A deep learning-based method for automatic detection of epileptic seizure in a dataset with both generalized and focal seizure types

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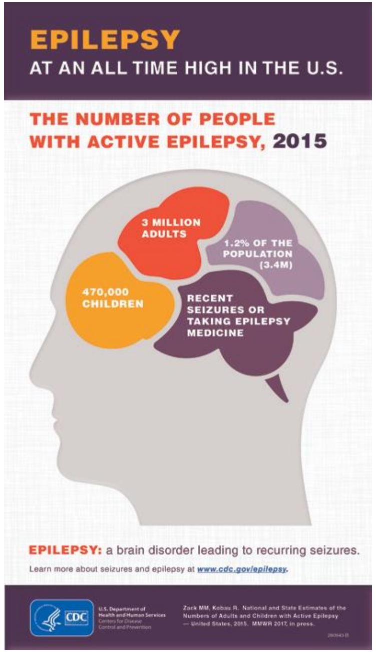
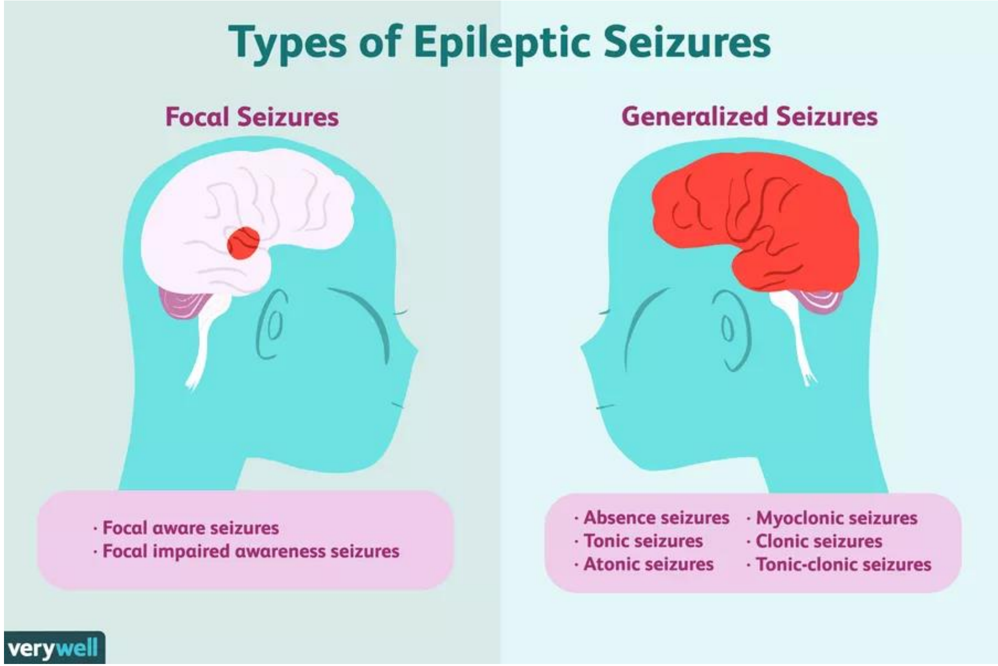




A general seizure detection outline

EEG signal recording → Preprocessing (ICA, segmentation of entire epochs, etc.) → Automatic or Hand-engineered feature extraction → Seizure detection using some Machine Learning method

Performance metrics of the previous studies on Seizure detection

Related works	Method	Accuracy	Sensitivity	Specificity	Precision	F-measure	Dataset
Vidyarante et al.	DRNN on raw EEG data	–	100	99.2	–		CHB-MIT
Birjandtalab et al.	Normalized Spectral features + MLP for each subject	–	96.27	–	94.21	95.3	21 patients
Bolagh et al.	Subject-selection and Subject-clustering to select relevant individuals	89.84	85.87	89.64	–	–	CHB-MIT
Talha Avcu et al.	SeizNet, a CNN for seizure detection	–	95.8	–	–	–	29 patients

public datasets used in the literature of the seizure detection

Name of dataset	# subjects	recording	Types of seizure
CHB-MIT [11]	22	21 channel scalp EEG	Not mentioned
Freiburg [9]	21	126 channels Intracranial electrodes	Focal
Bonn [4]	–	Intracranial electrodes, single channel	Focal
TUH [12]	ongoing	21 channel scalp EEG	Generalized and Focal

