

# Regularized Gaussian Functional Connectivity Network with Post-Hoc Interpretation for Improved EEG-based Motor Imagery-BCI Classification

Daniel Guillermo García Murillo  
[dgarciam@unal.edu.co](mailto:dgarciam@unal.edu.co)



Universidad Nacional de Colombia  
Signal Processing and Recognition Group - SPRG  
**Advisor:** Andrés Marino Álvarez-Meza, Ph.D.  
**Co-advisor:** César Germán Castellanos-Domínguez, Ph.D.

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# Outline I

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2 Problem statement

3 State of the art

- Single-Trial FC in MI-BCI
- Subject-Specific EEG Representation for MI-BCI
- Interpretability Strategies in MI-BCI

4 Aims

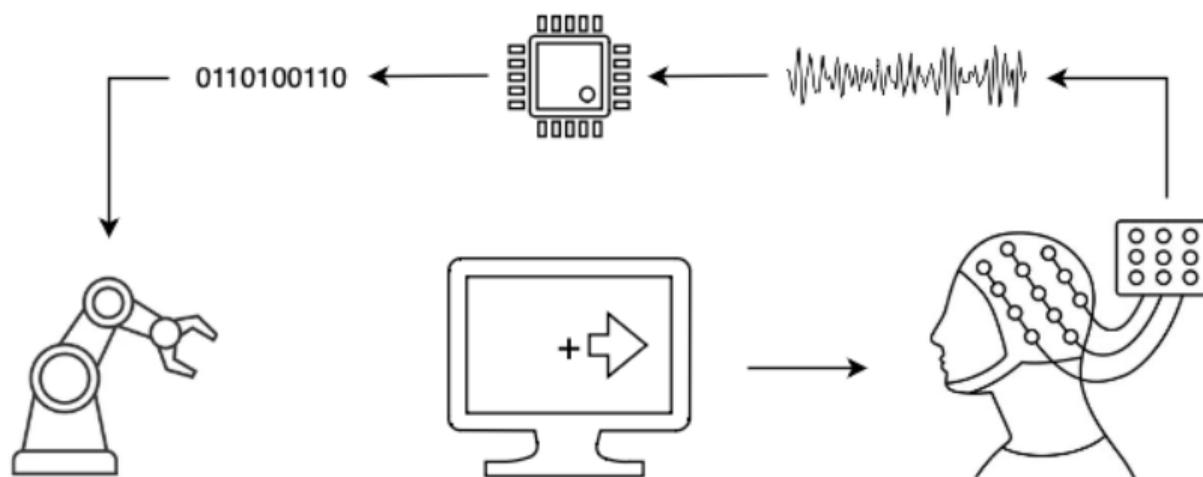
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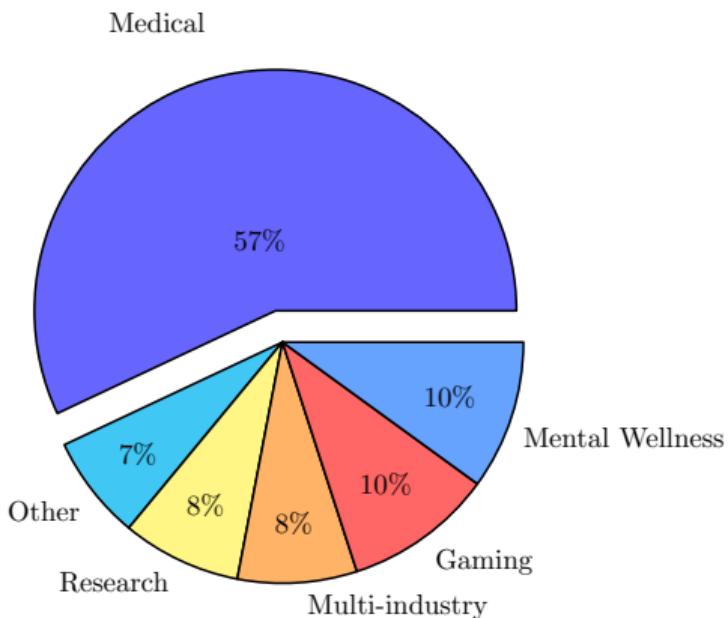
# Brain Computer Interface (BCI)

BCI provides people with external world communication by translating brain signals. [Khan et al., 2020]





# Socioeconomic Facts



- More than 87 BCI startups across the U.S. as of 2022 <sup>2</sup>.
- BCI market valued at 1800 million in 2022, projected to reach 6100 million by 2030 <sup>3</sup>.

<sup>1</sup>Image: Adapted from The World Economic Forum 2024

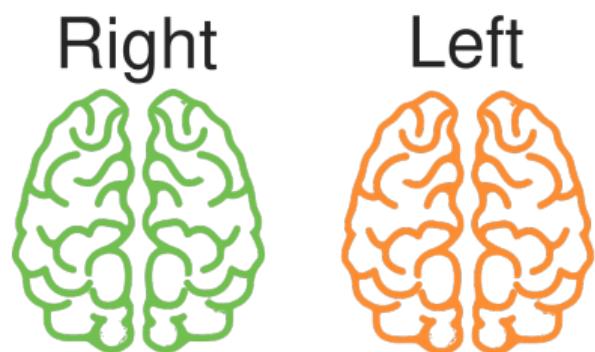
<sup>2</sup>Brain Computer Interface Market Size, Report 2024-2033

<sup>3</sup>Brain-Computer Interface Market 2022



# Motor Imagery (MI)

MI is a widely studied BCI paradigm that allows external motor communication [Cattan et al., 2018].



