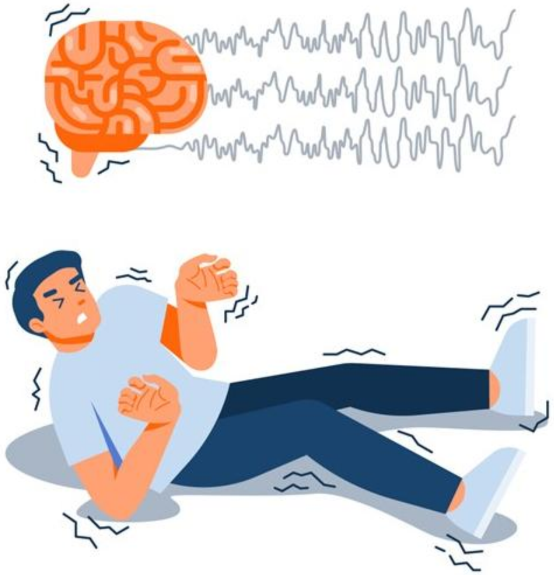
Computationally Efficient and Generalizable Machine Learning Algorithms for Seizure Detection from EEG Signals

Zheyun Shou

Motivation

- **Global health challenge**:
  - A **seizure** is a sudden burst of abnormal electrical activity in the brain that can cause a variety of symptoms, ranging from brief lapses of awareness or muscle jerks to prolonged convulsions.
  - Epilepsy is a chronic neurological disorder characterized by a tendency for recurrent, unprovoked epileptic seizures, affecting over 50 million individuals worldwide.
  - Diagnosis is primarily clinical, dependent on subjective reporting. Potentially inaccurate and challenging.

