Towards a unified framework for the validation of EEG-based seizure detection algorithms

EPFL

ETH zürich

CHUV

Jonathan Dan

Biomedical Signal Processing and Control
Volume 87, Part A, January 2024, 105464

Self-supervised Learning with Attention Mechanism for EEG-based seizure detection

Tiantian Xiao, Ziwei Wang, Yongfeng Zhang, Hongbin lv, Shuai Wang, Hailing Feng, Yanna Zhao

Highlights

- We developed an seizure detection framework based on self-supervised contrastive learning.
- We adopt the attention mechanism based Transformer to capture the global dependency of EEG signals.
- Patient-specific and cross-patient experiments on CHB-MIT dataset demonstrate satisfactory

F1-score: 77%

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Seizure Types Classification by Generating Input Images With in-Depth Features From Decomposed EEG Signals for Deep Learning Pipeline

Anand Shankar, Samarendra Dandapat, *Member, IEEE*, and Shovan Barma

***Index Terms*—Convolution neural network, continuous wavelet transform, electroencephalogram, hilbert vibration decomposition, long short-term memory, seizure types.**

***Abstract*—Electroencephalogram (EEG) based seizure types classification has not been addressed well, compared to seizure detection, which is very important for the diagnosis and prognosis of epileptic patients. The minuscule changes reflected in EEG signals among different seizure types make such tasks more challenging. Therefore, in this work, underlying features in EEG have been explored by decomposing signals into multiple subcomponents which have been further used to generate 2D input images for deep learning (DL) pipeline. The Hilbert vibration decomposition (HVD) has been employed for decomposing the EEG signals by preserving phase information. Next, 2D images have been generated considering the first three subcomponents having high energy by involving continuous wavelet transform and converting them into 2D images for DL inputs. For classification, a hybrid DL pipeline has been constructed by combining the convolution neural network (CNN) followed by long short-term memory (LSTM) for efficient extraction of spatial and time sequence information. Experimental validation has been conducted by classifying five types of seizures and seizure-free, collected from the Temple University EEG dataset (TUH v1.5.2). The proposed method has achieved the highest classification accuracy up to 99% along with an *F*1-score of 99%. Further analysis shows that the HVD-based decomposition and hybrid DL model can efficiently extract in-depth features while classifying different types of seizures. In a comparative study, the proposed idea demonstrates its superiority by displaying the uppermost performance.**

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Towards a unified framework

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F1-score: 99%

bioengineering

IMPACT FACTOR 4.6
Indexed in: PubMed
CITESCORE 4.2

Article

SeizFt: Interpretable Machine Learning for Seizure Detection Using Wearables

Irfan Al-Hussaini and Cassie S. Mitchell

Special Issue
Advances in Smart Sensing and Data Computing for Sleep Analysis, Sleep Disorders Detection and Epileptic Seizure Detection and Prediction

Edited by
Dr. Chen Chen, Prof. Dr. Wei Chen, Dr. Maarten De Vos and Dr. Christos Chatzichristos

MDPI
https://doi.org/10.3390/bioengineering10080918

Sensitivity: 62%

Towards a unified framework

Dataset

- CHB-MIT Scalp EEG Database

Cross-Validation

- **Personalized model: random** cross-validation
- **Generalized model:** Leave-one-**subject**-out

Performance metrics

- **Sample-based** metric on sensitivity, specificity, F1-score, AUC

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Dataset

- subset of TUH EEG Sz Corpus

Cross-Validation

- **Generalized model: random** cross-validation

Performance metrics

- **Sample-based** metric on F1-score, accuracy

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Dataset

- Training: SeizeIT1
- Testing: SeizeIT2

Cross-Validation

- **Independent** dataset

Performance metrics

- **Event-based** to measure sensitivity
- **Sample-based** to measure False Alarm rate


