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LIGHTWEIGHT MACHINE LEARNING FOR SEIZURE DETECTION ON WEARABLE DEVICES

Baichuan Huang, Azra Abtahi, Amir Aminifar

Department of Electrical and Information Technology, Lund University, Sweden
{baichuan.huang, azra.abtahi_fahliani, amir.aminifar}@eit.lth.se

ABSTRACT

For patients with epilepsy, automatic epilepsy monitoring, i.e., the process of direct observation of the patient's health status in real time, is crucial. Wearable systems provide the possibility of real-time epilepsy monitoring and alerting caregivers upon the occurrence of a seizure. In the context of the ICASSP 2023 Seizure Detection Challenge, we propose a lightweight machine-learning framework for real-time epilepsy monitoring on wearable devices. We evaluate our proposed framework on the SeizeIT2 dataset from the wearable SensorDot (SD) of Byteflies. The experimental results show that our proposed framework achieves a sensitivity of 73.6% and a specificity of 96.7% in seizure detection.

Index Terms— Seizure Detection, Lightweight Machine learning, Wearable IoT.

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders that affects around 65 million people worldwide. Despite the advances in anti-epileptic drugs, one-third of epileptic patients still suffer from recurrent seizures with a high relapse rate. Furthermore, people with epilepsy (PWE) have a 2–3 times higher mortality rate compared to the corresponding healthy population, mainly because of seizure-triggered accidents and Sudden Unexpected Death in Epilepsy (SUDEP). Video-electroencephalogram (EEG) recording is the gold standard of epilepsy monitoring. However, the standard full scalp-EEG recording setup has several limitations for patient monitoring outside the hospital environment. In contrast, automated EEG-based seizure detection on wearable devices provides the possibility of real-time patient monitoring in ambulatory settings.

Smart wearable techniques can detect the onset of seizures in real time and alert family members and caregivers for rescue. However, wearable devices have stringent resource constraints, including limited memory storage, computing power, and battery lifetime. Hence, lightweight machine-learning models tailored to wearable devices are indispensable for the realization of real-time epilepsy monitoring. In the context of the ICASSP 2023 Seizure Detection Challenge, we propose a lightweight machine-learning framework for automated seizure detection on wearable devices. Our experimental evaluation on the dataset from the wearable SensorDot (SD) of Byteflies demonstrates that our framework achieves a sensitivity of 73.6% and a specificity of 96.7% in seizure detection on the validation data.

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2. LIGHTWEIGHT MACHINE LEARNING

2.1. Lightweight Seizure Detection

As discussed before, in this paper, we consider epilepsy monitoring using resource-constrained wearable technologies. Here, we propose a lightweight seizure detection framework for such wearable systems. Our proposed framework is based on the Random Forest (RF) algorithm and power features in certain frequency bands of the EEG data.

Power features are extracted from several frequency bands, namely $[0, 0.1]$ Hz, $[0.1, 0.5]$ Hz, delta $[0.5, 4]$ Hz, theta $[4, 8]$ Hz, alpha $[8, 12]$ Hz, $[12, 13]$ Hz, beta $[13, 30]$ Hz, and gamma $[30, 45]$ Hz [1]. The time complexity of computing the power features can be reduced to the theoretical lower bound of $O(n)$, where n is the length of the EEG data [2]. Towards this, we first filter the signal in the desired frequency band using a time-domain band-pass filter. Next, we use Parseval's theorem on the filtered signal to obtain the power of the signal in the desired frequency band.

Once the power features are calculated, we use the RF algorithm to obtain the final prediction outcome. The RF algorithm uses an ensemble of decision trees to make predictions. Each individual decision tree in the forest is relatively shallow compared to a single deep decision tree and only needs to perform a limited number of comparisons during the inference process. Finally, the final prediction of the RF algorithm is obtained by simply voting on the prediction outcomes of all decision trees in the forest, which is a lightweight process in terms of computational complexity for real-time inference on wearable devices.

