A New 1D-CNN Paradigm for Onset Detection of Absence Seizures in Children

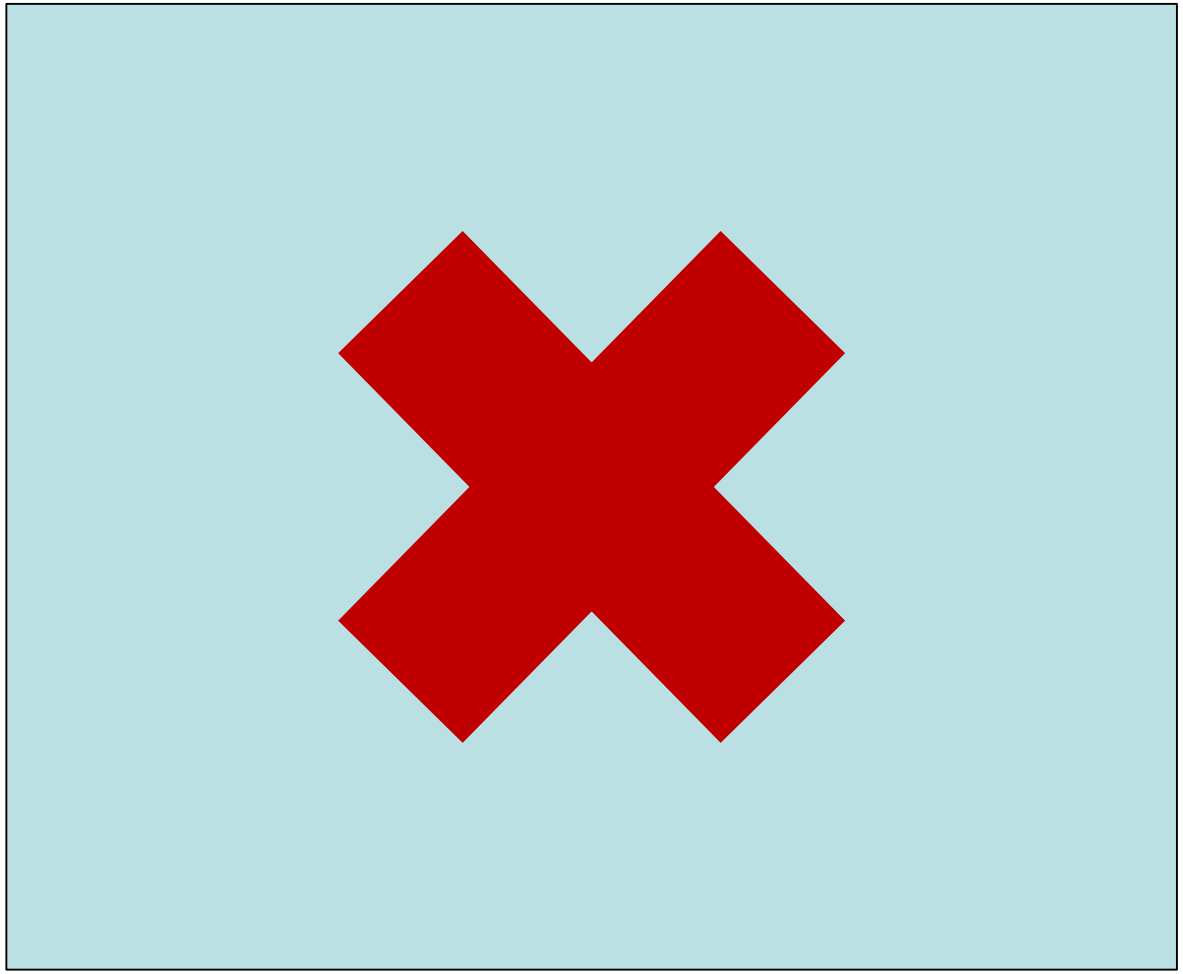
M. Yochum **A. Kachenoura** M. Aud'hui A. Kaminska R. Nabbout F. Wendling M. Kuchenbuch P. Benquet

Laboratoire Traitement du Signal et de l'Image
LTSI
Université de Rennes 1
Inserm
Necker Enfants Malades Hôpital Universitaire
Inserm
La science pour la santé
From science to health
Université de Rennes
BAA
Bretagne Atlantique Ambition

Childhood Absence Epilepsy (CAE)

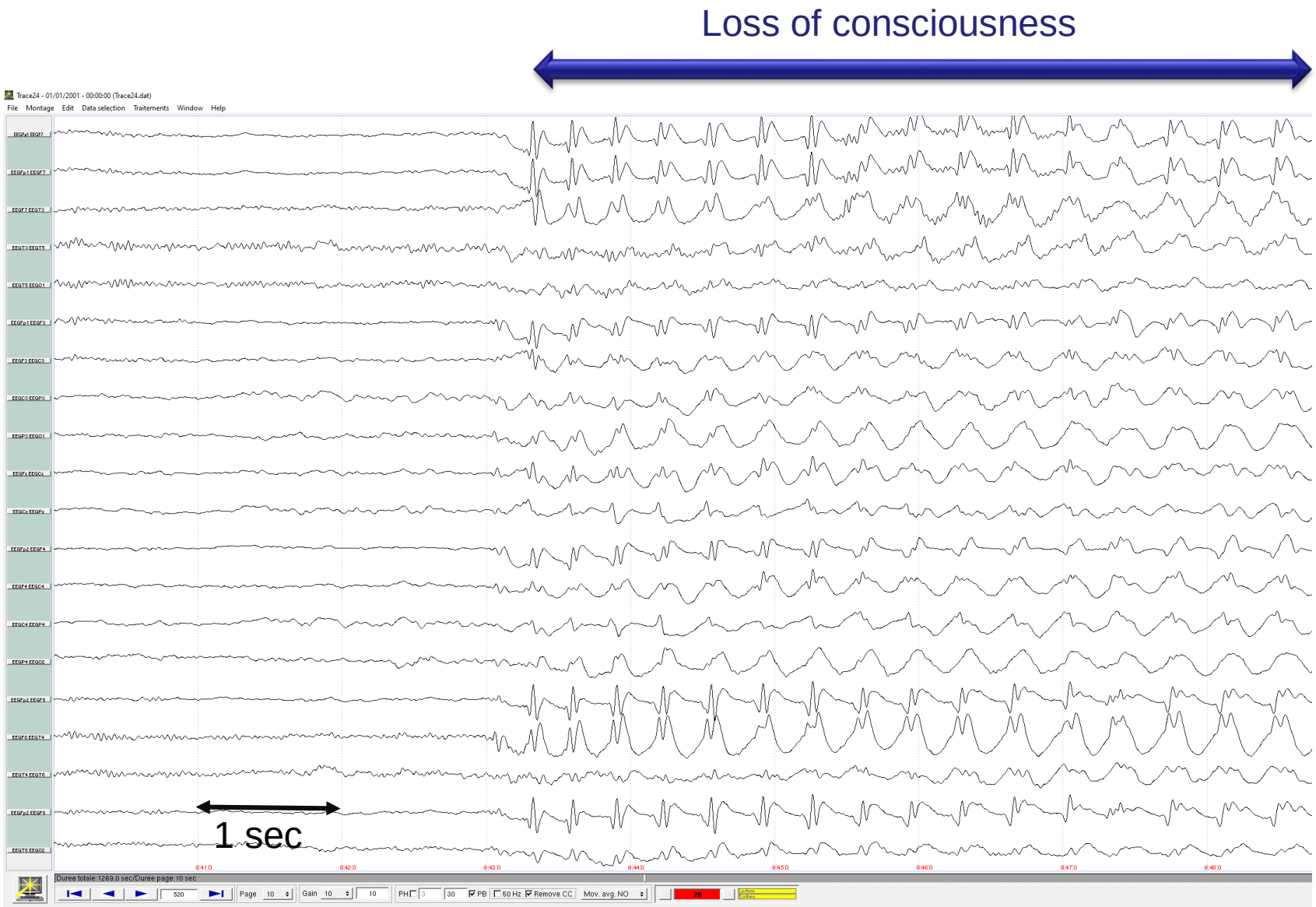
Seizure(15-20sec) with loss of contact and absence of voluntary movement

https://www.cen-neurologie.fr/fr/files/videos/absence-video-eeg



- 18% of epilepsy in school-aged children
- Incidence of 6.3-8.0 children per 100 000 per year
- May present Attention Deficit Hyperactivity Disorder (ADHD)
- Learning difficulties in around 30% of cases
- Frequent seizures up to 200 seizures a day
- Drug-resistant rate of about 30%

