A GENERALIZABLE MODEL FOR Seizure Prediction BASED ON DEEP LEARNING USING CNN-LSTM ARCHITECTURE

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Motivation

Epilepsy

- The fourth most common neurological disorder
- Affecting about 65 million people around the world
- Sudden seizures

Seizure Prediction

- Uncontrollable seizures in about $\frac{1}{3}$ of the patients
- The importance of seizure prediction systems
- EEG signals

Information obtained from www.epilepsy.com/learn/about-epilepsy-basics

Outline

- Introduction
- Literature Review
- Methods and Material
- Results and Discussion
- Conclusion

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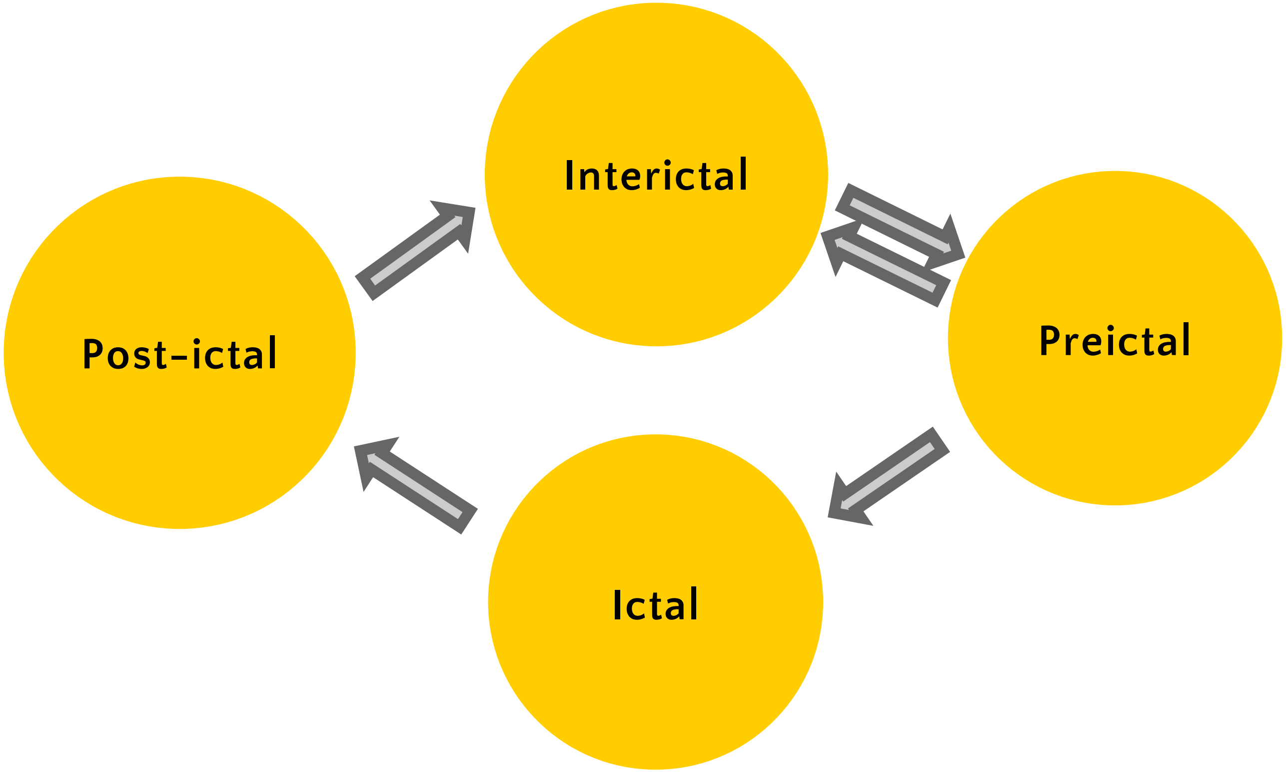
Epilepsy Temporal States