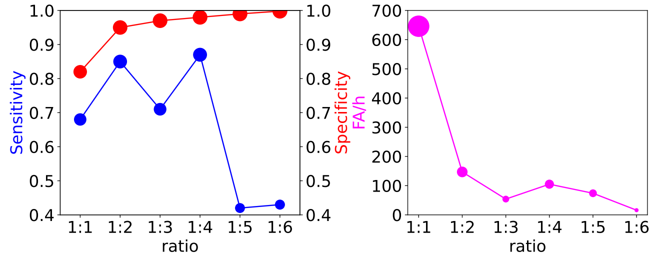

Fig. 1. *Sensitivity*, *Specificity*, *FA/h* for different values of *ratio* between seizure and non-seizure.

2.2. Data-Centric Seizure Detection

In epilepsy monitoring, *Sensitivity* captures the performance of the machine-learning algorithms in detecting positive samples, i.e., seizures. On the other hand, the false-alarm rate captures the number of incorrectly detected seizures over a certain time interval. Excessive false-alarm rates often lead to unnecessary disruptions, inconvenience, and costs in seizure detection. Therefore, False Alarm (*FA*) Rate or *FA/h* is highly relevant in the context of seizure detection. Figure 1 illustrates the relevant evaluation metrics based on the *ratio* of seizure and non-seizure data in the training set. If *ratio* increases from $1:1$ to $1:6$, *Specificity* gradually increases to 1.0 and *FA/h* shows a rapid decline. Although *Sensitivity* does not manifest an apparent decreasing trend, high values of *ratio* lead to a significant reduction in *Sensitivity*. In conclusion, the value of *ratio* should be carefully selected to make an optimal trade-off between *FA/h* and *Sensitivity*.

Here, we utilize the ChronoNet architecture [3] and focus on the data manipulation techniques. The hyperparameter *monitor* is to save the best Keras model by monitoring the assigned metric and the hyperparameter *class_weights* is for weighted average loss between seizure and non-seizure. We optimize the values of *ratio*, *monitor*, and *class_weights* to strike a balance between *Sensitivity* and *FA/h*.

3. EXPERIMENTAL RESULTS

In this section, we consider two datasets: SeizeIT1 [4] and SeizeIT2 [5]. The SeizeIT1 dataset is acquired by the gold standard video-EEG system. The SeizeIT2 dataset is acquired by the wearable SensorDot (SD) of Byteflies. We evaluate our proposed framework on *Validation Data*, i.e., Patients 25, 45, and 69 in SeizeIT2.

3.1. Lightweight Seizure Detection

We use the *Validation Data* with leave-one-patient-out cross-validation to train the RF model with the power features. We consider $ratio = 1:3$ following the insights illustrated in Figure 1. Table 1 shows the performance of our proposed framework for lightweight seizure detection. For evaluation on *Validation Data*, the average value of the leave-one-patient-out cross-validation is calculated. The cross-validation is conducted three times. Our lightweight framework achieves a *Sensitivity* of 73.6% and a *Specificity* of 96.7% on average. For the final RF model, we use all the *Validation Data* to train a RF model with the power features.

Table 1. Performance of Lightweight Seizure Detection

Evaluation	Sensitivity(%)	Specificity(%)
Validation Data	73.6	96.7

3.2. Data-Centric Seizure Detection

We use SeizeIT1 data to train the ChronoNet with $monitor = val\_spec$, $class\_weights = 1:1$, and $ratio = 1:3$. Table 2 presents the performance of data-centric seizure detection. For evaluation on *Validation Data* in SeizeIT2, we train a ChronoNet model using the 85% of patients in SeizeIT1 (the remaining 15% is for *monitor*). This leads to a *Sensitivity* of 15.2% and a *Specificity* of 99.8% on the *Validation Data*.

Table 2. Performance of Data-Centric ChronoNet

Evaluation	Sensitivity(%)	Specificity(%)
Validation Data	15.2	99.8

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