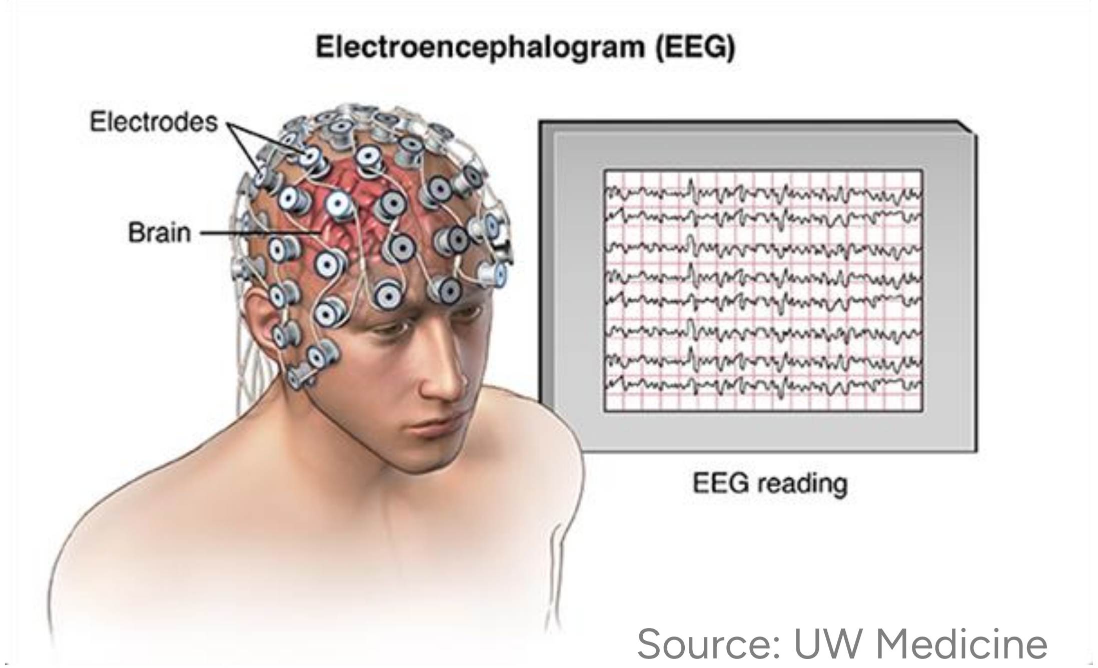
Source: Wikipedia



Source: Dr. Habib's Foster CDC

Motivation

- **Need for automated seizure detection algorithms**: Electroencephalography (EEG) is the most widely used and reliable method for monitoring brain electrical activity and detecting seizures.
  - Manual interpretation: look for distinct characteristics, e.g. spikes, slow wave morphology, continuity, and frequency. Labor-intensive, time-consuming and susceptible to variability.
  - Increasing availability of long-term EEG monitoring systems amplified volume of data requiring analysis.



Source: UW Medicine

Motivation

- **Problems with existing ML approaches**: Recent advances in machine learning and time series analysis have opened new possibilities for EEG analysis.
  - Traditional approaches relied heavily on the quality and relevance of handcrafted features in time frequency domains -> may not generalize well
  - Deep learning approaches -> good performance but typically require large amounts of labeled data for training and computationally intensive

Address the challenges of computational efficiency and model generalizability in the field of automated seizure detection from EEG signals.