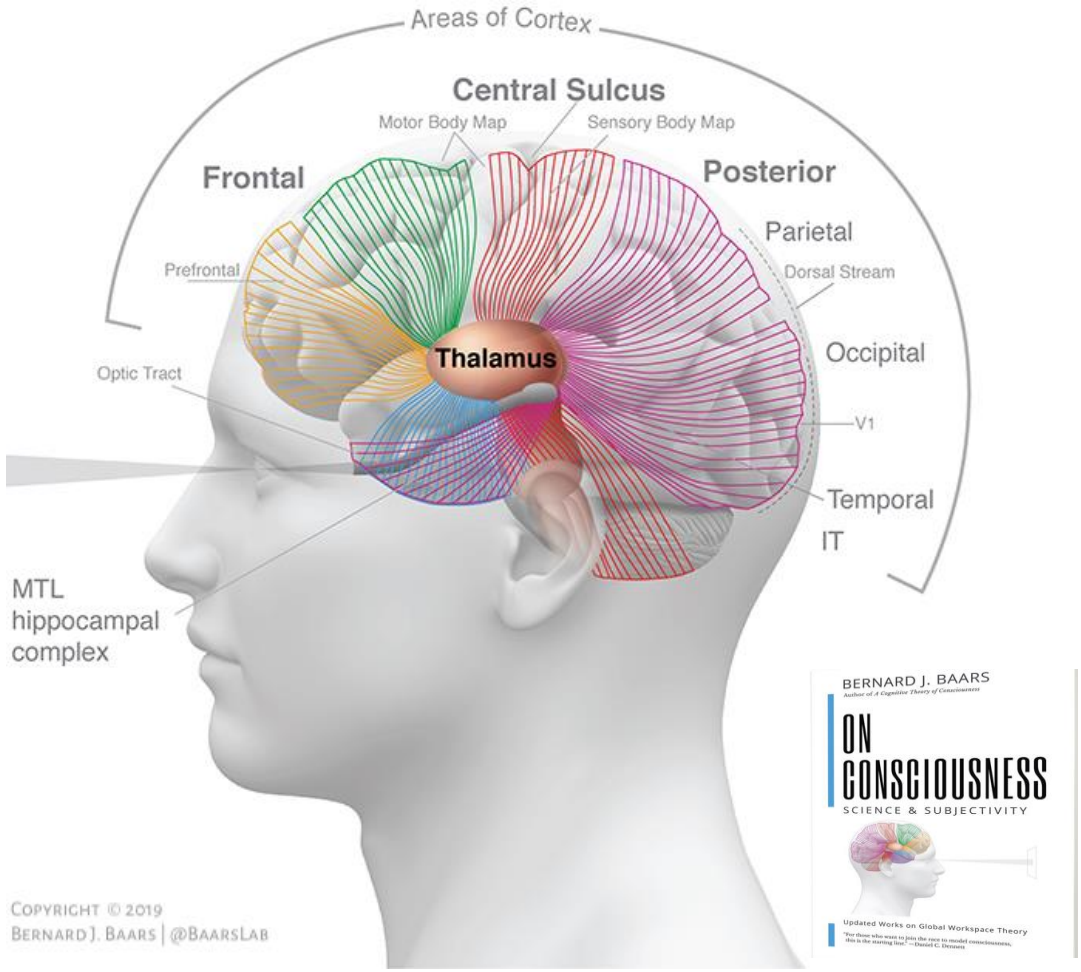
CAE: scalp EEG



- Seizures associated with the 3-4 Hz generalized Spike-Waves (GSW) patterns
- GSW may be faster, asymmetric, and asynchronous in the first 500 ms
- Polyspikes may also be observed
- GSW lasting 2-20 s

CAE: challenge and objective

Thalamo-cortical Loop



- Sensory or electrical stimulations could prevent seizures
- Stimuli must be delivered within the first 3 s of seizure onset [Rajna and Lona, 1989]

Challenge Detecting the seizure's onset as early as possible allows for prompt application of the stimuli

Objective Need of a fast detector of the seizure onset for triggering such stimulation

