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Graph Convolutional Networks For IED Detection From Scalp EEG

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What is epilepsy?

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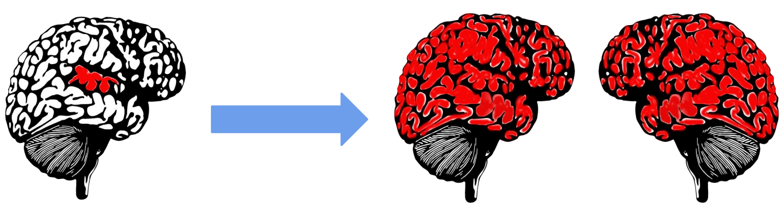
Epilepsy: a long-term brain condition where a person has repeated seizures.

Seizure: bust of uncontrolled electrical activity among neurons - cause muscle convulsions and loss of consciousness.

Focal **Generalized**



50 mil patients worldwide

3% population In Australia

How epilepsy is diagnosed?

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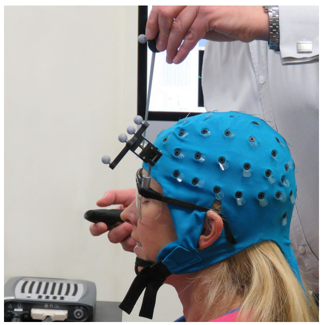
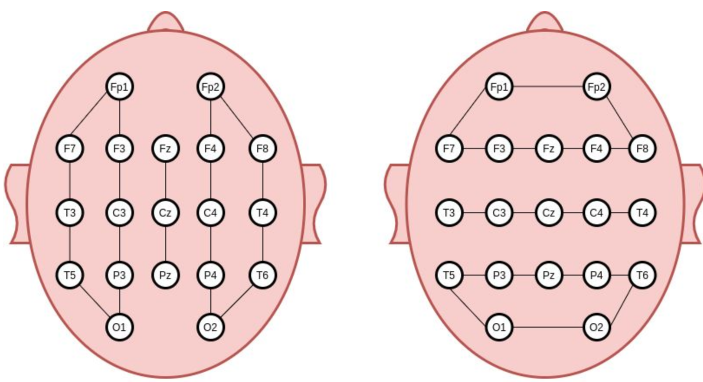
Electroencephalography (EEG) is used to monitor voltage fluctuations from ionic current among neurons inside the brain.