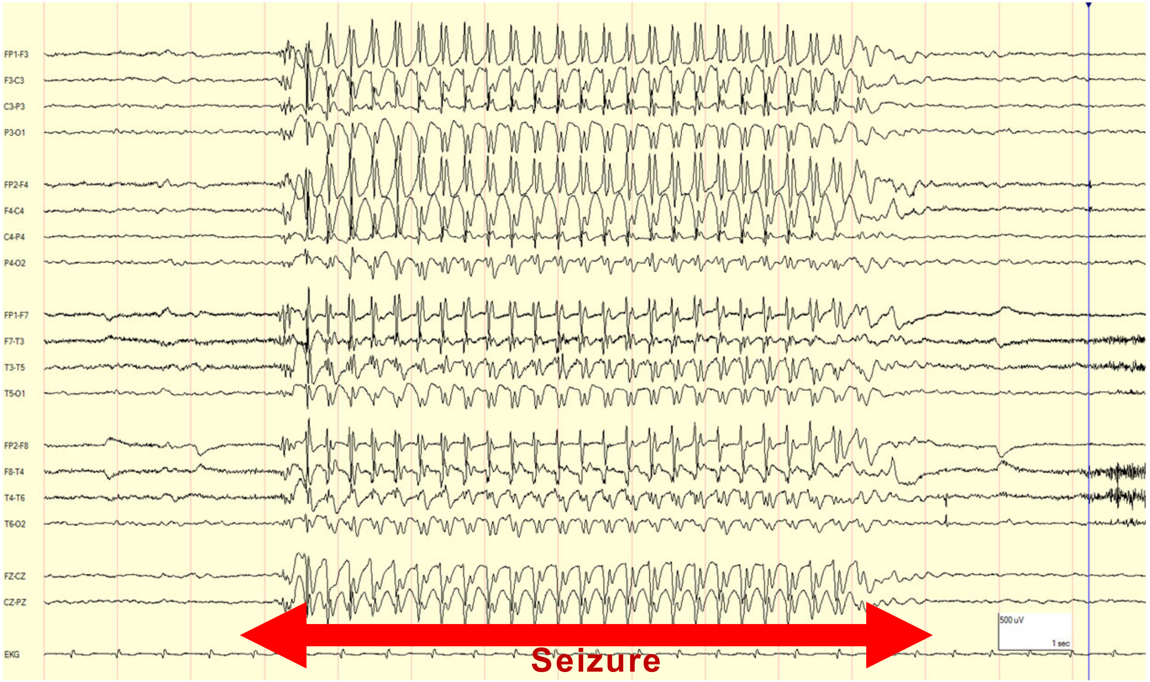


Challenges

- complexity and variability preictal patterns
  - different patients
  - different seizures of the same patient

- Preictal Labels

Epileptic EEG Signals



https://www.epilepsydiagnosis.org/seizure/absence-typical-eeg.html

Deep Neural Networks

- Proved to be powerful in many areas
- Convolutional Neural Networks (CNN)
  - Extracting the best features from the best channels using trainable filters
- Recurrent Neural Networks (RNN)
  - Sequences
  - Long Short-term Memory (LSTM)

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Literature Review

- Studies based on hand-crafted Features [1]
  - Complex and time consuming feature extraction and selection
- Studies based on CNNs [2],[3],[4]
  - 2D images constructed from EEG segments as input
  - Mediocre performance
- Hand-crafted Features + RNN [5]
  - Suffers from the problems of hand-crafted feature extraction

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The Whole Picture

Dataset

- CHB-MIT Dataset*
  - Non-invasive continuous EEG recordings
  - 22 patients, 23 cases
  - 23 channels (most cases)
  - Annotation contains the start and the end of each seizure
- Extra annotation for this work
  - **Preictal**: up to 30 minutes before each seizure onset
  - **Interictal**: recordings at least 2 hours away from seizures and their annotated preictal state