Main drawbacks of the mentioned studies on Seizure detection

Hand-engineered features

We process raw EEG signals using a DL framework

Using a dataset that consists of only one kind of seizure

We use a dataset with both generalized and focal seizure types

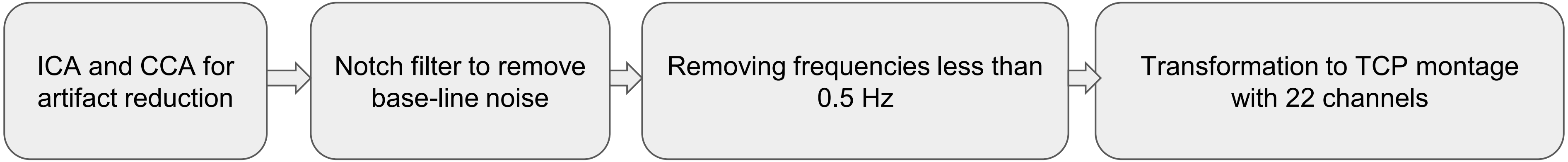
Less attention to the cross-subject learning

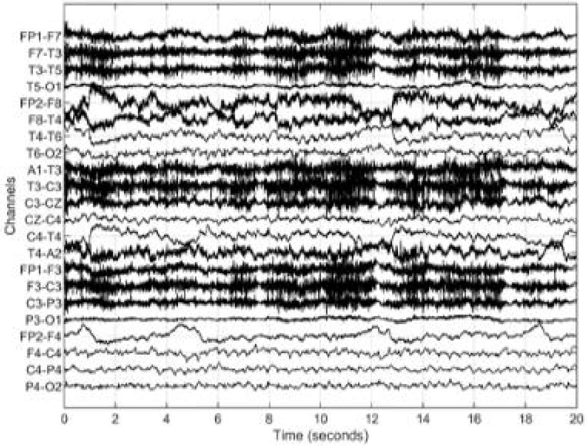
We use LOSO as a cross-subject scenario

Dataset used in this paper

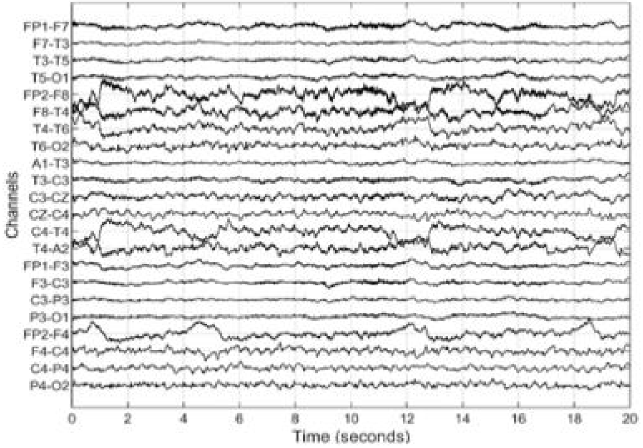
Name of dataset	# subjects	recording	Types of seizure	Sampling frequency	Length of recordings
TUH	Ongoing (>70)	21 channel scalp EEG	Generalized and Focal	250 or 256 Hz	Between 10 to 60 minutes

➢ **Preprocessing scheme:**

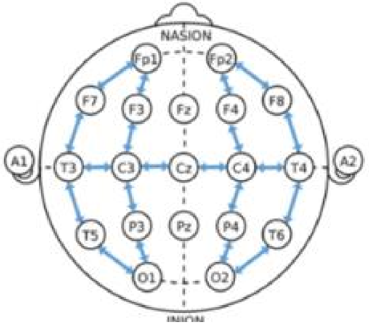




EEG signal contaminated with EMG artifacts. This artifact can be seen with high frequency (>30 Hz) activity in some channels such as FP1-F7 (patient ID 00000177).



