Seizure Detection and Prediction on Siena Scalp EEG Dataset

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Introduction to Current Research

Epileptic Seizure Detection and Prediction

Patient-specific

- Tailored to the seizure characteristics of one patient and applied to this patient.
- Better performance.
- Less applicable clinically.

Patient non-specific

- Trained with a group of patients and later applied directly to detect seizures in new patients.
- Worse performance.
- Assist the neurologist in an efficient and effective evaluation of epilepsy.

Seizure detection is currently based on visual inspection of video-EEG in clinical settings: time-consuming and prone to human error and subjectivity.

Understanding Epileptic Seizures

Background and Challenges

Why are seizure detection and prediction important?

1. Epilepsy is the second most common neurological disorder
2. Accurate seizure detection is important for diagnosis and treatment of epilepsy.
3. Sudden unexpected deaths in epilepsy (SUDEP), which is the major cause of epilepsy-related mortality, is 2-3 times higher for epileptic patients, therefore an early and correct prediction of seizures is crucial for the management of epilepsy.

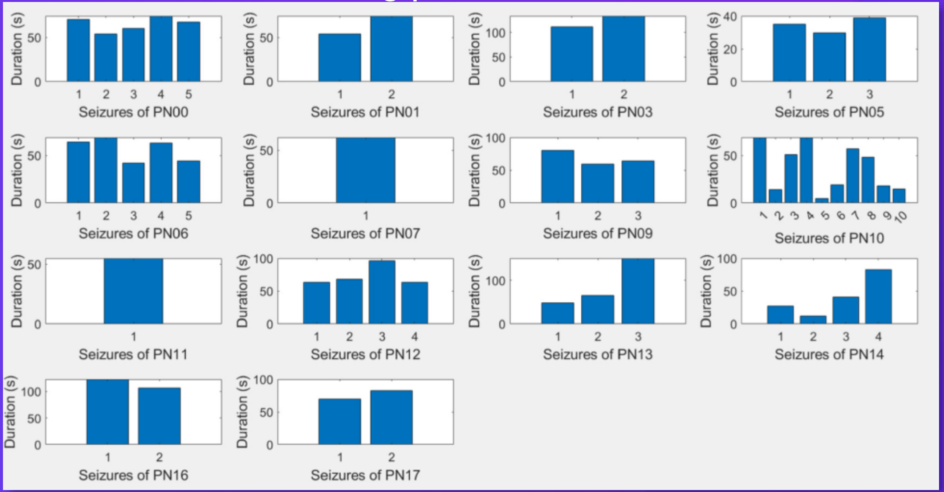
Dataset Overview

Siena Scalp EEG Database: Characteristics and Relevance

- **14** patients with focal epilepsy: nine males (ages 36-71) and five females (ages 20-58).
- Monitored with a non-invasive scalp Video-EEG, sampling rate of 512Hz.

- The exact times of seizure events were annotated by expert clinicians.
- **47** seizure instances with a <u>mean seizure duration of 61s</u> on ≈144h of monitoring time → **Extremely unbalanced**.

Seizure duration among patients.



Patient’s information.

Pat. Id	Age	Gender	Seizure	Locali.	Laterali.	# Chan.	# Seiz.	Time
PN00	55	Male	IAS	T	R	29	5	192
PN01	46	Male	IAS	T	L	29	2	809
PN03	54	Male	IAS	T	R	29	2	1453
PN05	51	Female	IAS	T	L	29	3	362
PN06	36	Male	IAS	T	L	29	5	723
PN07	20	Female	IAS	T	L	29	1	524
PN09	27	Female	IAS	T	L	29	3	410
PN10	25	Male	FBTC	F	Bilateral	20	10	1122
PN11	58	Female	IAS	T	R	29	1	145
PN12	71	Male	IAS	T	L	29	4	366
PN13	34	Female	IAS	T	L	29	3	520
PN14	49	Male	WIAS	T	L	29	4	1408
PN16	41	Female	IAS	T	L	29	2	293
PN17	42	Male	IAS	T	R	29	2	308

- **IAS**: focal onset impaired awareness.
- **WIAS**: focal onset without impaired awareness, and lastly.
- **FBTC**: focal to bilateral tonic-clonic.
- **Localization** refers to which brain lobe the seizure originates.
- **Lateralization** refers to the side of origin in the brain.

