA


**<u>Lattice iCE40UP5k FPGA</u>**

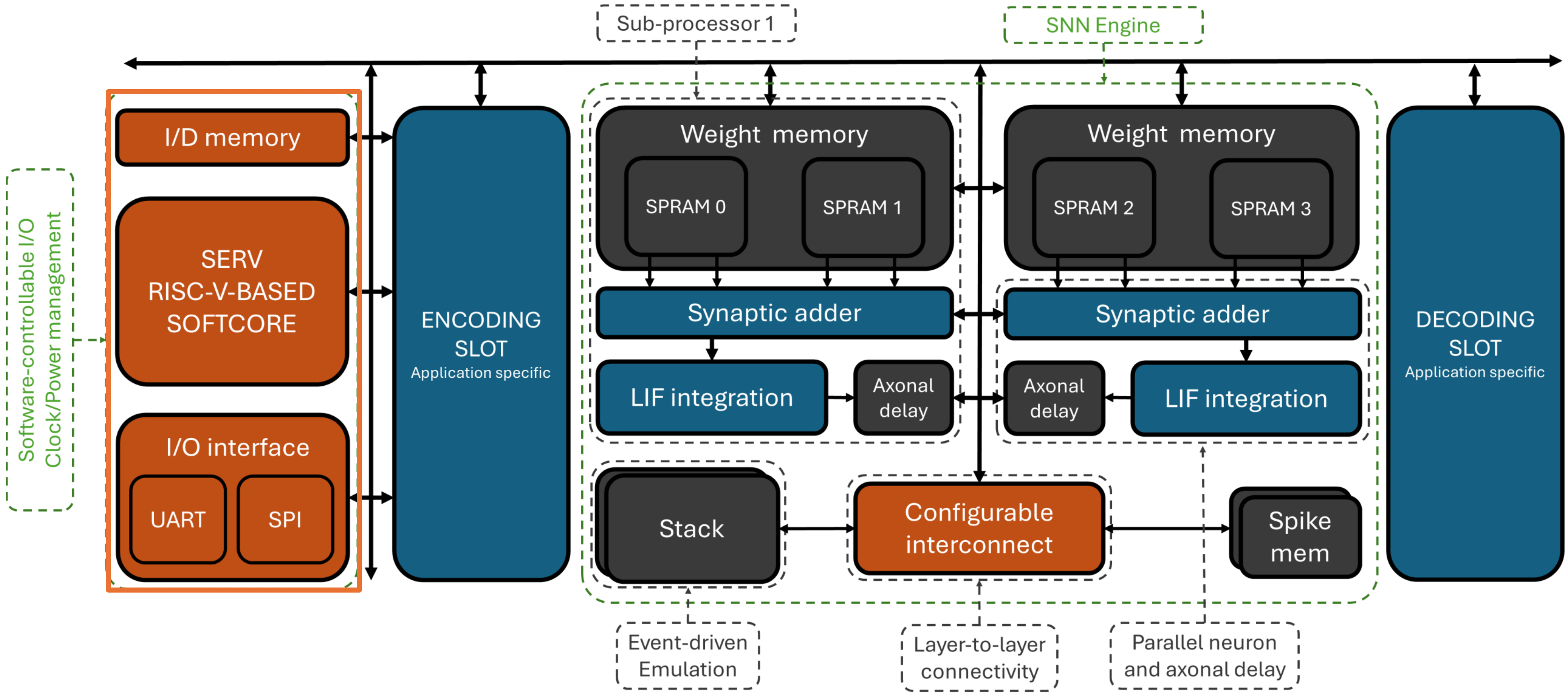
- **5280 logic cells** (4-LUT + Carry + FF)
- **8 DSP** multiplier blocks
- Around **1 Mbit** on-chip **SRAM**
- PLL, 2 internal oscillators (10 kHz and 24 MHz)



# Approach overview

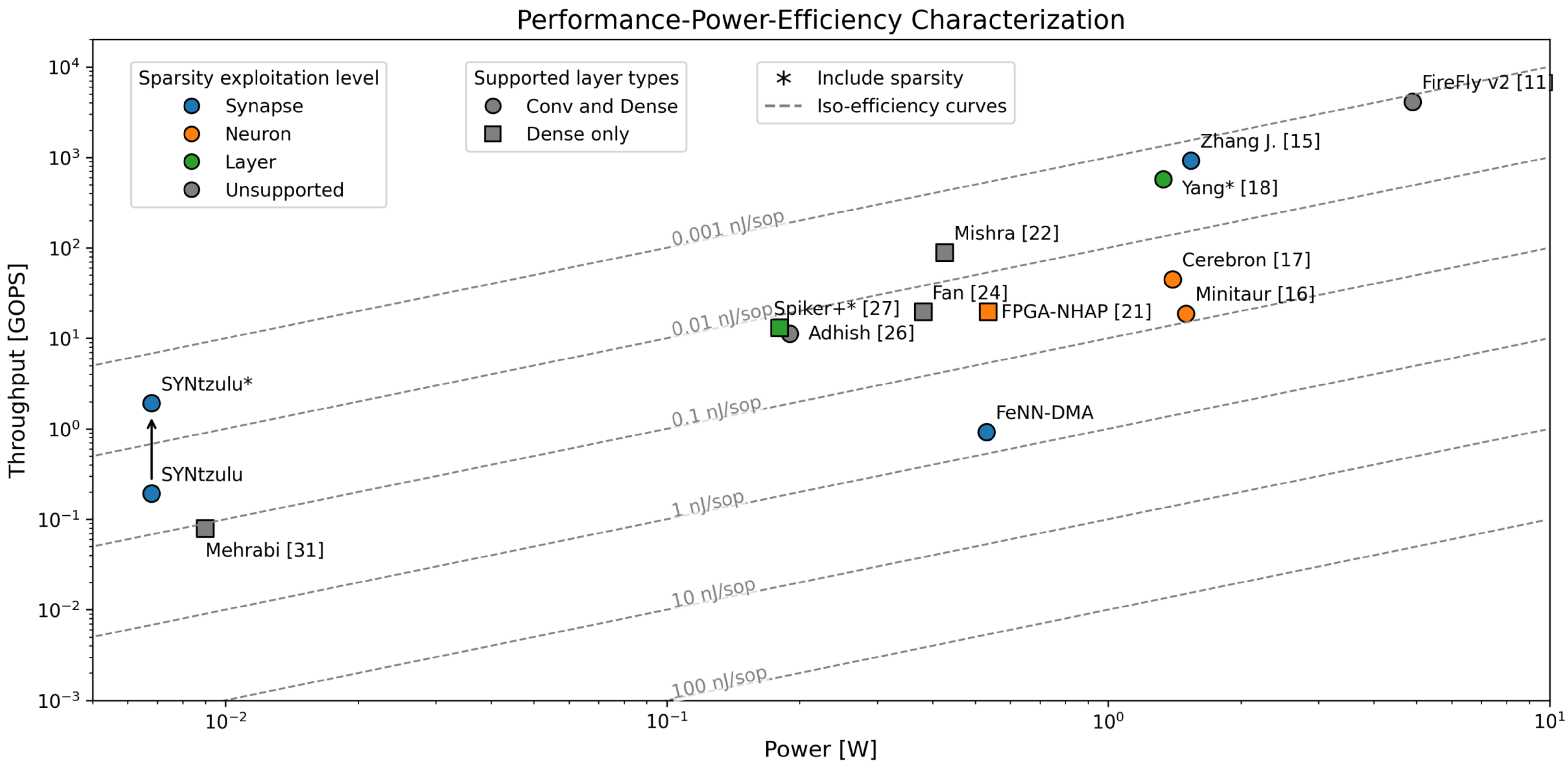


# SYNtzulu Architecture




Leone, Gianluca, et al. "SYNtzulu: A Tiny RISC-V-Controlled SNN Processor for Real-Time Sensor Data Analysis on Low-Power FPGAs." IEEE Transactions on Circuits and Systems I: Regular Papers (2024)