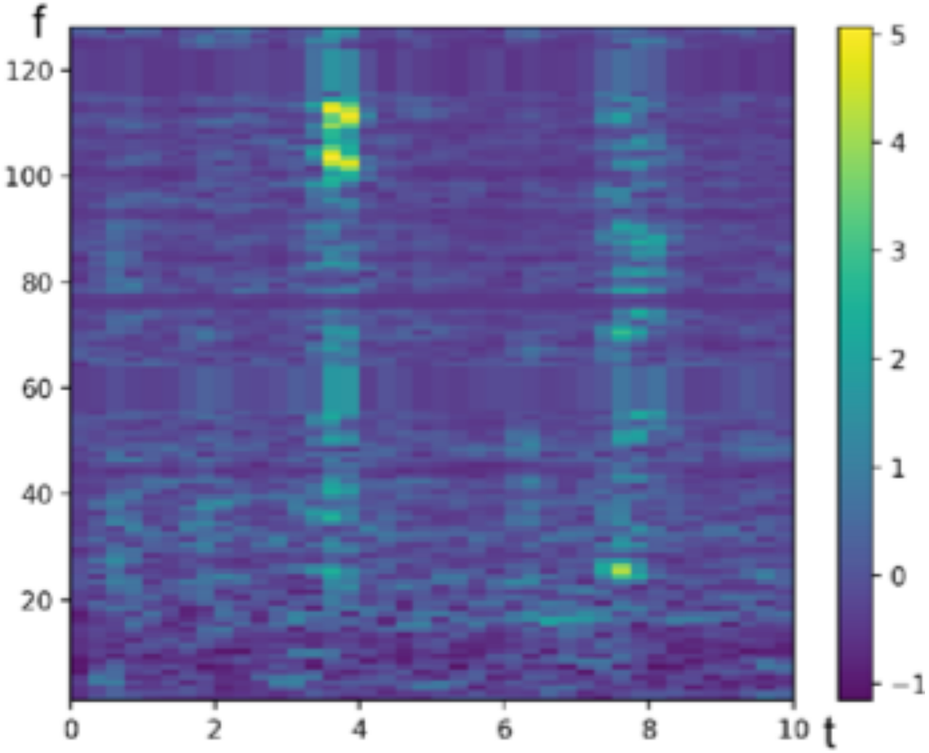
* Dataset is available at https://www.physionet.org/pn6/chbmit/

Preprocessing

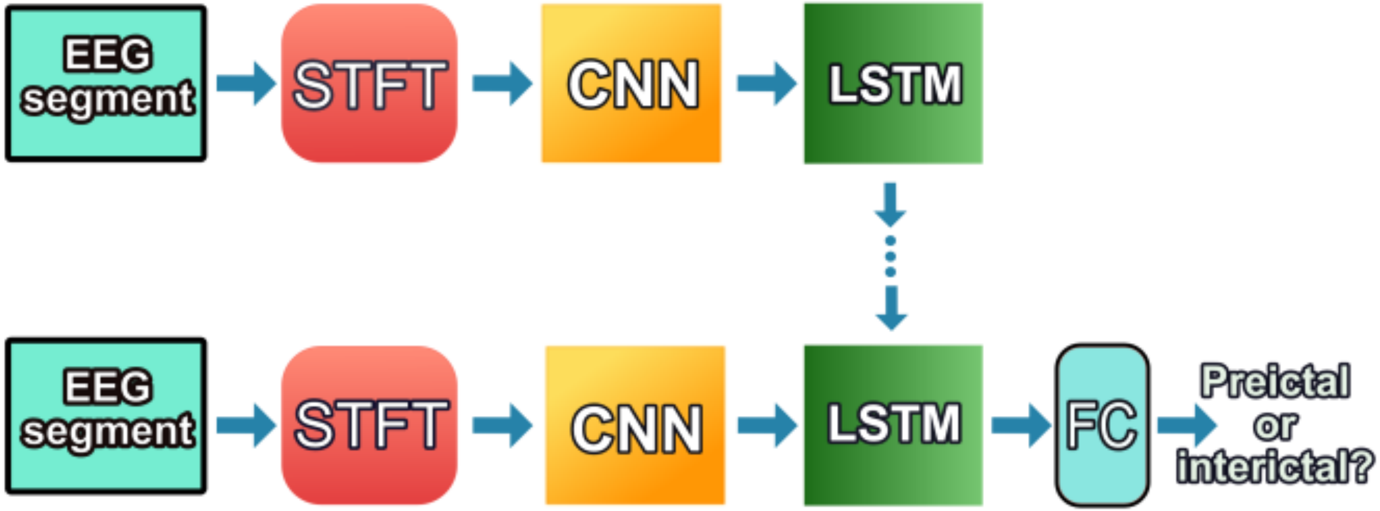
- Split EEG recordings into sequence of segments
  - Sequences of six 10-second overlapping segments
- Short-Time Fourier Transform
  - 1-second sliding window with 75% overlap
  - Removing DC frequency and frequencies related to power line noise
  - Standardizing each frequency along the time axis