Focus of our Research

Seizure Detection and Prediction

Proposed Tasks:

Patient-Specific Seizure Detection/Prediction:

Combining EEG and ECG features to enhance detection and prediction accuracy.

Patient-Specific Seizure Prediction:

Utilizing raw EEG signals to predict seizures, focusing on the untapped potential within the raw data.

Patient Non-Specific Seizure Detection and Prediction:

Exploring methods applicable across a broader patient base, not limited to individual-specific characteristics.

Vocabulary

Detection and Prediction

- Both detection and prediction are **classification** tasks.
    - Detection refers to a binary classification task: non-seizure vs seizure.
    - Prediction refers to discriminating a pre-ictal phase from the non-seizure and seizure phases.
- The length of the preictal states is not univocally defined in the literature: concept of prediction interval, i.e., a time window immediately preceding a given seizure.
- A seizure is correctly predicted if at least a record inside the prediction interval is classified as positive.
    - The prediction time is the period between the first record correctly classified inside the prediction interval of a seizure and its onset.
    - A false positive is generated when the algorithm classifies as positive a record outside the prediction interval.

Patient-specific seizure Prediction using raw EEG signals and CNNs.

Methodology

Introduction to the approach

The task consists of using a CNN for the classification of Electroencephalogram (EEG) signals.

The model has to classify between 3 classes:

- Non-seizure.
- Pre-ictal phase: include signals 15 minutes before the seizure on-set.
- Seizure.

Methodology: Pre-processing

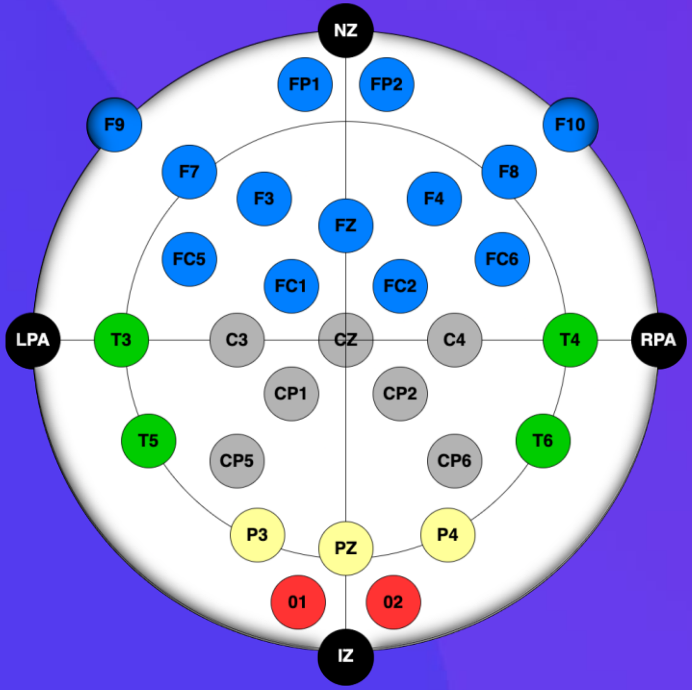
Preparing the Data for the Training

Given the patient-specific approach:

1. Personalized steps for specific seizure types
   - Select the most representative channels, depending on the area of the brain where there is a greater chance of detecting abnormalities.
2. Apply Filtering [8-13] Hz band, which is the range of Hz mostly involved during the sleep, condition of the patients of our dataset.
3. Generate the images.