# FPGA-based **SNN** Accelerators




Leone, Gianluca, et al. "SYNtzulu-Conv: Enabling Spiking 2D Convolutions for SensorData Analysis on Low-Power FPGAs." HEART 2026 International Symposium on Highly Efficient Accelerators & Reconfigurable Technologies

# SYNtzulu on ExG applications

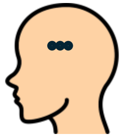
Can lightweight (1 Mb) SNN models solve real-world problems?

iEEG

ECG

sEMG

EEG



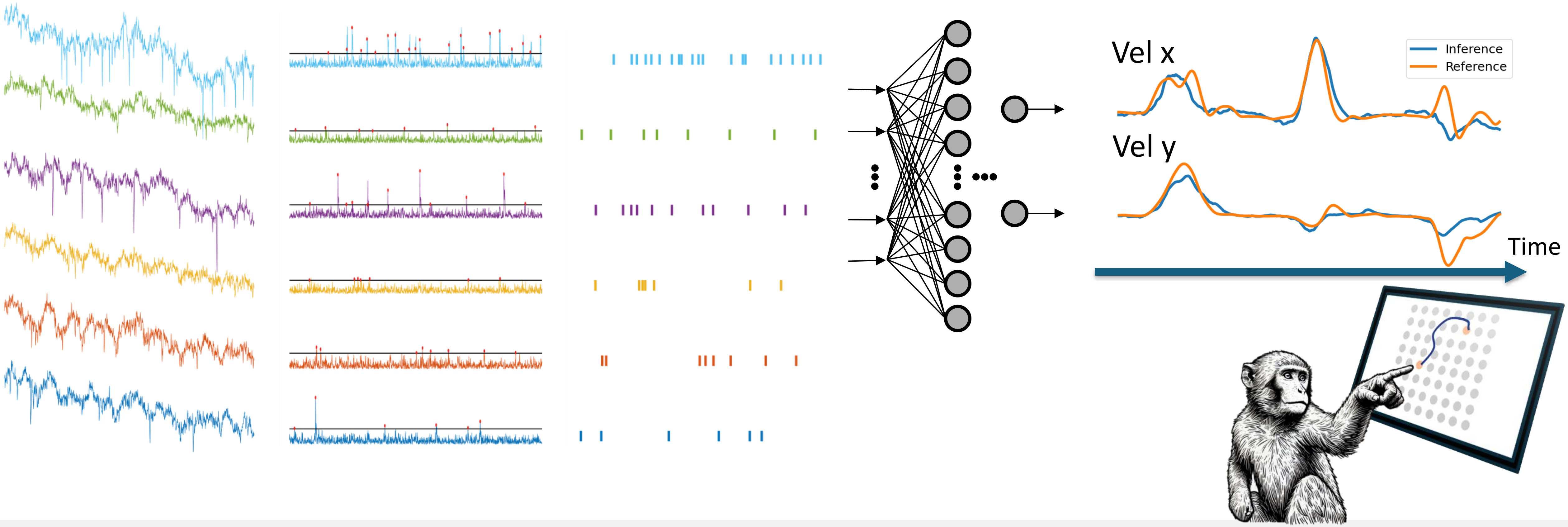
# Use Case 1: Finger motion tracking from intracortical signal

Raw signal
64 channel @12kHz

Encoding: denoising – spike emphasis – thresholding – binning

SNN
4 layers

Regression results
Finger velocity (x,y)





***Reference dataset***: *J. E. O'Doherty, et al. "Nonhuman Primate Reaching with Multichannel SensorimotorCortex Electrophysiology," May 2020*

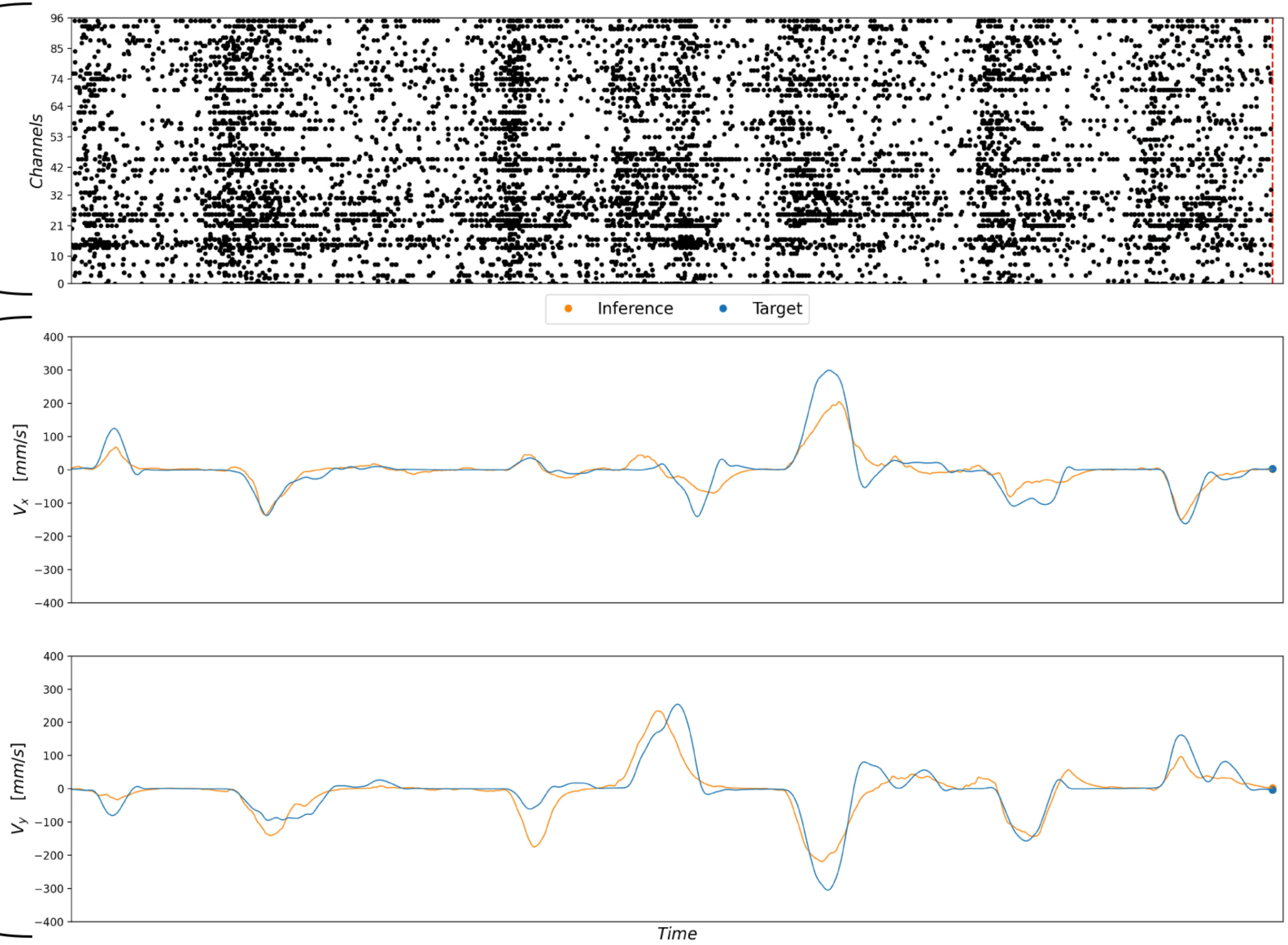
***Pubblications***: *Leone, Gianluca, et al. "Enabling SNN-Based Near-MEA Neural Decoding with Channel Selection: An Open-HW Approach." 2025 Design, Automation & Test in Europe Conference (DATE). IEEE, 2025.*