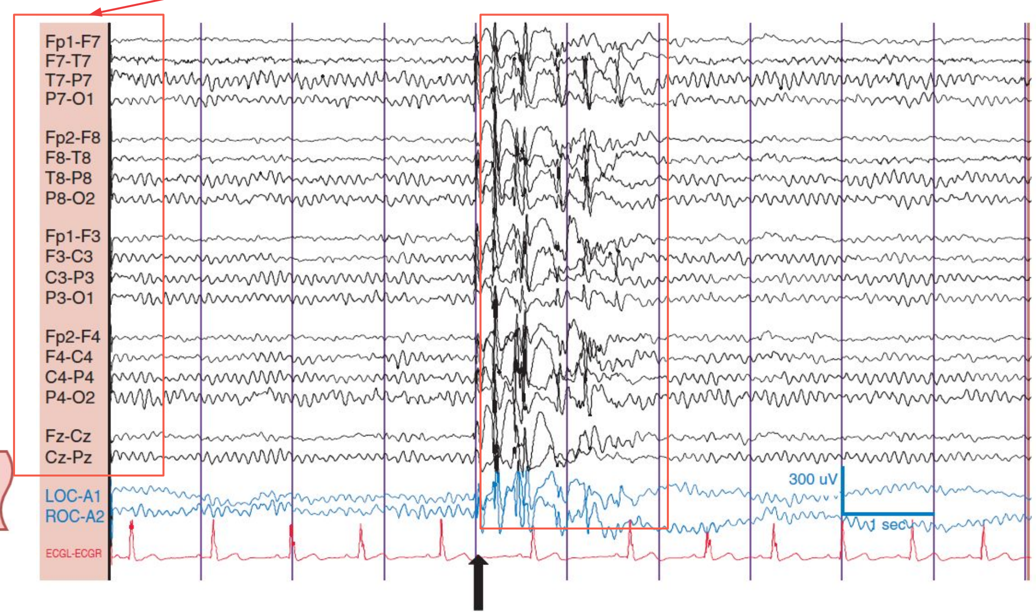




A B

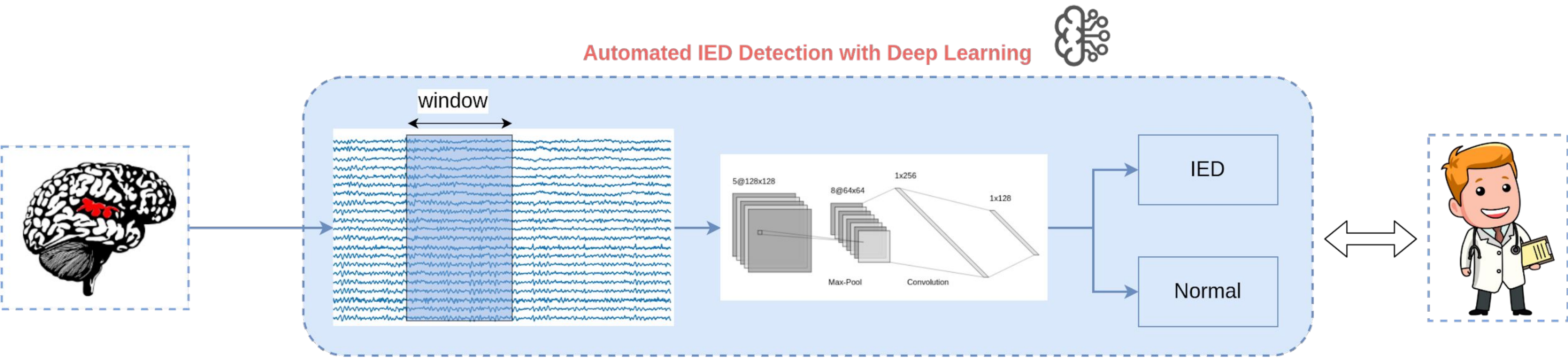
A. Longitudinal bipolar montage.
B. Transverse bipolar montage.

montage



Interictal epileptiform discharges (IED)

Overview - IED detection



Objective: automatically detect IEDs - general model for all patients:

- An EEG recording is viewed as a time series
- Split EEG into smaller windows, windows with or without IED
- Artifact removal - bandpass filter
- Classification: channel-wise (univariate) or epoch (multivariate)

Evaluation:

- Windows classification - False positives per minute → Review
- EEG recordings classification
- Patients classification

Diagnosis

Overview - Evaluation

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Specificity = \frac{TN}{TN + FP}$$

Where:

- TP: True classified windows with IED
- FP: False classified windows with IED
- FN: False classified normal windows
- TN: True classified normal windows

Note: Window dataset is highly imbalanced. # Normal >> # IEDs

High FP means more work for the clinicians ✗

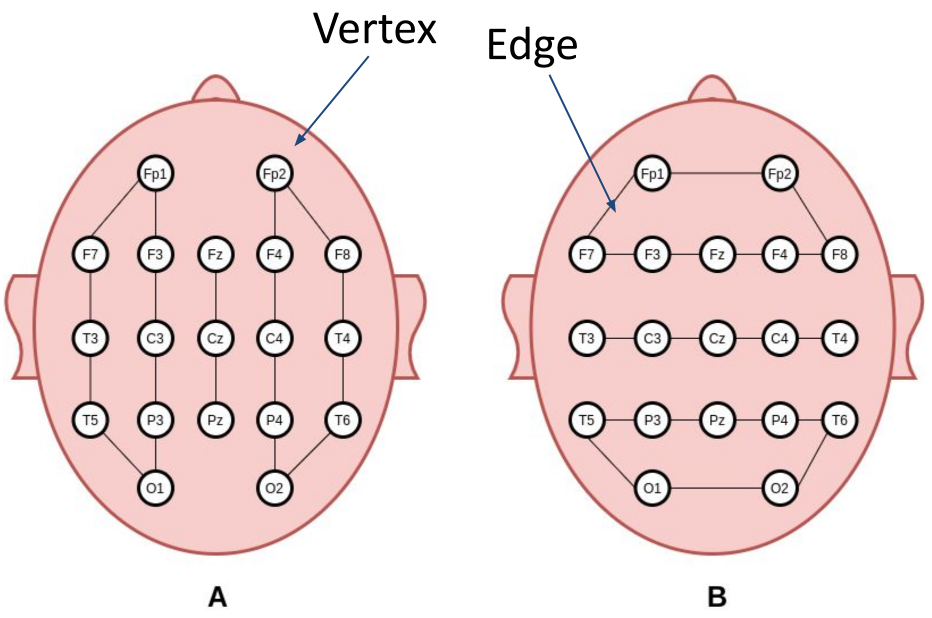
A good model should have both high precision and high sensitivity. This can be measured with F1. ✓