Methodology: Pre-processing

Selecting representative channels



Frontal Lobe

Temporal Lobe

Central sulcus

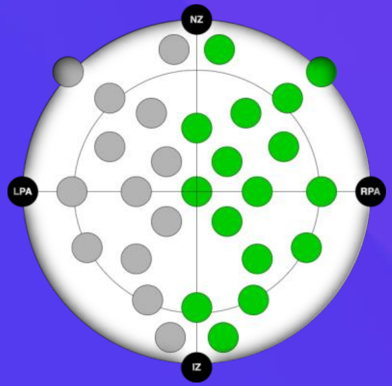
Occipital Lobe

Parietal Lobe

Methodology: Pre-processing

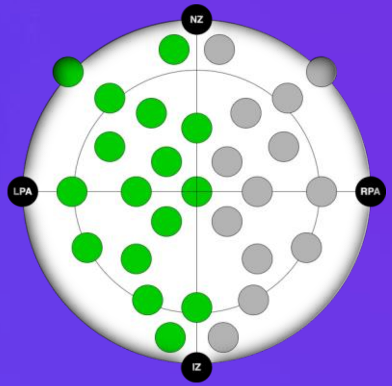
Selecting representative channels

Patient 0



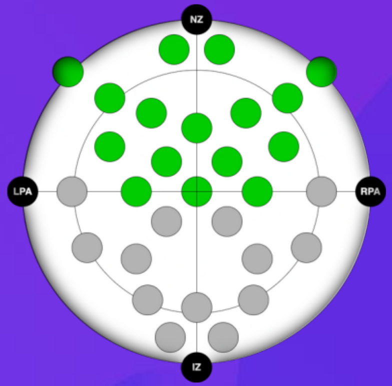
Right Temporal Lobe

Patient 6



Left Temporal Lobe

Patient 10



Frontal Bilateral

Methodology: Pre-processing

Undersampling and Data Augmentation

Each image has been generated as follow:

- Splitting the data in seconds.
- Concatenate 5 images for each sample:
  - The final dimension of each sample is 5 x 16 x 512

The strong class unbalance can be mitigated by changing the overlap of the time windows:

- The Non-seizure class has no overlapping.
- The Pre-ictal class has 2 seconds of overlap.
- The Seizure class has 3 seconds of overlap.

Model Architecture

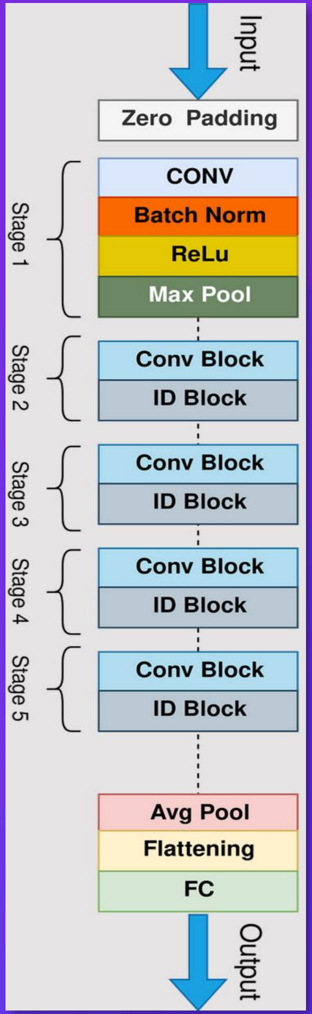
Convolutional Neural Network

According to the scientific literature, we tried different approaches:

- A basic CNN composed by:
  - Convolutional layers.
  - Pooling layers.
  - Fully Connected layers.
- A CNN with residual connection.
- Pre-trained models (AlexNet, ResNet).

The best results have been obtained by the ResNet50, which has been adapted for our task.
The improvements of this model may be attributed to:

- ability to automatically learn and extract hierarchical features from the input data.
- the depth of ResNets can capture the high-level abstractions of the EEG signals.