*Martis, L., Leone, G., Raffo, L., & Meloni, P. (2024). Low-Power FPGA-based Spiking Neural Networks for Real-Time Decoding of Intracortical Neural Activity. IEEE Sensors Journal.*

*Leone, Gianluca, Luigi Raffo, and Paolo Meloni. "On-FPGA spiking neural networks for end-to-end neural decoding." IEEE Access 11 (2023): 41387-41399.*

Intracortical spikes
→ SNN input

Finger velocity (x,y)
SNN output →



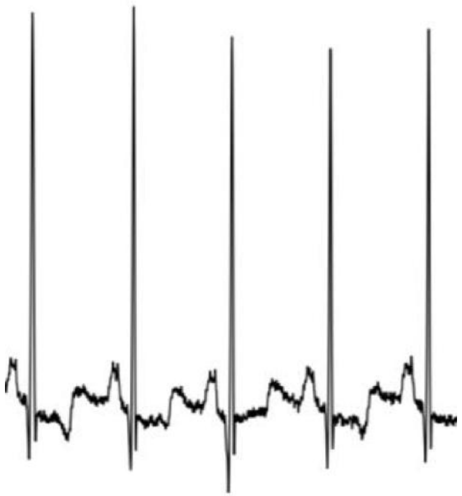
# Use Case 2: Arrythmic cardiac beats classification from single-lead ECG signal

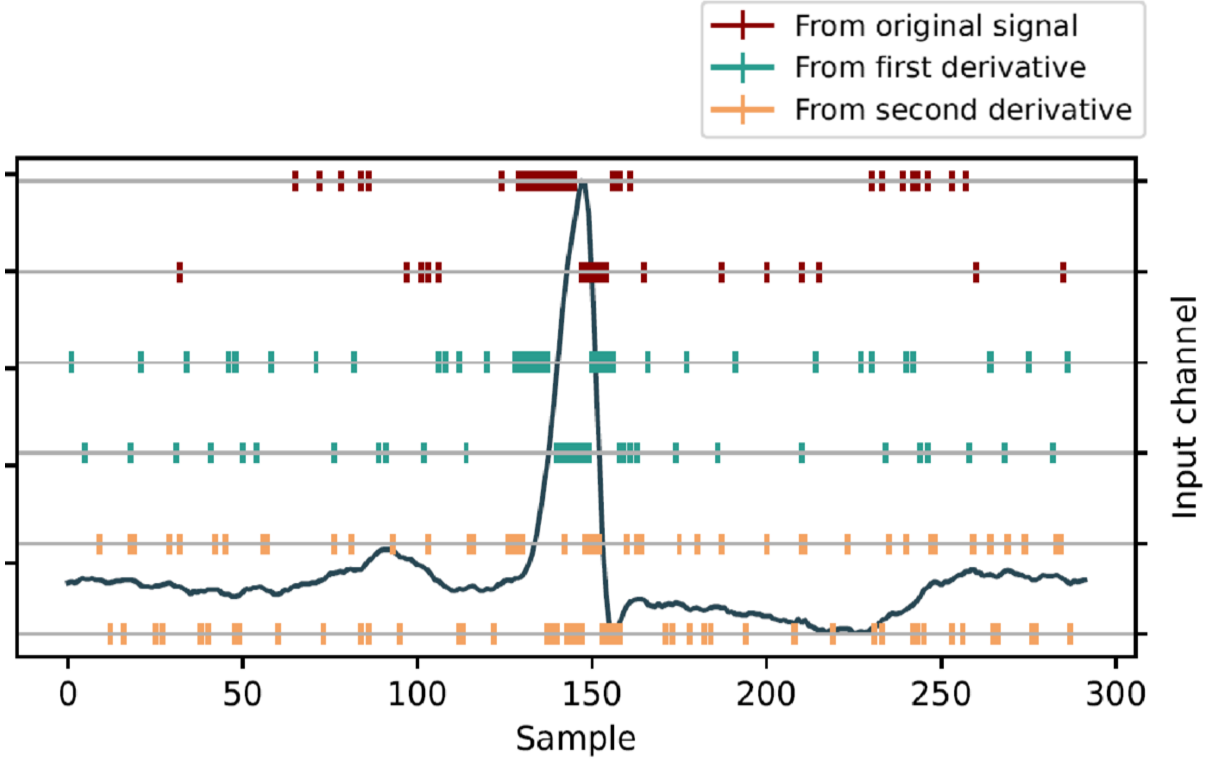
Raw signal
1 channel @ 360 Hz

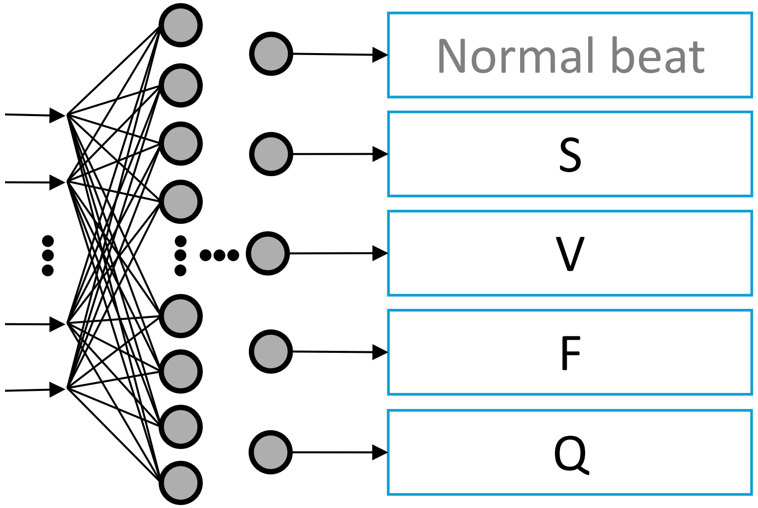
Encoding: denoising – peak detection –
delta modulation of ECG and derivatives

**SNN**
**4 layers**

Classification
Normal/Arrythmic






***Reference dataset****: A. L. Goldbergeret al. "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals,"*
***Pubblication****: Scrugli, M. A., Busia, P., Leone, G., & Meloni, P. (2024, March). On-FPGA spiking neural networks for integrated near-sensor ECG analysis. In 2024 Design, Automation & Test in Europe Conference & Exhibition (DATE) (pp. 1-6). IEEE.*
*Scrugli, M. A., Leone, G., Busia, P., Raffo, L., & Meloni, P. (2026). All-Spiking ECG Analysis for Arrhythmia Classification on Low-Power FPGA. IEEE Sensors Journal.*

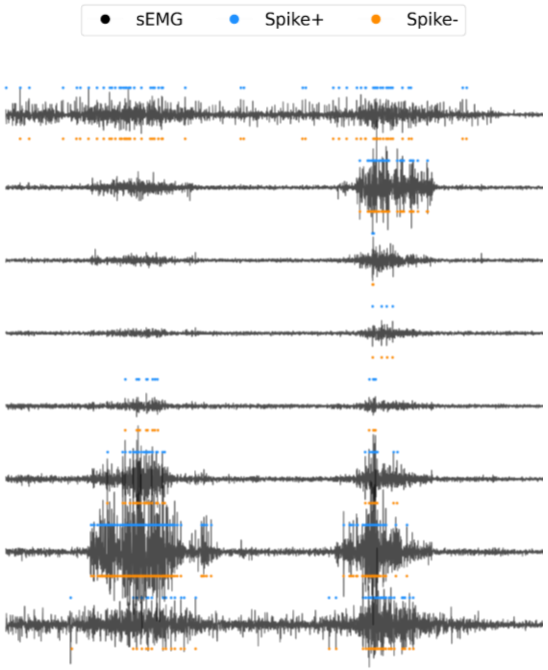
# Use Case 3: Fingers force tracking from HD-sEMG signal