Preprocessing

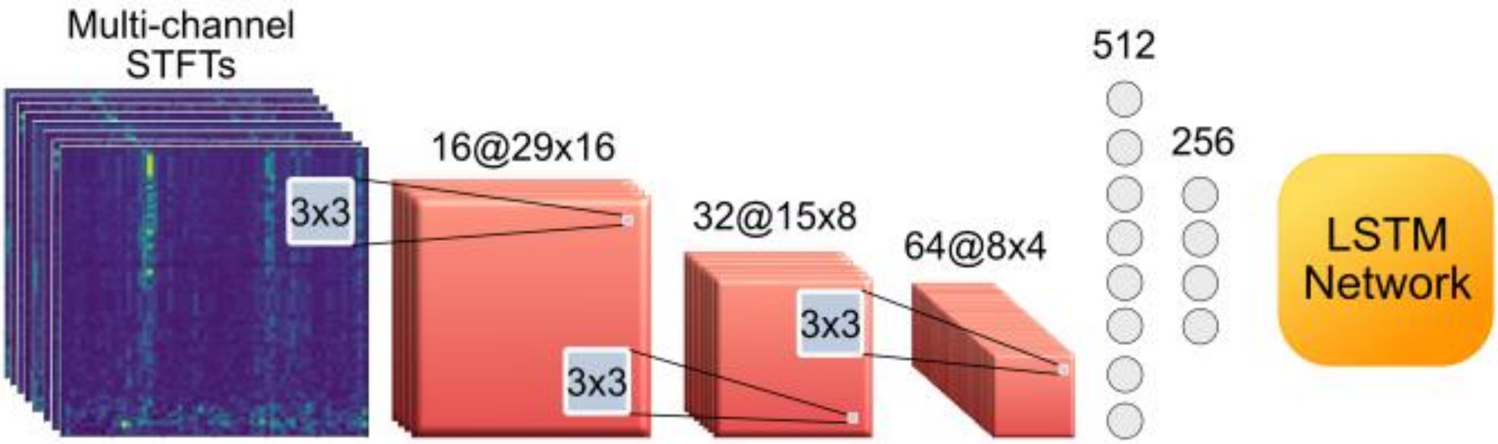
An example of a standardized STFT image extracted from a 10-second EEG segment