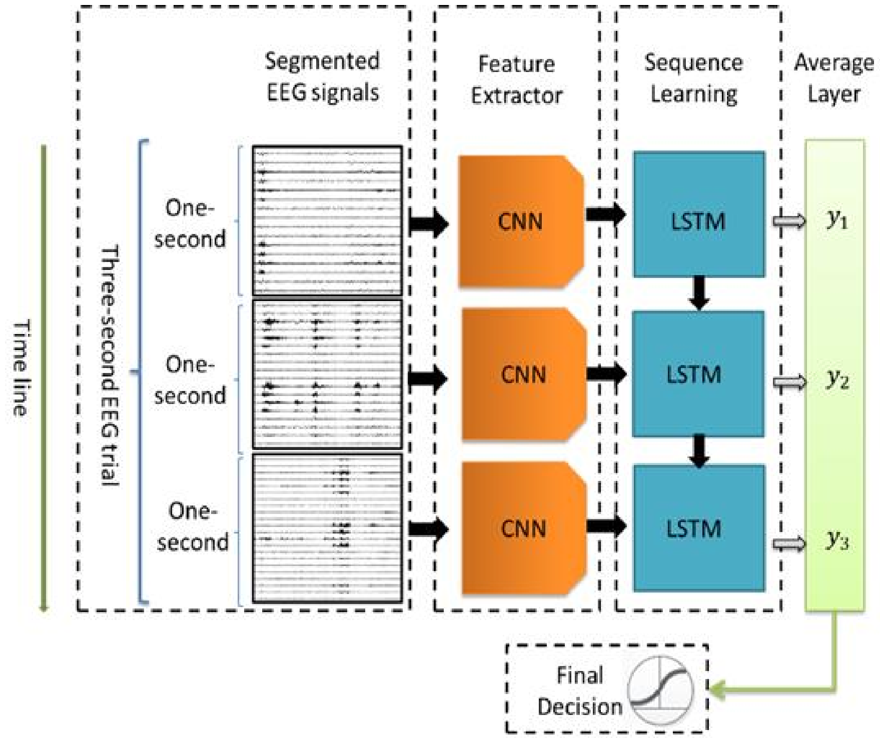
EEG signals after automatic artifact reduction. EMG artifacts in channels such as FP1-F7 are reduced using BSS method (patient ID 00000177).



Montage0	FP1-F7	Montage11	CZ-C4
Montage1	F7-T3	Montage12	C4-T4
Montage2	T3-T5	Montage13	T4-A2
Montage3	T5-O1	Montage14	FP1-F3
Montage4	FP2-F8	Montage15	F3-C3
Montage5	F8-T4	Montage16	C3-P3
Montage6	T4-T6	Montage17	P3-O1
Montage7	T6-O2	Montage18	FP2-F4
Montage8	A1-T3	Montage19	F4-C4
Montage9	T3-C3	Montage20	C4-P4
Montage10	C3-CZ	Montage21	P4-O2