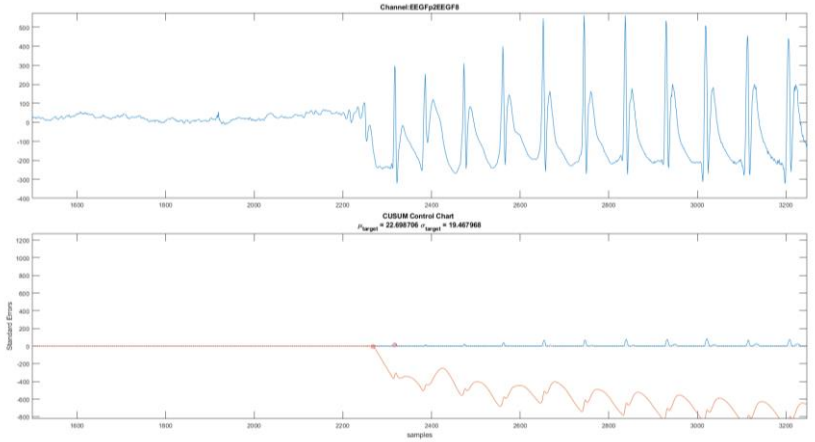
CAE: ultimate goal

Develop an effective closed-loop system for aborting absence seizures

Specific sensors → Detector

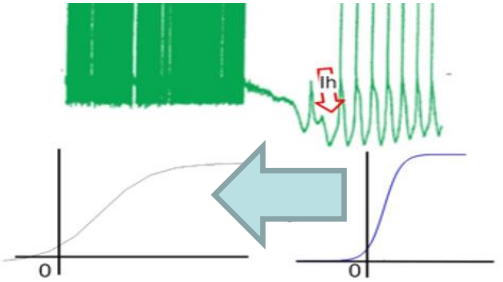
Stimulation

1. Onset early detection (arround 50ms)

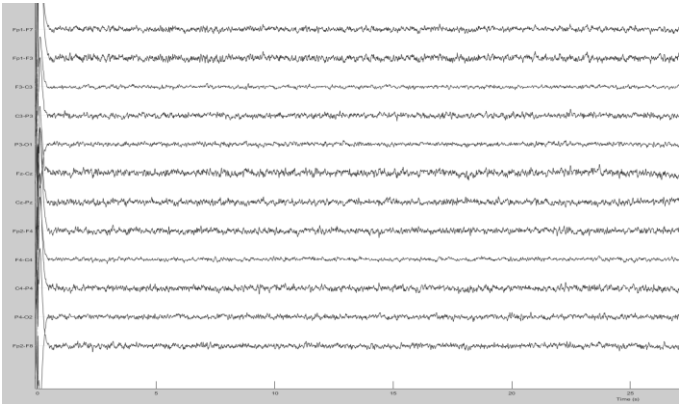


2. Application of sensory stimulation

3. Exit the association nuclei of the thalamus

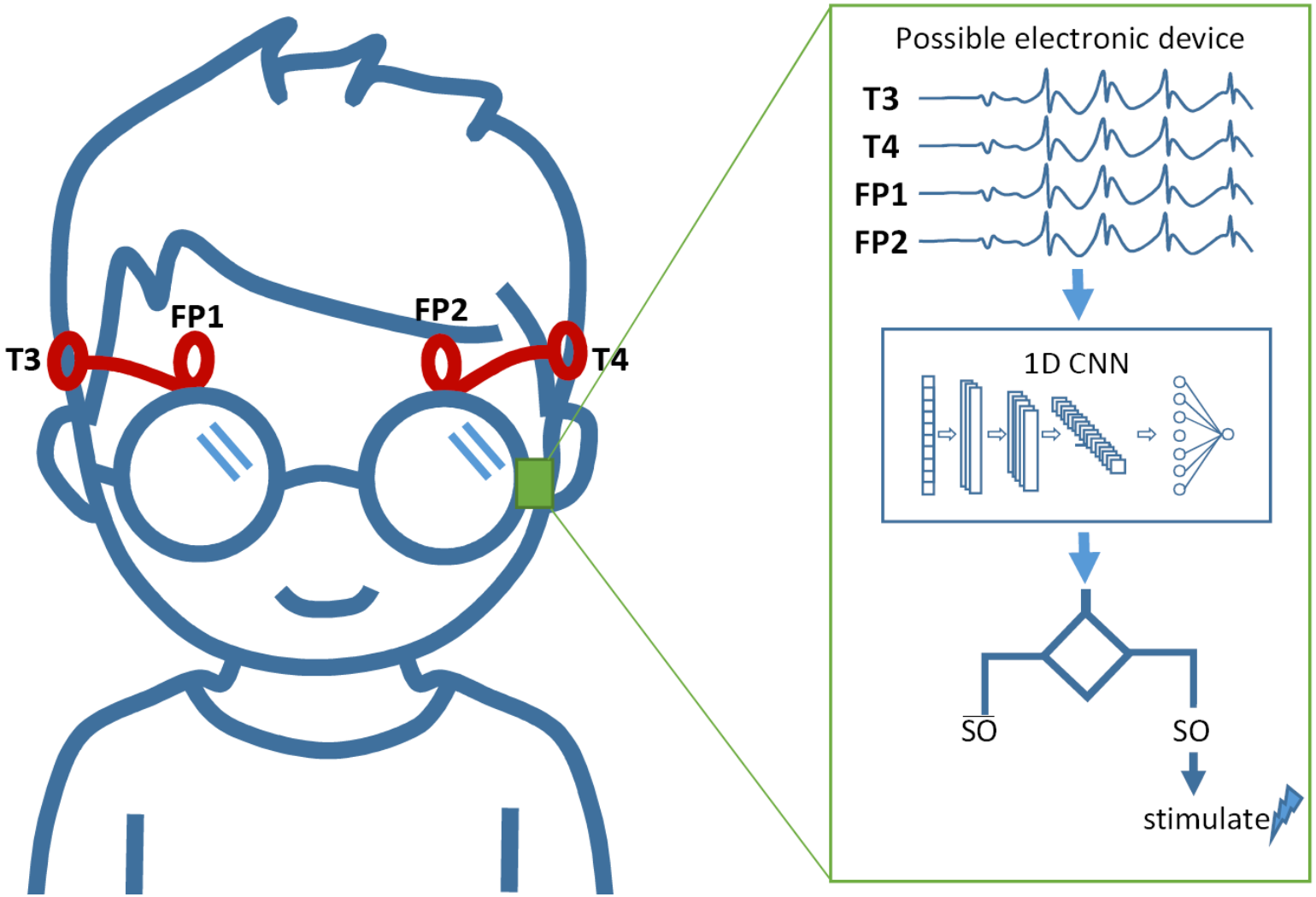


4. Stop or reduce seizure activity



CAE: iconography of a possible wearable device configuration

Operates directly on raw EEG data without any time/memory consuming preprocessing → embed the model in a wearable device (Fig. 1) able to process EEG in real-time



CAE: EEG dataset

Retrospective multicenter study conducted on children with CAE from august 2013 to 2019

- Two French hospital centers → Necker-Enfants Malades Hospital, APHP (reference center for rare epilepsies), and Saint-Brieuc Hospital
- Focused on children who experienced seizure onset at the age of 4 to 11 years
- Database encompasses a total of 117 children
- Average duration of the EEG recording session was at least 20 minutes
- Number of acquired electrodes, this latter varies between 11 electrodes to 19 electrodes
- Cumulative duration EEG recording is 2.75 days
- Sampling frequency of 256 Hz with a notch-filter of 50 Hz and a classical z-score standardization for all channels

CAE: onset of the absence seizures annotation

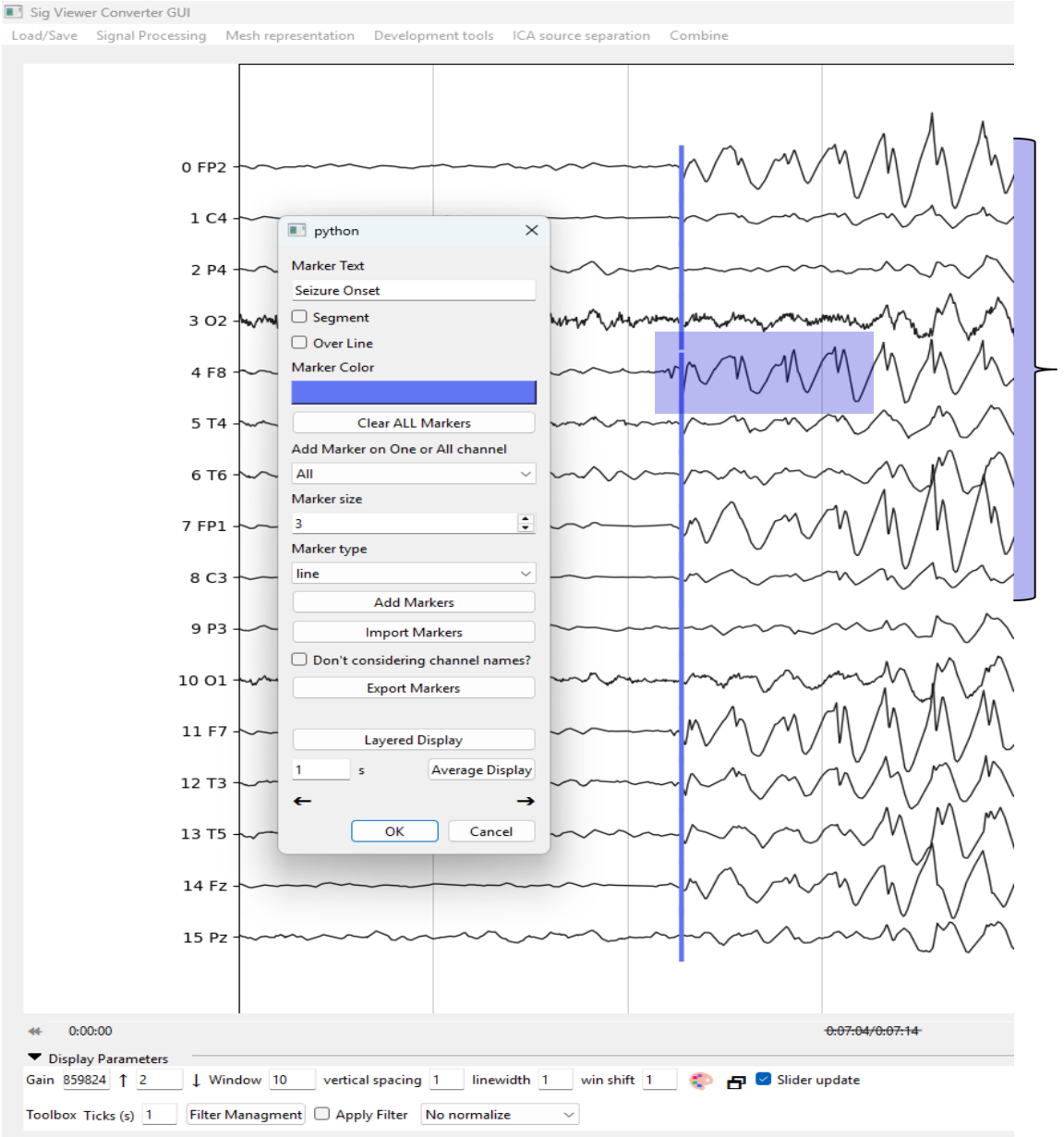
Expert annotation of the onset of absence seizures

- Use a dedicated software platform
- Seizure onset times were uniformly defined across all channels