bioengineering

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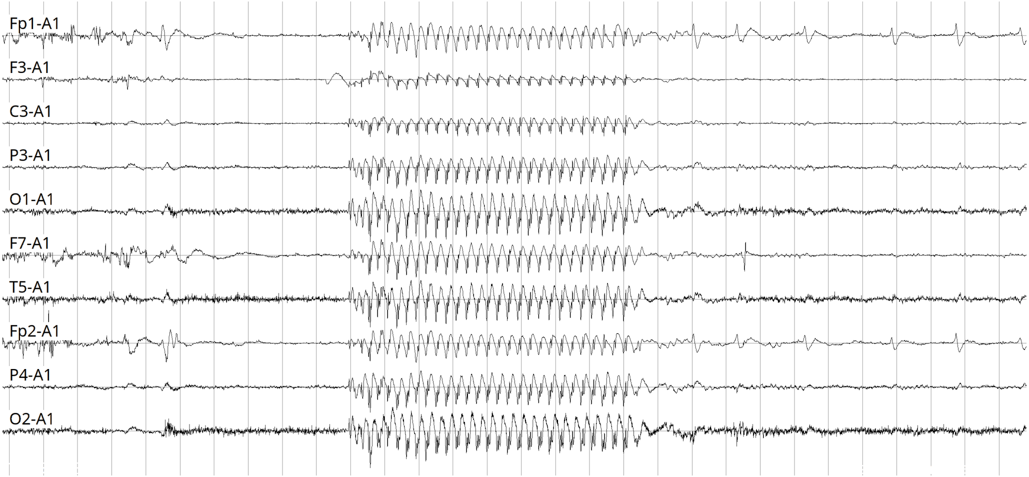
It is **difficult** to compare papers

Datasets

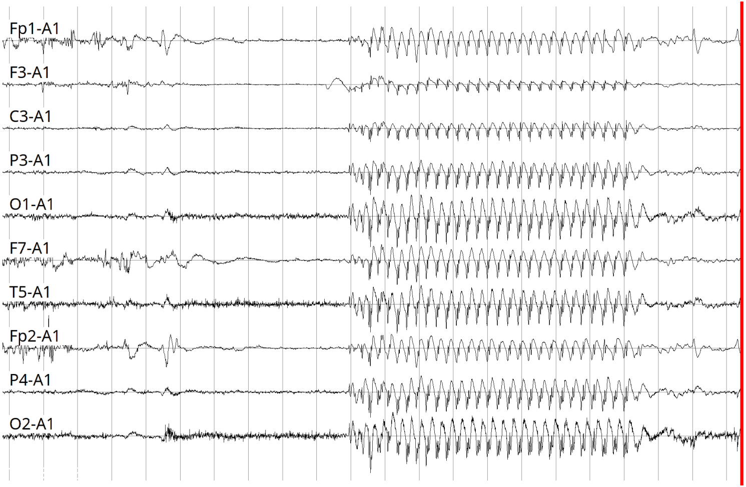
Cross-Validation

Performance

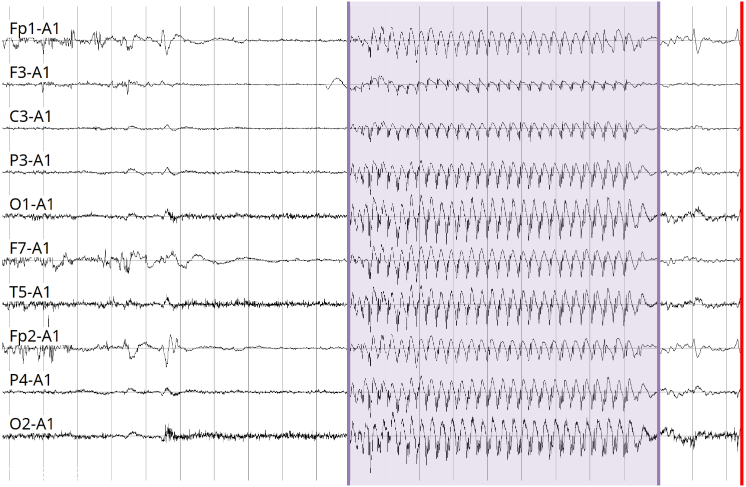
Task: **Seizure Detection** on scalp EEG