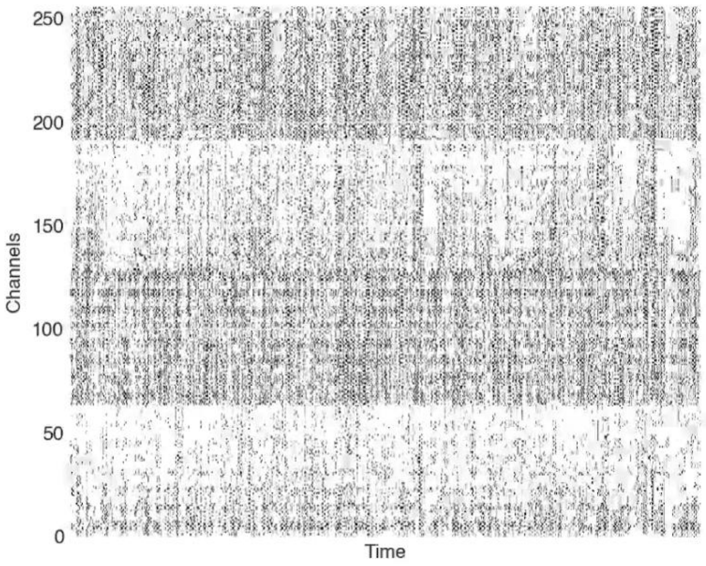
Raw signal
128 channels @1 kHz

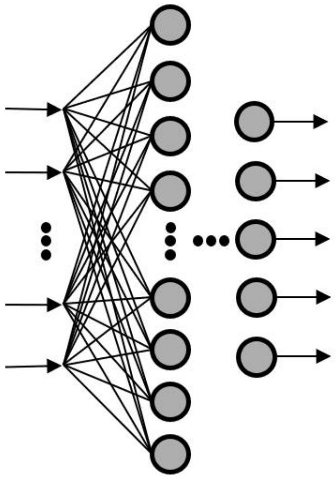
Encoding: delta modulation
256 encoded channels

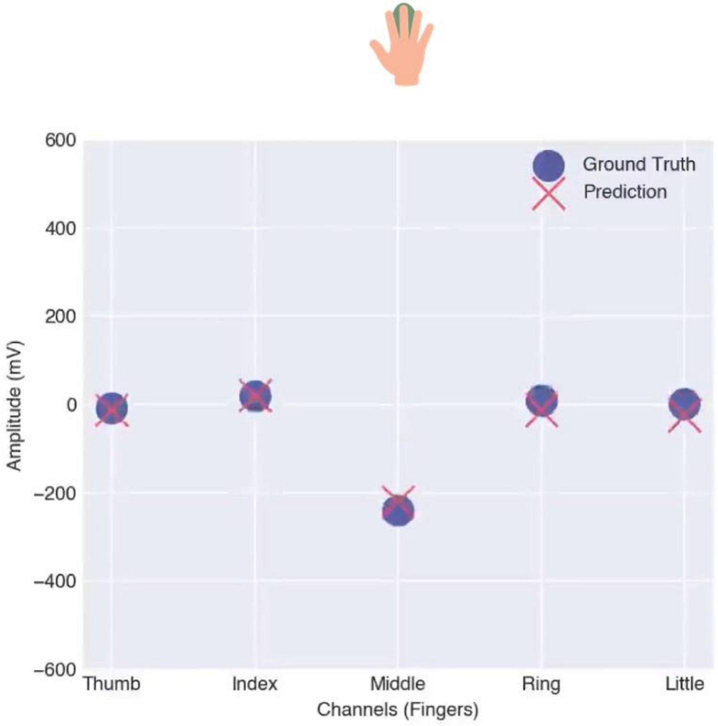
**SNN**
**4 layers**

**Finger Force**






**Reference dataset**: *X. Jiang et al., "Open Access Dataset, Toolbox and Benchmark Processing Results of High-Density Surface Electromyogram Recordings," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 1035-1046, 2021, doi: 10.1109/TNSRE.2021.3082551.*

***Pubblications***: *Scrugli, M. A., Leone, G., Busia, P., Raffo, L., & Meloni, P. (2024). Real-time sEMG processing with spiking neural networks on a low-power 5K-LUT FPGA. IEEE Transactions on Biomedical Circuits and Systems.*

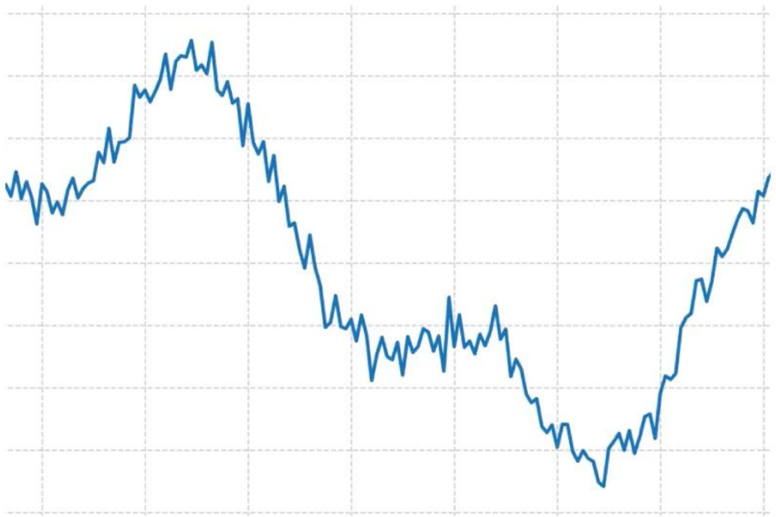
# Use Case 4: Seizure detection on limited EEG channel count

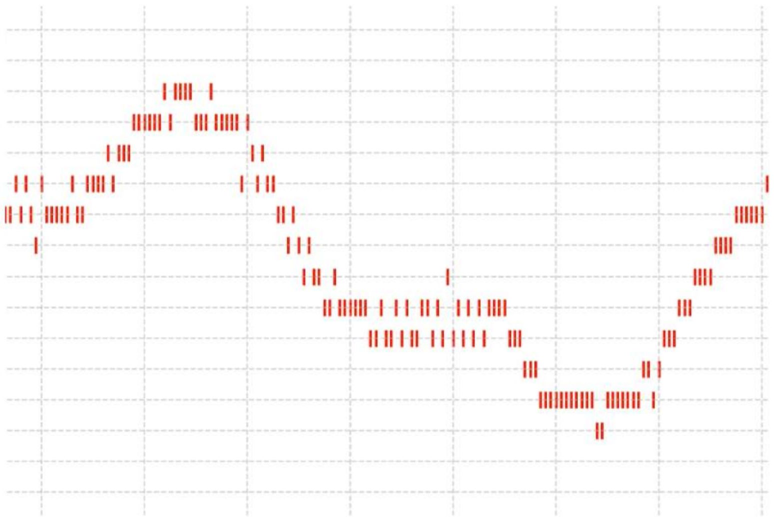
Raw signal
4 channels @256 Hz

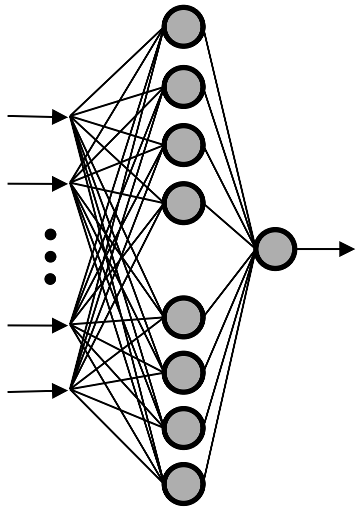
Encoding: one hot
1-to-16 channels (64)