Annotation rules

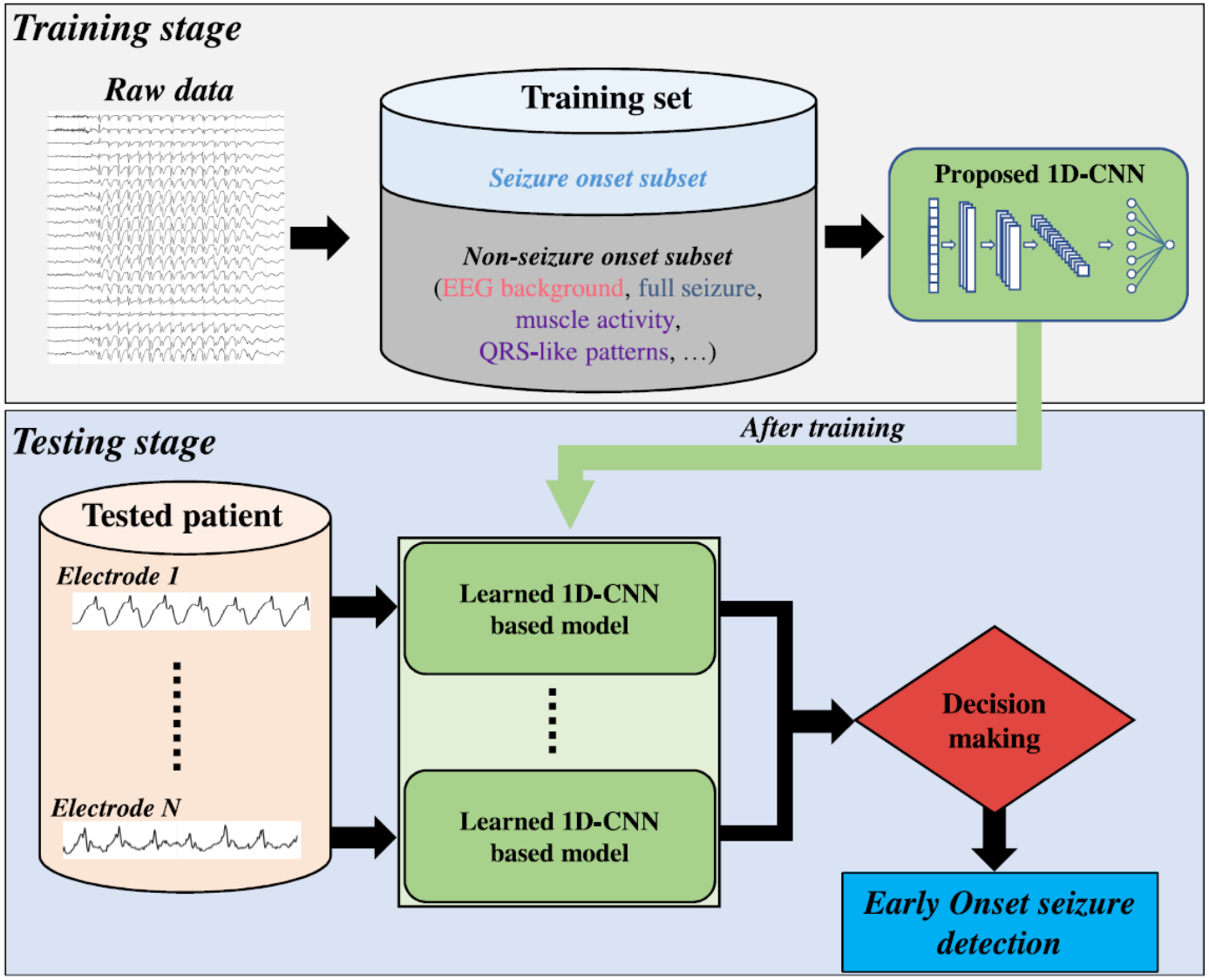
- Presence of a minimum of four consecutive spike-wave occurrences → exclude very short spike train
- Presence of spike-waves on at least half of the exploited EEG channels → ascertain the generalized nature of the seizure

Overall Tagging process yielded a total of 827 early seizure positions that met the stringent criteria



CAE: early onset seizure detection workflow

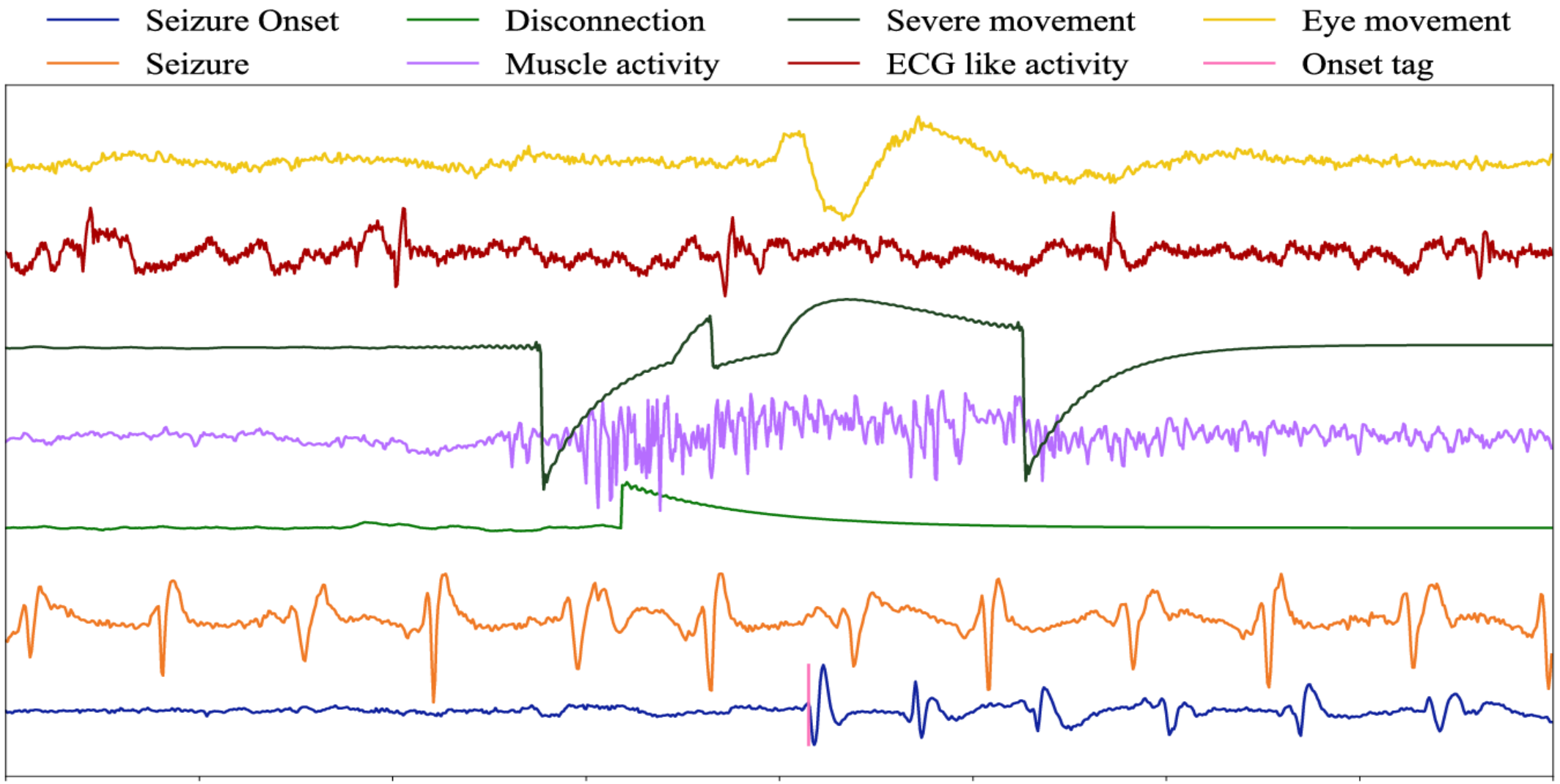
Supervised procedure based on Deep Learning → two main phases are needed (training and testing)



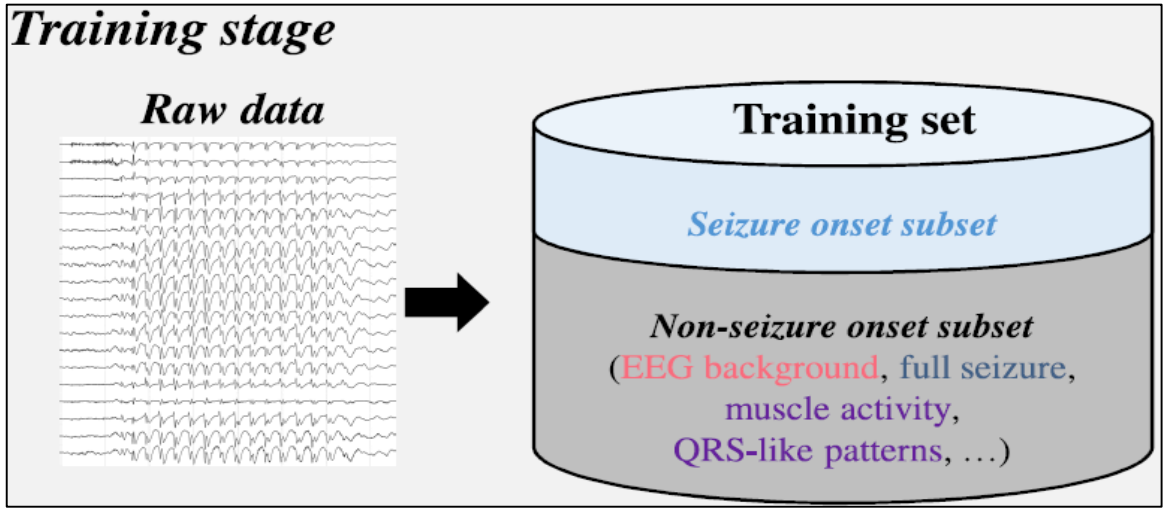
- Construction of 12 bootstrap by randomly picking 80% of patients for training and 20% for testing
- Non-patient specific detection strategy → patients in the training set were excluded from the testing set