Task: **Seizure Detection** on scalp EEG



Task: **Seizure Detection** on scalp EEG



Input Data

10-20 scalp EEG

Task

Segment **seizures**

Output

```
start, end
10   , 18
```

Framework overview

Datasets

Data Formats

Cross-Validation

Performance

Framework overview

Online platform

- Datasets
- Data Formats
- Cross-Validation
- Performance

Framework overview

Online platform

Datasets

Data Formats

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Performance

Benchmark

Framework

Datasets

Data formats

Cross-Validation

Performance metrics

Publicly available**, annotated, scalp EEG** datasets of people with **epilepsy**

Dataset	# subjects	duration [h]	# seizures
CHB-MIT	24	982	198
TUH EEG Sz Corpus	675	1476	4029
Siena Scalp EEG	14	128	47
SeizeIT1	42	4211	182

Framework

Datasets

Data formats

Cross-Validation

Performance metrics

Datasets use **different EEG** formats

Sampling frequency [Hz] 250, 256, 512, 1000

Channels 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 41, 45, 49, 128

Montage monopolar (`A1/A2`), monopolar (`Fz`), bipolar (dBanana),

Datasets use **different EEG** formats

Sampling frequency [Hz] 250, 256, 512, 1000

Channels 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 41, 45, 49, 128

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Peltola, M. E. el al.
"Routine and sleep EEG: Minimum recording standards of the IFCN and the ILAE".
Epilepsia, 2023.

Datasets use **different EEG** formats

Sampling frequency [Hz]	250, **256**, 512, 1000
Channels	17, 18, **19**, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 41, 45, 49, 128
Montage	monopolar (A1/A2), monopolar (Fz), bipolar (dBanana), **monopolar (common average)**

Peltola, M. E. el al.
"Routine and sleep EEG: Minimum recording standards of the IFCN and the ILAE".
Epilepsia, 2023.

Datasets use **different annotation** formats

CHB-MIT
Text file

- start time
- stop time

TUH
Table (`.csv`)

- start time
- stop time
- seizure type
- channel

Siena
Text file

- start time
- stop time

SeizeIT1
Table (`.tsv`)

- start time
- stop time
- seizure type
- comments

Standardized annotation format

A table (`.csv`) stores annotations in a standardized format

subject	AXXYB24
session	S1
recording	R1
dateTime	2023-07-24 13:58:32
duration	1800
event	sz-gen
startTime	20
endTime	132
confidence	1
channels	all
filepath	path/to/file-s1.edf

Standardized annotation format

A table (`.csv`) stores annotations in a standardized format

subject	session	...	event	startTime	endTime	...
AXXYB24	S1	.	sz-gen	20	132	.
AXXYB24	S1	.	sz-gen	840	902	.
AXXYB24	S2	.	bckg	0	7200	.
AXXYB24	S3	.	sz-gen	490	546	.

sz-

Focal Onset foc

-

Aware	a
Impaired Awareness	ia
Unknown Awareness	ua

-

Motor Onset m
- -automatisms
- -atonic
- -clonic
- -spasms
- -hyperkinetic
- -myoclonic
- -tonic

Nonmotor Onset nm
- -autonomic
- -behavior
- -cognitive
- -emotional
- -sensory

Focal to bilateral tonic-clonic f2b

Unknown motor um

Generalized Onset gen

-

Motor m
- -tonic_clonic
- -clonic
- -tonic
- -myo_tc
- -myo_atonic
- -atonic
- -spasms

Nonmotor (absence) nm
- -typical
- -atypical
- -myoclonic
- -eyelid_myo

Unknown motor um

Unknown Onset uon

-

Motor m
- -tonic_clonic
- -spasms

Nonmotor nm
- -behavior

Unknown motor um

ILAE Seizure classification, *Epilepsia*, 2017.