$$F1 = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity}$$

Graph Convolutional Network - GCN

Montage is a graph G= (V,E)
where:

- V is a set of electrodes (vertices)
- E is a set of edges connecting paired electrodes.



A. Longitudinal bipolar montage.
B. Transverse bipolar montage.

Chebyshev convolutional operation on a graph x

$$y = g_\theta * x = g_\theta(L)x = \sum_{k=0}^{K-1} \theta_k T_k(L) x$$

Graph Convolutional Network

The Laplacian matrix of a graph G(V,E) is

$$L(u,v) = \begin{cases} 1 & \text{if } u = v \text{ and } d_v \neq 0, \\ -\frac{1}{\sqrt{d_u d_v}} & \text{if } u \text{ and } v \text{ are adjacent,} \\ 0 & \text{otherwise} \end{cases}$$

Where: d_v is the degree of vertex v

Chebyshev convolutional operation is used to estimate the Fourier transform of the graph

$$y = g_\theta * x = g_\theta(L)x = \sum_{k=0}^{K-1} \theta_k T_k(L)x$$

Where:

- T_k is the Chebyshev polynomials of order K
- θ_k are the polynomial coefficients

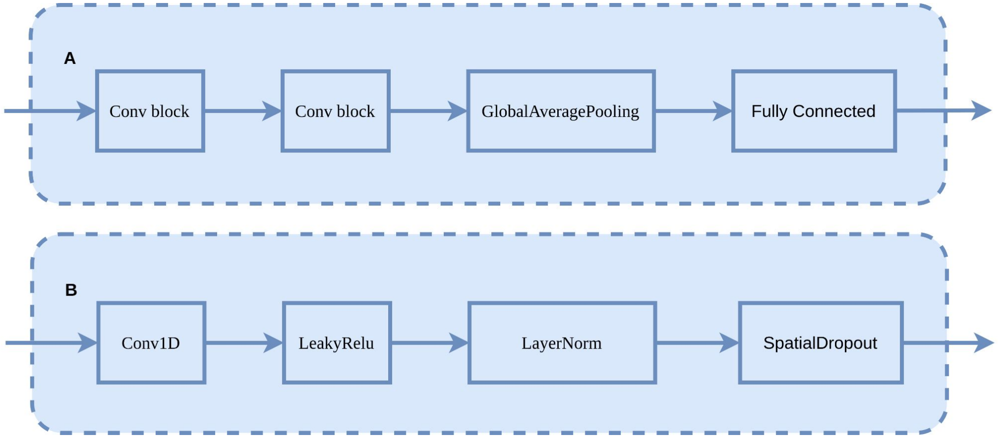
Recap: Chebyshev recurrence

$$T_k(\tilde{\Lambda}) = 2\tilde{\Lambda} T_{k-1}(\tilde{\Lambda}) - \tilde{\Lambda} T_{k-2}(\tilde{\Lambda})$$