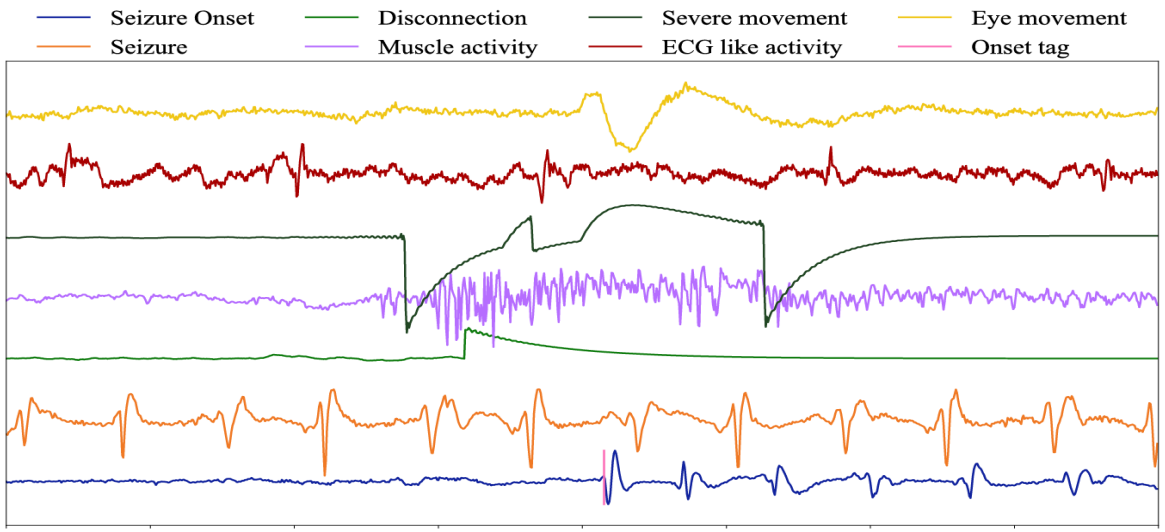
CAE: surface EEG description

Scalp EEG often contaminated by various physiological and non-physiological artifacts of non-interest



CAE: reliable and complete training data set construction

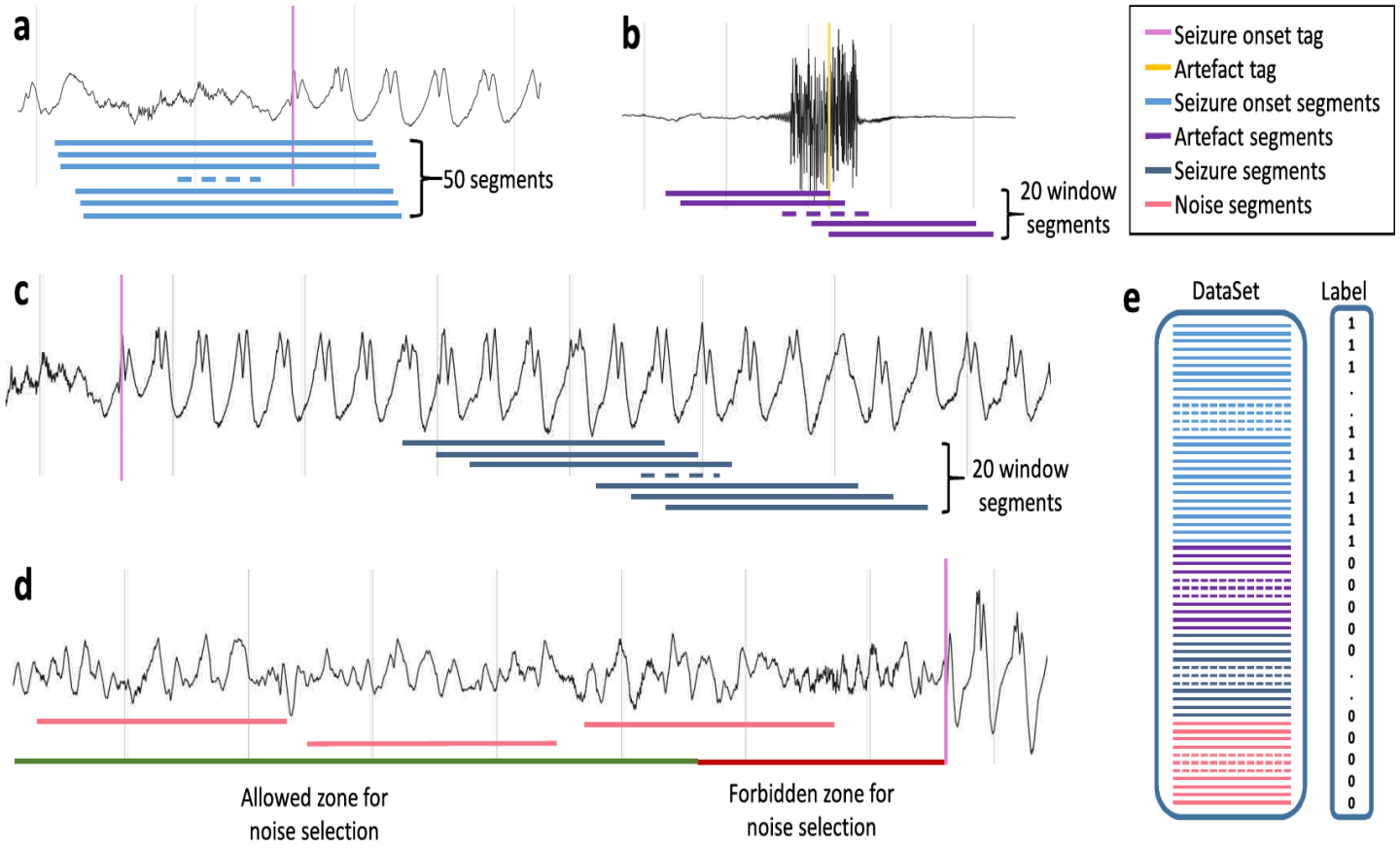




Rules

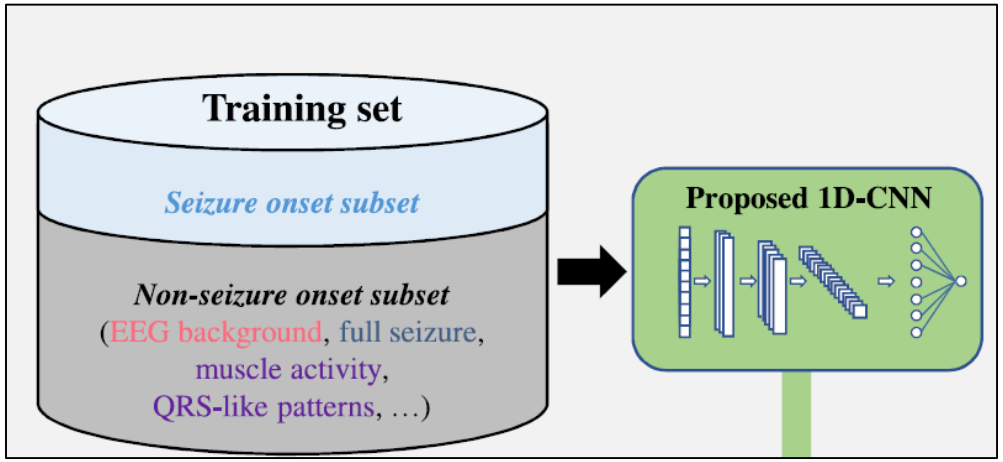
- Two training subsets of → 2 seconds segments
  - Seizure onset subset → segment containing a seizure onset tag
  - Non-seizure onset subset → including three subcategories (EEG background, physiological and non-physiological artifacts, and full seizure subset
- Unbalanced training dataset → emphasis the balance inclusion of all non-seizure onset events
- Excluded windows closer than 2 s to seizure onset tags → maintain the independence of seizure-onset segments and non-seizure-onset ones