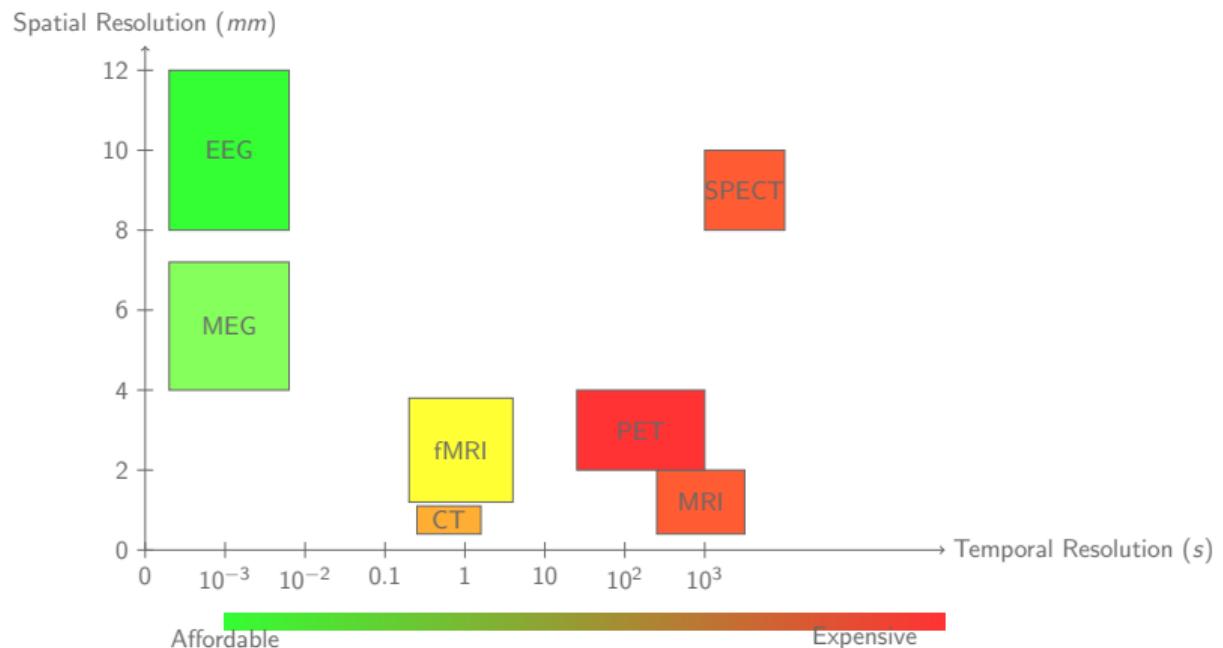
## Applications:

- Recovery of motor functionality [Bonci et al., 2021].
- Motor rehabilitation [Sitaram et al., 2017].
- Virtual reality [Cattan et al., 2018].
- Gaming [Ahn et al., 2014].
- Skill acquisition [Casimo et al., 2017].



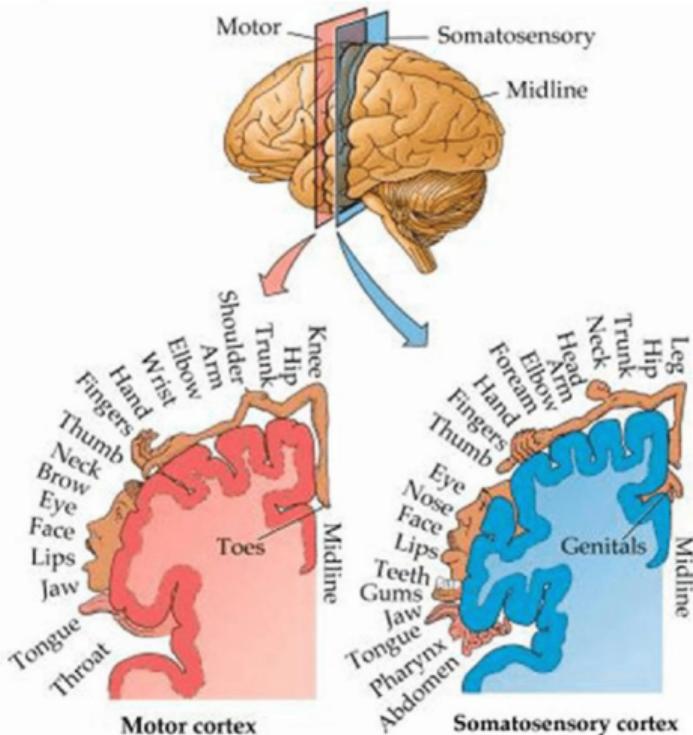
# Neuroimaging Techniques

- MI involves fast-evolving cognitive processes [Värbu et al., 2022]
- EEG and MEG have remarkable temporal precision [Alsharif et al., 2020]
- EEG is portable and cost-effective [Janapati et al., 2023, Hosseini et al., 2020]



