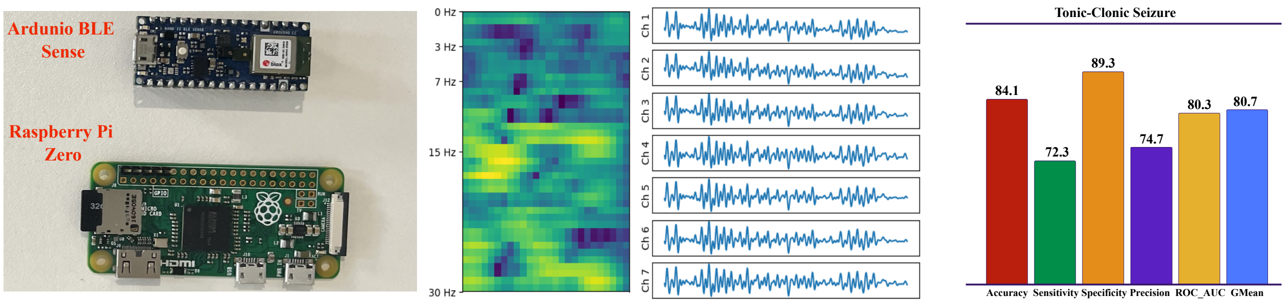
Epileptic seizure detection with Tiny Machine Learning - a Preliminary Study

Loic Lemoine, Nhat Pham
Cardiff University



a) Evaluation Platforms b) Tonic-Clonic Seizure Sample c) TFLite Model Post-Quantisation Performance

Figure 1: System overview

1 INTRODUCTION

With more than 50 million people worldwide affected by epilepsy and around 1200 deaths per year in the UK [1], the disease brings many social and economic burdens that negatively affect a person's everyday life. The conventional method of seizure detection is limited to in-hospital with support from medical professionals. However, many seizures are more likely to happen outside of hospitals. Thus, an automated home-based solution would not only drastically improve out-patient seizure care, but also improve the day-to-day lives of those who live with epilepsy. In this study, we will explore the development of a novel embedded algorithm that can detect three common types of seizures (absence, tonic-clonic and generalised non-specific) directly on a wearable device by employing a Tiny Machine Learning framework, i.e., TensorFlow Lite Microcontroller (TFLM). Our preliminary evaluations on an open dataset of 17 patients have demonstrated encouraging results with GMEAN scores of sensitivity and specificity of above 80%.

2 METHODS

We utilised an open-source seizure dataset by Temple University Hospital [2], featuring three types of seizures collected at multiple hospitals throughout a decade of work: Absence, Tonic-Clonic and Generalised Non-Specific. The data has been split into equal segments including overlap with neighbouring samples. Due to a large uneven ratio of background events to seizure events within the dataset, SMOTE was used to balance the dataset.

We first explore an adaptable and robust feature extraction framework that accommodates multiple seizure types whilst retaining key patterns within samples. Second, an adapted MobileNet [3] inspired architecture to ensure an efficient model with a small size. Finally, the deployment and configuration of a model-per-seizure system allow for efficient and accurate detection. A combined model for multi-seizure detection has also been explored.

We employed the Mel spectrogram feature extraction to create sufficiently detailed representations of data samples, capturing the frequency pattern over 2-second windows ((Fig. 1b). The representations are prepared for input by scaling their intensities and producing 40x26 images. The models are validated through 10-fold cross-validation and finally trained with a 70/20/10 dataset split. The designed model features 8,178 parameters and a model size of 47KB. A significant reduction of the small MobileNetV3 model which has over 1,000,000 parameters and over 6MB model size.

TensorFlow Lite conversion is leveraged to allow for the models to be deployed onto an Arduino BLE Sense and a Raspberry Pi Zero (Fig. 1a). Before converting the model, post-training quantisation is applied to convert all neural operations to 8-bit integers (INT8), further optimising the model size. This project is targeted towards an unobstructed headband solution, using the positions of an EEG's front-facing electrodes to capture signals. The possible unobstructed and subtle nature of a headband device allows for multiple use cases, many within a user's day-to-day life. It can allow for seizure detection whilst driving a car, practising sports or other common activities. A customisable threshold system can adjust the sensitivity of seizure detection depending on the use case.

3 EVALUATIONS.

Preliminary results show that our models can achieve 95%, 86% and 84% ROC AUC scores for Absence, Tonic-Clonic, and Generalised seizures, respectively. The Tonic-Clonic seizure's best model within the 10-fold cross-validation features 73% sensitivity and 89% specificity. Following the INT8 quantisation and TFLite conversion, the model sizes decrease to 23KB, a 51% reduction (Tab. 1). The converted models see a minimal performance drop. The tonic-clonic model's specificity lowers from 73% to 72% (Fig. 1c). Due to the models being trained on hospital-collected EEG data, which may be performed during routine EEG scans, real-world applications may result in increased false detection as the increased activity will create more varied EEG events that a routine EEG may not capture.

Table 1: Quantization performance.

Metrics	Original	TFLite	+/-
Size	47KB	23KB	-51%
Accuracy	84.29%	84.1%	-0.19%
Sensitivity	72.96%	72.33%	-0.63%
Specificity	89.26%	89.26%	0%
GMean	80.70%	80.35%	-0.35%

REFERENCES

[1] World Health Organization. *Epilepsy*, 2024. https://www.who.int/news-room/fact-sheets/detail/epilepsy.
[2] *Temple University EEG Dataset*. https://tinyurl.com/38vjv4u3.
[3] Andrew Howard et al. Searching for mobilenetv3. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1314–1324, 2019.