Supplementary Materials for the paper:

A deep learning epileptic seizure detection based on matching pursuit algorithm and its time-frequency graphical representation

by

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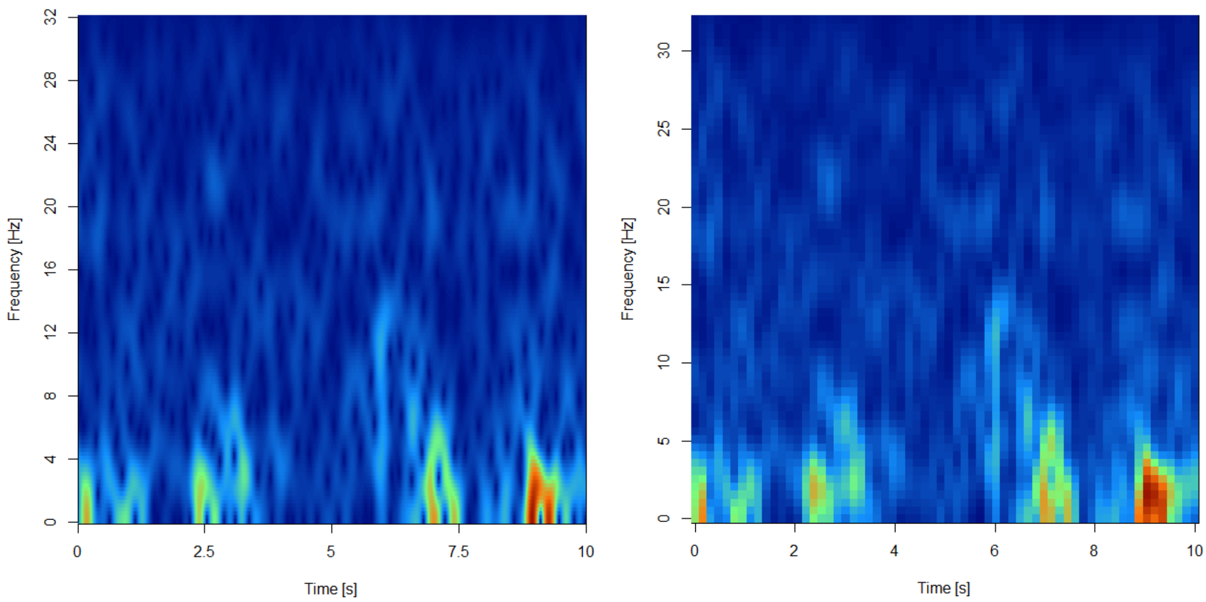
1 Sample spectrograms

Two sample spectrograms are shown below, one in high resolution and the other at 64×64 pixels. The spectrograms were created using the exact same data used to generate the maps shown in Figure 2 of the article.



(a) (b)

Figure 1: Spectrograms of an sample signal with high resolution (a), the same spectrogram but after limiting the resolution to the size of 64×64 pixels (b). Note: the visible colors are for visualization only and have no significance in the analysis.

2 Performance results for spectrogram-based time-frequency maps

Model: IndExpA					Model: IndExpB				
Fold No.	Loss	Accuracy	Precision	Recall	Fold No.	Loss	Accuracy	Precision	Recall
1	0.2591	0.9153	0.9670	0.8896	1	0.3515	0.8883	0.9056	0.8697
2	0.2863	0.8746	0.9138	0.8612	2	0.3563	0.8682	0.9460	0.8612
3	0.2658	0.9007	0.9539	0.8486	3	0.3435	0.8682	0.9103	0.9008
4	0.3083	0.8909	0.9735	0.8107	4	0.3662	0.8596	0.9100	0.8017
5	0.2711	0.8811	0.9496	0.8486	5	0.3567	0.8639	0.8707	0.9433
Mean	0.2781	0.8925	0.9516	0.8517	Mean	0.3548	0.8696	0.9085	0.8753
Std	0.0196	0.0161	0.0232	0.0284	Std	0.0083	0.0110	0.0267	0.0523
Model: IndExpC					Model: MergExps				
Fold No.	Loss	Accuracy	Precision	Recall	Fold No.	Loss	Accuracy	Precision	Recall
1	0.2800	0.8929	0.9302	0.8707	1	0.1547	0.9491	0.9499	0.9541
2	0.2519	0.9000	0.9927	0.8592	2	0.1652	0.9446	0.9545	0.9450
3	0.2515	0.9101	0.9525	0.8879	3	0.1310	0.9545	0.9801	0.9501
4	0.2280	0.9159	0.9367	0.9310	4	0.1530	0.9471	0.9617	0.9439
5	0.3022	0.8986	0.9558	0.8937	5	0.1447	0.9441	0.9735	0.9378
Mean	0.2627	0.9035	0.9536	0.8885	Mean	0.1497	0.9479	0.9639	0.9462
Std	0.0287	0.0093	0.0243	0.0274	Std	0.0128	0.0042	0.0127	0.0062

Table 1: Performance metrics obtained for models trained on time-frequency maps obtained by transforming the EEG signals using the spectrogram algorithm, for datasets labeled by individual experts and on the merged multi-expert dataset. For each model, results for all five folds of the cross-validation procedure are reported, along with the mean and standard deviation across the folds.

3 Model Complexity and Memory Metrics

To facilitate the comparison presented in Table 2 of the main paper, we provide detailed definitions of the reported metrics. These measures are used to characterize the computational complexity and storage requirements of neural network architectures.

- Total mult-adds is the number of elementary multiply–accumulate operations (MACs) performed during a single forward pass of the network for a given input. This value reflects the computational complexity of the model and is used as a proxy for the number of floating-point operations (FLOPs).
- The memory footprint required to store only the model's trainable parameters (e.g., weights and biases), typically represented in 32-bit floating-point precision. This measure does not account for additional memory used during training, such as gradients or optimizer states.
- Total Size refers to the total storage size of the model file on disk, including both trainable parameters and supplementary metadata (e.g., layer definitions, architecture configuration, and file format overhead). This value reflects the actual size of the serialized model that is saved and later loaded into memory.