# Sensorimotor Rhythms (SMRs)

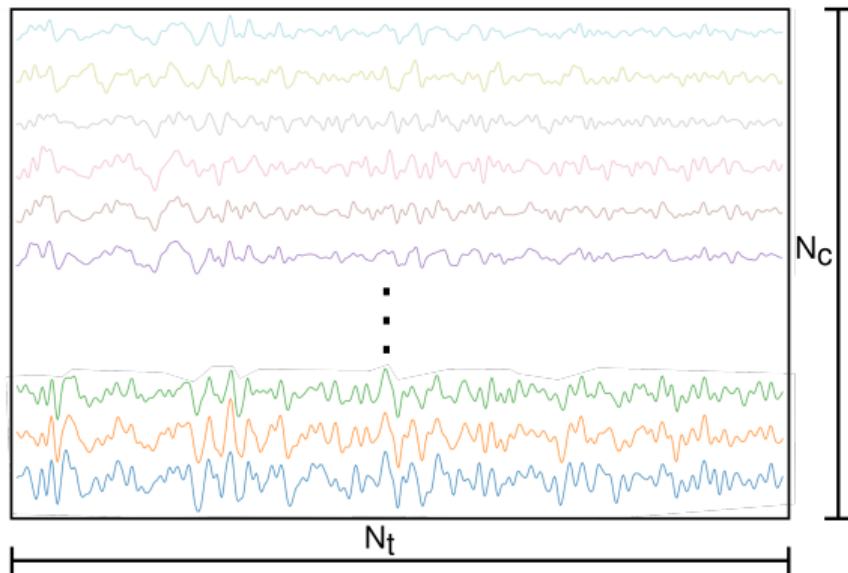
- EEG signals contains multiple electrical variations (rhythms) [Barrios et al., 2019].
- Sensorimotor Rhythms (SMRs) occur in the sensorimotor cortex [Altaheri et al., 2023].
- SMRs contain spectral-spatio-temporal patterns of MI tasks [Li et al., 2019].



<sup>1</sup>Image: Adapted from [Purves, 2001]



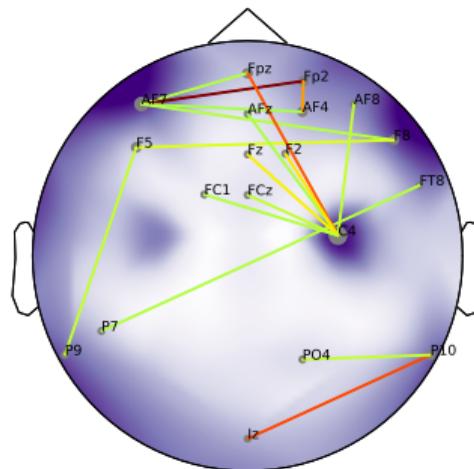
# MI-EEG Feature Extraction



- High number of channels and sampling rate [Chevallier et al., 2024].
- Huge number of data points [Singh et al., 2021].
- Feature extraction strategies are required to reduce dimensionality [Ai et al., 2019].

# Single Channel Feature Extraction

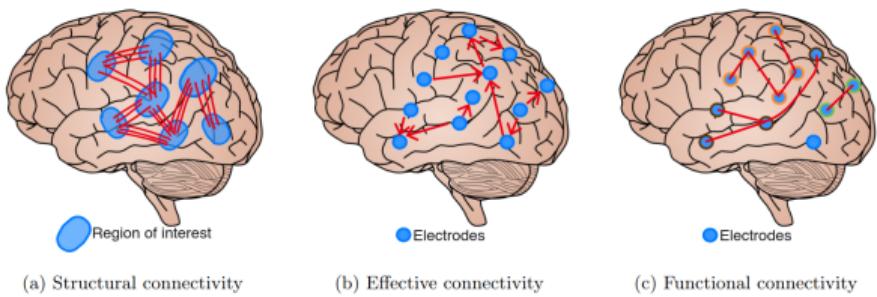
- Capture rhythms on specific EEG channels [Samuel et al., 2017].
- Time domain: statistical [Hamed et al., 2014], Hjorth [Yilmaz et al., 2018], etc.
- Spectral domain: Power spectral density [Oikonomou et al., 2017], Welch's periodogram [Roy et al., 2022], spectral entropy [Sarraf, 2017], etc.



Executing or imagining motor tasks activates multiple brain areas, patterns that single-channel features fail to capture [Chiarion et al., 2023].



# Multi Channel Feature Extraction



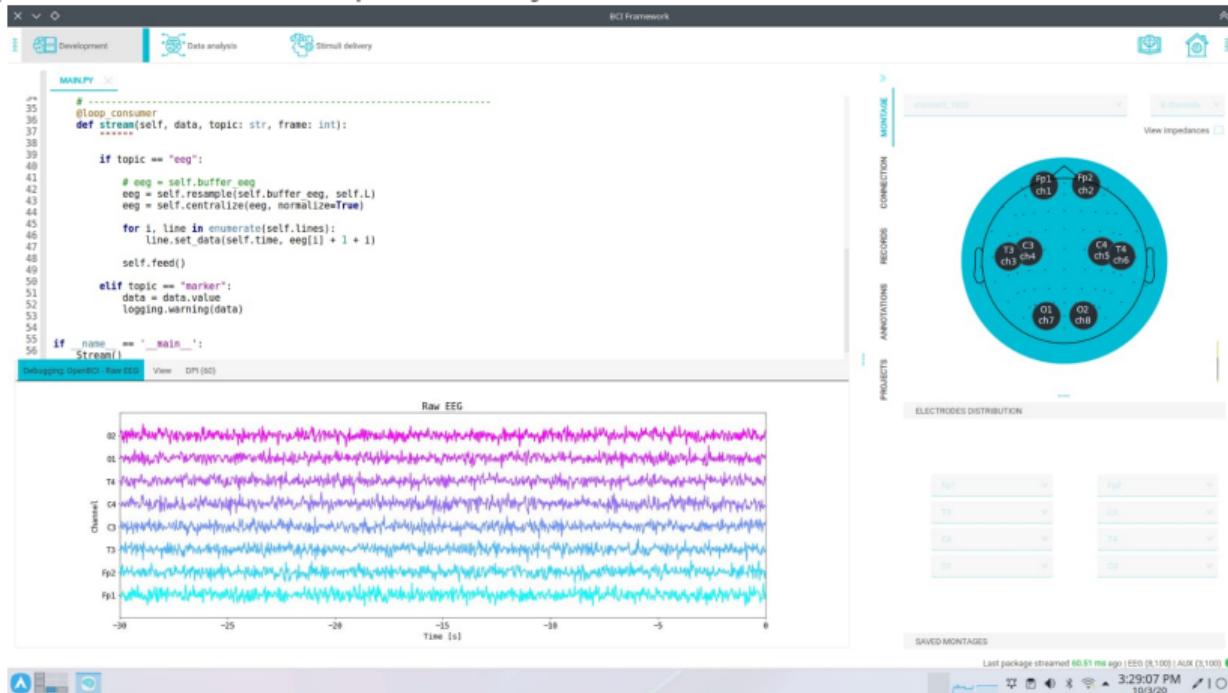
- Structural connectivity (SC) focuses on physical connections, fails to capture short-living events [Thiebaut de Schotten et al., 2020]
- Effective connectivity (EC) describes direct connections and requires deep cognitive process understanding to select the best causal model [Chiarion et al., 2023].
- Functional connectivity (FC) can describe directed or non-directed connectives usually via statistical correlation [Cao et al., 2022a]

