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► **To cite this version:**

Igor Carrara, Bruno Aristimunha, Marie-Constance Corsi, Raphael Yokoingawa De Camargo, Sylvain Chevallier, et al.. Augmented SPDNet: Second-Order Neural Network for Motor Imagery-Based BCI. Soph.IA summit 2023, Nov 2023, Sophia Antipolis, France. hal-04308549

HAL Id: hal-04308549

<https://inria.hal.science/hal-04308549>

Submitted on 27 Nov 2023

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Augmented SPDNet:

Second-Order Neural Network for Motor Imagery-Based BCI



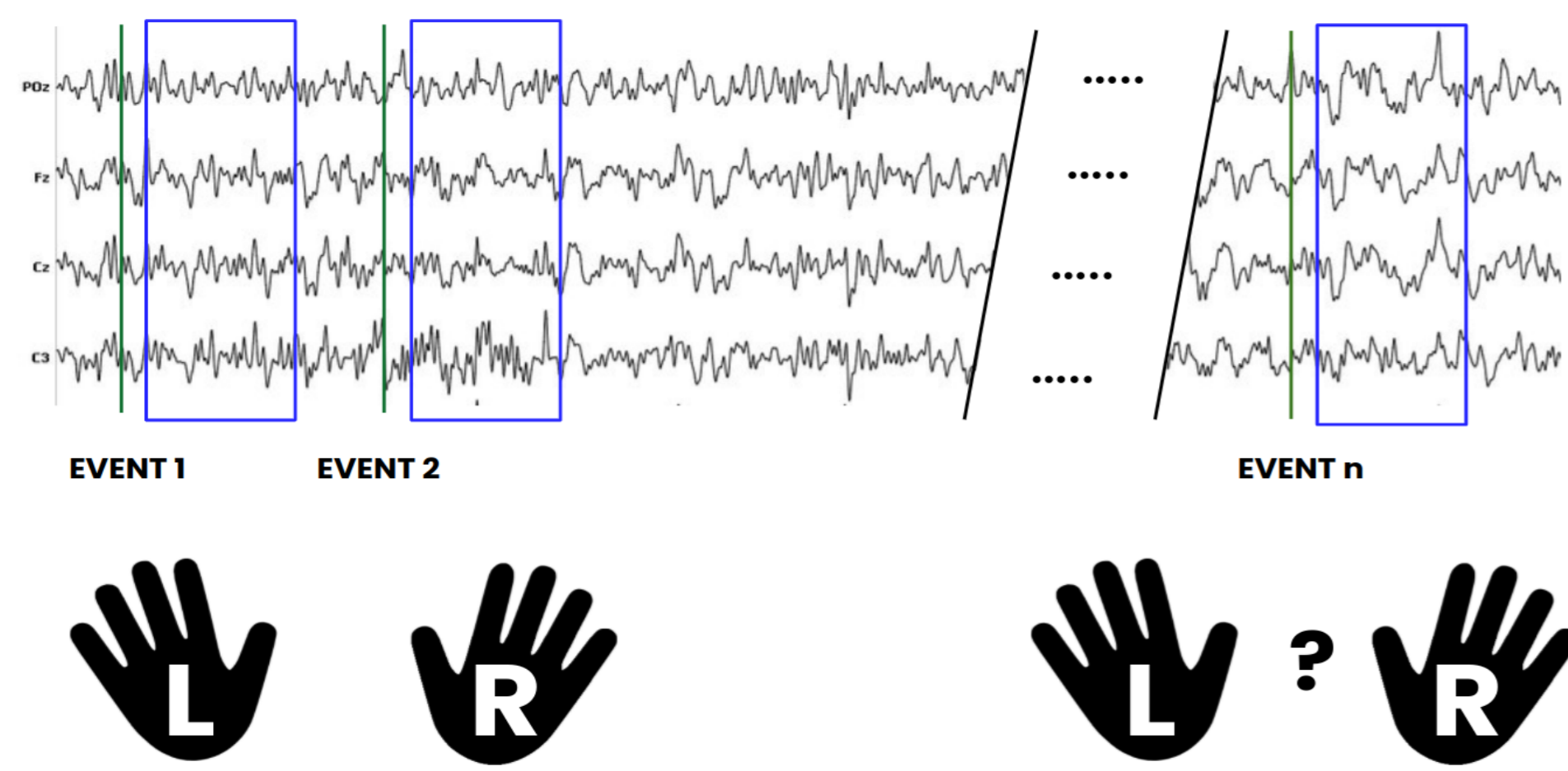
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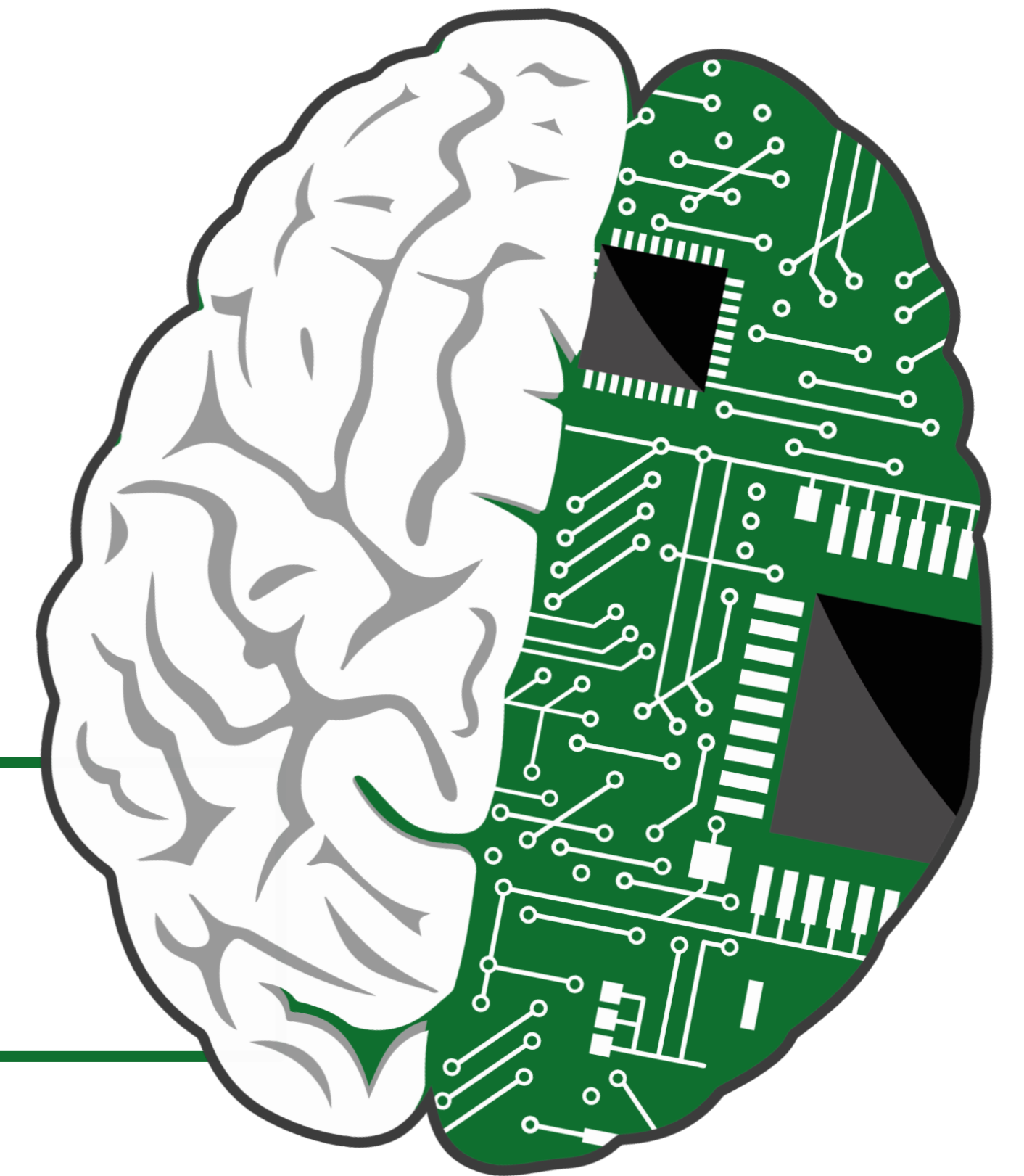
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Brain Computer Interfaces (BCI) can be defined as a technology that measures brain activity and translates it into instructions for a digital system. We will focus on **non-invasive (EEG)-based BCI (BCI-EEG)**.