CAE: training dataset (construction details and augmentation)



- For each expert onset tag, 50 segments for the seizure onset are constructed → first segment is selected such that the onset tag is located at 1.5 seconds within the 2 seconds window
- An artifact was tagged at the yellow position → 20 segments were picked from -2 to 2s around each artefact tag
- 20 full seizure segments were picked starting from 2s to 4s after each seizure onset tag
- Noise and EEG background segments were picked where seizure onset tags were not present within 2s from the starting noise segment

CAE: deep learning-based model architecture

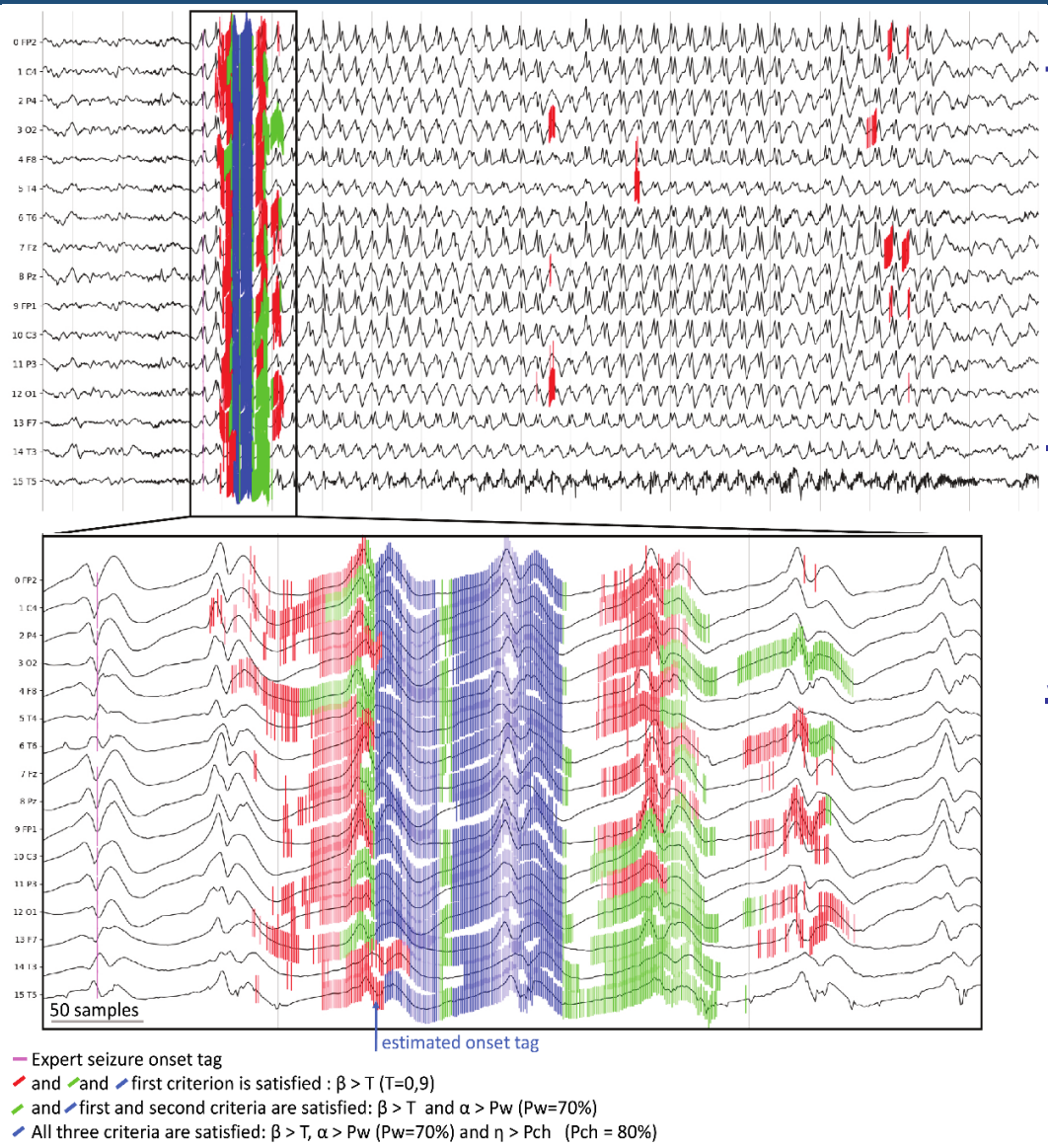


Layer	Type	Output Shape	Param
1	reshape	512×1	0
2	Convolution	508×32	192
3	Average Pooling	254×32	0
4	Convolution	250×64	10304
5	Average Pooling	125×64	0
6	Convolution	121×128	41088
7	Average Pooling	60×128	0
8	Convolution	56×256	164096
9	Average Pooling	28×256	0
10	Flatten	7168	0
11	Dense	256	1835264
12	Dropout	256	0
13	Dense	128	32896
14	Dropout	128	0
15	SoftMax	1	129
Total parameters			2,083,969

Why 1D_CNN

- Analyze independently each electrode of the studied EEG → adaptability to various EEG recording protocols
  - EEG recordings obtained from different systems, hospital centers, and electrode configurations
  - Difference in the original sampling frequency could be resampled to match the learned model's input requirement
- Reasonable complexity
- 1D-CNN layers can be parallelized effectively on modern hardware → operations within each layer are independent

CAE: detection phase



For each patient of the testing set

- The learned 1D-CNN model was applied on each electrode separately
- Use of a 2 s (512 samples) overlapping sliding window, with an overlap of 511 samples → shift of 1 sample
- Segments were classified as EoI 1D-CNN output >T

Problem

- Resulting in an artificially high False Detection Rate (FDR) → red, green, and blue bar (multiple detections of the same seizure onset)

Solution

- For a multiple detection of the same seizure onset → take into account only
  - Consecutive detections within a 50 consecutive windows > Pw → green, and blue bar
  - Detected on a minimum EEG channels > Pch% → blue bar
- Last sample of the 2 s onset segment who satisfies the three criteria (T, Pw and Pch) is considered as the detected onset → blue arrow → froze the detection process for 2 seconds

CAE: evaluation metrics

Four metrics → Sensitivity, Precision, F1-score and FDR per hour (FDR/H)

$$Sensitivity = \frac{TP}{TP + FN}$$

$$FDR = \frac{FP}{FP + TP}$$

$$Precision = \frac{TP}{FP + TP} = 1 - FDR$$

$$F1 - score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}$$

- True Positive (TP) → count of correctly detection of the seizure onset
- False negative (FN) → count of incorrectly detection of the seizure onset
- False Positive (FP) → number of wrongly detected onset seizure (the limit for the detection was fixed to 2 s from an expert tag)
- F1-score → used to have the optimal compromise between these two scores

CAE: results - on the feasibility of a robust and universal detector

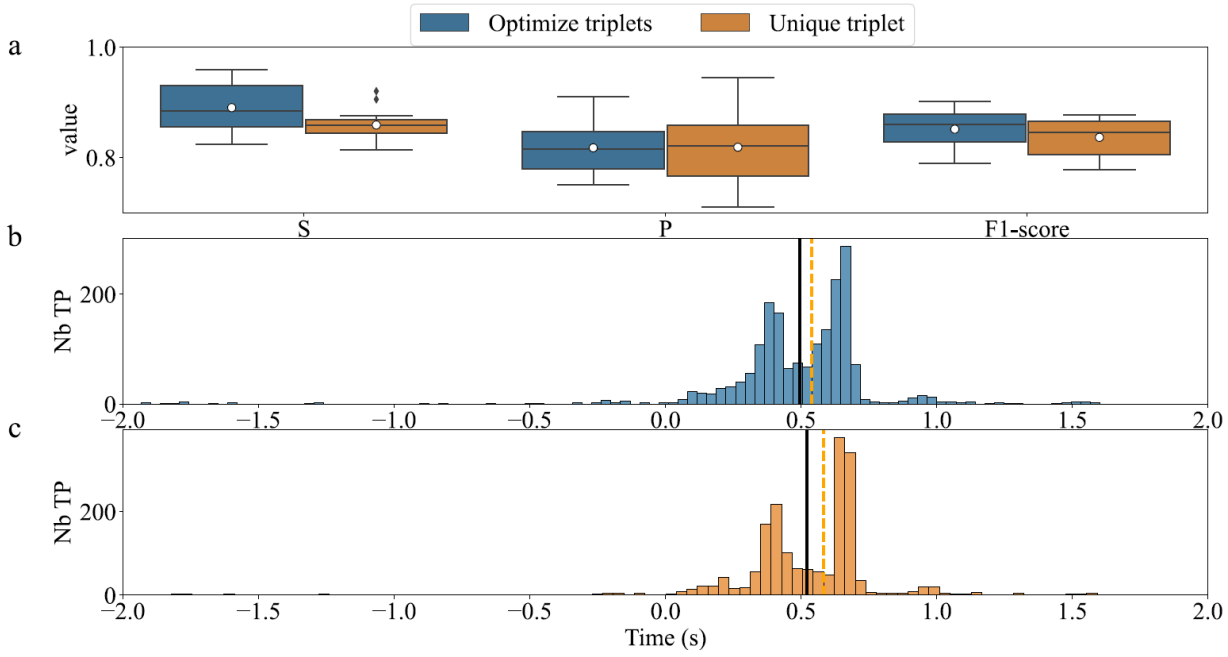
Result for all Bootstrap independently, for All EEG trace

