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EPILEPSY DETECTION GRAND CHALLENGE

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ABSTRACT

In this paper, we describe the epilepsy detection grand challenge, in association with ICASSP 2023. The challenge was centered on seizure detection using wearable behind-the-ear EEG. Two separate tasks were set for the participants: 1) obtain the best overall performance in seizure detection; 2) systematically engineer the data in a data-centric task to optimize a given AI model for seizure detection.

***Index Terms*—** Seizure detection, wearable EEG, AI

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders, affecting almost 1% of the population worldwide. Focal onset seizures are the most common type of seizure in adults with epilepsy. Of patients with epilepsy, around 30% are not seizure-free despite the use of anti-seizure medication. It is therefore paramount to accurately monitor and log seizures of the patients to improve therapeutic decisions. Nevertheless, patients will report less than 50% of their seizures (1). As such, under-reporting of seizures renders the seizure diary an unreliable method in clinical practice. Automated electroencephalography (EEG)-based seizure detection systems are important to objectively detect and register seizures during long-term video-EEG (vEEG) monitoring. However, this standard full scalp EEG recording setup is of limited use outside the hospital. A discreet, wearable device is needed for capturing seizures in the home setting. The SensorDot (SD), of Byteflies, is a wearable device that records EEG with behind-the-ear (bte) electrodes that has been developed during the SeizeIT1 study (2). This CE-marked device is a user-friendly wearable that makes use of two bte channels to detect seizures. Additionally, it allows the recording of electrocardiography (ECG) data.

Within the ICASSP 2023 context, we organized a grand challenge where we encourage the development of accurate seizure detection frameworks on data recorded with the wearable device. The focus of this challenge was limited to patients with Focal Impaired Awareness (FIA) seizures. The challenge involved completing two different tasks and two different datasets were available to participants for the development of their frameworks.

2. DATASETS

2.1. SeizeIT1

The SeizeIT1 dataset was obtained during an ICON project in collaboration with KU Leuven (ESAT-STADIUS), UZ Leuven, UCB, Byteflies, and Pilipili (3). The dataset was acquired in the hospital-setting during presurgical evaluation. Patients were monitored using video, a full 10-20 scalp EEG setup, four additional Ag/AgCl cup electrodes attached to the mastoid bone (bte), and a single-lead ECG (typically lead II). The measurements usually lasted multiple days (typically a week) and patients were restricted to move within their rooms. Seizures were annotated by clinicians based on the gold standard vEEG system. In total 82 patients were recorded between 23/01/2017 and 26/10/2018. Of those patients, 42 were recorded with the bte channels and had seizures. In total, 182 seizures were recorded. The number of seizures per patient ranged from 1 to 22, with a median of 3. The duration of the seizures, varied between 11 and 695 seconds with a median of 50 seconds. The majority of the seizures were Focal Impaired Awareness seizures (89%). A larger part (91%) of seizures originated from the (fronto-) temporal lobe. For more information concerning the dataset, see (2). The participants of the challenge were given a dataset containing 4211 hours or recordings corresponding to the data of the 42 patients that had epileptic episodes.

2.2. SeizeIT2

The second iteration of the SeizeIT project, SeizeIT2 (4), focused on constructing an international multicenter dataset (containing EEG and ECG) of more than 350 patients suffering from epilepsy and recorded both in home and in-hospital environments (the first ever phase-4 clinical trial for a wearable for in-home monitoring for seizure detection). Similar to SeizeIT1, patients underwent monitoring using the standardized 25-electrode array of the International Federation

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of Clinical Neurophysiology. The bte electrodes were connected to the SD device for concomitant recording. The SD was attached to the upper back using a patch. Two bipolar channels were created: one unilateral, by taking the top and lower ipsilateral electrodes of the side of the seizure onset, and one cross-lateral, taking the difference between one electrode of each side. An extra SD was attached on top of the left deltoid muscle to measure ECG and EMG. In the context of this challenge, the data from the in-hospital recordings of the adult focal patients in UZ Leuven was used for the test set, but also for the validation set.

The SD recordings from three patients were provided to the participants in order to validate the performance of their models. The validation set was composed of 292 hours of recordings containing 17 seizures (with a duration ranging from 21 and 111 seconds with a median of 35 seconds). The test dataset was not shared and was composed of 30 patients (2485 hours of recordings), in which 139 seizures were recorded (with a minimum, maximum and median duration of 5, 228 and 25 seconds respectively).

3. CHALLENGE TASKS

1. In the first task of this challenge, the contestants were requested to train Machine Learning (ML) models to accurately detect seizure events in data obtained from the SD. There were no imposed limitations on the type of model or the pre- and post-processing methodologies. Participants were allowed to use the SeizeIT1 dataset for development and the SeizeIT2 validation dataset for checking the performance on the SD data. Additionally, participants were allowed to use external public datasets. The deliverables for this task included a framework that receives two-channel bte EEG from the SD or both bte EEG and single-lead ECG as input. The output of the framework was defined as a vector of ones and zeros (indicating a positive or negative seizure alarm respectively) for every second of the input time series.
2. Most researchers have focused on developing state-of-the-art AI architectures in order to achieve better classification performance in many diverse tasks. Recently, the concept of 'data-centric AI' has risen as a promising option for achieving higher and better performances in hard classification problems. Usually, training a model with high volumes of data tends to aid its robustness and reliability. However, it is also known that data quality highly impacts the behavior of ML models. Poor performances are seen in out-of-distribution data instances and within heterogeneous regions of in-distribution data. In the epilepsy use case, datasets suffer from a high imbalance between classes, where seizure events are short and rare. The objective of task 2 is to apply data manipulation techniques in order to obtain the best performance (in terms of robustness and generalizability) of a fixed model for wearable seizure detection. In this task, participants had access to the same development and validation datasets as in task 1 and were provided with a Deep Learning model (an adapted version of ChronoNet (5)). The participants were encouraged to apply any pre-processing techniques, data augmentation, subsampling strategies, etc., in order to build a representative training set to feed the model.

4. EVALUATION

Researchers in ML typically report performance in terms of sensitivity and specificity. In a highly unbalanced use case, such as seizure detection, False Alarm (FA) rate is commonly used instead of specificity. In this challenge, sensitivity was measured on an event basis which does not consider individual windows (with the any-overlap method (6)). False Positives (FPs) or FAs correspond to situations in which a hypothesis does not overlap with the corresponding event in the reference. In order to penalize the duration of each false alarm, the traditional epoch-based FA rate was used in the challenge's scoring. The score of each task constitutes a weighted sum of the sensitivity and false alarm rate (1). The final scoring is then composed by a weighted sum of the score in each task (2).

$$Points_x = Sensitivity_x\% - 0.4FAs_x/hr \quad (1)$$

$$Score = 0.6Points_1 + 0.4Points_2. \quad (2)$$

In the context of the challenge, we have received 49 registrations from 18 distinct countries and 9 submissions. The final results and the standings of the participants will be announced during the special session of ICASSP 2023.

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