FC's simplicity, low computational demands, and lack of rigid assumptions make it ideal for MI-BCI applications [He et al., 2019].



# Signal Processing and Recognition Group - SPRG

The SPRG designs Machine Learning (ML) and Deep Learning (DL) models to improve the performance and explainability of EEG-based MI-BCIs [Collazos-Huertas et al., 2023].





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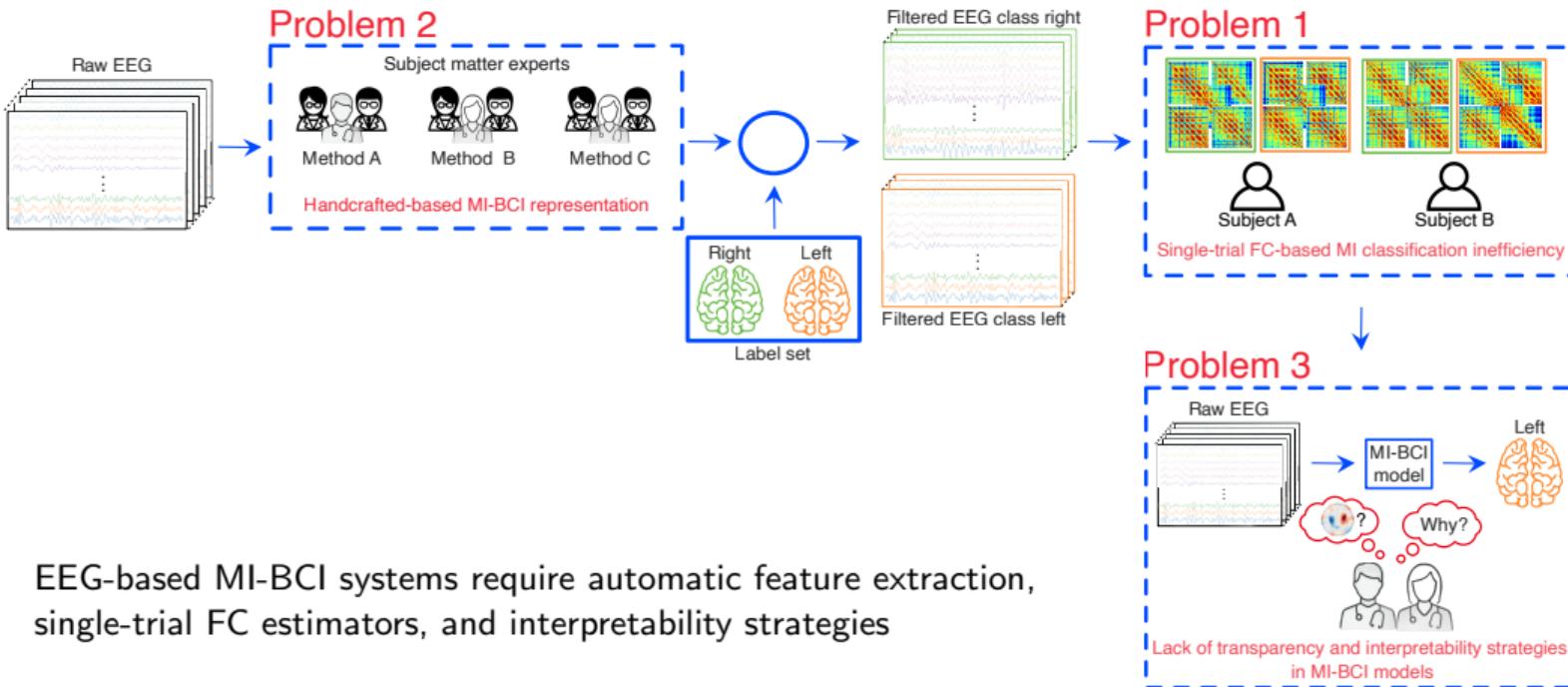
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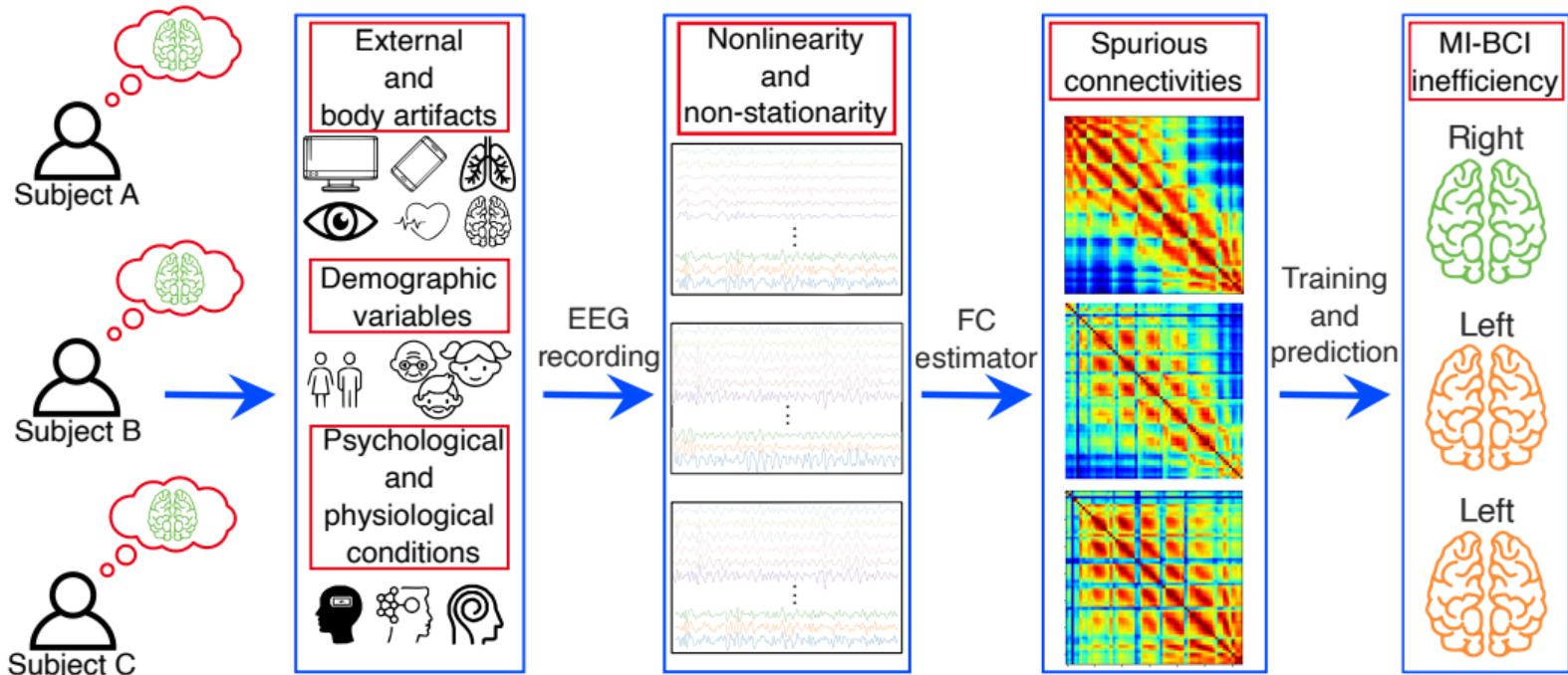
# Problem Statement



