



DEEPHEALTH

Use Case 13

Lab 3: Epileptic Seizure Detection

Winter School 25/01/2022



The project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 825111.



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Epilepsy Detection

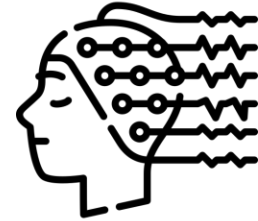


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Epilepsy Detection

Introduction

- Epilepsy
 - Neurological disorder characterized by **recurrent seizures**
 - Episodes of **involuntary movement**
 - Around **50 million** people diagnosed in the world
- Electroencephalogram (**EEG**)
 - Recording the **electrical activity** of the brain
 - **Electrodes** located on the scalp
 - Continuous **signal** composed of different channels





Epilepsy Detection

Brain stages



Interictal

Normal activity.



Pre-ictal

Strange brain activity, usually before an actual seizure.



Ictal

Period while a patient is suffering a seizure.



Post-Ictal

The patient is recovering from a seizure.

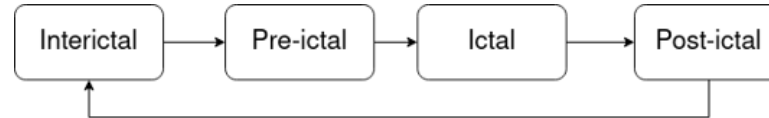




Epilepsy Detection

Brain Stages

- General cycle of stages



- Automatic **seizure detection** task (not prediction few minutes before seizures)

Class 0
Interictal + Pre-ictal + Post-ictal

Class 1
Ictal

- **High variability** between subjects
 - **Patient-Dependent** classifiers

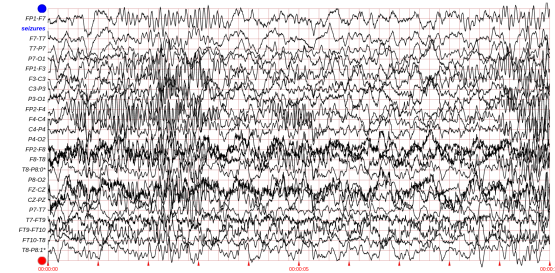


Dataset



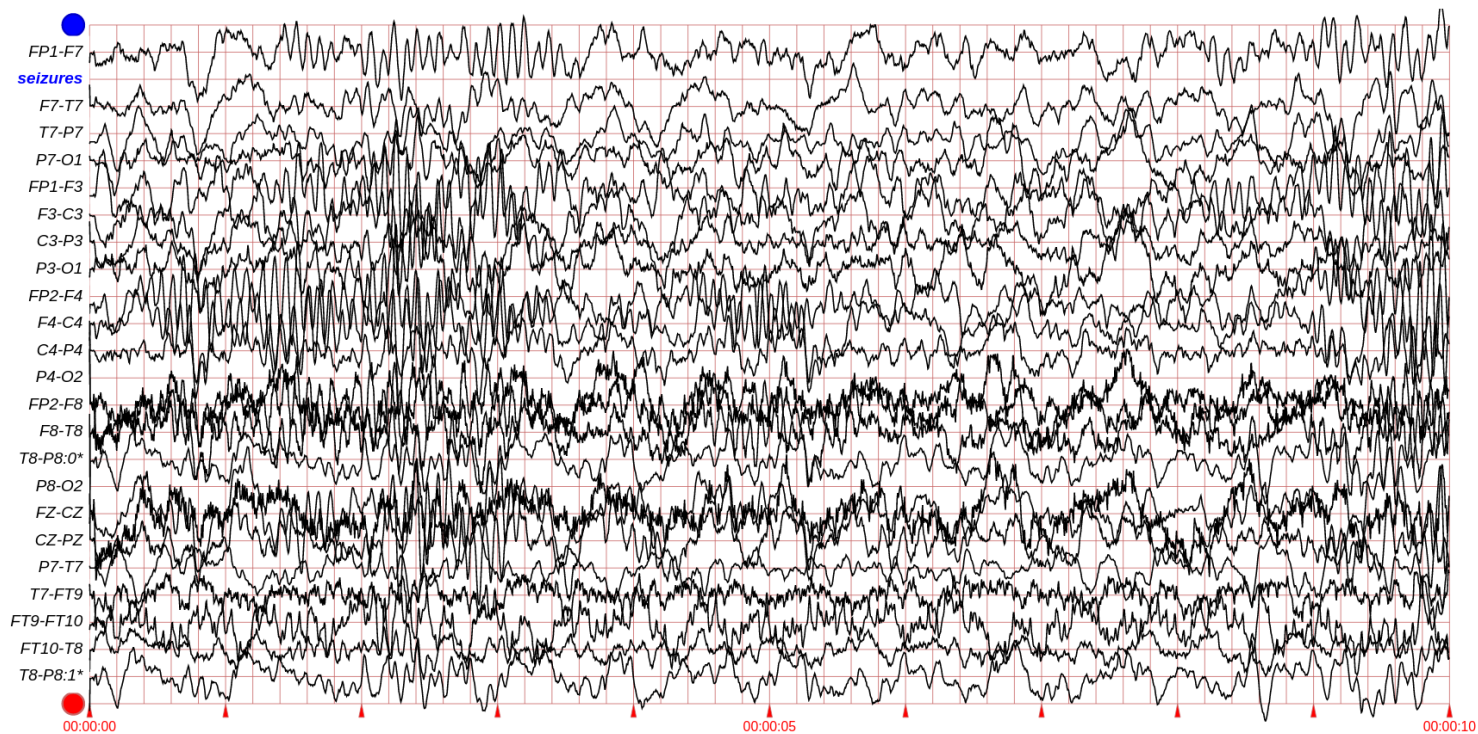
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Dataset