Let us consider a typical EEG signal after preprocessing. In the figure on the left, we show an EEG signal measured with 4 different electrodes. Our work will be focused on **Motor Imagery (MI) BCI**, so we want to understand if the subject, for example, is thinking about moving the left or the right hand.



Can a combination of Phase Space Reconstruction and Deep Learning enhance MI-BCI decoding in a low number of electrodes regimes?

METHODS: AugSPDNet

Standard Riemann approach [1]:

Extract sample spatial covariances which are Symmetric Positive Definite (SPD) matrices and classify them using Minimum Distance to Mean (MDM) or classical machine learning procedure on the tangent space (SVM, LDA, ...)

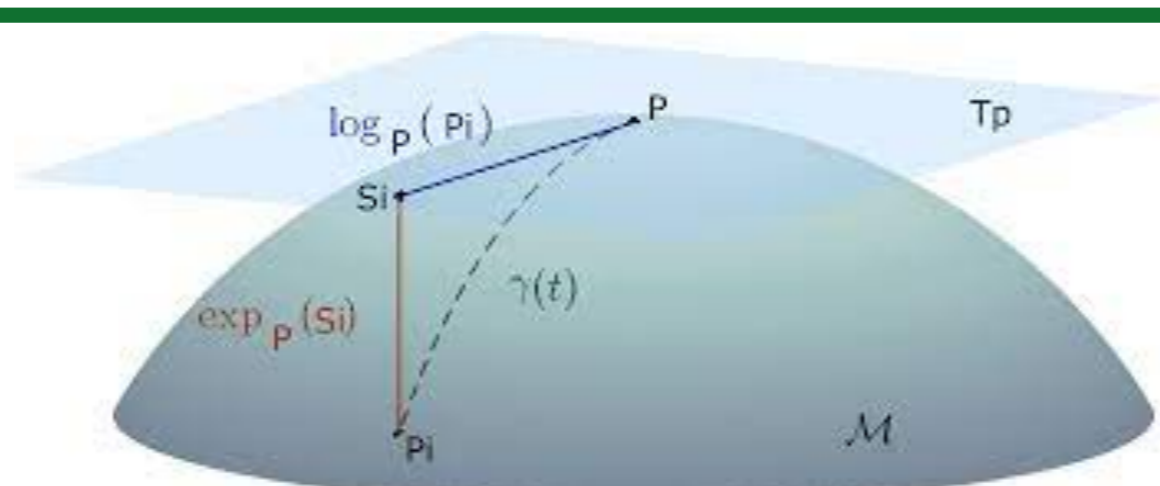


Figure extracted from [1]

SPDNet [2]:

To work with **SPD matrices**, we use the **SPDNet** architecture [2] instead of the classical Convolutional Networks, and the **RiemannAdam** optimizer [3] a Riemannian variant of the Adam algorithm.

