Automatic detection of epileptic spikes on EEG and MEG

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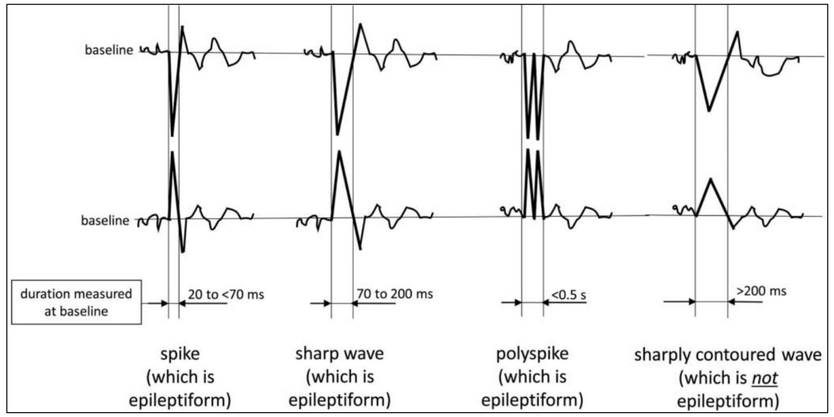
Context

- **Spikes → epilepsy diagnosis signature**
- **EEG/MEG → noisy & long recordings**
- **Manual analysis → time consuming & tedious**

Epileptic spikes in EEG



Hirsch, Lawrence J. et al. "American Clinical Neurophysiology Society's Standardized Critical Care EEG Terminology: 2021 Version" *Journal of Clinical Neurophysiology* vol. 38 p. 1-29 (January 2021)

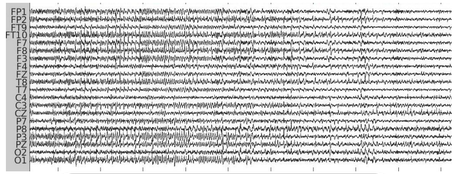
→ We propose an AI-powered pipeline to automatically detect epileptic spikes

Methods

Acquisition system

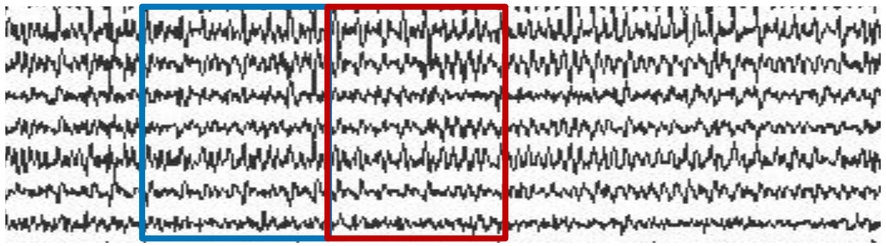
32/64/256 channels

Preprocessing



- Artifact removal
- Notch filter

Segmentation in trials of 2 seconds



2 seconds

trial = segment of data

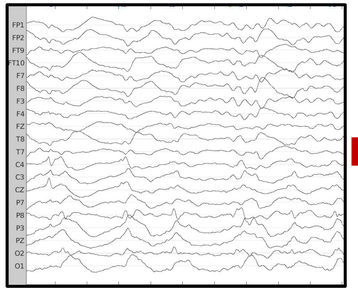
Powered by Brainstorm

https://neuroimage.usc.edu/brainstorm/

Epileptic Spike Detection

Deep Learning Pipeline

Input EEG trial



2 seconds

Powered by ivadomed

https://ivadomed.org

Focus on relevant channels

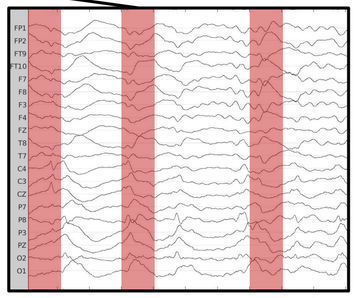
Features extraction

Focus on relevant time segments

Detect epileptic spikes

200 ms epileptic time window

Inference



2 seconds

Results

Average metrics with a Leave-One-Out Cross-validation on 10 subjects

Method	Type of signal	F1 score	Precision	Sensitivity
Proposed method (code)	**multi-channel EEG**	**0.38 ± 0.20**	**0.58 ± 0.20**	**0.33 ± 0.20**
3D-UNet (code)	**multi-channel EEG**	0.19 ± 0.11	0.43 ± 0.11	0.16 ± 0.12