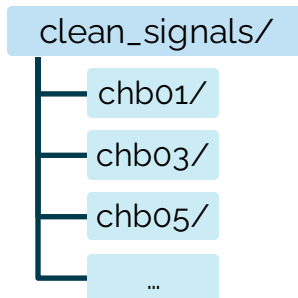
Data description



Dataset

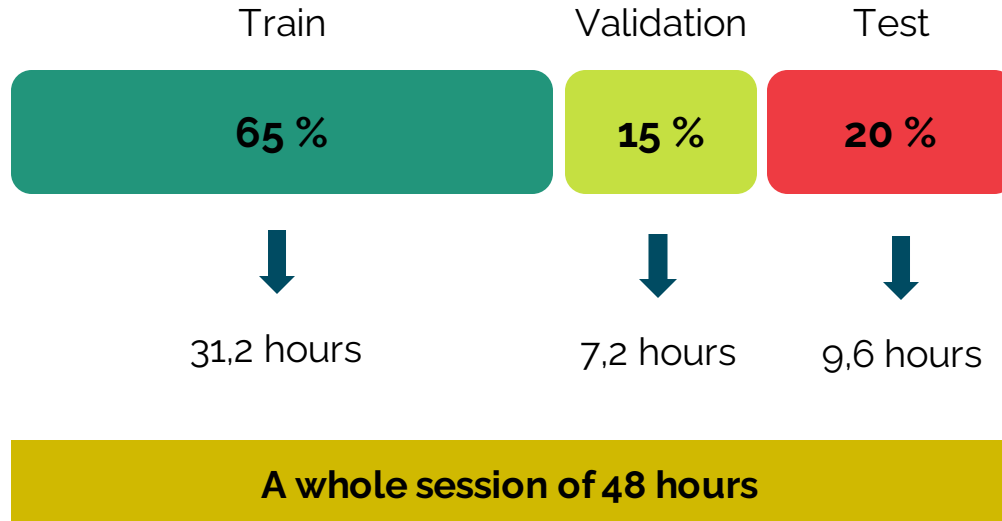
Data preparation, cleaning and selection

- Preparation preprocess (Data cleaning process done by Winter-School team):
 1. Read signals from EDF format
 2. Homogenize signals to have each channel in the same position
 3. Store the data in a Python dictionary (containing signals and seizure information)
 4. Serialize the object in Pickle to save it (.pbz2 files)
- We provide a subset of the original dataset already cleaned



Dataset

Splits



Splits not in
chronological order

Dataset

Class imbalance

Seizures normally last few seconds, so there is a high class imbalance.