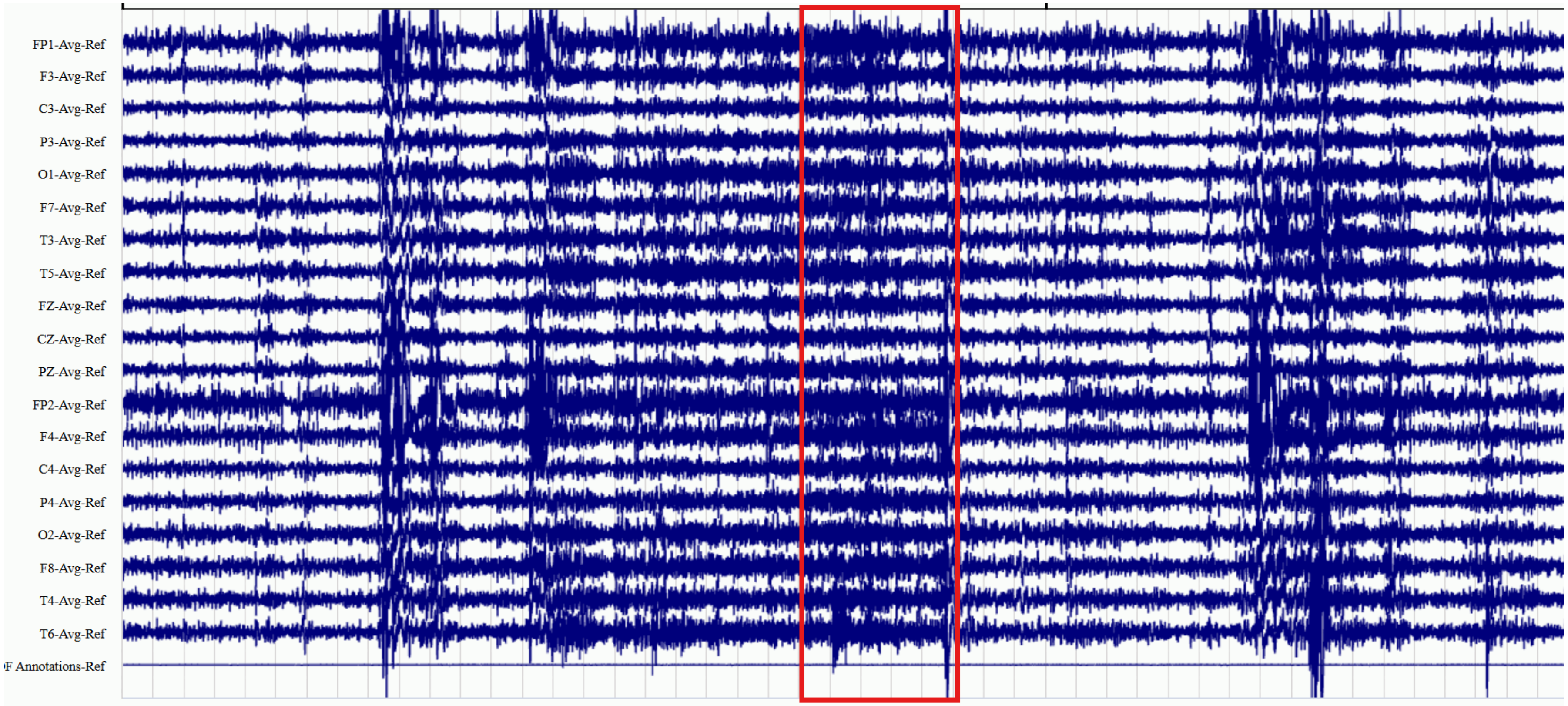
Approach

- This study investigates the Detach-ROCKET algorithm and its variant, Detach Ensemble, to develop a seizure detection methodology.
- Our goal is to achieve a compelling balance between the tradeoff of **high predictive performance**, **exceptional computational speed**, and **robust generalization.**

Why Detach-ROCKET?

The challenging task

- High dimensional
- Complexity of seizure patterns
- Inter-channel correlation
- Difficult to distinguish from pre- and post-ictal patterns



Seizure event in an EEG recording, from TUSZ

Why Detach-ROCKET?

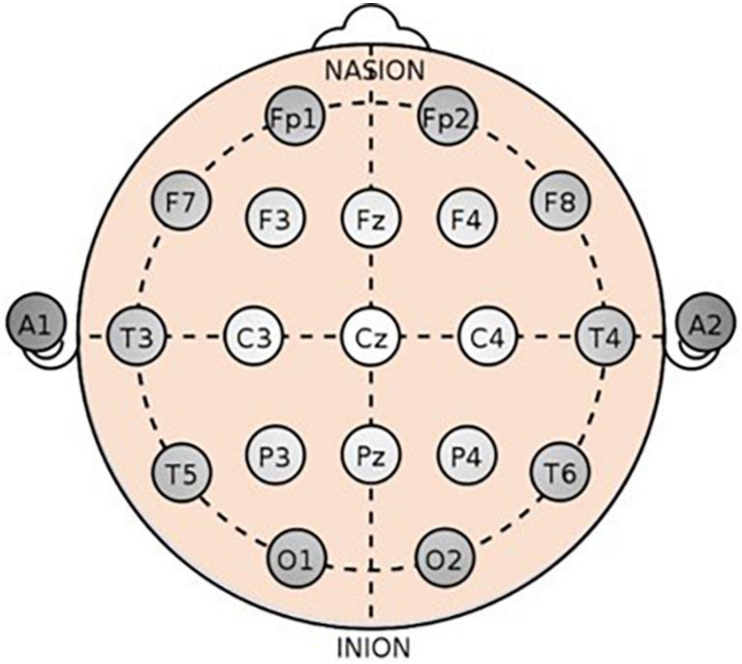
- **What is Detach-ROCKET?**
  - Variant of ROCKET(Random Convolutional Kernel Transform)
  - Redundant or non-informative features are pruned using Sequential Feature Detachment
- **Multivariate solution; inter-channel correlation**
- **Computationally efficient and lightweight**
- **Detach Ensemble:** an ensemble of N independent Detach-ROCKET models
  - Enables the exploration of a much larger pool of kernels than a single ROCKET
  - Built-in method for channel relevance analysis

Research Question

To what extent can the Detach-ROCKET framework achieve a superior balance of **predictive performance**, **generalizability**, and **computational efficiency** for EEG seizure detection compared to established time-series classification benchmarks?