SNN
2 layers

Seizure detection







Normal

Seizure

***Reference dataset***: *A. H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, MIT, 2009.*
*A. L. Goldberger et al., "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," circulation, vol. 101, pp. e215–e220, 2000*
***Pubblication***: *Busia, P., Leone, G., Matticola, A., Raffo, L., & Meloni, P. (2025). Wearable Epilepsy Seizure Detection on FPGA with Spiking Neural Networks. IEEE Transactions on Biomedical Circuits and Systems.*

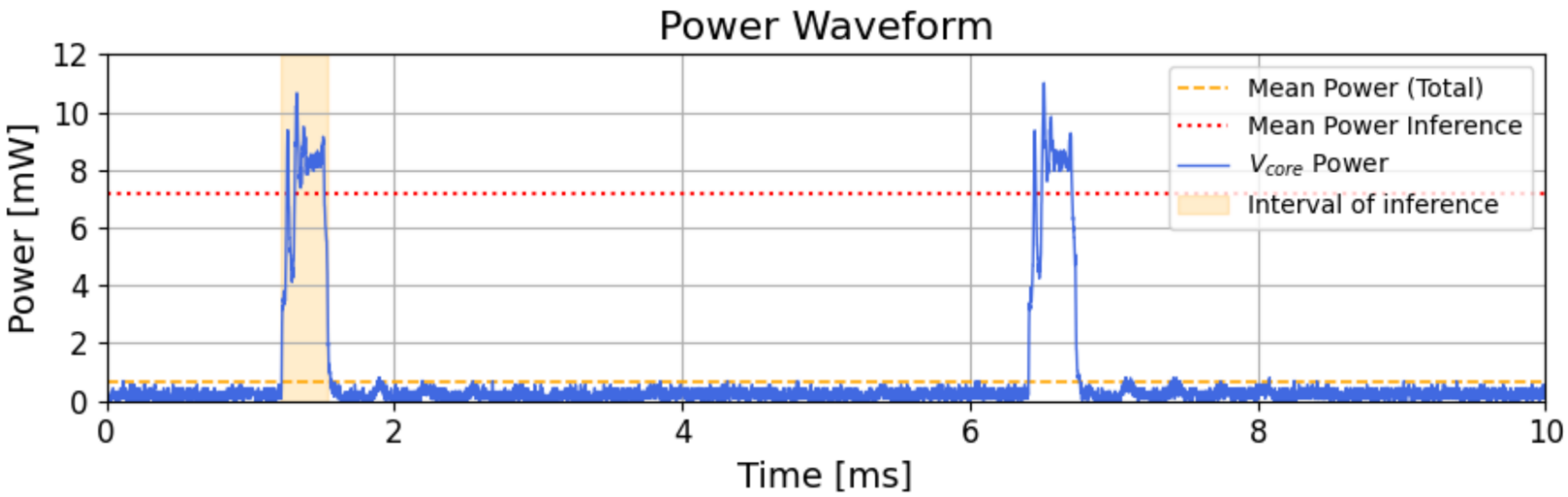
# Flexibility

| Signal | Application | Number of channels | Sampling Frequency | Bandwidth | Encoding | Output |
|---|---|---|---|---|---|---|
| **iEEG** | Neural decoder | 64 | 12 KHz | 18 Mbps | Spike detection | Regression |
| **ECG** | Arrhythmia classification | 1 | 360 Hz | 6 Kbps | Peak detection & delta encoding | Classification |
| **sEMG** | Finger force modelling | 128 | 1 kHz | 2 Mbps | Delta modulation | Regression |
| **EEG** | Seizure detection | 4 | 256 Hz | 16 Kbps | One-hot encoding | Anomaly detection |

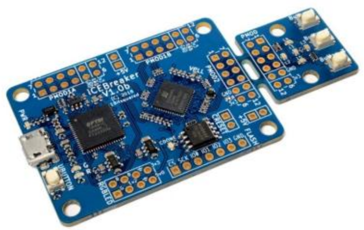
# Hardware report

YosysHQ

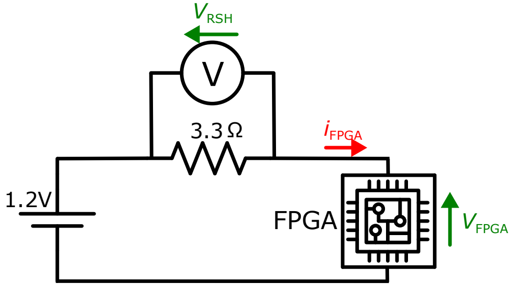
| | LUT | DSP | BRAM | SPRAM | Pavg [mW] |
|---|---|---|---|---|---|
| **UC1** | 4484 | 4 | 22 | 4 | **8.5** |
| UC2 | 4690 | 3 | 28 | 4 | 1.45 |
| UC3 | 4262 | 2 | 29 | 4 | 3.11 |
| **UC4** | 3271 | 2 | 14 | 4 | **0.25** |

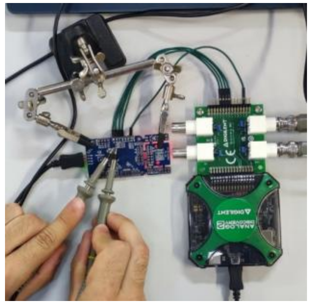



**iCEBreaker**



**USB Oscilloscope**

# SNN model accuracy

| USE CASE | Reference | Accuracy metric | Reference accuracy | Our accuracy | Ref model size | Model size | Ref power [mW] | Our power [mW] |
|---|---|---|---|---|---|---|---|---|
| iEEG | PC [1] | CC | 0.85 | 0.86 | 327K params | 22k params (0.17 Mb) | - | 8.5 (PLL) |
| ECG | FPGA [2] | Interclass | 98.3% | 98.4% | 435k params | 17k params (0.13 Mb) | 250 | 7 |
| sEMG | PC [3] (deep forest) | $R^2$ | 0.87 | 0.87 | - | 24k params (0.19 Mb) | - | 7 |
| EEG | ASIC 130nm [4] | Event Level Detection FP/h | 100% N.A. | 100% 0.3 FP/h | 0.07 Mb | 0.5k params (0.004 Mb) | 1.37 | 7 (0.25) |

## Lightweight (1 Mb) SNN models can solve real-world problems


*[1] N. Ahmadi, T. Adiono et al., "Improved spike-based brain-machine interface using bayesian adaptive kernel smoother and deep learning," IEEE Access, vol. 10, pp. 29 341–29 356, 2022.*
*[2] Y. Xing, et al. "Accurate ecg classification based on spiking neural network and attentional mechanism for real-time implementation on personal portable devices," Electronics, vol. 11, no. 12, 2022.*
*[3] X. Jiang, K. Nazarpour, and C. Dai, "Explainable and robust deep forests for EMG-force modeling," IEEE J. Biomed. Health Inform., vol. 27, no. 6, pp. 2841–2852, Jun. 2023.*
*[4] A. Muneeb and H. Kassiri, "Customized development and hardware optimization of a fully-spiking snn for eeg-based seizure detection," in 2024 IEEE Biomedical Circuits and Systems Conference (BioCAS), 2024, pp. 1–5.*