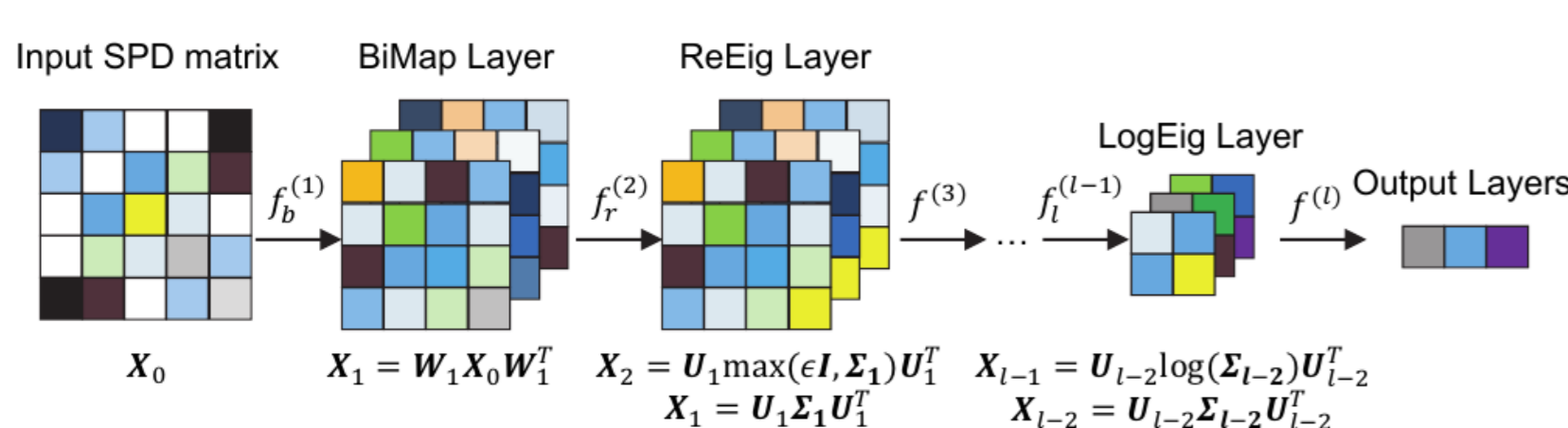


Figure extracted from [2]

Augmented Covariance Method [4]:

To understand the dynamic of the systems in low dimensional space, we used the **Takens Theorem** [5] that enables to extract **new SPD matrices (ACM)**. ACMs, in addition to spatial information, contain also temporal one, enabling an improvement of the classification performance [4]. **The geometrical structure of a multivariate system can be revealed by embed the signal $s(t)$ in a high dimensional space as follows:**