Patient id	# files without seizures	# files with seizures	# interictal hours	# ictal hours
chb01	35	7	40,43	0,12
chb03	31	7	37,89	0,11
chb05	34	5	38,85	0,16
chb08	15	5	19,75	0,26
chb12	11	10	20,41	0,28
chb14	19	7	25,95	0,05
chb15	25	14	38,46	0,55
chb24	10	12	21,15	0,14
Total	180	67	242,89	1,67

Recurrent Approach



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Recurrent Approach

Introduction

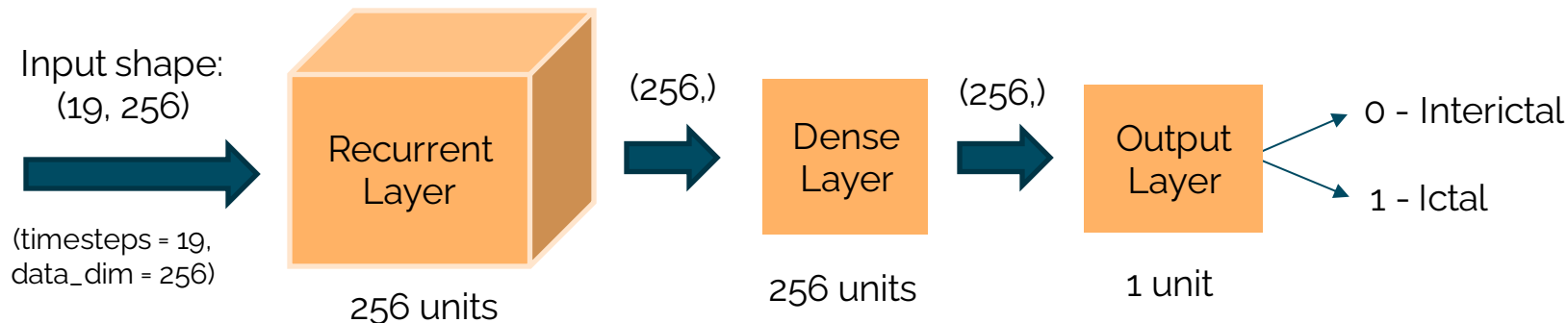
- Recurrent Neural Networks
 - LSTM / GRU layers
- Data Loader
- Post inference process
- Metrics
 - Neural Network Metrics
 - Post inference Metrics
- Results





Recurrent Approach

RNN topologies based on LSTM and GRU layers



In the first example provided we are using **19** timesteps of one-second-long sliding windows, that is why the input shape is **(19, 256)**. Because each one of the 23 channels is processed independently.



Recurrent Approach

Data Loader

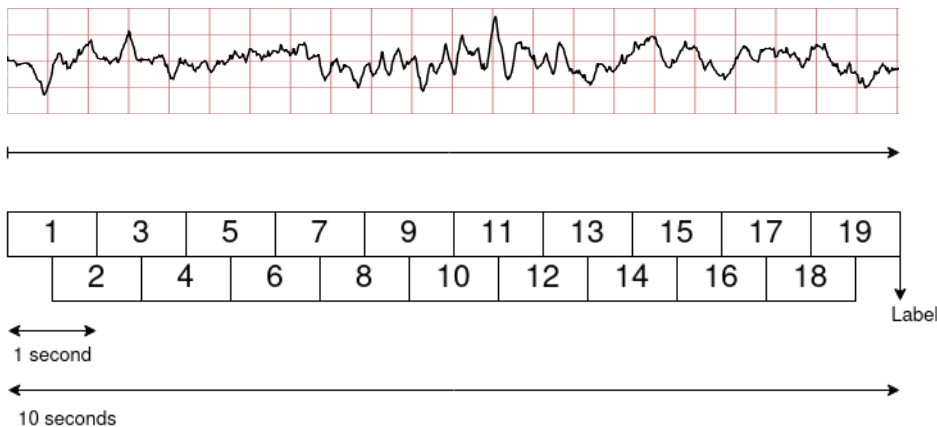
- Data Loader Sequence Parameters
 - window_length (in seconds)
 - shift (in seconds)
 - timesteps

```
dg = RawRecurrentDataGenerator(index_filenames=['../indexes_detection/chb01/test.txt'],  
                                window_length = 1, # in seconds  
                                shift = 0.5, # in seconds  
                                timesteps = 19, # in seconds  
                                sampling_rate = 256, # in Hz  
                                batch_size = 10,  
                                do_standard_scaling = True,  
                                in_training_mode = True,  
                                balance_batches = True,  
                                patient_id = 'chb01')
```


Recurrent Approach

Data Loader - Example

- Example of sequence generation
 - window_length = 1 second
 - shift = 0.5 seconds
 - timesteps = 19