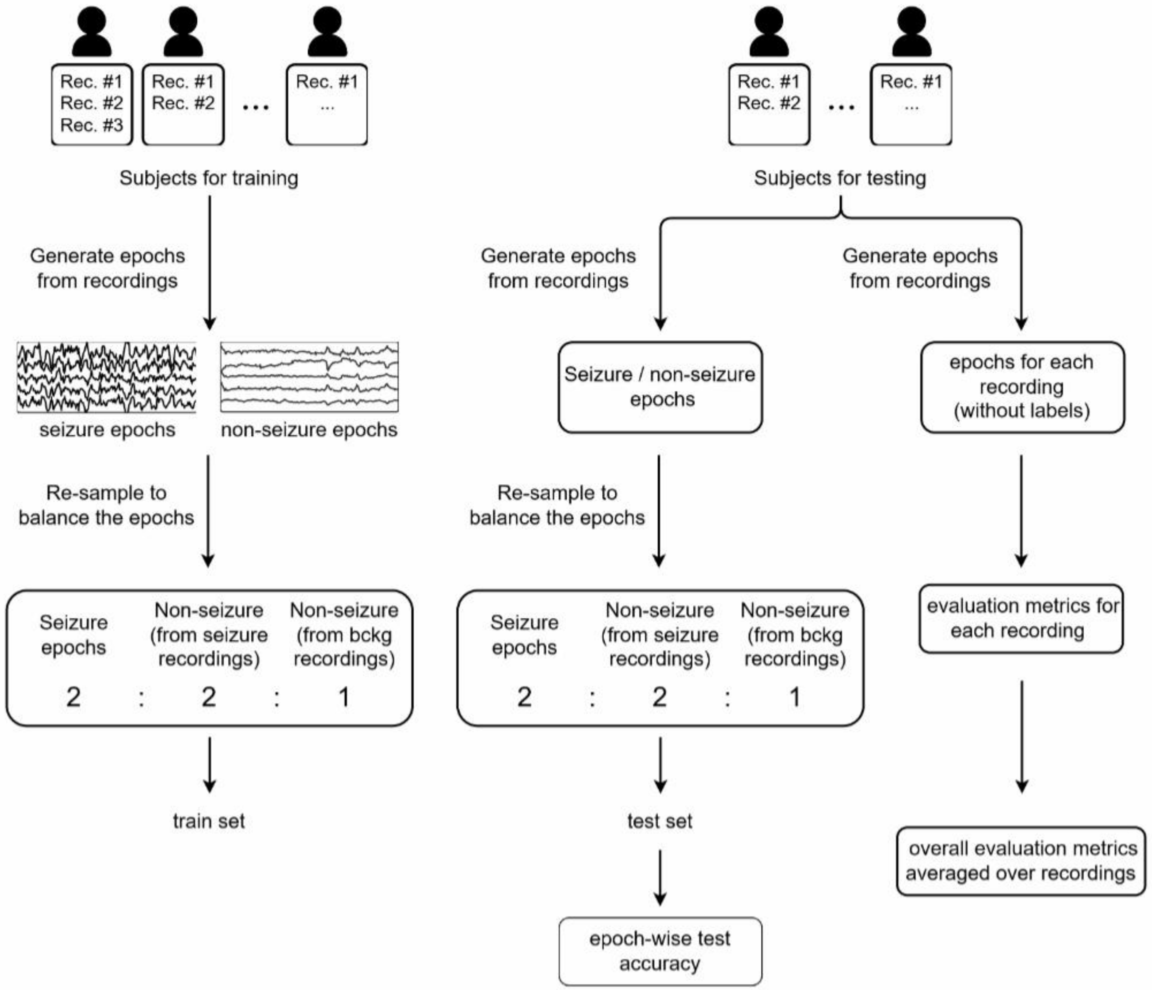
Experiment setting

- Dataset
  - Train and test on the TUH EEG Seizure Corpus(TUSZ), including 459 subjects
  - Cross-data evaluation on the Siena Scalp EEG Database, including 14 subjects
  - Each recording consists of 19 channels corresponding to the standard 10–20 system scalp electrode montage, with a sampling rate of 256 Hz
  - Downsampled to 128 Hz before training