EPFL

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CHUV

Framework

Datasets

Data formats

Cross-Validation

Performance metrics

Poor cross-validation **overestimates** performance

Generalized models

Shafiezadeh, S. et al. "Methodological Issues in Evaluating Machine Learning Models for EEG Seizure Prediction: Good Cross-Validation Accuracy Does Not Guarantee Generalization to New Patients". *Applied Sciences*, 2023.

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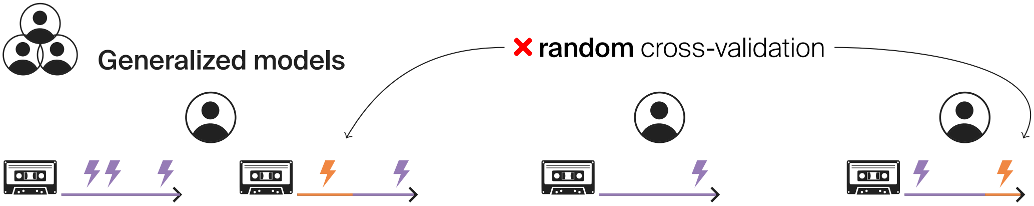
Personalized models

Pale, U., et al. “Importance of methodological choices in data manipulation for validating epileptic seizure detection models”. *Proceedings of the 45th IEEE EMBC*, 2023.

Provide guidelines to ensure **independence** between **training** and **testing** data



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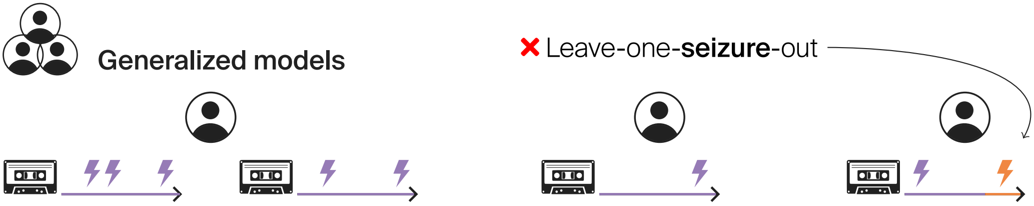

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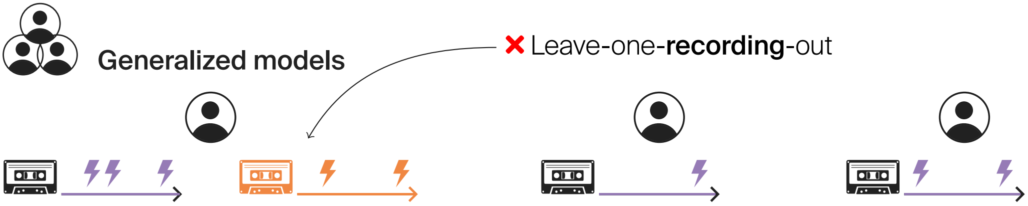

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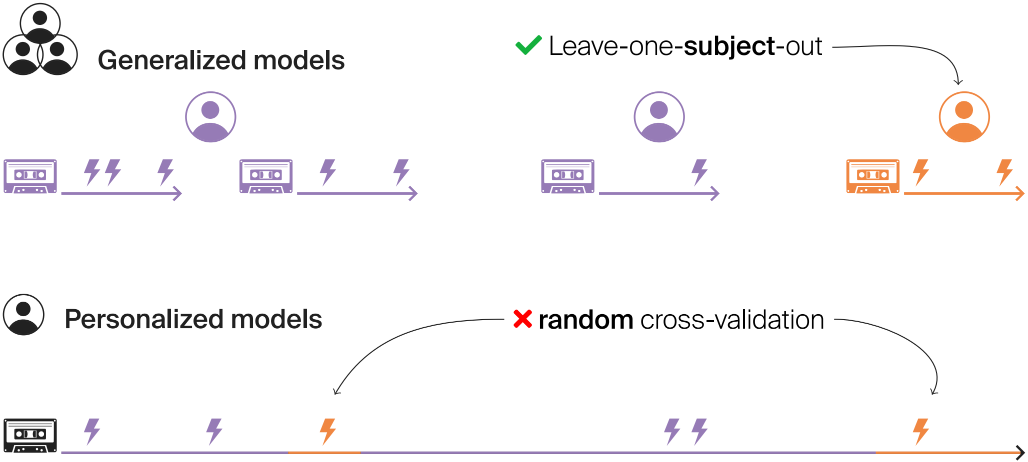