Training

Focal Loss

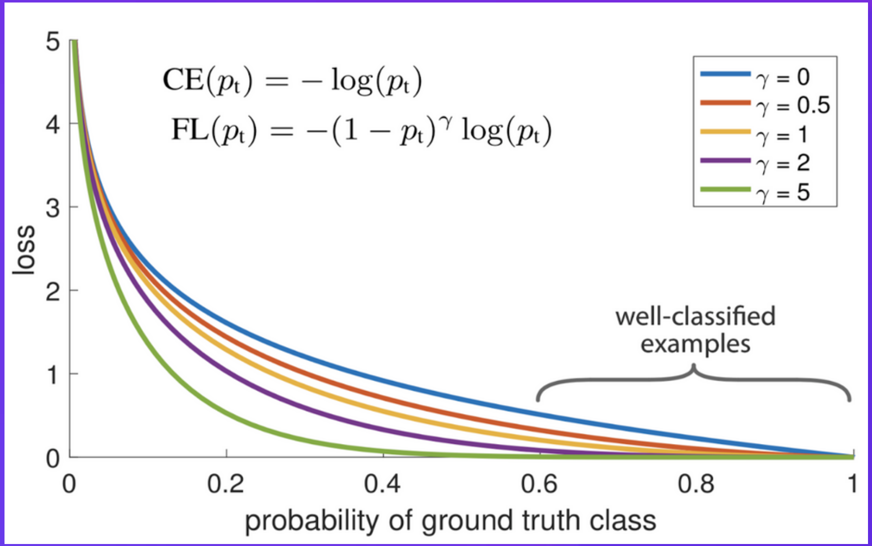
$$FL(p_t) = -\alpha_t (1-p_t)^{\gamma} \log(p_t)$$

Another approach we used to mitigate the class unbalance is using focal loss.

This loss function allowed us to fix two hyper-parameters:

- modulating factor γ
- weighting parameter α

so that easy examples have less importance than hard ones.



Patient-specific seizure Detection and Prediction combining EEG and ECG features Using ML.

Methodology: Pre-processing

Preparing the Data for the Training

- Patients chosen for the analysis:
  - PN00, PN05, PN06, PN10.
- Channel selection:
  - Based on the lateralization and localization of the patient’s seizure.
- Filtering:
  - ECG channel: low pass filter of (0 – 50Hz).
  - EEG channels – low pass filter pf (1-40 Hz).
- Epoching:
  - 6 seconds epoch duration.
  - Overlap of 1 in seizure segments.
- Labeling.
- Undersampling.

EEG Feature Description

Time-domain features.

- **Number of zero crossings** refers to the number of times the signal goes from a positive voltage value to a negative one or vice versa.
- **Maximum** represents the largest voltage value.
- **Minimum** represents the smallest voltage value.
- **Skewness** is a measure of the lack of symmetry in the amplitude distribution. Larger values mean more skewness.
- **Kurtosis** gives information about the extent of the peak in the amplitude distribution.
- **Root mean square** measures the magnitude of the varying quantity.
- **Mobility** measures the standard deviation of the slope with reference to the amplitude's standard deviation.
- **Complexity** gives an estimate of the bandwidth of the signal indicating the similarity of the shape of the signal compared to a pure sine wave

EEG Feature Description

Frequency-domain features.

- First, power spectral density (PSD) was calculated using the fast Fourier transform (FFT) with Welch's method. According to brain status and cognitive activities, the EEG can be classified into five different frequency sub-bands namely δ (0.5 − 4Hz); θ (4 − 8Hz); α (8 − 13Hz); β (13 − 30Hz); γ (30 − 80Hz) = HF.
  - **Total power.**
  - **Peak frequency** is the frequency with the highest spectral power.
  - **Mean power** in five frequency sub-bands δ, θ, α, β, and high frequency (HF).
  - **Normalized** power in five frequency sub-bands δ, θ, α, β, and high frequency.

EEG Feature Description

Entropy features.

- In general, entropy is an information measure that represents the amount of uncertainty associated with events from a given distribution
  - **Sample entropy** is proposed by Richman and Moorman and is used to assess the complexity of physiological time-series signals.
  - **Spectral entropy** is a measure of the degree of EEG irregularity because the entropy of the power spectrum represents the relative peakedness or flatness of the spectral distribution.

ECG Feature Description

- Mean Heart Rate
- Maximum Heart Rate
- Minimum Heart Rate
- Mean RR Interval
- QRS Duration
- QT Interval

- Mean T-Wave Energy
- Mean P-Wave Energy
- P-Wave Amplitude
- T-Wave Amplitude
- ST Segment Duration
- Mean QRS Energy

Patient Non-specific Seizure Detection and Prediction using EEG features:

a comparison between XGBoost and LSTMs.

Methodology: Pre-processing

Preparing the Data for the Training

Channel Selection: 19 EEG channels consistent across 14 patients were analyzed.