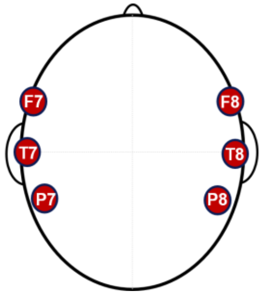
# From static models to self-adaptive intelligence

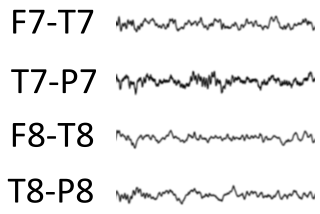
- Challenge: input variability degrades trained model accuracy
  - Noise levels oscillation
  - Electrodes shift
  - Inter-session and inter-day variability

- Approach: always-on unsupervised online refinement
  - Brain-inspired plasticity mechanisms: Short-Term Plasticity

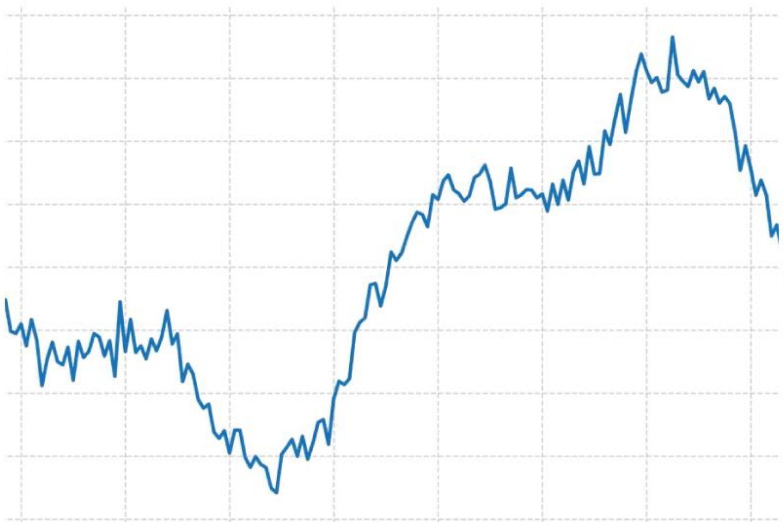
# Long-term EEG monitoring for seizure detection

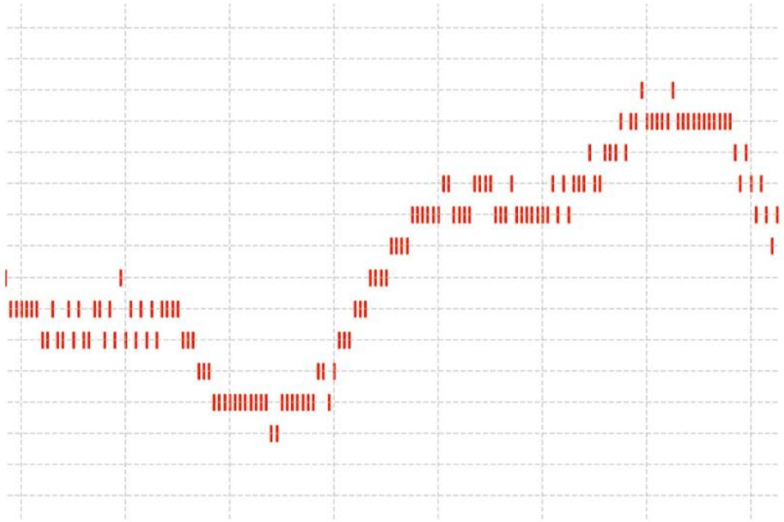
**Dataset:** CHB-MIT
Scalp EEG Database
*Shoeb, A.H.: Application of machine learning to epileptic seizure onset detectionand treatment. Ph.D. dissertation, MIT (2009)*

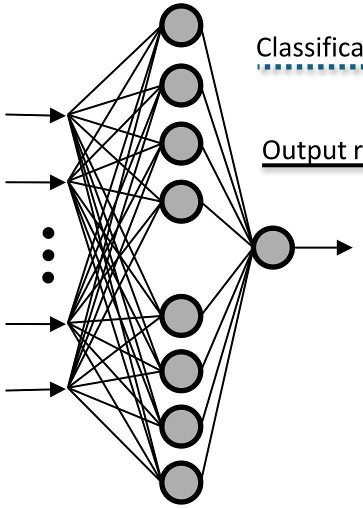


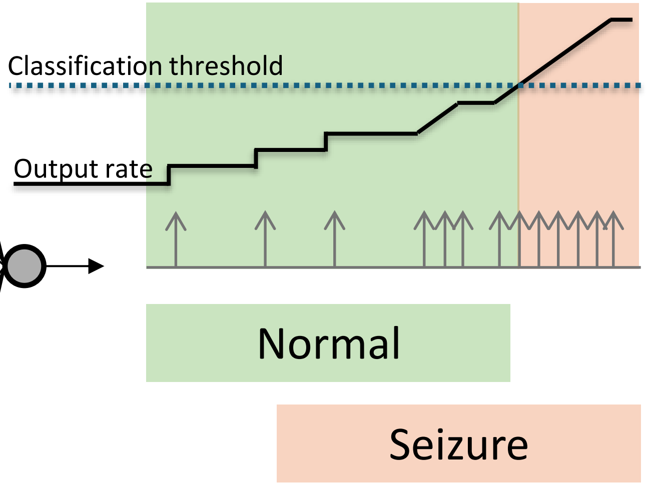




- Unobtrusive acquisition from temporal channels
- Subject-specific training
- **Leave-last-one-out** test
- Low-power long-term monitoring










Raw signal
4 channels @256 Hz

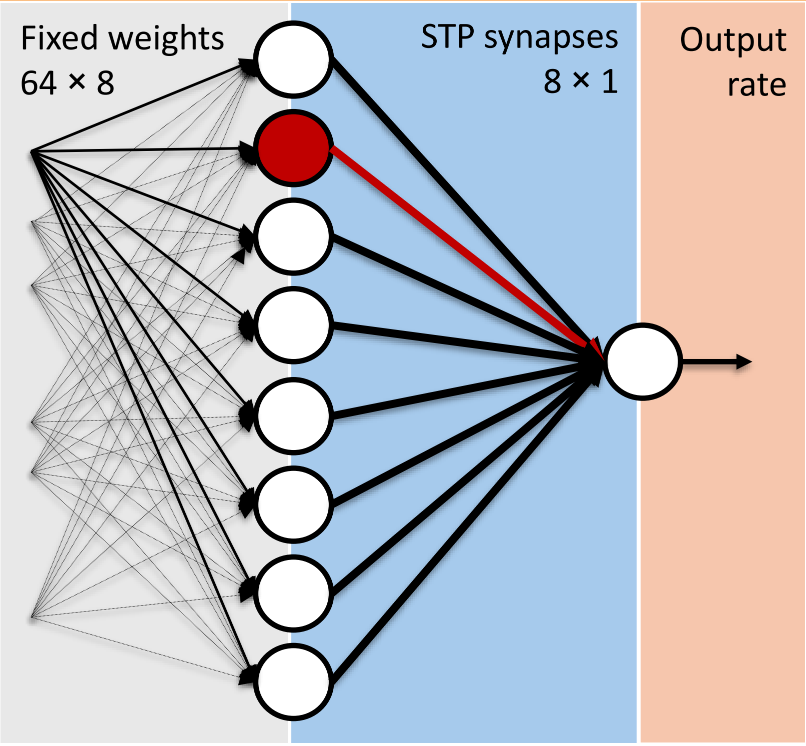
Encoding: one hot
1-to-16 channels (64)