$$T_0(\tilde{\Lambda}) = 1,\ T_1(\tilde{\Lambda}) = \tilde{\Lambda}$$

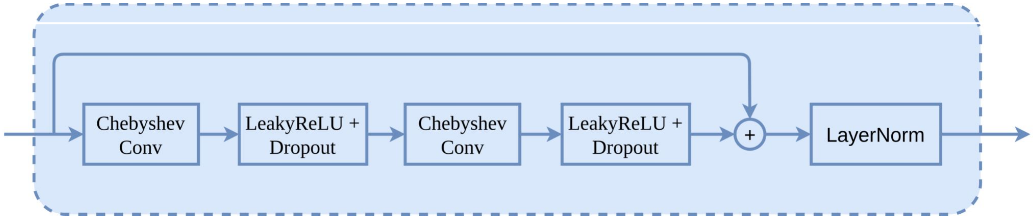
GCN - Components

Learning temporal features

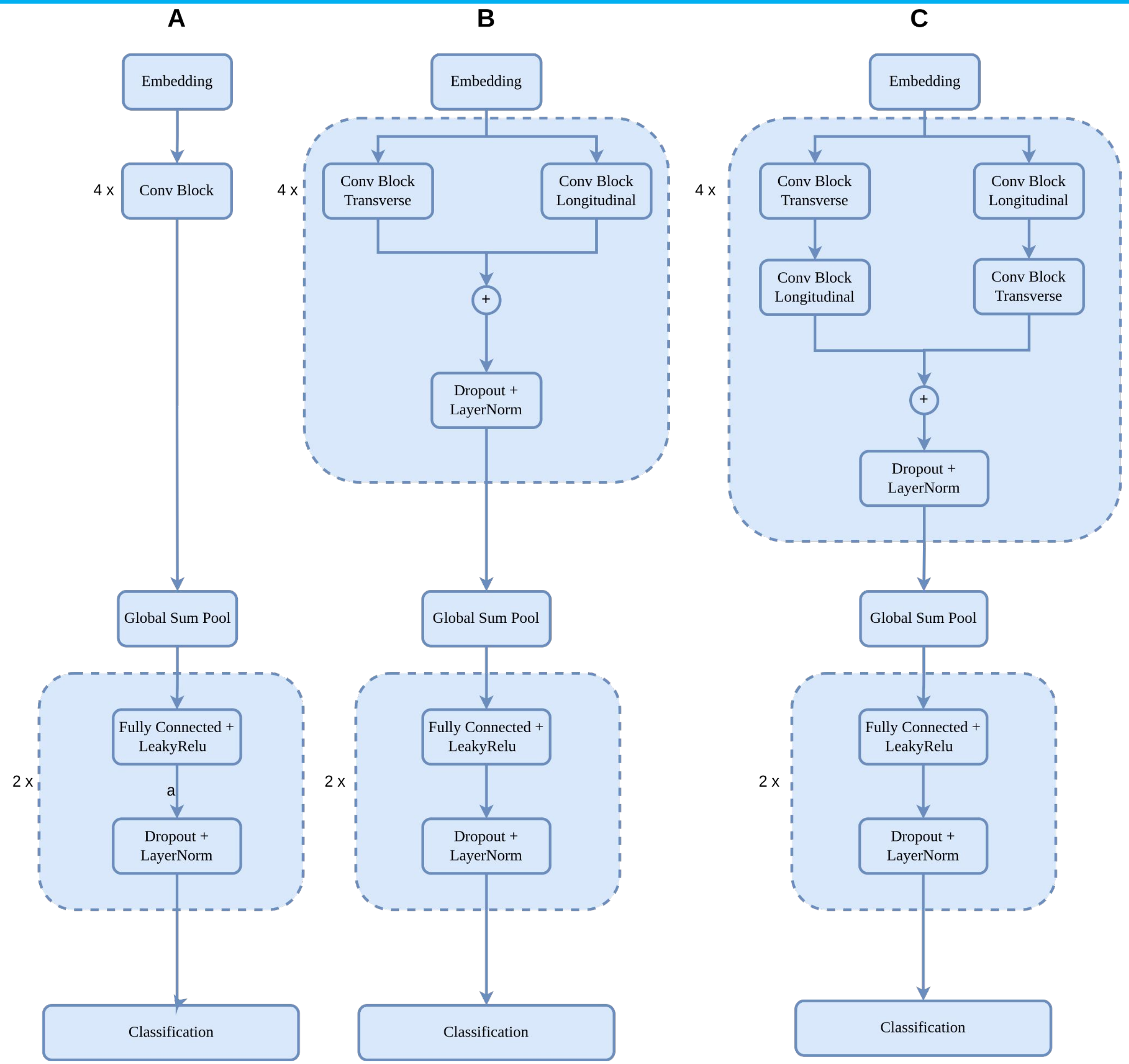


A. Embedding block.
B. Design of 1D CNN block.

Learning spatio features - Chebyshev block



GCN - Architecture



Dataset & Preprocessing

Dataset:

- We collected a set of routine EEG recordings from **Alfred Hospital in Melbourne, Australia**
- 10-20 system
- Average duration of IED is 2s

Preprocessing:

- Window: 2s with 50% overlap
- Bandpass filtering: 0.5-50Hz
- Resampling to 256 Hz with polyphase filtering
- Excluding auricular (M1 and M2) channels.

	Train	**Test**	**Total**
Epileptic EEG	80	30	110
Normal EEG	92	24	116
IEDs			1, 413
IED windows	1, 934	615	2,549

Results

Table 1: 2s window classification at probability threshold of 0.5

Model	Sens	Spec	Prec	F1	AUC
A - Trans (1)	0.51	0.98	0.24	0.32	0.91
A - Long (2)	0.64	0.95	0.16	0.26	0.91
Architecture B	0.60	0.98	0.32	**0.42**	0.92
Architecture C	0.62	0.97	0.14	0.25	0.91