Filtering Approach:

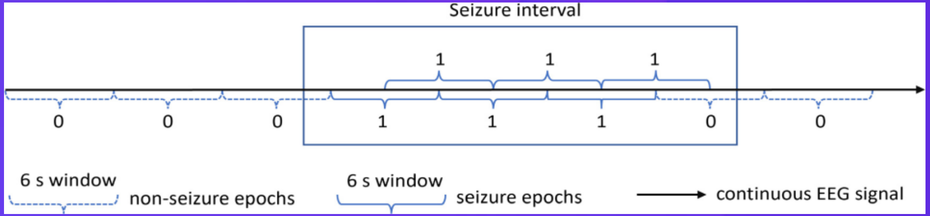
- High-pass Butterworth filter (4th order) at 0.5Hz to eliminate baseline wander and low-frequency noise.
- 50Hz notch filter to counteract power line interference.

Signal Processing:

- Signals segmented into 6s epochs, considering the non-stationary nature of EEG signals.
- Utilized a 6-second moving window for epoch analysis, with $\boldsymbol{l} = \mathbf{1}, \ldots, \boldsymbol{L}$ indicating the total epoch count.

Labeling Strategy:

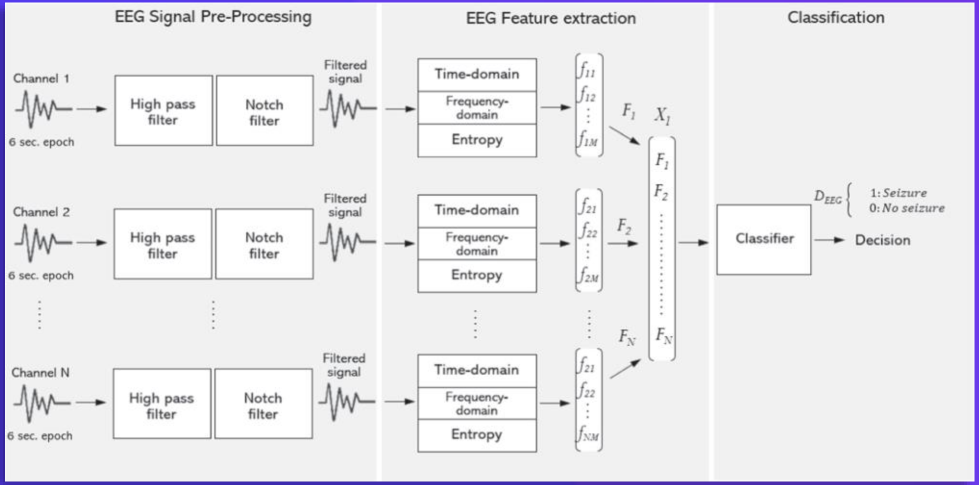
- Detection: Epochs fully within seizure periods labeled as '1' (seizure), with 50% overlap in training set. Non-seizure epochs labeled '0', under-sampled at a 9:1 ratio.
- Prediction: Pre-ictal phase identified as 150 epochs (15 minutes) before seizure onset, labeled '2'. No under-sampling or overlap applied.



Feature Engineering and Extraction

Common for both Detection and Prediction

- ➢ Deal with variability of patients with non-specific model: extraction of time-domain features, frequency-domain features, and entropy features, which reflect signal characteristics from different perspectives.*
  - ➢ Extracted from every 6-second epoch of every channel (N = 19 channels).



- ➢ $M = 22$ features extracted from every channel were concatenated into a feature vector X_l with length of $N \cdot M = 418$.
- ➢ The final matrix for one patient's recording will have shape $L \cdot (N \cdot M)$.