<sup>1</sup>[Chiarion et al., 2023, Cao et al., 2022a, Altaheri et al., 2023, Chamola et al., 2020, Xiao et al., 2018, Fan et al., 2021]



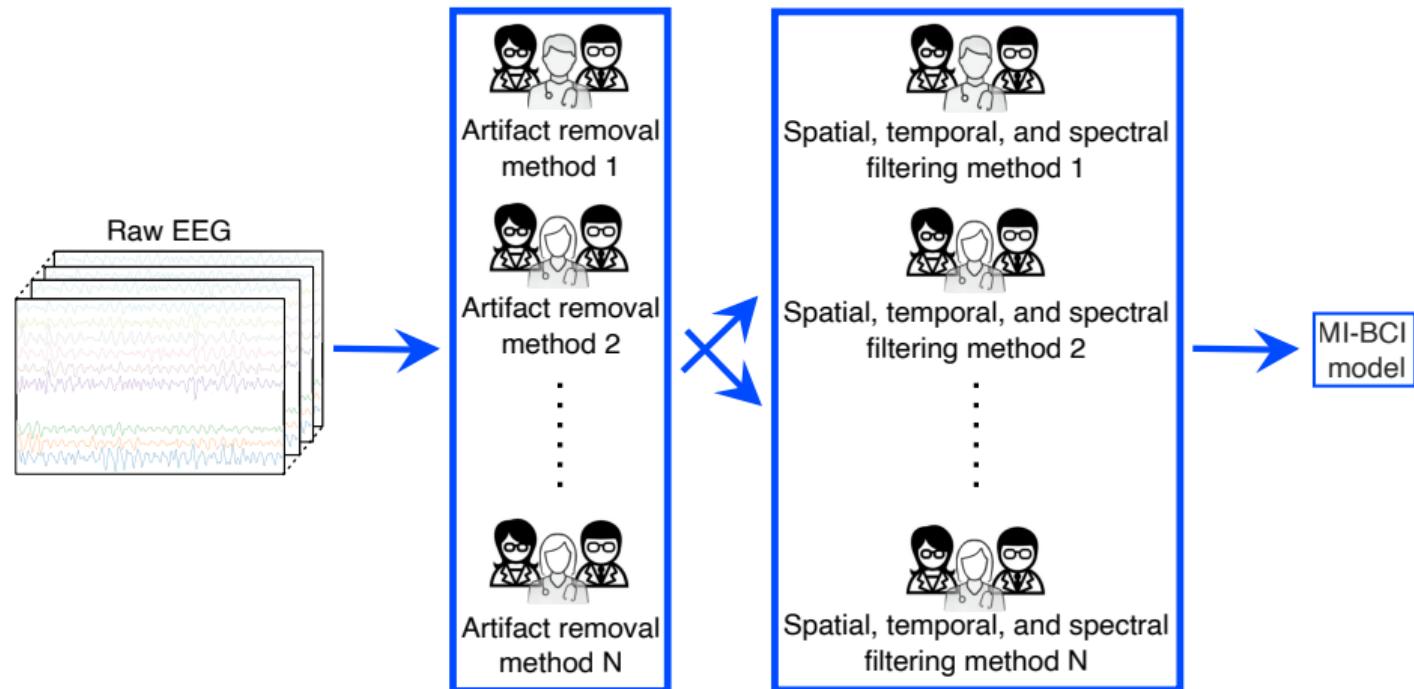
# Single-Trial FC MI Classification Inefficiency