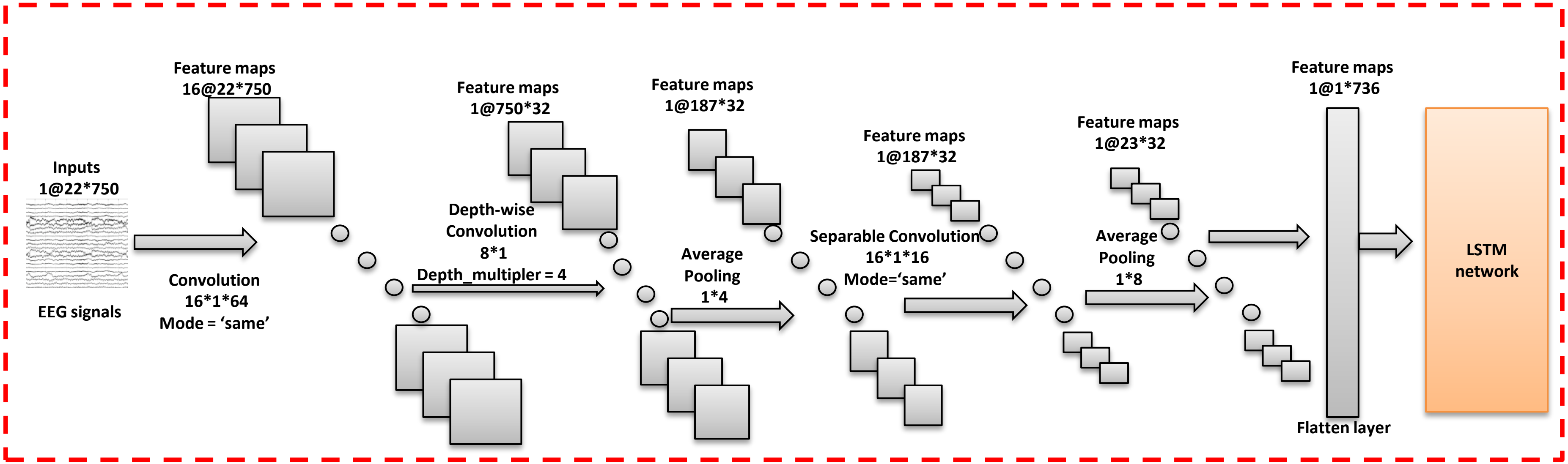
TCP or double banana montage which is used in clinical seizure detection.