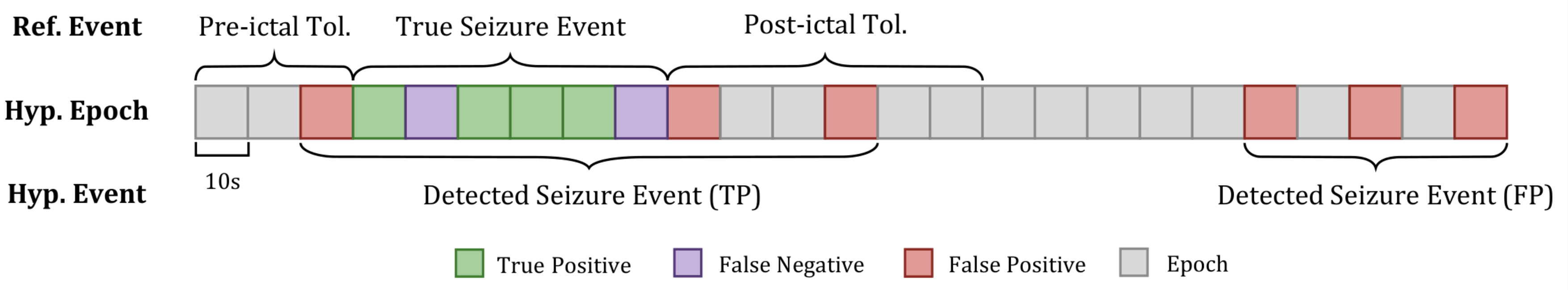


Electrode locations for EEG signals. From Shah, V. et al.

Experiment setting



Experiment setting



Epoch-wise and event-wise evaluation framework for seizure detection, suggested by the 2025 Seizure Detection Challenge.

- Merge the epochs predicted as seizure into a single, longer **event** if the epochs are separated by less than **90** seconds (30s pre-ictal tolerance, 60s post-ictal tolerance).
- Evaluation Metrics
  - Accuracy, Sensitivity, Precision, **F1 score**, False Positive Rate/24h
  - Epoch-wise and **event-wise**

Predictive performance

Config.	Level	Sens.	Prec.	F1	FPR/24h
D-MINI	Epoch	0.72	0.60	0.48	16 428
	Range	*(0.49, 0.72)*	*(0.46, 0.60)*	*(0.42, 0.58)*	*(10308, 20198)*
	Event	0.95	0.81	$\boxed{0.85}$	43
	Range	*(0.93, 0.98)*	*(0.80, 0.84)*	*(0.84, 0.88)*	*(35, 49)*
D-MINI Ens.	Epoch	0.73	0.63	0.57	17 298
	Range	*(0.54, 0.81)*	*(0.54, 0.70)*	*(0.49, 0.57)*	*(9080, 18829)*
	Event	0.97	0.87	$\boxed{0.89}$	29
	Range	*(0.91, 0.98)*	*(0.86, 0.89)*	*(0.87, 0.91)*	*(25, 35)*
catch22	Epoch	0.58	0.64	0.53	9 756
	Range	*(0.44, 0.62)*	*(0.62, 0.70)*	*(0.41, 0.56)*	*(9660, 10392)*
	Event	0.91	0.86	$\boxed{0.88}$	31
	Range	*(0.89, 0.95)*	*(0.86, 0.88)*	*(0.84, 0.88)*	*(25, 34)*

Model performance for test subjects using 50% of the subjects of the TUSZ.

- Why catch22? A state-of-the-art TSC method; focus on feature selection relevant to Detach-ROCKET.
- Event-wise F1 score: Good performance on all three models.
- Subject-wise generalization capability.