$(19, 256)$



When using all the 23 channels

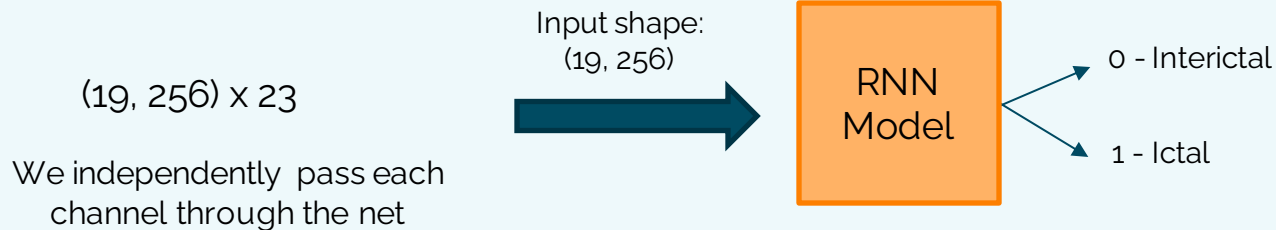
$(19, 256) \times 23$



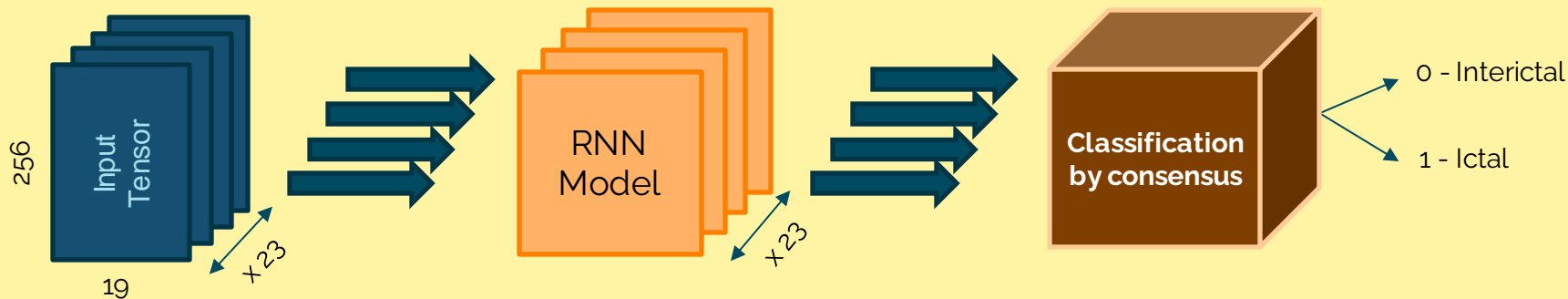
Recurrent Approach

Data Loader - Example

Training Mode



Inference Mode

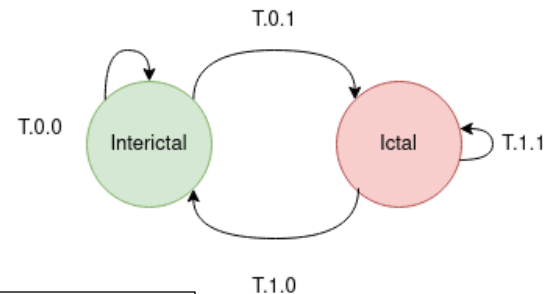
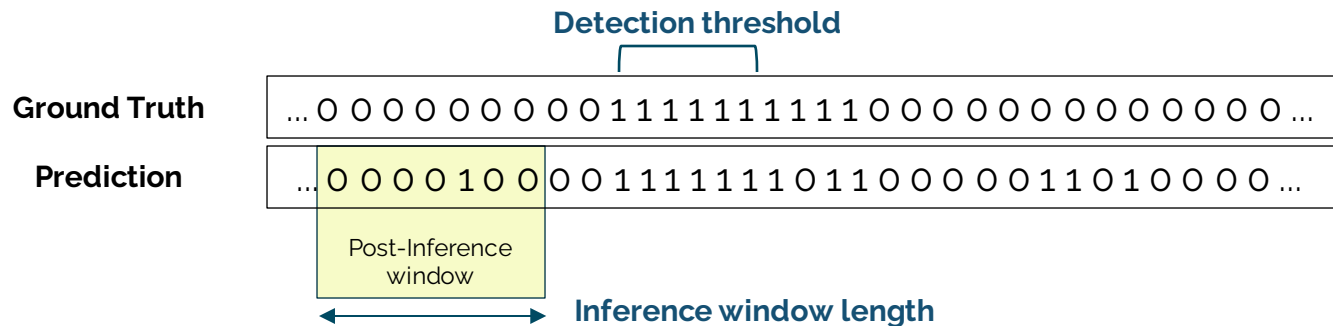




Recurrent Approach

Post inference process

- Post inference function to act as a detector
 - Analyses the consecutive outputs
 - Raises alarms when it detects a seizure