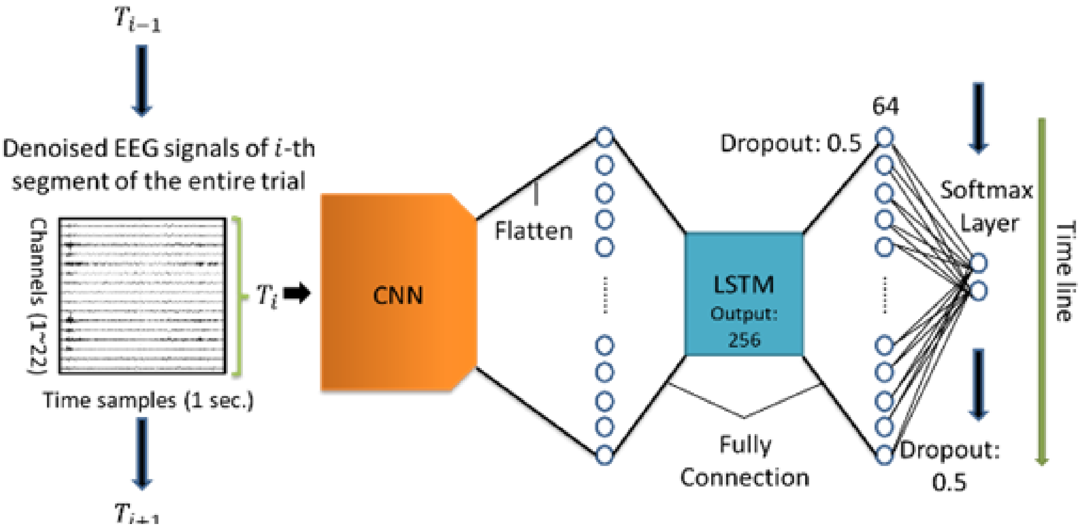
- **Deep Learning (DL) based network:**



General framework of the proposed method

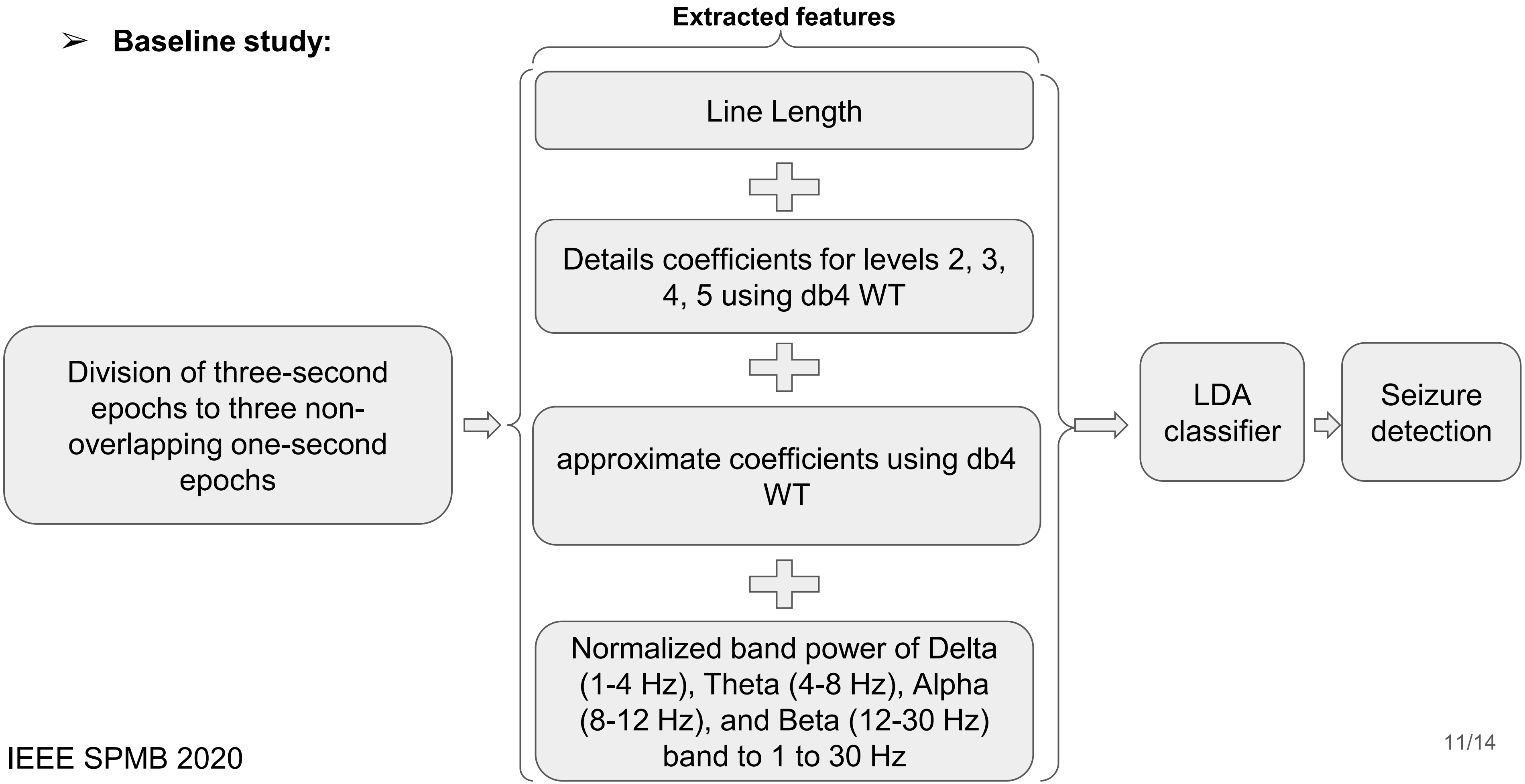
➢ **CNN architecture (inspired by EEGNET) :**





General structure of our model for data processing in one time-step.

- **Baseline study:**



- **Mozafari et al**:
  - A seizure detection method on the same subset of the TUH dataset
  - consists of clustering, classification, and voting on each cluster

- **Another challenge in our work:** severe imbalance in our classification problem
  Our solution: the weighting technique of two-class samples

Classification results of our proposed method (over ten random runs) and the other two methods (Baseline and Mozafari et al.) for seizure detection task

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Mozafari et al.	80.72	80.00	**81.08**	67.55
Baseline study	71.12	67.10	71.44	67.98
Proposed Method	**82.00$\pm$0.63**	**85.01$\pm$0.84**	80.22$\pm$0.93	**71.69$\pm$1.01**

➢ **Main advantages of our work:**

Automatically extraction of features from raw EEG signals with no pre-defined restrictions

+

Considering the changes in the pattern of the EEG signals in an epoch

+

Robustness of our model due to the great performance on a cross-subject scenario

Thank you,
Any questions?