* See features from patient-specific approach

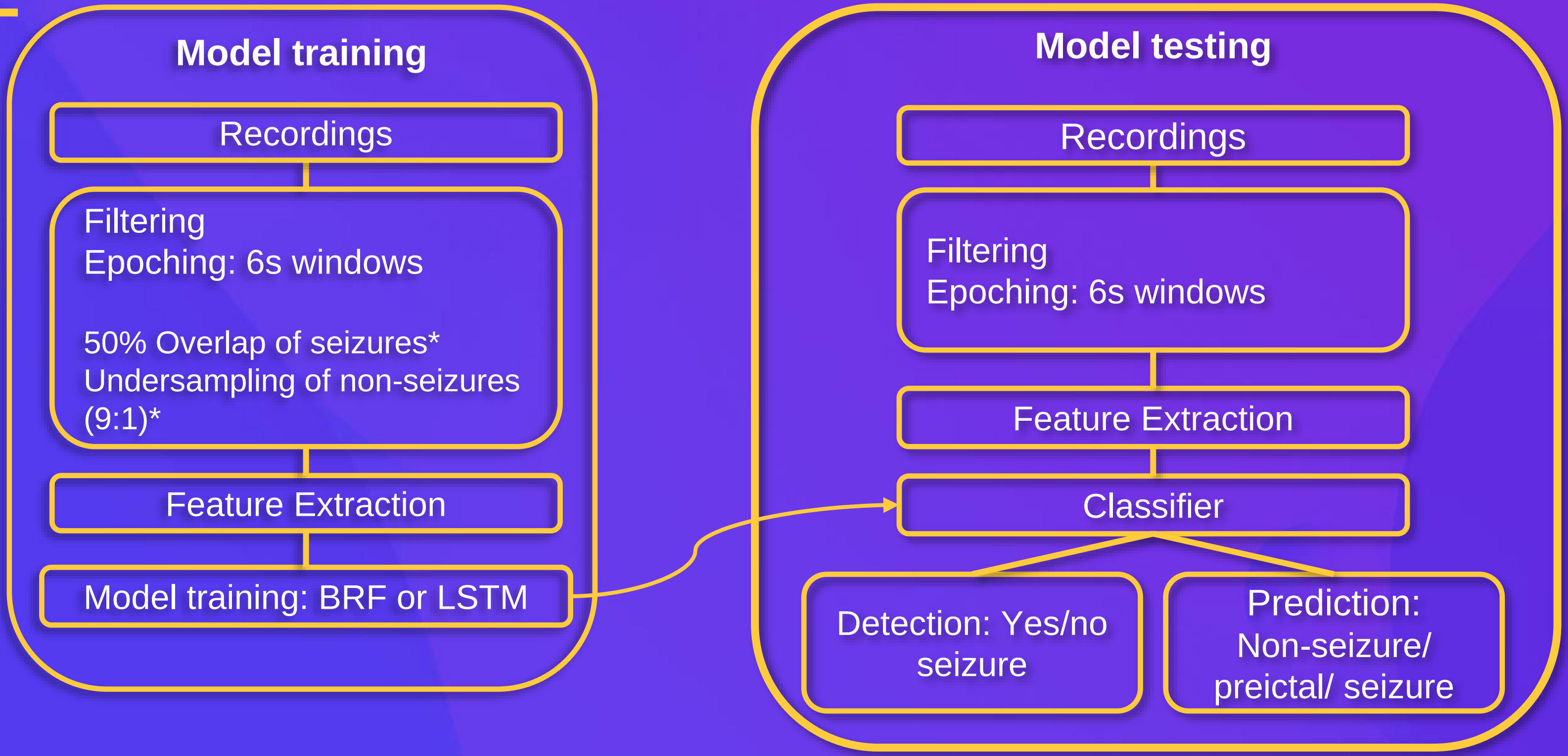
Model Training and Testing

- The features extracted served as an input to a detector based on random forest.
  - Features reflecting different perspectives of the signal were used to represent the variability among patients.
  - The randomly selected subset from features for developing decision trees in random forests will improve the model's generalization and reduce the over-fitting.

- **Leave-one-patient-out cross-validation** scheme was used:
  - One patient left out (testing subset) was used to validate the classifier trained on the remaining patients (training set).
  - Process repeated until each patient had been validated once. Each recording was validated separately, and the mean performance for the patient was computed.
- Grid search was used to find the optimal model parameters.
- The classification performance was evaluated in terms of **sensitivity**, **specificity**, and **false positives* per hour** (FP/h).