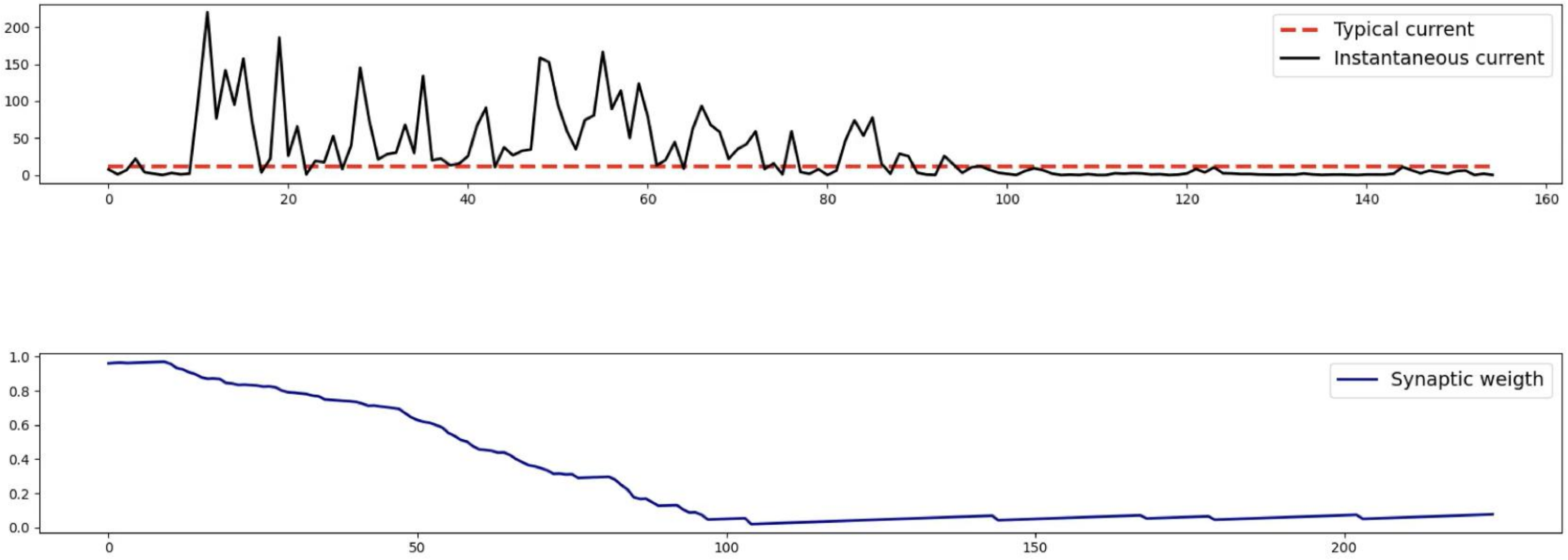
SNN
2 layers

Seizure detection

P. Busia, G. Leone, A. Matticola, L. Raffo and P. Meloni, "Wearable Epilepsy Seizure Detection on FPGA With Spiking Neural Networks," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 19, no. 6, pp. 1175-1186, Dec. 2025, doi: 10.1109/TBCAS.2025.3575327

# Short-Term Plasticity



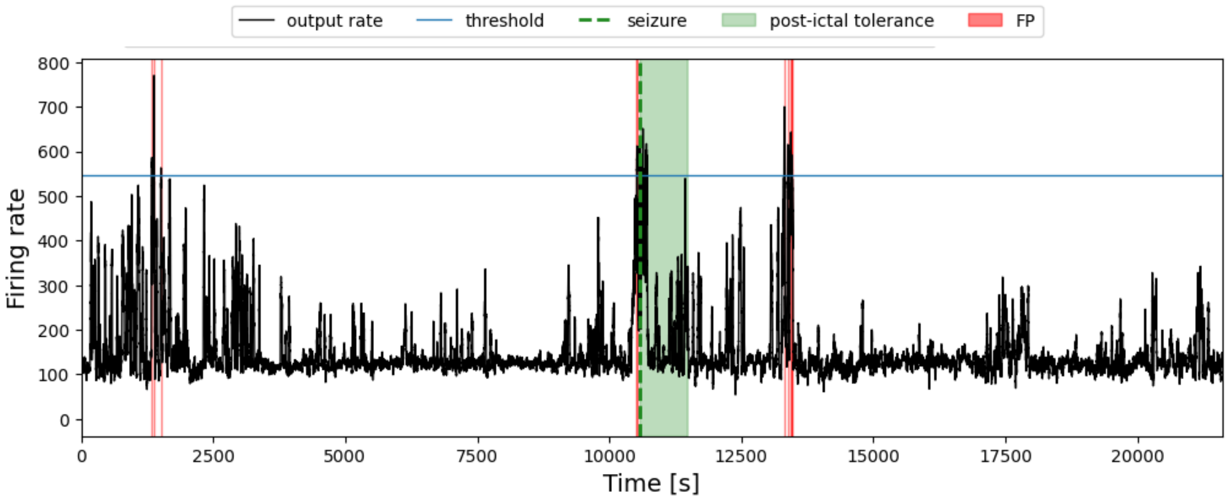

- Using the **static pre-trained model**, we evaluate the **typical current** for each synapse on normal training segments.
- During **STP-based inference**, we compare the **instantaneous current** with the **typical current**

**Every 16 seconds**, each weight is:

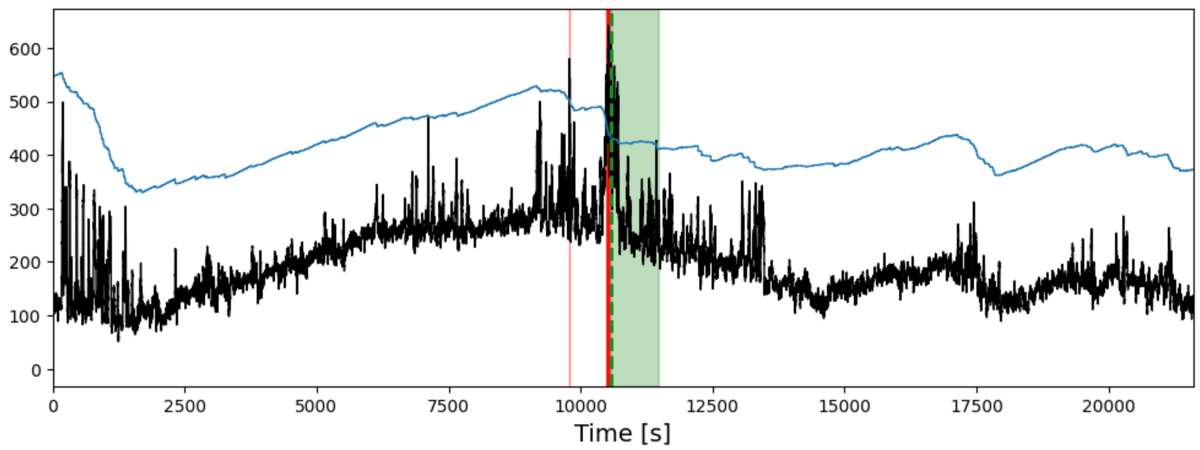
- Potentiated when **instantaneous current > typical current**
- Depressed when **typical current > instantaneous current**