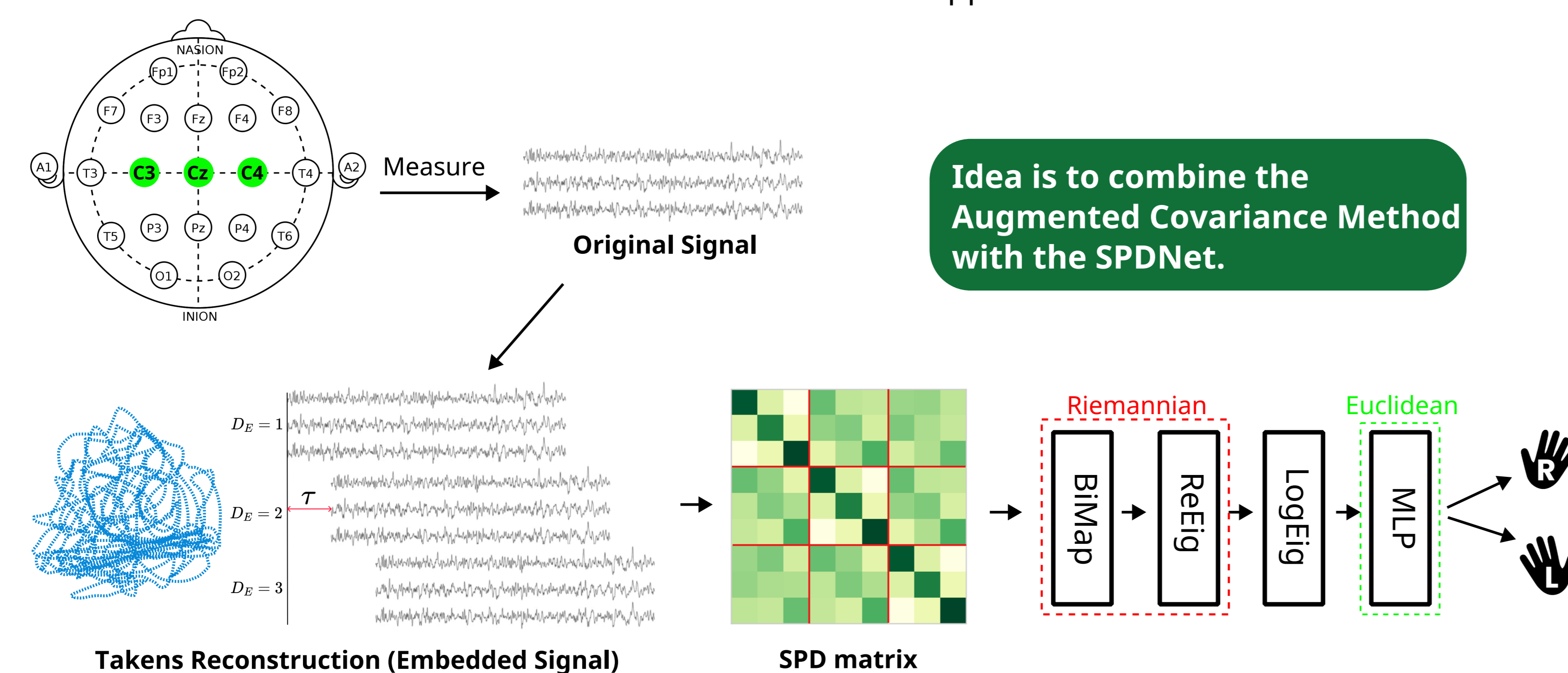
$$s_R(t) = [s(t), \dots, s(t - (D_E - 1)\tau)]^T$$

The ACM model depend on 2 hyper-parameters:

- Embedding Dimension (D_E)
- Embedding Delay (τ).

We optimise them using **MDOP** algorithm based Takens approaches.

Idea is to combine the Augmented Covariance Method with the SPDNet.