<sup>1</sup>[Chiarion et al., 2023, Cao et al., 2022a]



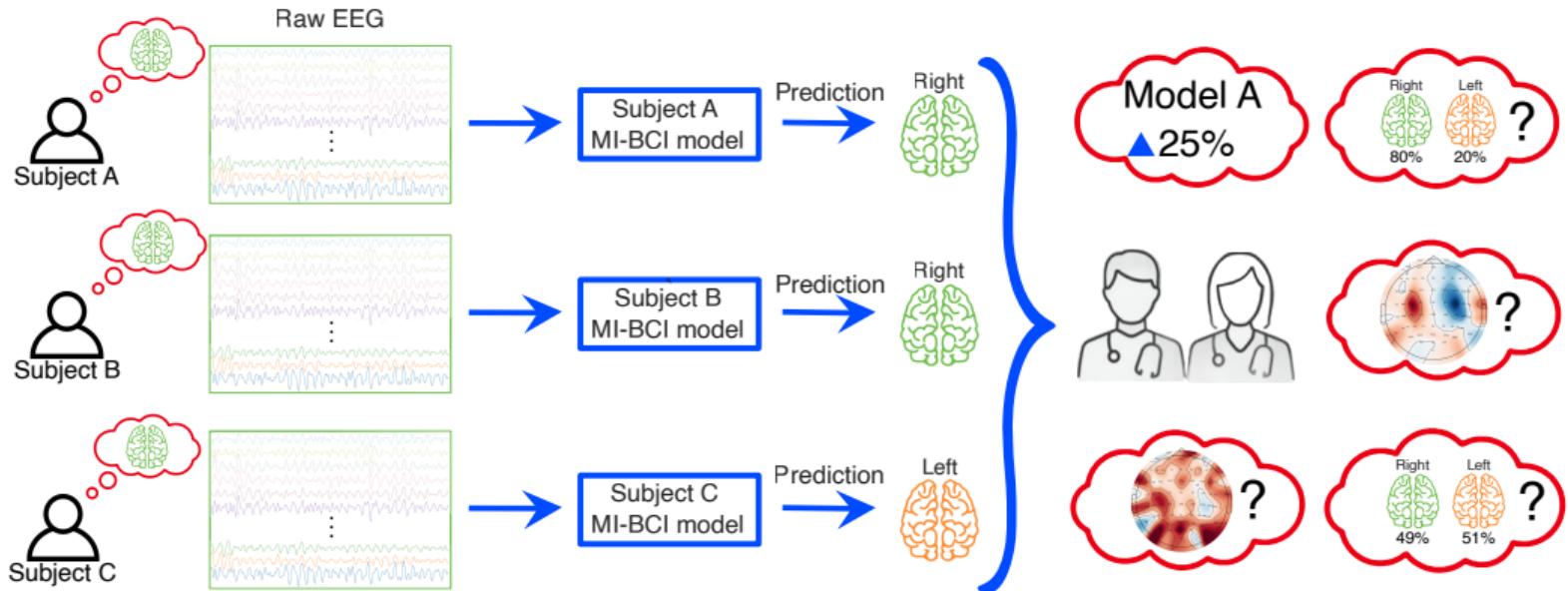
# Handcrafted-based Subject-Specific EEG-based MI-BCI Representation



<sup>1</sup>[Altaheri et al., 2023, Chamola et al., 2020]



# Lack of Transparency and Interpretability Strategies in MI-BCI



<sup>1</sup>[Xiao et al., 2018, Fan et al., 2021]



# Research Question

How can a **single-trail FC** be developed to manage non-stationary EEG subject-specific representations, handle spurious connectivities, and encode non-linear spatial, temporal, and spectral **discriminative** and **interpretable** MI patterns?



