Energy-Efficient Tree-Based EEG Artifact Detection

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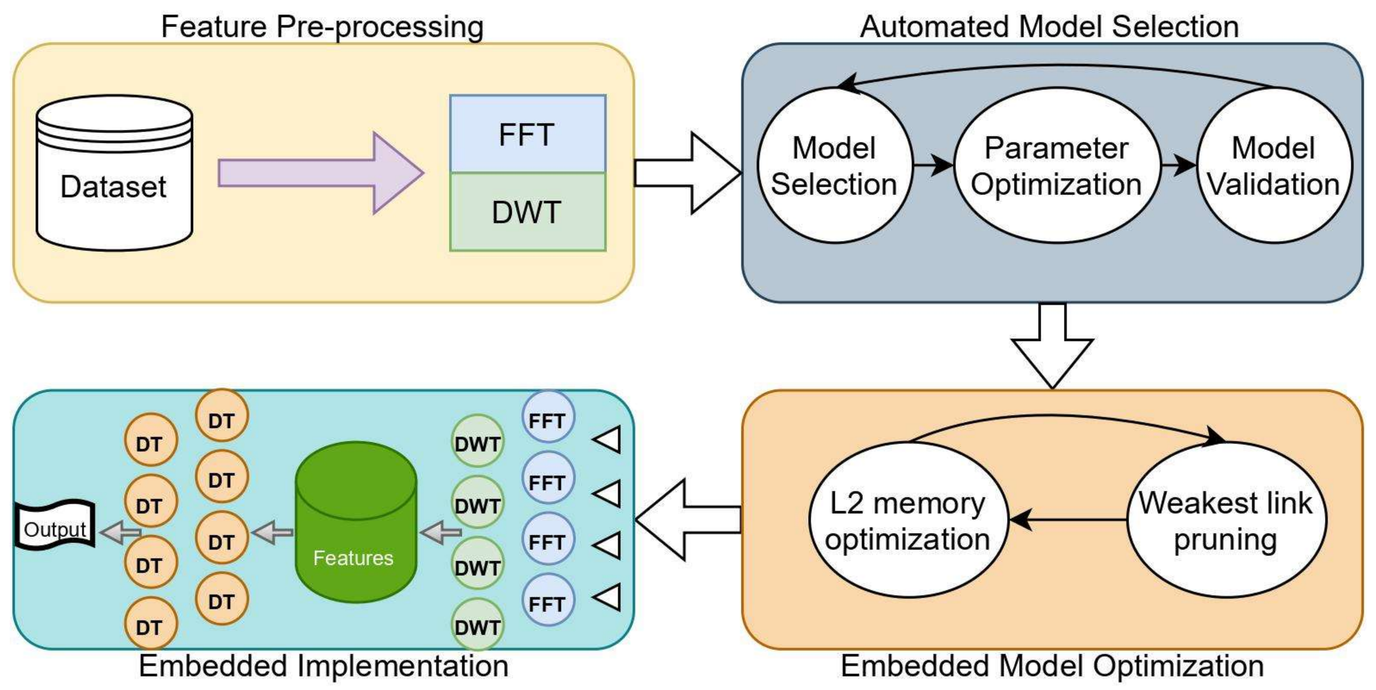
INTRODUCTION

In the context of epilepsy monitoring, **EEG artifacts** are often mistaken for seizures due to their morphological similarity in both amplitude and frequency, making **seizure detection systems susceptible to higher false alarm rates.** In this work we present the implementation of an artifact detection algorithm based on a minimal number of EEG channels on a parallel ultra-low-power **(PULP)** embedded platform.

CONTRIBUTIONS

- Optimal model selection using a publicly available **automated machine learning** framework;
- A comprehensive evaluation of models on 15 datasets extracted from the TUH EEG Artifact Corpus;
- Achieved **state-of-the-art ≈94% artifact detection accuracy** considering a 4 temporal channel EEG setup;
- Implementation and performance optimization of the above framework on **real PULP chip target,** namely Mr. Wolf achieving **state-of-the-art 4 μJ per inference.**



Schematic representation of the workflow.

METHODS & RESULTS

Dataset

We use the Temple University Artifact Corpus (TUAR), containing **310 annotated EEG files from 213 patients** with annotations of every artifact on every channel separately.

We therefore consider three classification approaches:

- Binary Classification **(BC)**
- Multilabel Classification **(MC)**
- Multiclass-Multioutput Classification **(MMC)**

Features

For features we extract the energy from a 4 level **Discrete wavelet- transform (DWT)** and use FFT to calculate the **energy of high-frequency parts** of the EEG (above 80Hz).