If the proportion of ones inside the post-inference window while being in the **Interictal** state is greater than **alpha_pos**, it makes the transition from Interictal to Ictal: T.0.1

If the proportion of ones inside the post-inference window while being in the **Ictal** state is lower than **alpha_neg**, it makes the transition from Ictal to Interictal: T.1.0





Recurrent Approach

Metrics

Classifier Metrics

- Accuracy
- Macro F1-score
- Balanced Accuracy
- Metrics at two levels
 - Channel independent
 - Ensemble: all 23 channels combined

Post Inference process Metrics

- Post-inference window accuracy
- Percentage of detected seizures
- Average Latency (in seconds)
- False Alarms per hour





Recurrent Approach

Results

Experiment configuration

Window Length (s)	Shift (s)	Timesteps	Model	Optimizer	Initial LR	Epochs
1	0,5	19	GRU	Adam	0,0001	10

Post-Inference Parameters

Post-Inference Window Length (in timesteps)	Alpha_pos	Alpha_neg	Detection Threshold (s)
20	0,4	0,4	20



Recurrent Approach



	Test						Post-Inference Process with Test subset					
	Channel Independent			Combined channels			Acc	# Seizures	Detected seizures	Latency (s)	False Alarms per Hour	Hours
Patient	Acc	F1-Score	Balanced Acc	Acc	F1-score	Balanced Acc						
chb01	99,75%	0,8828	86,34%	99,93%	0,9667	94,45%	99,90%	2	100,00%	11,75	0,00	9,62
chb03	99,62%	0,6117	57,53%	99,64%	0,4991	50,00%	99,64%	2	0,00%	-	0,00	8,97
chb05	99,75%	0,8553	87,35%	99,90%	0,9335	88,46%	99,87%	1	0,00%	-	0,13	7,98
chb08	97,60%	0,7215	83,11%	99,49%	0,9054	87,71%	99,49%	1	100,00%	18,00	0,80	4,99
chb12	95,26%	0,5774	63,09%	97,63%	0,6018	58,85%	97,53%	11	54,55%	13,92	2,67	5,98
chb14	99,76%	0,5856	58,21%	99,85%	0,5252	51,32%	99,85%	2	0,00%	-	0,00	6,98
chb15	96,70%	0,6383	67,83%	97,86%	0,6363	61,32%	97,71%	7	28,57%	11,75	1,89	8,98
chb24	99,34%	0,7385	69,23%	99,49%	0,7586	67,56%	99,44%	4	100,00%	11,50	0,16	6,28

Convolutional Approach



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Convolutional Approach

Introduction

- Time Delay Convolutional Neural Networks
- Post Inference Process
- Metrics
 - Neural Network Metrics
 - Post inference Metrics
- Results