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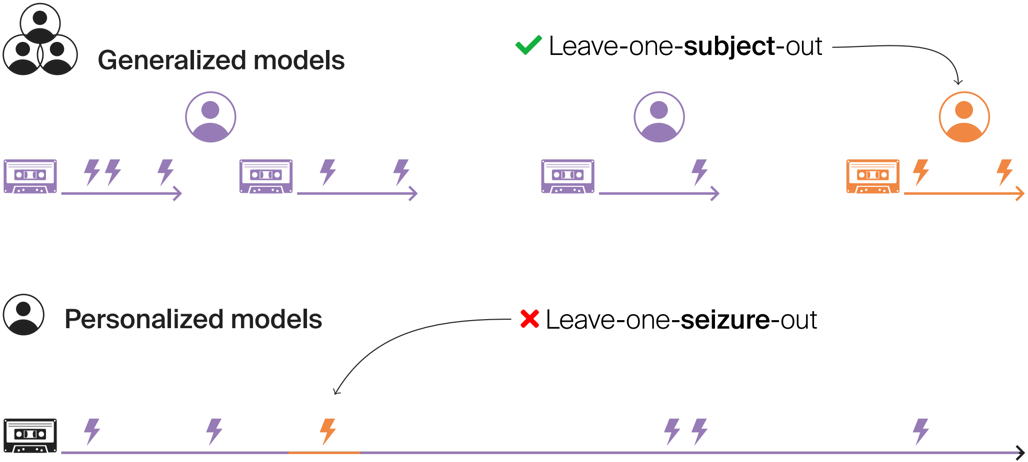


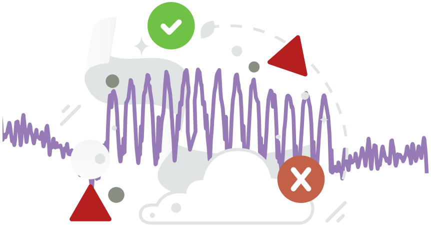
Provide guidelines to ensure **independence** between training and testing data