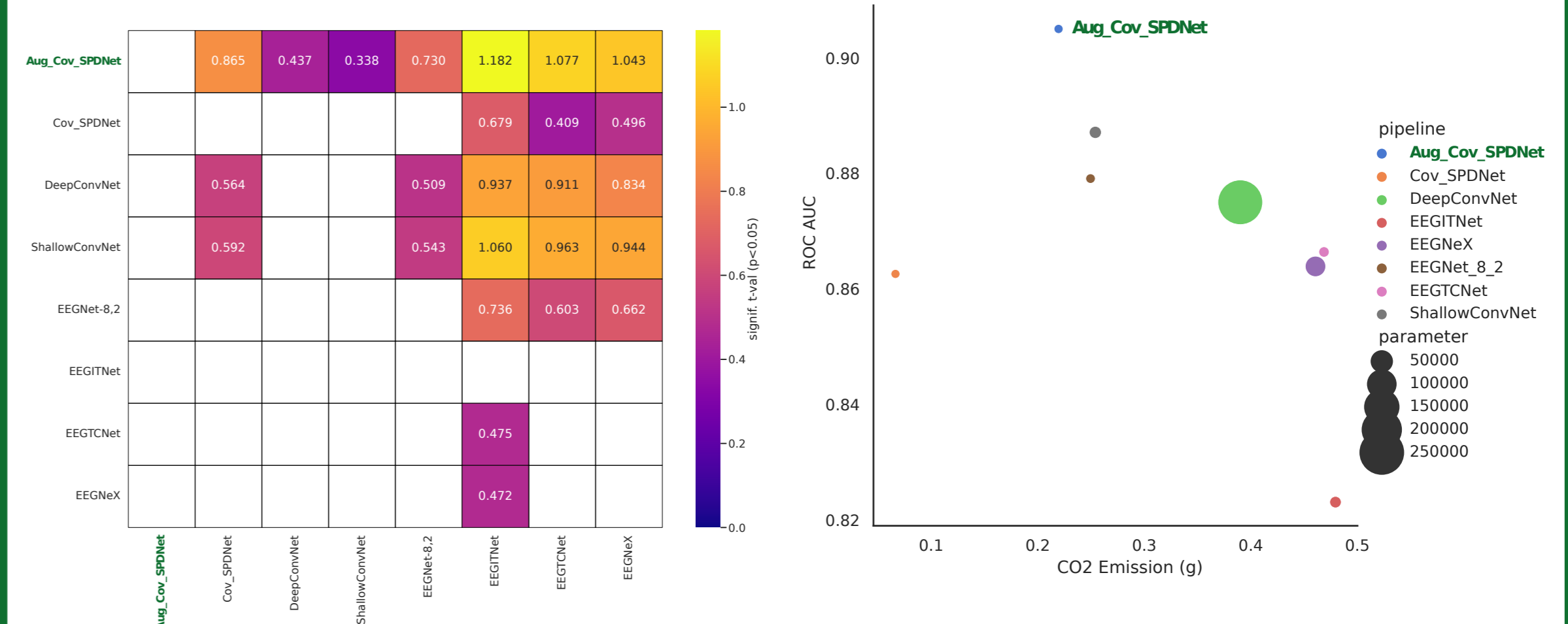


RESULTS

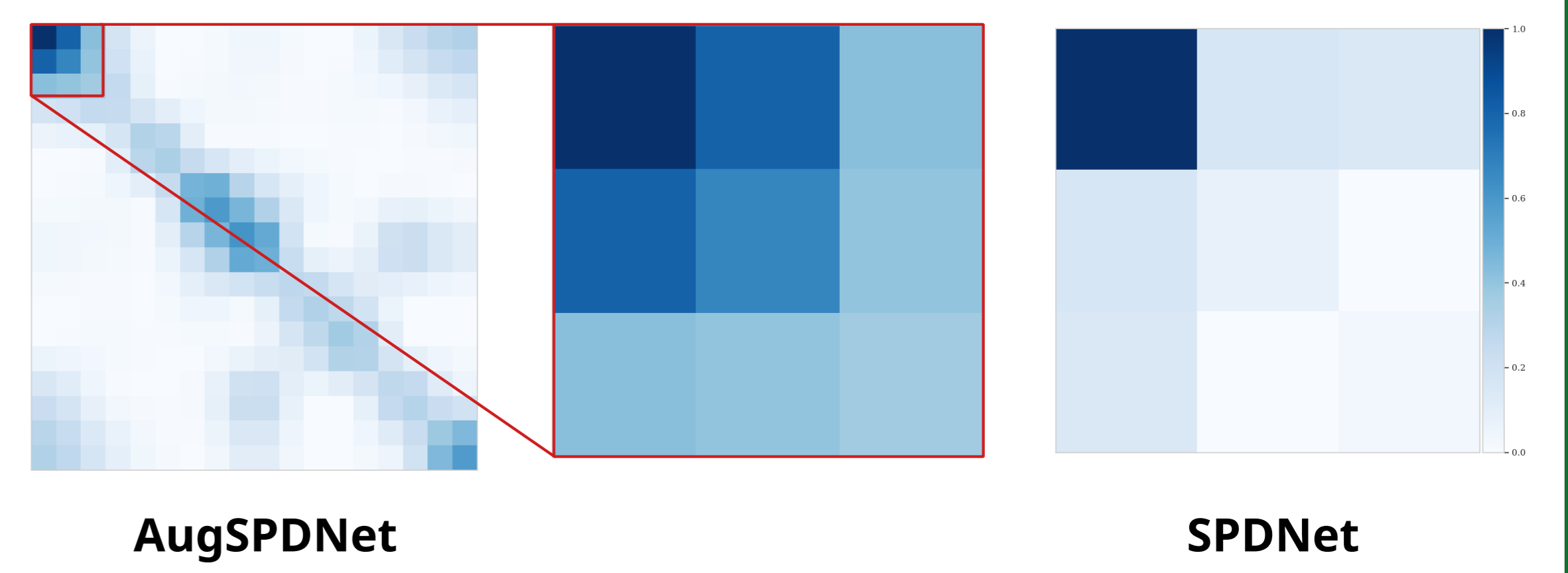
To validate our approach and assess its replicability, we applied it on several open datasets through the **MOABB framework** [6]. We compared the obtained results with the **state-of-the-art DL algorithms**. Results are tested on task **right hand vs left hand** in a **within-session evaluation**.