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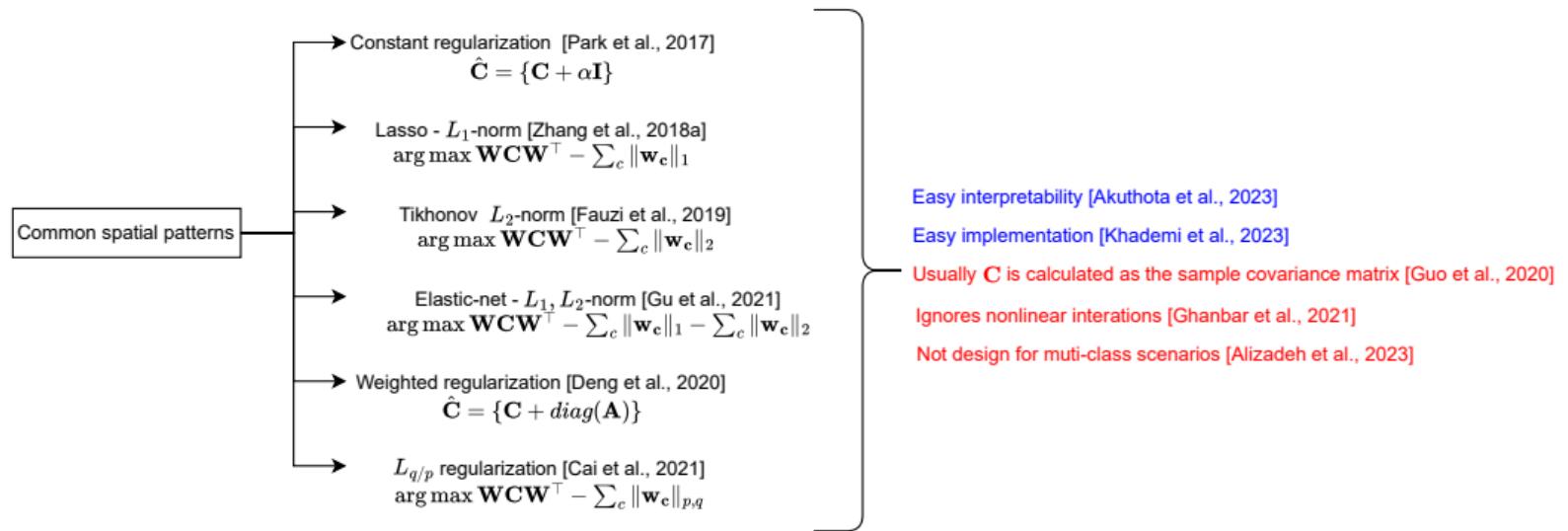
# Functional Connectivity Estimators

	Time Domain	Frequency domain	
Indirect	Corr [Fagerholm et al., 2020]	IPC [Cao et al., 2022a] MSC [Cattai et al., 2021] PC [Gonzalez-Astudillo et al., 2020]	Linear
	MI [Gu et al., 2023]	PLI [Siviero et al., 2023] PLV [Cattai et al., 2021]	Nonlinear
	SL [Gonzalez-Astudillo et al., 2021]	WPLI [Gonzalez-Astudillo et al., 2020]	
	Cross-corr [Roy et al., 2022]	DTF [Rezaei & Shalbaf, 2023]	Linear
	GC [Rezaei & Shalbaf, 2023]	PDC [Gaxiola-Tirado et al., 2017]	
	TE [Rezaei & Shalbaf, 2023]		Nonlinear
<span style="color: orange;">█</span> High sensitive <span style="color: #FFDAB9;">█</span> Sensitive <span style="color: #FFCCBC;">█</span> Less sensitive <span style="color: #FFF176;">█</span> Robust			

- Orange shades indicate sensitivity to volume conduction (VC).
- Linear estimators are simple but may miss complex interactions, nonlinear ones capture them but are noise-sensitive [Gonzalez-Astudillo et al., 2020].
- Direct and Indirect connectivity achieve similar performance in MI, being indirect connectivity less sensitive to the VC [Cao et al., 2022b]



# Feature Extraction from FC I





# Feature Extraction from FC II

Vector representation [Meng et al., 2023, Georgiadis et al., 2018] } CSP-like when followed by linear classification [Reuderink et al., 2011]  
Frequently hard to extract features [Xu et al., 2020]  
Easy integration with deep learning [Zoumpourlis & Patras, 2022]

Graph measures [Gu et al., 2023] } Intuitive representation [Rodrigues et al., 2022 ]  
Oversimplified the cognitive process [Gonzalez-Astudillo et al., 2020]

Riemannian geometry [Ding et al., 2023] } Take into account  $\mathbf{C}$  inter-links [Liu et al., 2024]  
Hard to find best  $\mathbf{C}_{ref}$  [Miah et al., 2020]

Topological representation [Altaheri et al., 2023, Collazos-Huertas et al., 2021] } Potentially loss information [Altaheri et al., 2023]  
Performance relies on sufficient channels [Zhao et al., 2019a]  
Seamless integration with convolutional neural networks [Xu et al., 2020b]