Generalized models

✓ Leave-one-**subject**-out

Personalized models

✓ Respect **chronology**



Framework

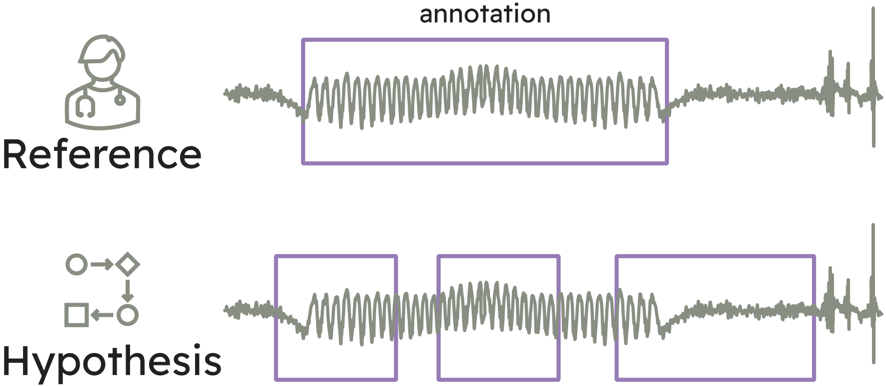
Datasets

Data formats

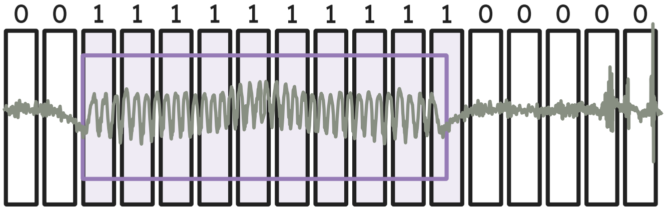
Cross-Validation

Performance metrics

Counting detections and errors is **not universal**



Sample-based scoring is used in the **ML** community



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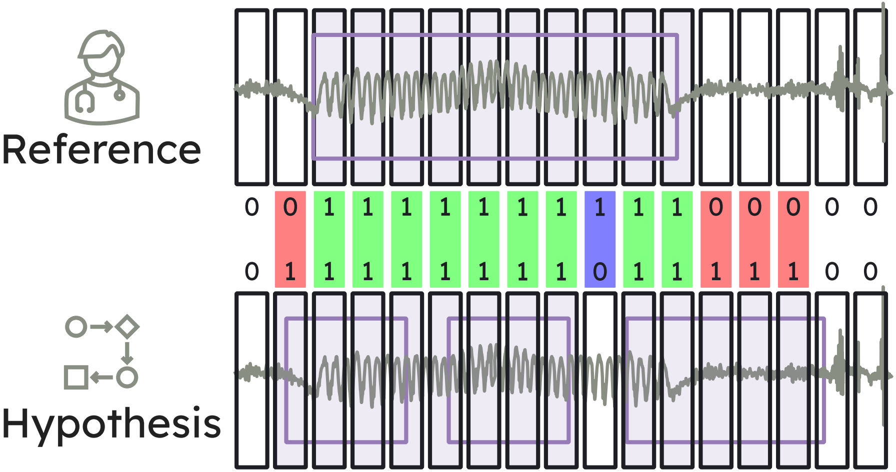
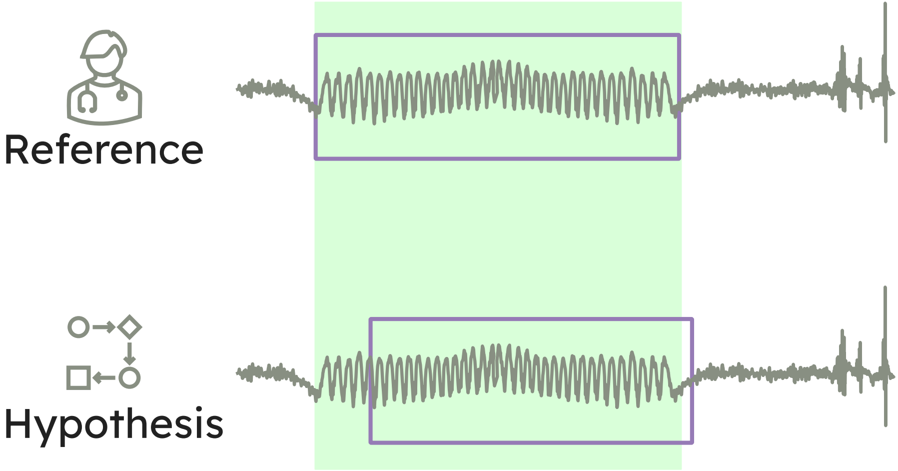