# STP example

## Static baseline




## STP

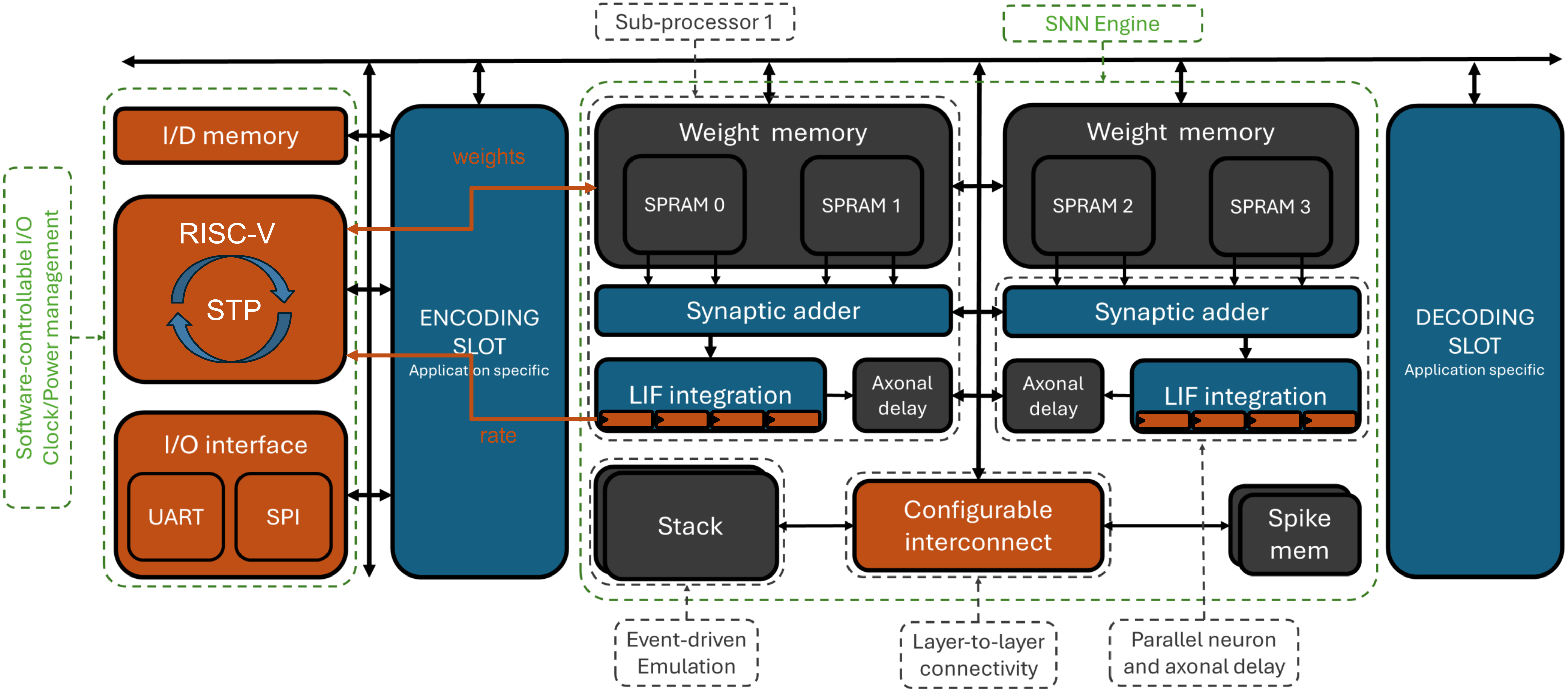



**100%** event-level **detection** in **both** cases

By applying STP, the **false positive rate** per hour **decreases** from **0.2** to **0.06** on average

P. Busia, A. Matticola, L. Raffo and P. Meloni, G. Leone, "Enabling Plasticity in FPGA-based SNNs: an EEG Seizure Detection Study" in *The 22 International Symposium on Applied Reconfigurable Computing (ARC 2026), Cagliari, Italy*

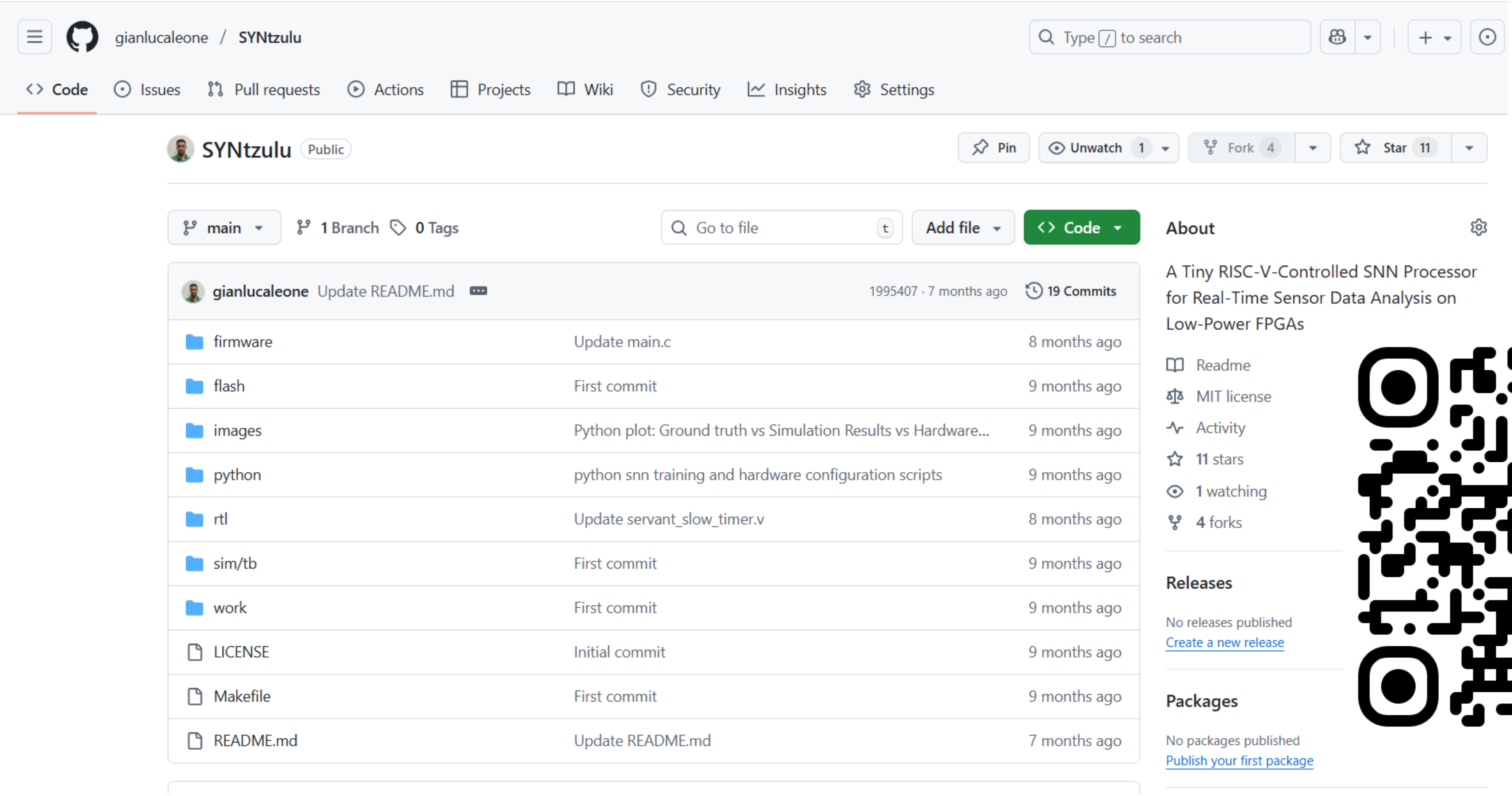
# Hardware support



# Conclusions

- SYNtzulu: low-cost and easy access SNN accelerator
- Enable sensor data processing at less than 10 mW during inference
- High flexibility thanks to
  - RISC-V controller and configurable encoding and decoding slots
  - Four real-world use case applications
- Online model refinement

# SYNtzulu is an Open Source Architecture



It’s sỳntzulu, not syntzùlu!


SYNtzulu is here!

gianluca.leone94@unica.it