Bootstrap	1	2	3	4	5	6	7	8	9	10	11	12
F1-score	0.885	0.812	0.789	0.801	0.845	0.866	0.862	0.859	0.835	0.878	0.902	0.886
sensitivity	0.929	0.856	0.825	0.860	0.824	0.876	0.959	0.926	0.855	0.950	0.893	0.937
precision	0.844	0.772	0.756	0.750	0.867	0.856	0.782	0.802	0.815	0.816	0.911	0.841
FDR/H	1.55	2.19	1.88	1.61	2.26	1.77	1.68	1.02	2.80	1.05	1.93	1.65
T	0.68	0.66	0.90	0.90	0.88	0.90	0.68	0.64	0.96	0.62	0.88	0.66
Pw	90	100	100	95	95	90	80	100	40	100	65	55
Pch	60	55	40	40	60	40	60	75	55	50	45	85

Optimize triplet [T, Pw, Pch] Fixe the best triplet per bootstarp

Unique triplet [T, Pw, Pch] Fixe the best triplet that whatever the explored bootstrap

- ✓ **Unique triplet**
  - Sensitivity of **0.859 ± 0.030**, precision of **0.819 ± 0.064**, F1-score of **0.837 ± 0.032**, and FDR/H of **1.78 ±0.49**
  - Times delays of onset detection with a mean delay and a median delay of **522** and **582 ms**



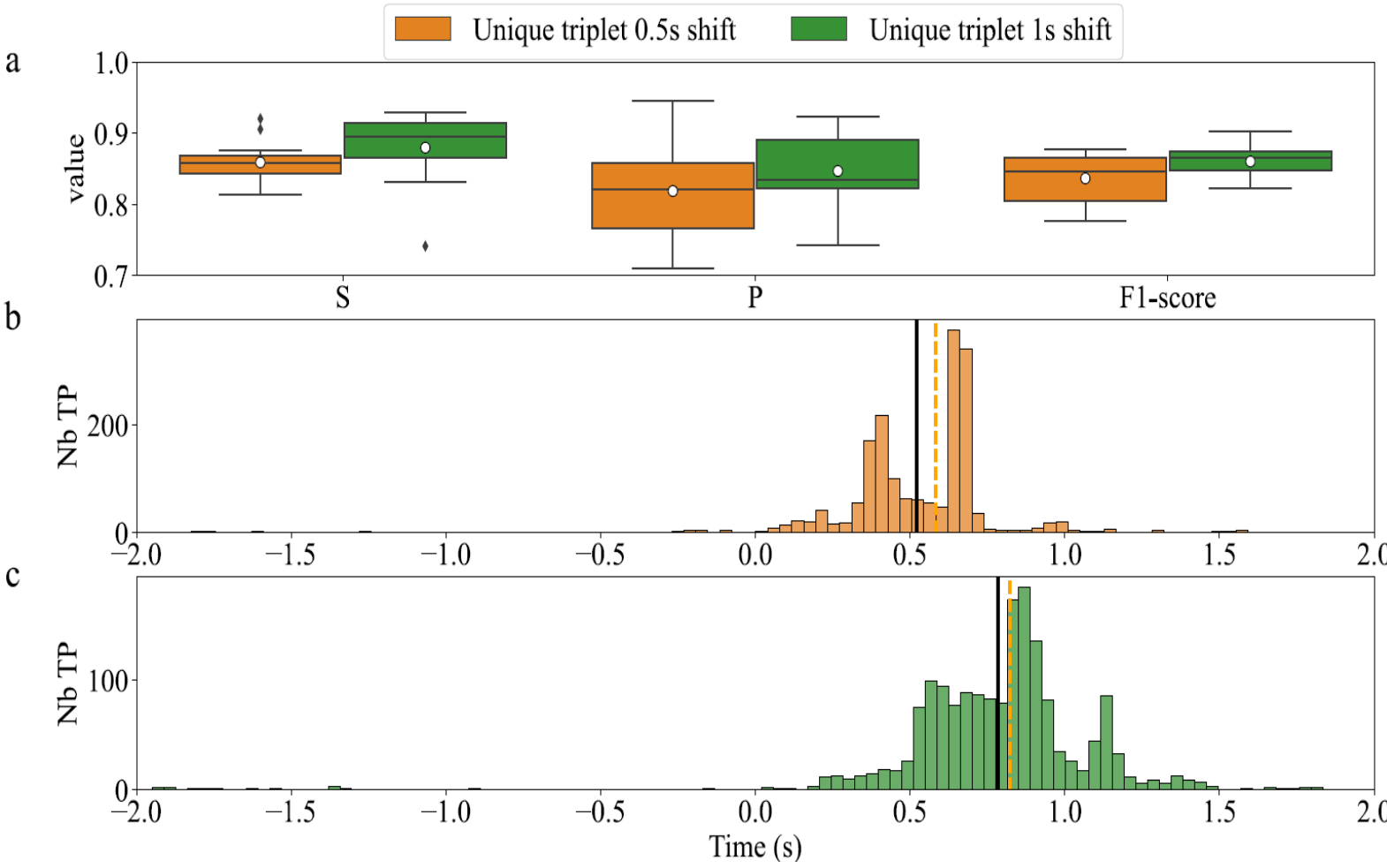
CAE: results - influence of the sliding window

Orange Window with a length of 2 s

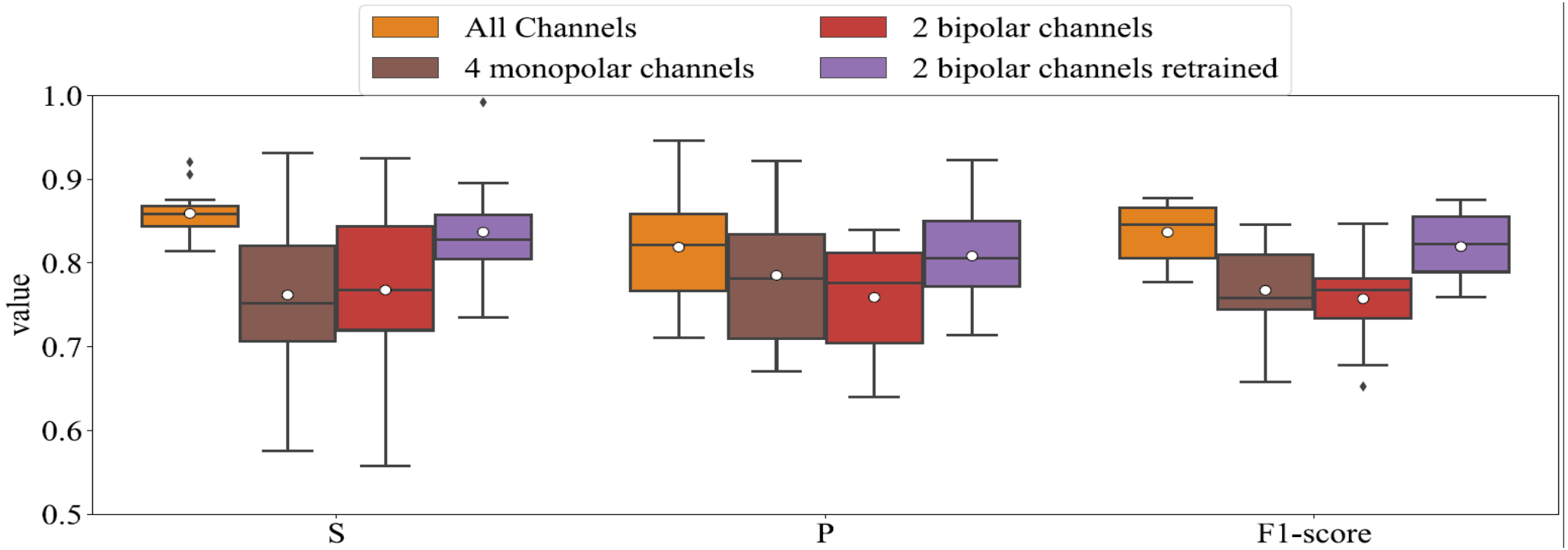
Green Window with a length of 3 s

✓ **As expected**

- Superior detection performances are obtained with a 3 s windows
- Better mean detection delays with a 2 second window