Event-based scoring is based on **overlap**



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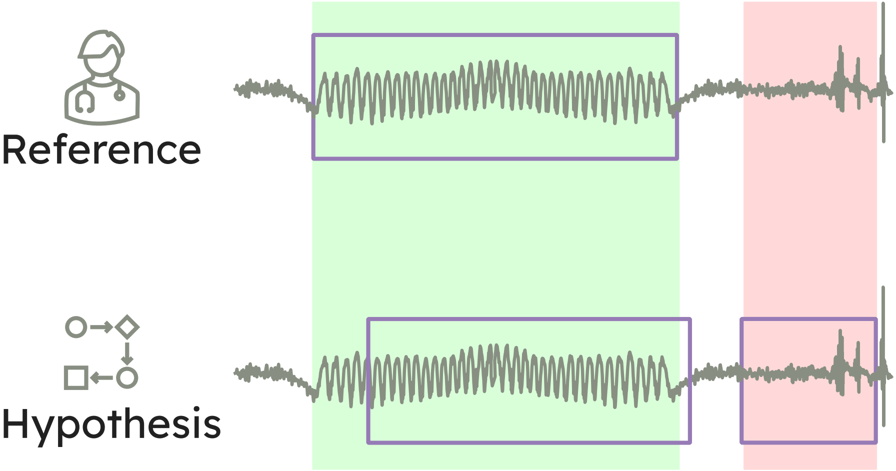
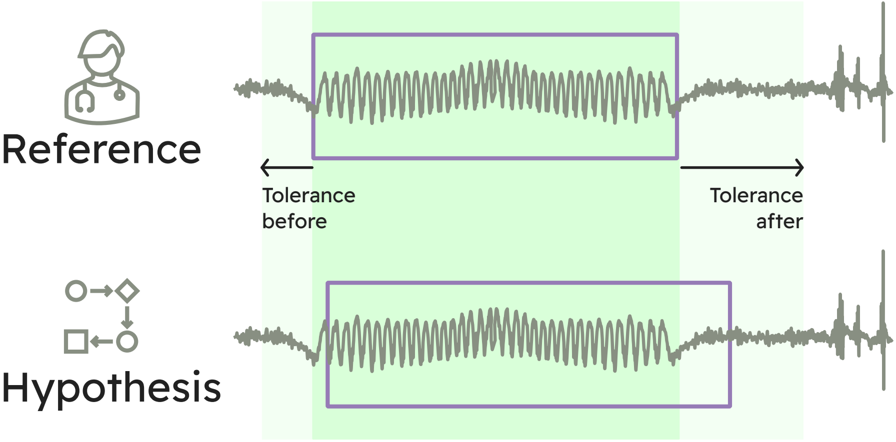
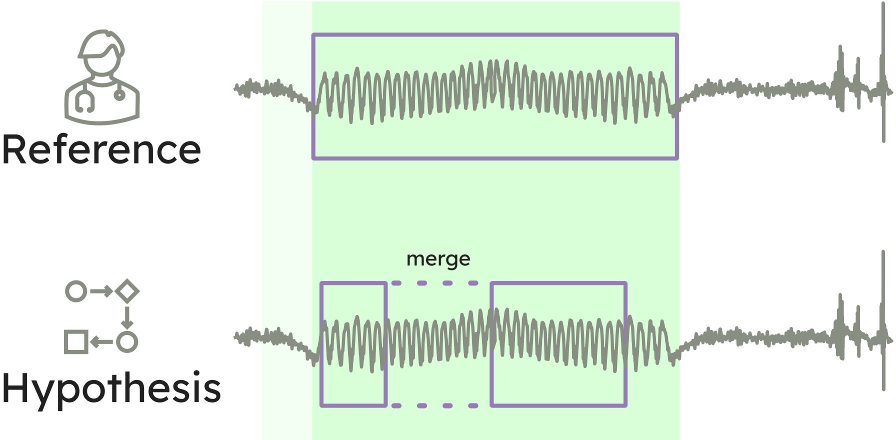


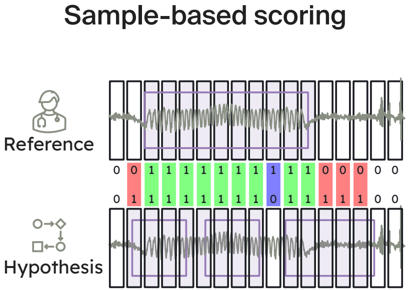
Event-based scoring is based on overlap with some **tolerance**