Proposed CNN-LSTM Architecture



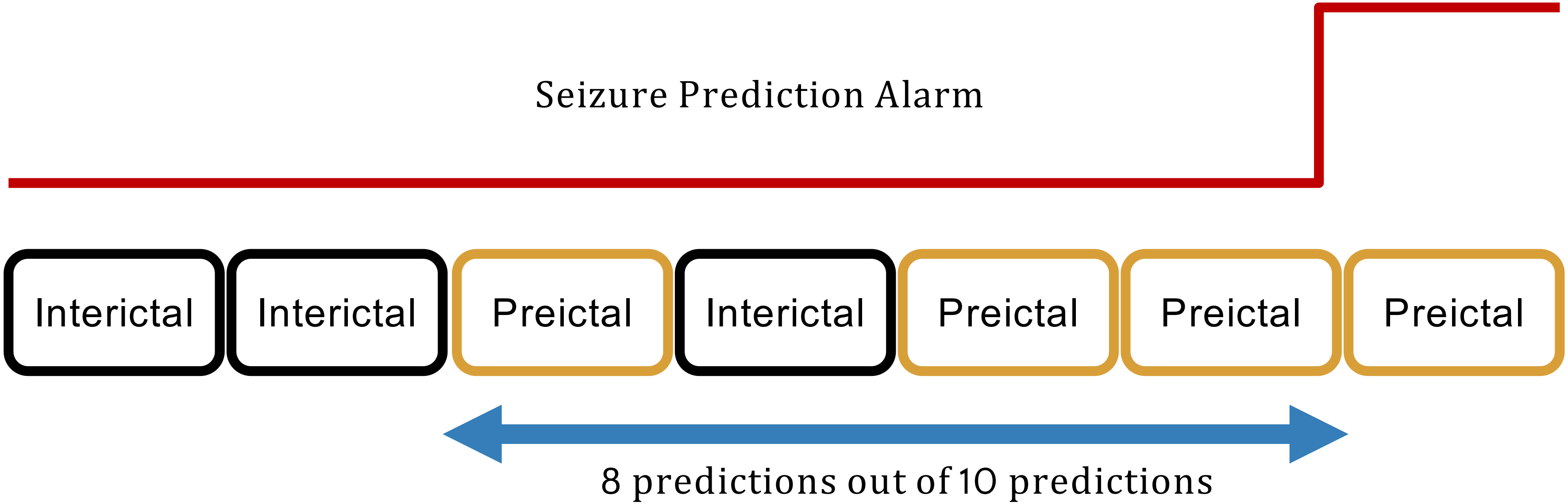
CNN Architecture



Network Training

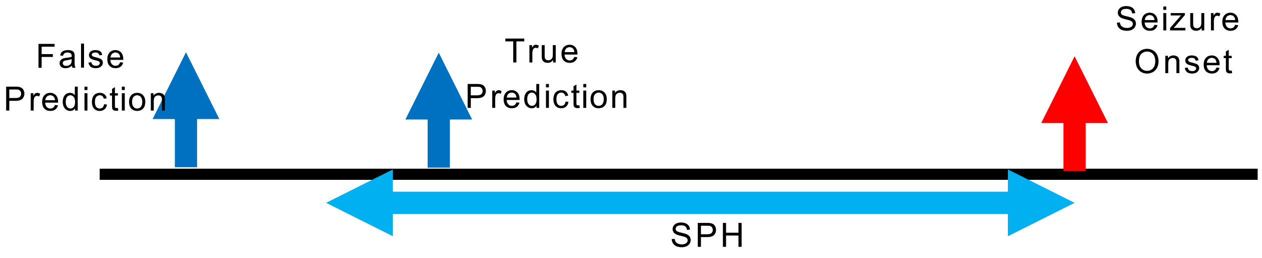
- Patient-specific training
- Pre-training of the CNN weights
- Train and test sets
  - Preictal data
    - Leave one seizure out
  - Interictal Data
    - 40% of non-seizure files as test set

Post-Processing



Evaluation

- $\text{Sensitivity} = \frac{\text{TP}}{\#\text{seizures}} \times 100$
- $\text{FPR} = \frac{\text{FP}}{\#\text{hours}} \times 100$
- Seizure prediction Horizon (SPH)
  - 30 minutes



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Results

Sensitivity:
98.21 %

FPR: 0.13 /h

Prediction Time:
44.74 min.

Case	No. seizures	Sen. (%)	FPR (/h)	Pred. Time (Minutes)
01	5	100.00	0.08	29.50
02	2	100.00	0.06	50.00
03	4	75.00	0.00	32.00
05	3	100.00	0.00	35.00
07	3	100.00	0.16	49.00
09	3	100.00	0.00	103.00
10	7	100.00	0.50	32.00
17	3	100.00	0.22	43.00
18	4	100.00	0.13	37.00
19	2	100.00	0.00	46.00
20	4	100.00	0.00	26.00
21	4	100.00	0.50	51.92
22	3	100.00	0.18	40.00
23	2	100.00	0.18	52.00

Comparison with Related Works

Year	Authors	Dataset	Method	Sen. (%)	FPR (/h)	Pred. Time (min)
2009	Mirowski et al [13]	Freiburg 15 cases	Bivariate features + CNN	71	0	-
2017	Truong et al [14]	CHB-MIT 13 cases	STFT + CNN	81.2	0.16	-
2017	Khan et al [15]	CHB-MIT 13 cases	Wavelet + CNN	83.3	0.14	5.81
2018	Tsiouris et al [16]	CHB-MIT 24 cases	Hand-crafted features + LSTM	99.8	0.02	-
2018	This work	CHB-MIT 14 cases	STFT + CNN-LSTM	98.2	0.13	44.74

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Conclusion

- A novel method based on CNN-LSTM architecture
  - Outperforming studies based on CNN
  - Learning time-frequency features without human supervision
- Future Work
  - Optimal Preictal length for each patient
  - Unsupervised methods based on temporal clustering

References

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[5] K. M. Tsiouris, et al., "A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals," Computers in biology and medicine, 2018.

Thank You!

Any **questions** ?

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