Generalizability

	Epoch F1	Event F1	Event FPR
D-ROCKET	0.28	0.32	81
Range	*(0.22, 0.32)*	*(0.28, 0.42)*	*(58, 93)*
D-ROCKET Ens.	0.34	0.39	63
Range	*(0.32, 0.37)*	*(0.34, 0.45)*	*(51, 76)*
catch22	0.25	0.33	91
Range	*(0.24, 0.28)*	*(0.27, 0.37)*	*(82, 116)*

Cross-dataset performance comparison **on the Siena dataset.**

- Competitive compared with top ranking algorithms from 2025 Seizure Detection Challenge:

Event-wise

ALGORITHMS	F1-SCORE	SENSITIVITY	PRECISION
SeizureTransformer	43	37	45
Van Gogh Detect	36	39	42
S4Seizure v2	34	30	42

Computational Efficiency

D-MINIROCKET	D-MINIROCKET Ens.	Catch22
0.74	6.88	12.68

Model inference time (seconds) on a 1208s EEG recording.

- Detach-ROCKET framework is notably faster than catch22.
- Potential for applications requiring near real-time processing and decision making.

Conclusion

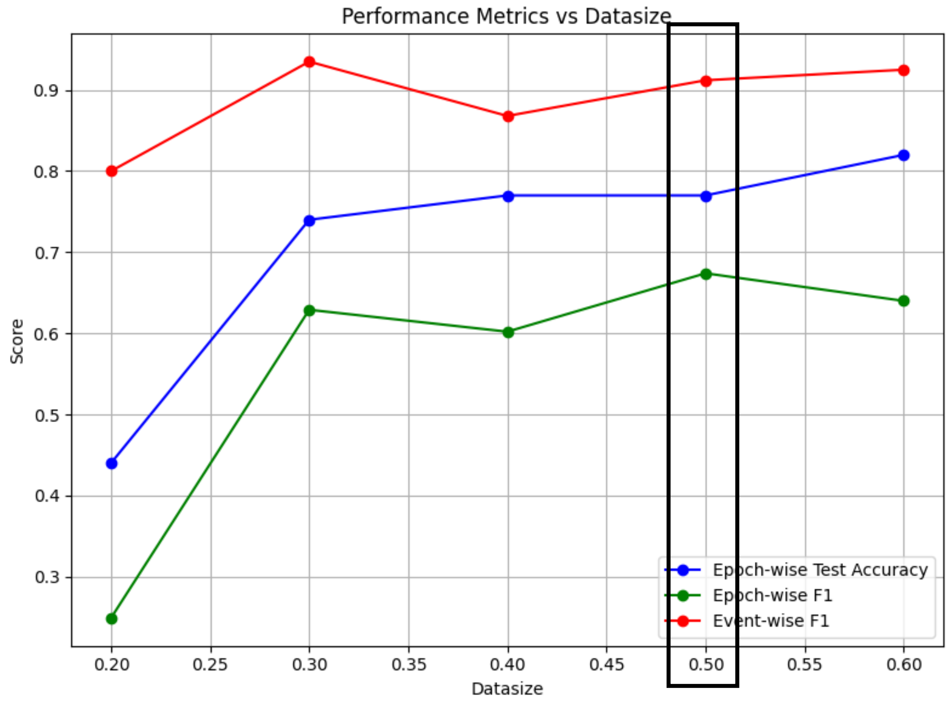
- To what extent can the Detach-ROCKET framework achieve a superior balance of **predictive performance**, **generalizability,** and **computational efficiency** for EEG seizure detection compared to catch22?
  - Predictive performance: good across all three models
  - Generalizability: competitive generalizability achieved with Detach Ensemble
  - Computational efficiency: both Detach-ROCKET models are more efficient than catch22, potential for real-time applications

Sensitivity Analysis

Number of models; epoch duration; training data size.