* (class 1 and 2 for detection and prediction, respectively)

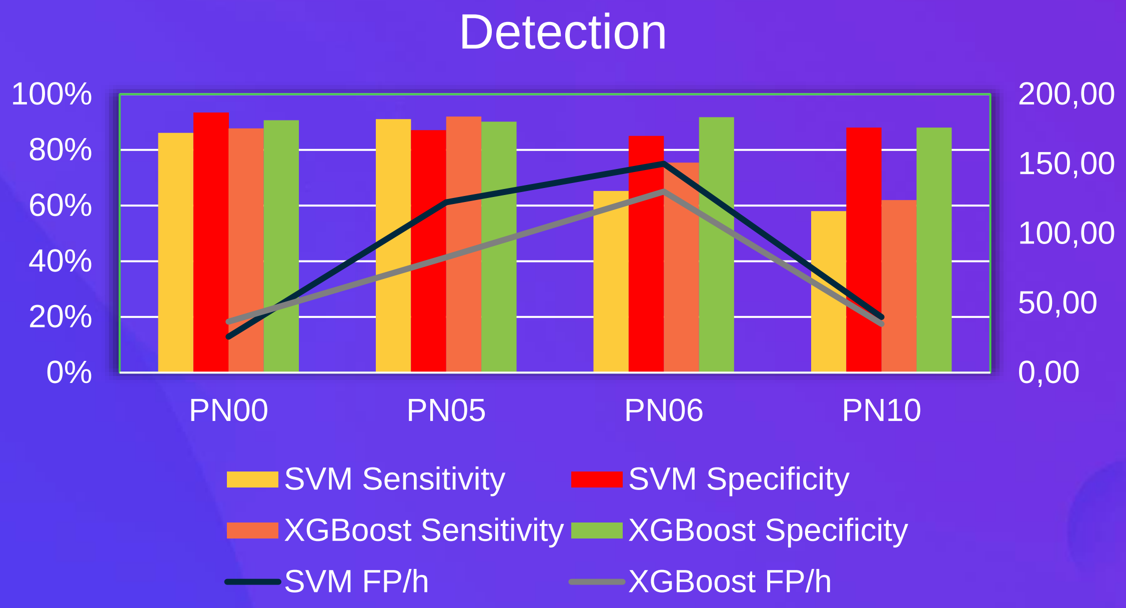
Model Training and Testing: Prediction



* Steps applied only for the detection task.

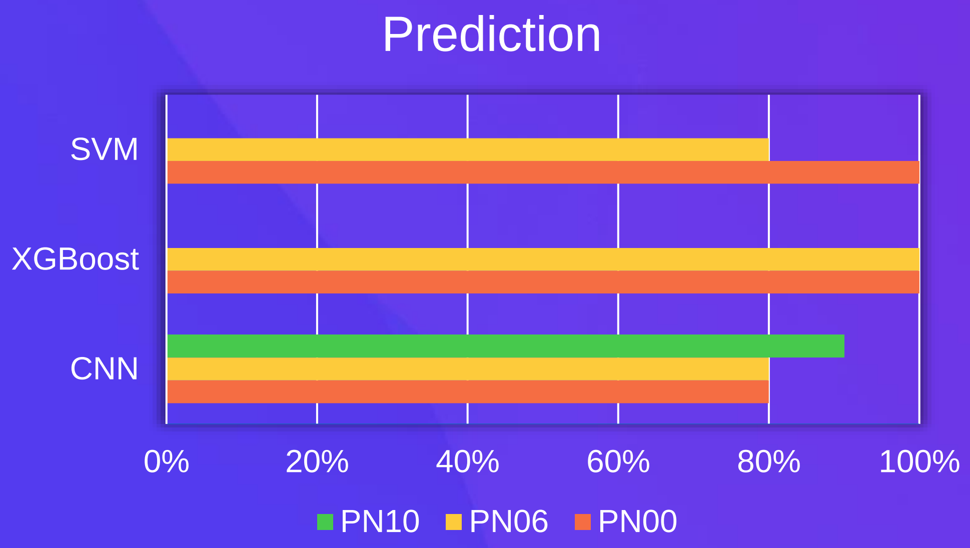
Patient-Specific Approach Results

Analysis and Findings



Patient-Specific Approach Results

Analysis and Findings



SVM

Patient ID	Prediction time	FP/h
PN00	12,88	26,4
PN06	14,86	95,89
Average	13,87	61,14