Convolutional Approach

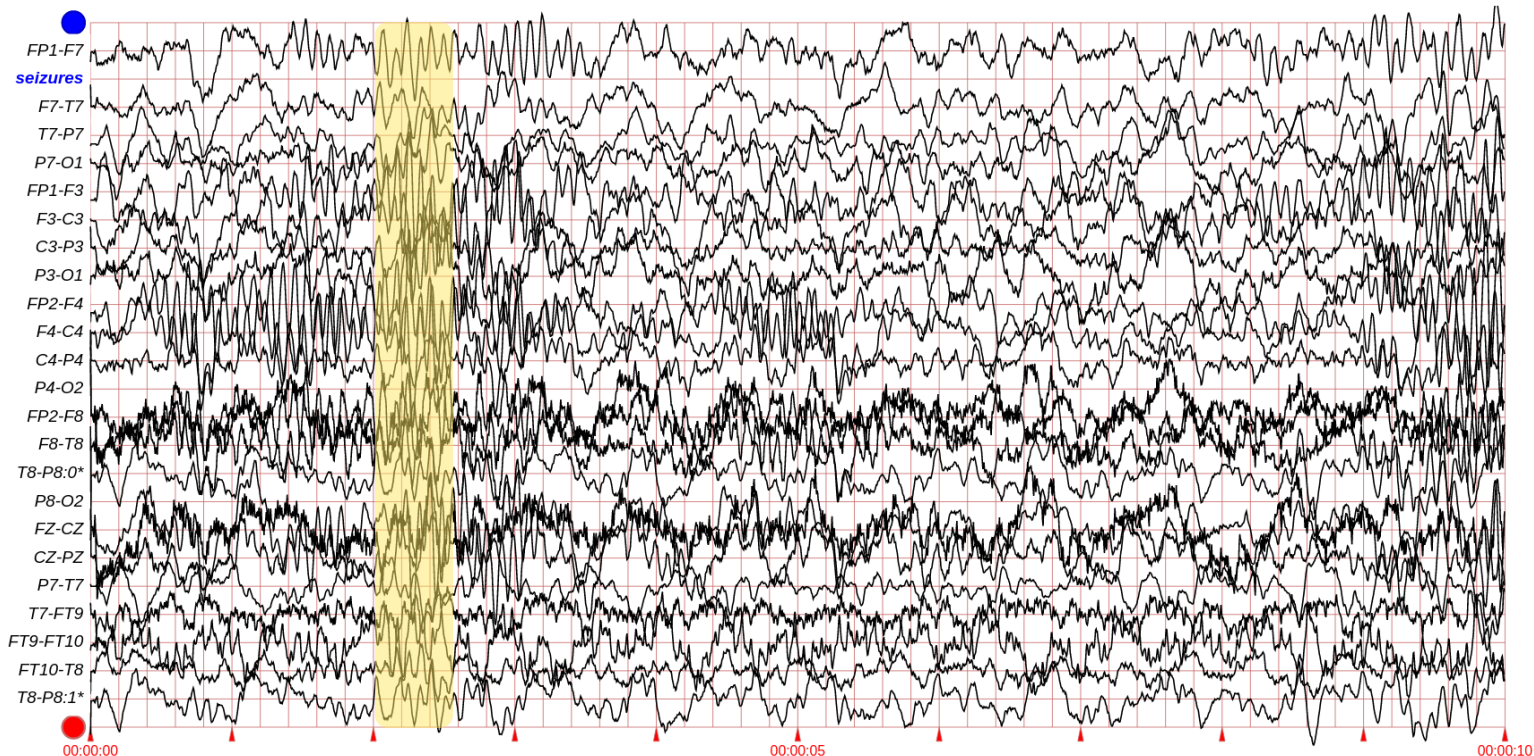
Time Delay Convolutional Neural Networks



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Kernel_size = (128, 23), strides = (64, 1) --> 500 ms long window shifted every 250 ms

Input shape: (2560, 23)





Convolutional Approach

- Models available in the pipeline
 - "conv1"

- Post Inference Process
- Metrics
 - Neural Network Metrics
 - Post inference Metrics

The same as in the recurrent approach





Convolutional Approach

Results

Experiment configuration

Window Length (s)	Shift (s)	Model	Optimizer	Initial LR	Epochs
10	0,25	Conv1	Adam	0,00001	10

Post-Inference Parameters

Post-Inference Window Length (in timesteps)	Alpha_pos	Alpha_neg	Detection Threshold (s)
20	0,4	0,4	20



Convolutional Approach



	Test			Post-Inference Process with Test subset					
Patient	Acc	F1-score	Balanced Acc	Acc	# Seizures	Detected seizures	Latency (s)	False Alarms per Hour	Hours
chb01	99,72%	0,8940	96,15%	99,69%	2	100,00%	9,00	0,73	9,62
chb03	99,62%	0,8086	91,86%	99,56%	2	100,00%	2,88	1,78	8,98
chb05	99,66%	0,8330	92,07%	99,59%	1	0,00%	-	1,76	7,98
chb08	99,2%	0,8477	81,74%	99,19%	1	100,00%	16,75	1,80	4,99
chb12	96,73%	0,5530	55,63%	96,51%	11	45,45%	15,90	7,52	5,98
chb14	98,83%	0,4971	49,49%	98,71%	2	0,00%	-	4,01	6,98
chb15	97,63%	0,7848	94,28%	97,52%	7	57,14%	10,44	3,01	8,98
chb24	99,22%	0,6435	60,05%	99,23%	4	75,00%	9,25	0,96	6,28

Conclusions



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Conclusions

Conclusions of the results

- We did not find an **ideal model** that works well with every patient
- In general, **slightly better accuracy** with the convolutional approach
- In some cases, the **recurrent approach** has more latency but less false alarms, and the **convolutional approach** has lower latency but more false alarms per hour.



Resources



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Resources

Original Dataset

[CHB-MIT Scalp EEG Database](#)

Prepared Dataset

clean_signals.zip (7.6 GB) [Option 1](#) [Option 2](#)

Pipeline Repository

[UC13_pipeline](#)





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Thank you!

Javier Martínez Bernia

jamarbe2@prhlt.upv.es



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