Pipeline	BNCI2014001	BNCI2014004	Cho2017	Weibo2014
AugCov + SPDNet	0.76 ± 0.17	0.81 ± 0.17	0.66 ± 0.13	0.78 ± 0.21
Cov + SPDNet	0.71 ± 0.16	0.70 ± 0.17	0.60 ± 0.13	0.67 ± 0.19
DeepConvNet	0.76 ± 0.16	0.73 ± 0.20	0.63 ± 0.15	0.74 ± 0.19
ShallowConvNet	0.76 ± 0.16	0.72 ± 0.19	0.64 ± 0.13	0.75 ± 0.17
EEGNet-8,2	0.71 ± 0.21	0.70 ± 0.19	0.60 ± 0.15	0.72 ± 0.19
EEGNet	0.67 ± 0.14	0.65 ± 0.15	0.55 ± 0.12	0.57 ± 0.19
EEGTCNet	0.66 ± 0.18	0.67 ± 0.19	0.56 ± 0.12	0.66 ± 0.17
EEGNetX	0.69 ± 0.18	0.68 ± 0.18	0.57 ± 0.13	0.59 ± 0.21

AugSPDNet is statistically significantly better than the state of the art DL pipelines, moreover our method produce **less carbon emission** and have **less trainable parameter**.



Explainability using GradCam++ [7], on subject 41 of dataset Cho2017: output of ReEig layer.



TAKE HOME MESSAGE

The combination of **ACM** and **SPDNet** improves the **classification performance of MI-BCI in a low number of electrodes regimes** over the DL state-of-the-art. Moreover the **AugSPDNet is explainable**, with a **low number of trainable parameter** and a **reduced carbon footprint**.



SCAN ME

Acknowledgements: This work has been partially financed by a EUR DS4H/Neuromod fellowship.

- References:**
- [1] Alexandre Barachant et al. "Riemannian geometry applied to BCI classification". In: International conference on latent variable analysis and signal separation. Springer. 2010, pp. 629–636.
 - [2] Huang, Zhiwu et al. "A riemannian network for spd matrix learning." Proceedings of the AAAI conference on artificial intelligence. Vol. 31. No. 1. 2017.
 - [3] Max Kochurov et al. "Geopt: Riemannian optimization in pytorch." arXiv preprint arXiv:2005.02819 (2020).
 - [4] Igor Carrara et al. "Classification of BCI-EEG based on augmented covariance matrix" arXiv preprint arXiv:2302.04508 (2023).
 - [5] Takens, F. (1981). Detecting strange attractors in turbulence. Lect. Notes Math. 898.
 - [6] Bruno Aristimunha et al. "Mother of all BCI Benchmarks". In: Zenodo (2023).
 - [7] Chattopadhyay, Aditya, et al. "Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks." 2018 IEEE WACV.