CAE: results - influence of the electrode number



Orange All available electrodes

Brown Four specific electrodes, two prefrontals [Fp1,Fp2], and two temporals [T3 ,T4] → recommended to wearable device

Red Bipolar montage Fp1-T3 and Fp2-T4 using classical trained model

Purple Bipolar montage Fp1-T3 and Fp2-T4 using retrained model on bipolar channel

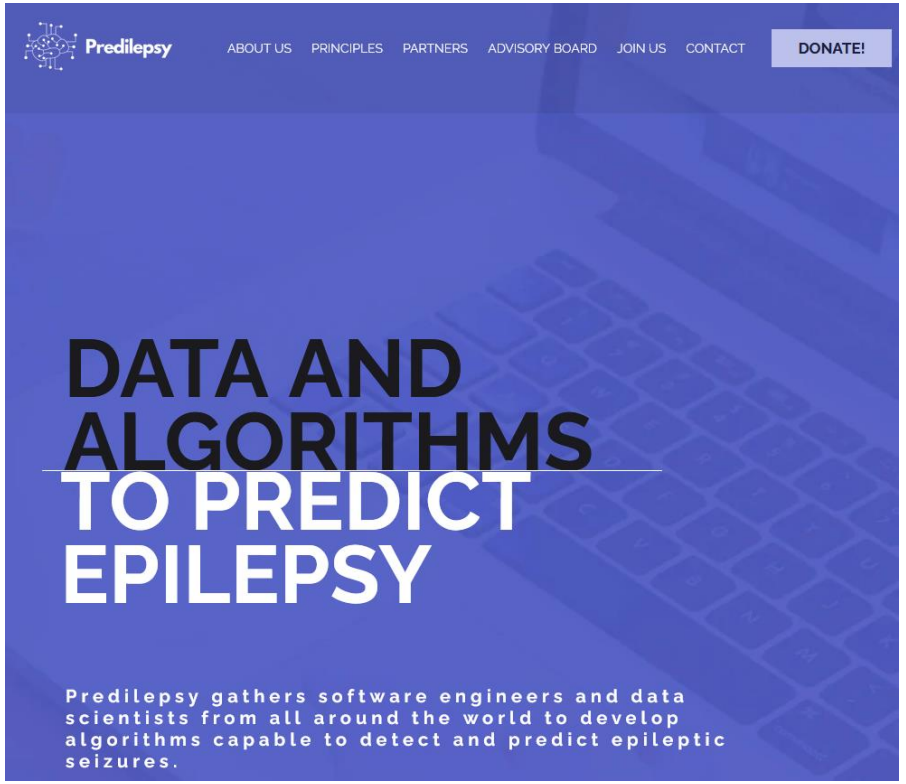
✓ Performance of the retrained model with a four electrodes are quasi-equivalent to the ones of classical model

CAE: conclusion and perspectives

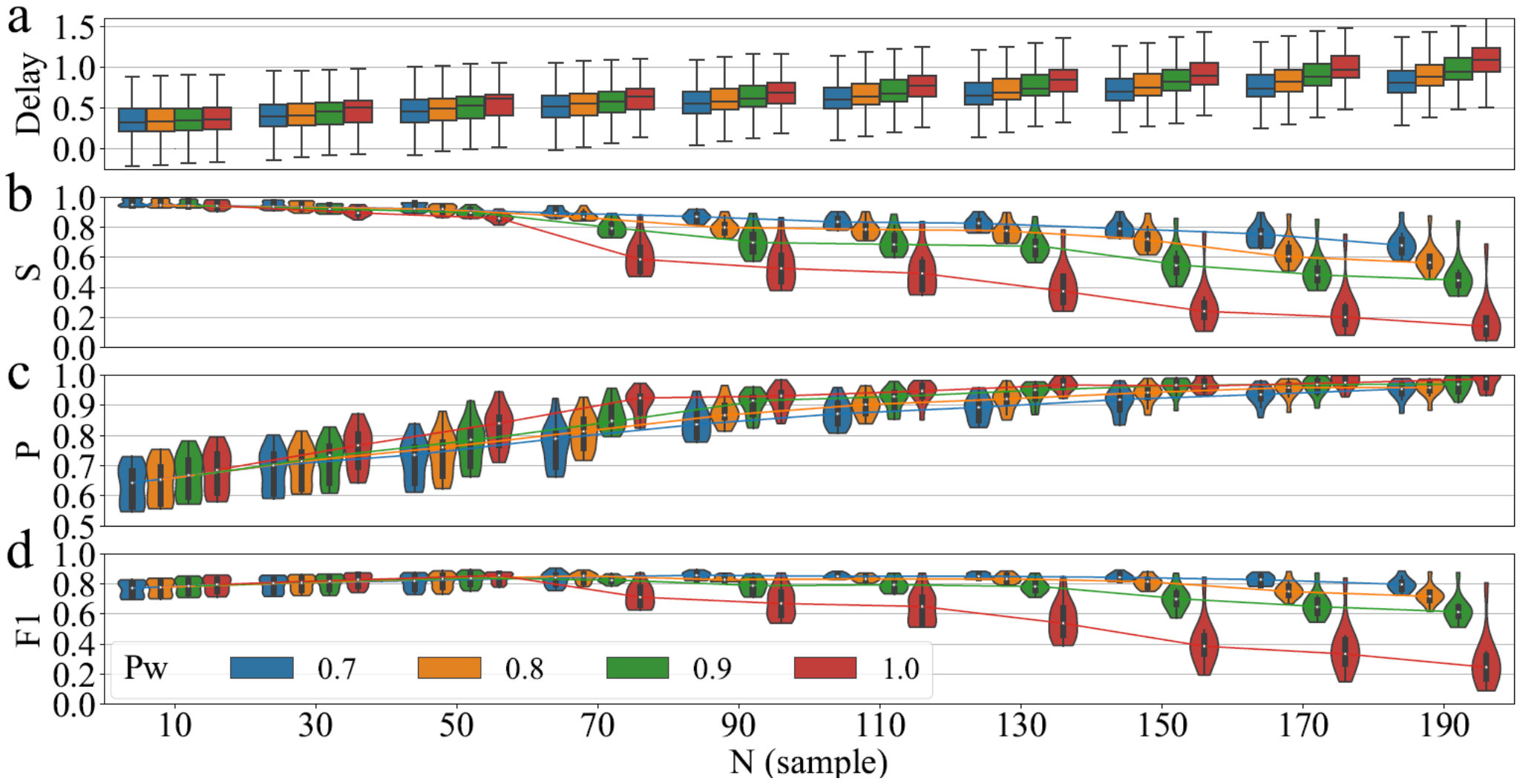
- ✓ Novel deep learning methodology for the early detection of absence epilepsy seizures in children
- ✓ High detection accuracy with a minimized detection delay of absence epilepsy seizure onsets → about 0.522 s
- ✓ All results were obtained using human clinical EEGs with non-patient specific detection strategy → 117 patients
- ✓ Good performances under wearable device configuration → 4 electrodes avoiding hair region
- × Evaluation of the proposed methodology on wearable device EEG recordings
- × Evaluation of the efficiency of a portable stimulator using our early onset detector on patients suffering from absence epilepsy

PROJET PREDILEPSY

https://www.predilepsy.org/



APP1: compromise between the number N of the consecutive 2 s time windows and the threshold Pw



APP2: example of result that the detection algorithm found in different conditions