Average of 1 & 2	0.39	0.99	0.36	0.37	0.92

Clean set of windows:

- Normal windows(without IED) from normal EEG

Table 2. Results of whole EEG recording classification.

Model	AUC
Architecture A - Trans (1)	0.45
Architecture A - Long (2)	0.80
Architecture B	0.84
Architecture C	0.77
Average of 1 & 2	0.72

Table 3. Mean FP/minute and mean sensitivity across all EEG recordings in test set at 0.8 probability threshold.

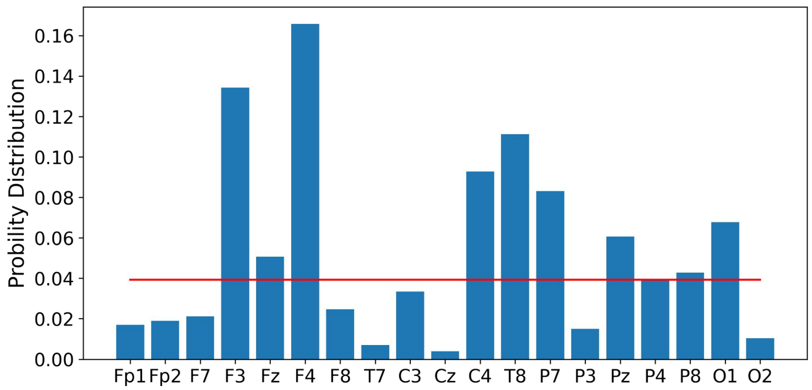
Model	Mean FP/minute	Mean Sensitivity
Architecture A - Trans (1)	0.35	0.43
Architecture A - Long (2)	2.59	0.71
Architecture B	5.0	0.73
Architecture C	2.44	0.68
Average of 1 & 2	0.44	0.64

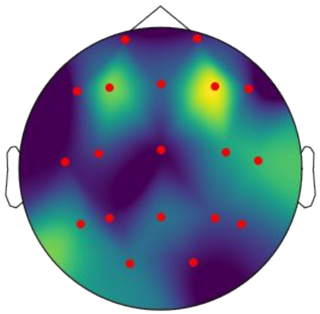
Include all windows from epileptic EEG recordings

Interpretability

Look at embedding of each electrode to see where the IED would be visible the most:

- Use output of the layer before the global sum pooling layer - 19 x 256
- Sum up all features per electrode -> z-score normalization -> softmax





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