Conclusion

→ **High heterogeneity of subjects hurts the performances**

→ **Robustness of the model must be improved**

→ **Agnostic to the number of electrodes**

→ **Automated and open-source framework (available in Brainstorm)**

Supplementary Materials

Database

Data description

Number of patients	Sample frequency (Hz)	Trial duration (ms)	Number of trials	Number of trials containing spikes
10	100	2000	2746	1373

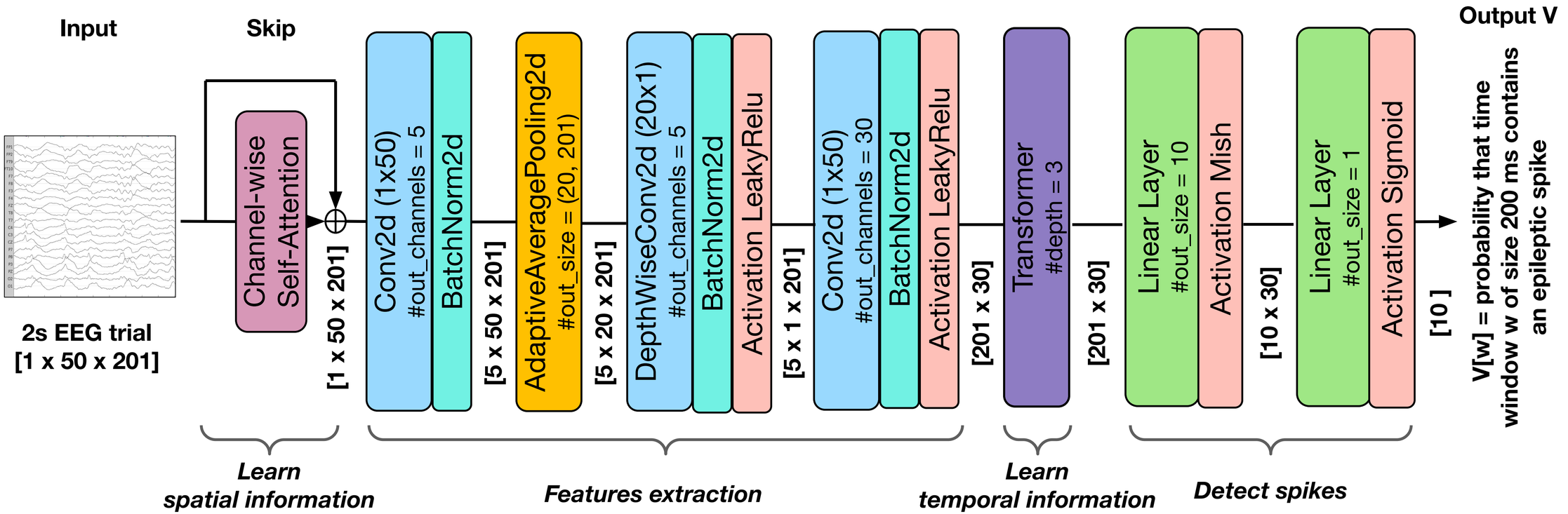
Epileptic spike annotations

Number of spike annotations	Number of non spike annotations	Time window duration (ms)	Number of time windows	Number of time windows containing spikes
2331	549615	200	27460	2299

Methods: Architecture

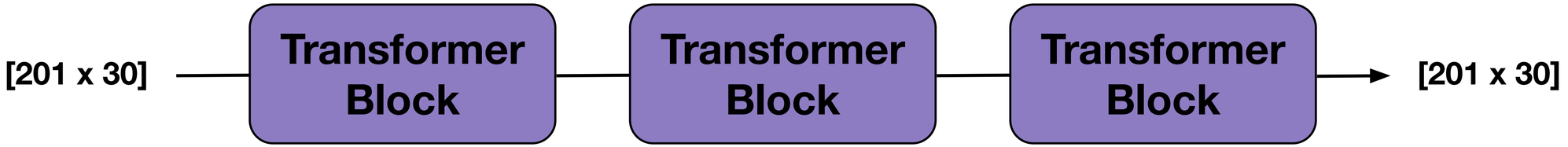
Code available here.
Transformer architecture presented in the next slide.
Input below is an EEG trial of 2 seconds with 50 channels.