N	Epoch Duration	Test Acc.	Epoch F1	Event F1
10	10	0.80	0.62	0.90
10	6	0.85	0.64	0.89
10	20	0.81	0.62	0.89
5	10	0.84	0.63	0.88
20	10	0.78	0.62	0.89

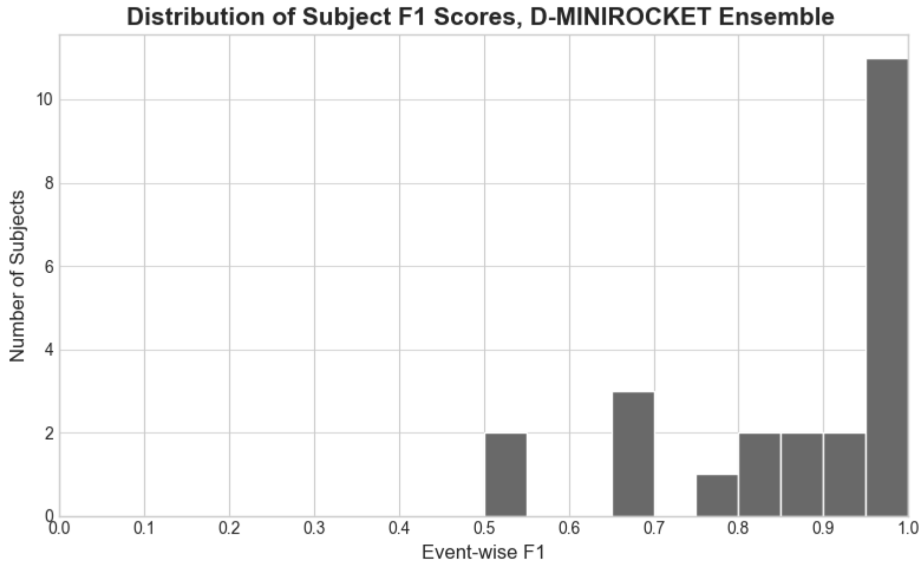
Performance evaluation of the Detach Ensemble under varying hyperparameter configurations. N denotes the number of models in the ensemble.

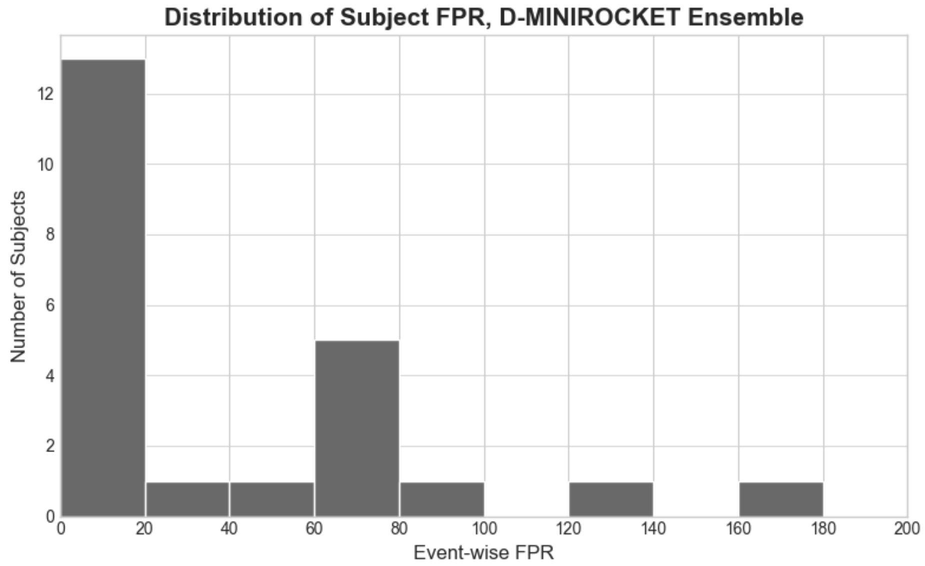


Performance of the Detach Ensemble model on varying training subjects proportions.

- Model performance (event F1) not very sensitive to N and epoch duration.
- Notable deterioration in performance when training subjects falls below 30%; relatively stable performance beyond this point.