XGBoost

Patient ID	Prediction time	FP/h
PN00	11,88	27,08
PN06	12,72	63,99
Average	12,30	45,53

CNN

Patient ID	Prediction time	FP/h
PN00	9,2	24,40
PN06	7,4	48,80
PN10	11,1	32,20
Average	9,23	**35,13**

Patient Non-Specific Approach Results

Detection

XGBoost

Patient ID	Sensitivitty	Specificity	FP/h
PN00	0.612	0.979	12.264
PN01	0.952	0.994	3.635
PN03	0.626	0.996	2.206
PN05	0.233	0.979	12.693
PN06	0.766	0.958	25.130
PN07	0.300	0.976	14.089
PN09	0.579	0.966	20.515
PN10	0.583	0.975	14.829
PN11	0.889	0.960	14.066
PN12	0.250	0.996	2.488
PN13	0.797	0.975	14.871
PN14	0.330	0.980	12.314
PN16	0.540	0.986	8.229
PN17	0.566	0.984	9.367
Average	0,573	**0.979**	**11,906**

LSTM

Sensitivitty	Specificity	FP/h
0.688	0.936	36.98
0.809	0.978	13.05
0.437	0.964	21.42
0.344	0.937	37.13
0.708	0.896	61.88
0.400	0.975	14.77
0.597	0.938	36.71
0.607	0.947	31.37
0.777	0.909	53.94
0.478	0.964	21.14
0.825	0.959	23.93
0.303	0.929	42.02
0.297	0.897	60.91
0.767	0.929	41.85
0.575	0.94	35.51

Patient Non-Specific Approach Results

Prediction

	XGBoost			LSTM		
Patient ID	N# Prediction	Prediction time	FP/h	Predictions	Prediction time	FP/h
PN00	0%	-	1,66	40%	6,75	4,82
PN01	50%	3,9	13,48	100%	10,3	6.60
PN03	100%	9,25	11,92	100%	14,85	28,84
PN05	33%	12,6	1,97	100%	7,90	8,77
PN06	40%	3,85	2,40	100%	12,74	29,43
PN07	0%	-	8,73	100%	12,7	12,48
PN09	66%	13,45	2,25	100%	14,3	63,69
PN10	40%	6,65	3,12	100%	9,98	16,94
PN11	100%	2,8	2,41	100%	14,4	32,36
PN12	0%	-	1,94	75%	7,83	13,66
PN13	0%	-	2,76	100%	12,9	56,74
PN14	50%	11,65	5,11	100%	10,6	23,72
PN16	0%	-	2,32	50%	12,0	25,88
PN17	0%	-	2,55	100%	9,2	21,52
Average	31,64%	8,01	**6,25**	**90,35%**	**11,17**	24,67

Challenges and Limitations

Improving the task pipeline

- Data Unbalance: The dataset comprised only 14 patients, with seizure episodes accounting for less than 1% of the total recording hours:
  - This extreme data imbalance poses significant challenges in model training and performance evaluation.
- Data Quality: The need for better denoising and advanced artifact removal algorithms, such as Independent Component Analysis (ICA) is critical.
  - However, these processes require the supervision of medical experts to ensure the validity and reliability of the procedure.
- Complex Task Pipeline:
  - Various steps in the task pipeline, including epoching, overlapping, undersampling, feature engineering, and the model itself, could be contributing to the current limitations.

Future Improvements

Exploring new strategies

- Fine-Tuning Approach: To leverage the existing strengths of the patient non-specific approach, we aim to implement a fine-tuning strategy.
  - This would allow the model to be initially trained on a broad dataset and subsequently tailored to include patient-specific information.

- Expanding the Dataset: Increasing the number of patients in the dataset and the diversity of seizure episodes can significantly enhance model training and generalization.

- Collaboration with Medical Experts: Continuous collaboration with medical experts to refine denoising and artifact removal algorithms, ensuring high-quality data for model training.

- Pipeline Optimization: A thorough review and optimization of the task pipeline, from data preprocessing to model evaluation, to identify and mitigate bottlenecks.