Embedded platform and optimization

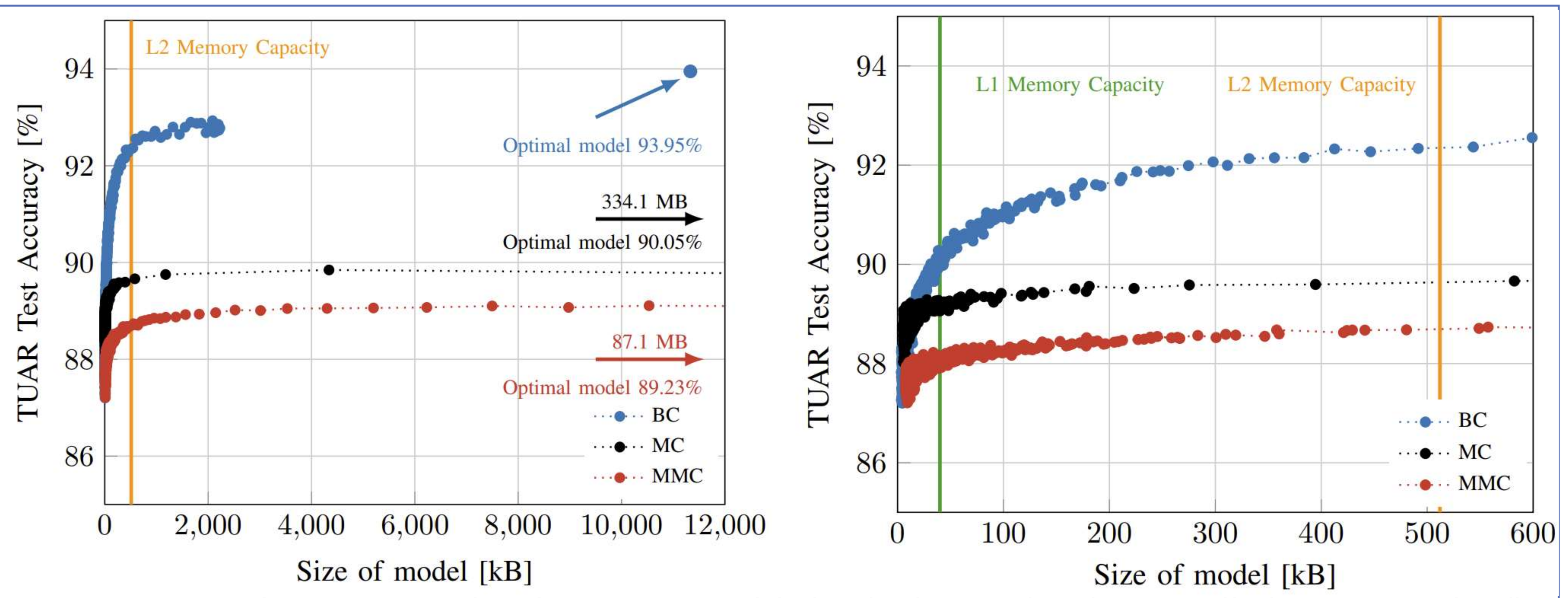
Detection framework implemented on the **BioWolf wearable ExG device**. Optimal models aggressively optimized using **Minimum Cost Complexity Pruning** with minimal effect on the accuracy.

Classification Results

For all three approaches: state-of-the-art performance and a very impressive **93.95%** accuracy in the **(BC)** case.

In the **(BC)** case the pruned model that fits the L2 has an accuracy of **92.4%.**

In the **(MC)** and **(MMC)** cases minimal drop in accuracy when optimizing for L2 memory.

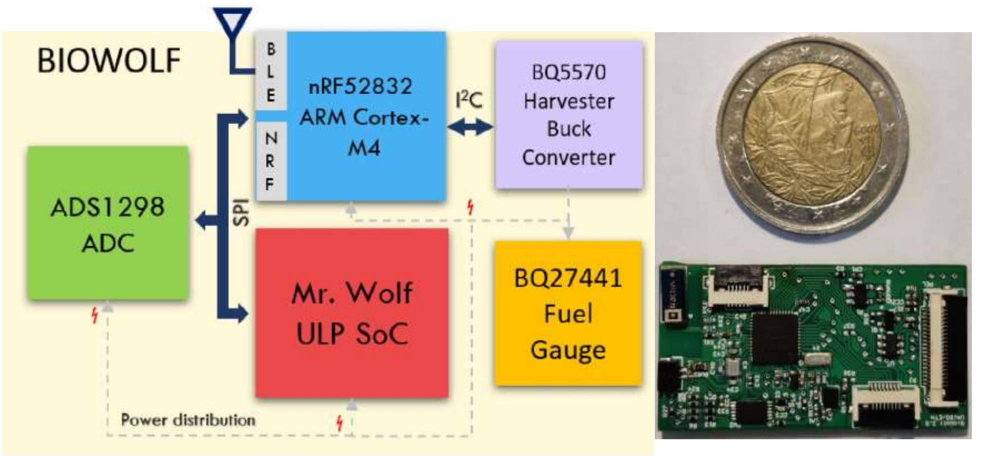


Left: *Accuracy vs size of Extra Trees model when implemented on the Mr. Wolf microprocessor for all three labelling methods considered. Regions where L1 and L2 are filled are marked with green and orange lines, respectively.* ***Right:*** *zoom of the left plot over the 0-600 kB range*

Dataset:	BC	MC	MMC
Accuracy [%]	93.95	90.05	89.23
F1 Score	0.838	0.600	0.867

Energy results

Implementation of framework requires a **power envelope of only ≈22 mW with sub-200 μs processing time.**



Dataset:	BC	MC	MMC
Time/inference[ms]	0.18	0.19	0.21
Power [mW]	22.41	22.43	22.44
Energy/inference [μJ]	4.03	4.26	4.71

CONCLUSIONS

Analysis of TUAR artifact dataset → ***DWT + FFT Features AutoML*** → State-of-the-art classification performance, **≈ 94% accuracy**

Model optimization and implementation → ***Multi-core edge platform (Mr. Wolf)*** → Minimal energy requirements **(≈4 μJ per inference)**

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