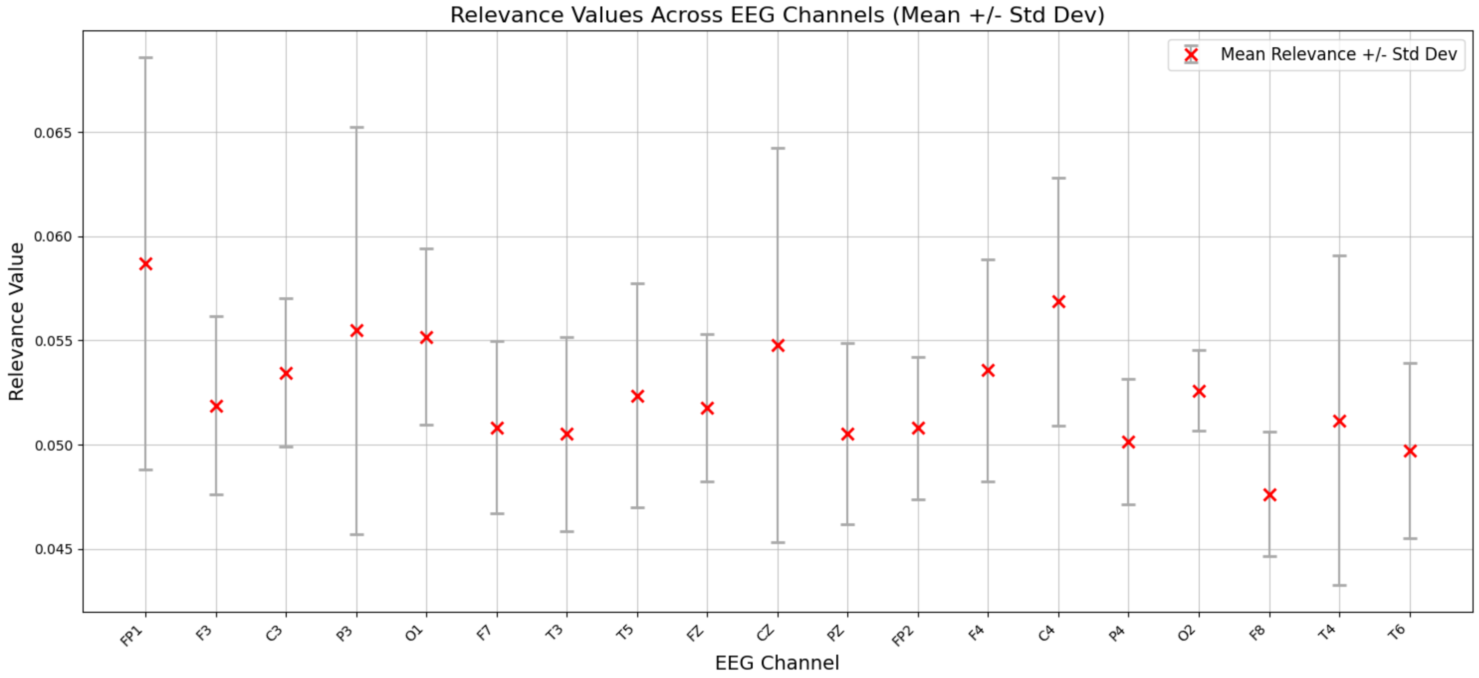
Subject Variations





- Potential reasons:
  - Subjects may have different seizure types
  - Variations in EEG Acquisition: electrode positions, scalp thickness, skull conductivity, and electrode-scalp impedance

Channel Relevance Analysis



Mean and std of estimated channel relevance values across well-performing Detach Ensemble models.

- None of the channels show comparably large relevance values. Potentially due to the subjects in the dataset having different types of seizures occurring in various regions of the brain.
- Fp1, C4 slightly more relevant; F8 slightly less relevant. Further experiments are needed for validation.

Discussion and Future Work

- **Benchmark selection**: catch22 is not specifically designed as a seizure detection method

  -> tailored method, e.g. methods based on FFT, DWT.

- **Channel relevance analysis**: train and evaluate models on a subset of EEG channels.
- **Ensemble diversity**: base models use different subset of the dataset, varying epoch duration, etc.

Computationally Efficient and Generalizable Machine Learning Algorithms for Seizure Detection from EEG Signals

Zheyun Shou