Deep Learning Architecture

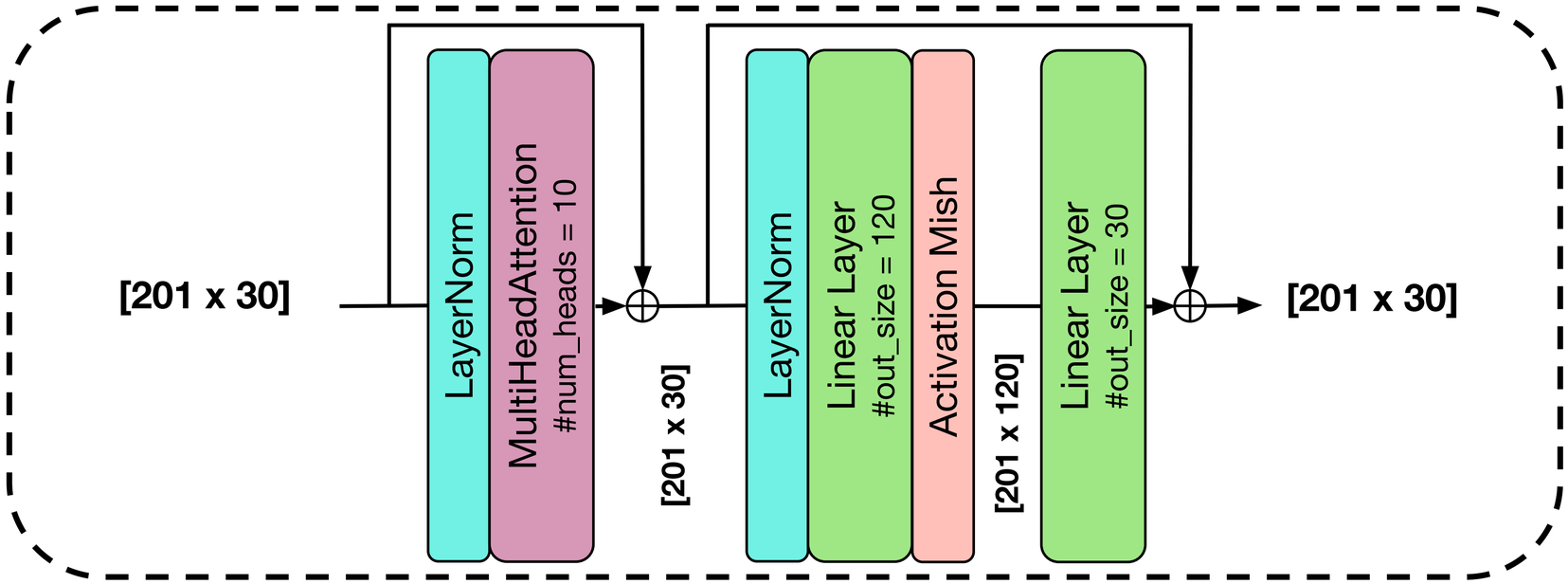


Methods: Transformer Architecture

Transformer → depth = 3



Transformer Block



Results

Challenging training strategy: Leave-One-Out Cross-Validation

- Each of the 10 subjects is chosen as test set while the training is done on the 9 remaining ones
- Inference is thus done on a subject the model has never seen

Discussion

High heterogeneity of subjects concerning epileptic spikes

→ **High variability of performances across the subjects**

→ **Proposed method lacks generalization capacity**

Acknowledgements

Study design and supervision

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Data acquisition and analysis

Roy W. Dudley and his team (Department of Pediatric Surgery, Division of Neurosurgery, Montreal Children's Hospital) for the data acquisition and annotations, as well as Sylvain Baillet and his team (McConnell Brain Imaging Center, Montreal Neurological Institute and Hospital, McGill University) for data analysis, ground truth annotation and discussions.

Preprocessing steps were performed with Brainstorm (Tadel et al. 2011) which is documented and freely available under the GNU general public licence (http://neuroimage.usc.edu/brainstorm).

Deep learning architecture

Samira Ebrahimi Kahou (Département de génie logiciel et des technologies de l'information, École de technologie supérieure, CIFAR, MILA - Quebec AI Institute) for her help and advice.

Model inspired by Song et al. 2021 (paper) and Vaswani et al. 2017 (paper).

Implementation available on github.

Contact information

Linkedin - mail - github