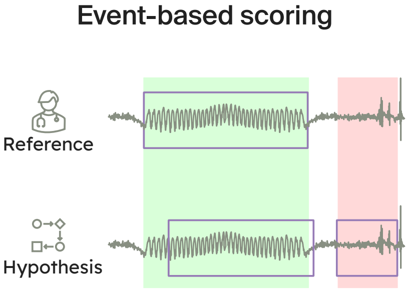


Event-based scoring is based on overlap, **merging** neighbouring events



Event and sample-based scoring allow computing standard **performance metrics**





True Positives

False Negatives

False Positives

Event and sample-based scoring allow computing standard **performance metrics**

True Positives | False Negatives | False Positives

Sensitivity

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

Event and sample-based scoring allow computing standard **performance metrics**

- True Positives
- False Negatives
- False Positives

Sensitivity

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

Precision

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

Event and sample-based scoring allow computing standard **performance metrics**

True Positives

False Negatives

False Positives

Sensitivity

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

F1-score

$$\frac{2}{sensitivity^{-1} + precision^{-1}}$$

Precision

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

Event and sample-based scoring allow computing standard **performance metrics**

True Positives | False Negatives | False Positives

Sensitivity

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

Precision

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

F1-score

$$\frac{2}{sensitivity^{-1} + precision^{-1}}$$

False Alarm rate

FP / 24 hours

Online platform

Framework is **available** online on a **website**

`https://eslweb.epfl.ch/epilepsybenchmarks/`

EPILEPSY BENCHMARKS

Framework Tools Benchmark Contact

Epilepsy benchmarks

This website provides a framework for the validation of EEG based automated seizure detection algorithms:

Framework

Here you can find a description of the framework for validation of seizure detection algorithms.

Tools

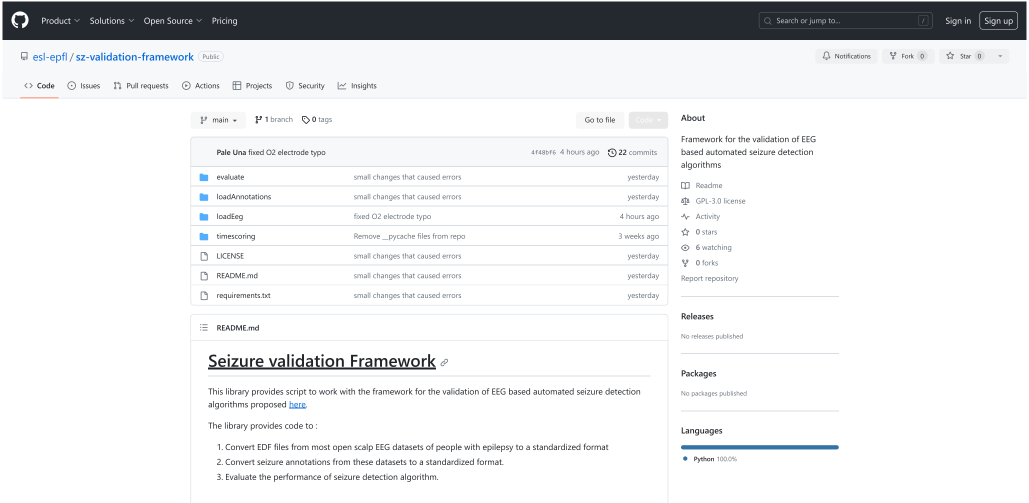
We provide tools to streamline the processing of EEG for the task of automated seizure detection.

Benchmark

The framework for validation of seizure detection algorithms is used to benchmark algorithms.

Framework is available online as a code library

https://github.com/esl-epfl/sz-validation-framework



Framework allows to **compare** algorithms

Submit a new entry!

Subject-independent models

Name	Training Data	Date	CHB-MIT F1-score Event	TUH F1-score Event	Siena F1-score Event	SeizeIT F1-score Event
ESL_RF...	CHB-MIT	06/10/2023	55.3			
ESL_RF...	Siena	06/10/2023			33.9	
ESL_Tr...	TUH	11/10/2023		63.2	32.2	
ESL_Tr...	Siena	11/10/2023			22.8	

Invitation to **contribute**

`https://eslweb.epfl.ch/epilepsybenchmarks/`

- Comment and **discuss** on the framework
- </> Contribute **code** to the software libraries
- Submit **results** on the benchmark platform
- Provide open **datasets** to the community

The future could be wearable, intracranial, forecasting, multi-modal, ...

We will be contacting you soon!

jonathan.dan@epfl.ch