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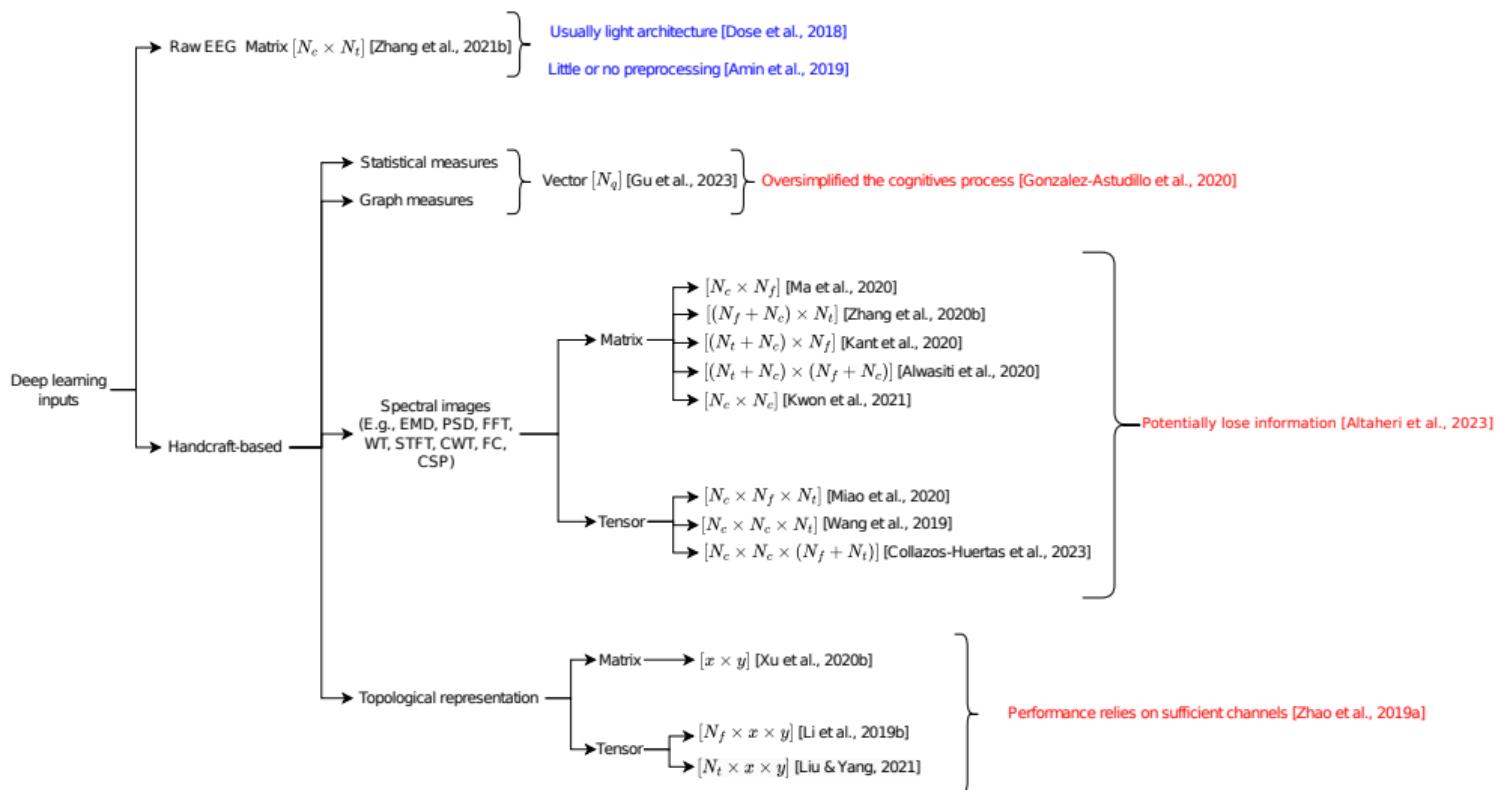
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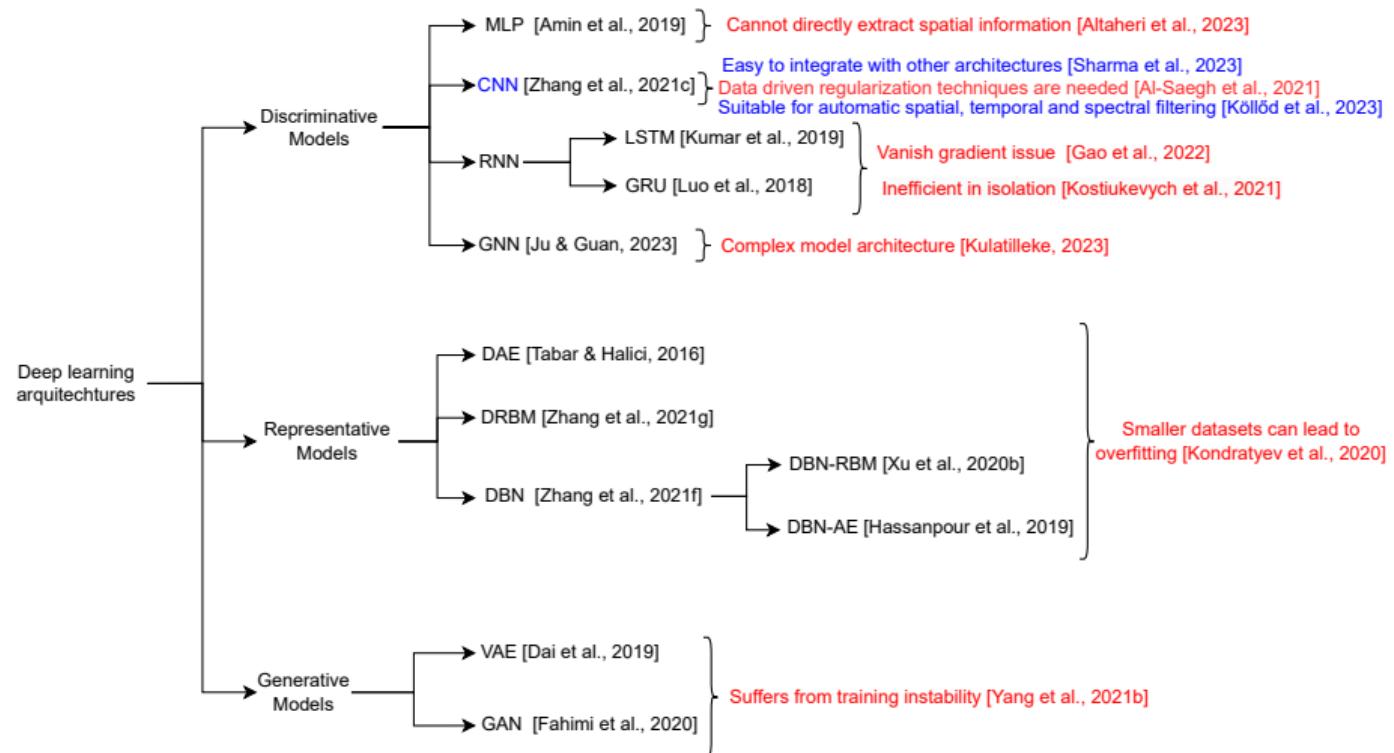


# Input Formulation in Deep Learning





# Deep Learning Architectures





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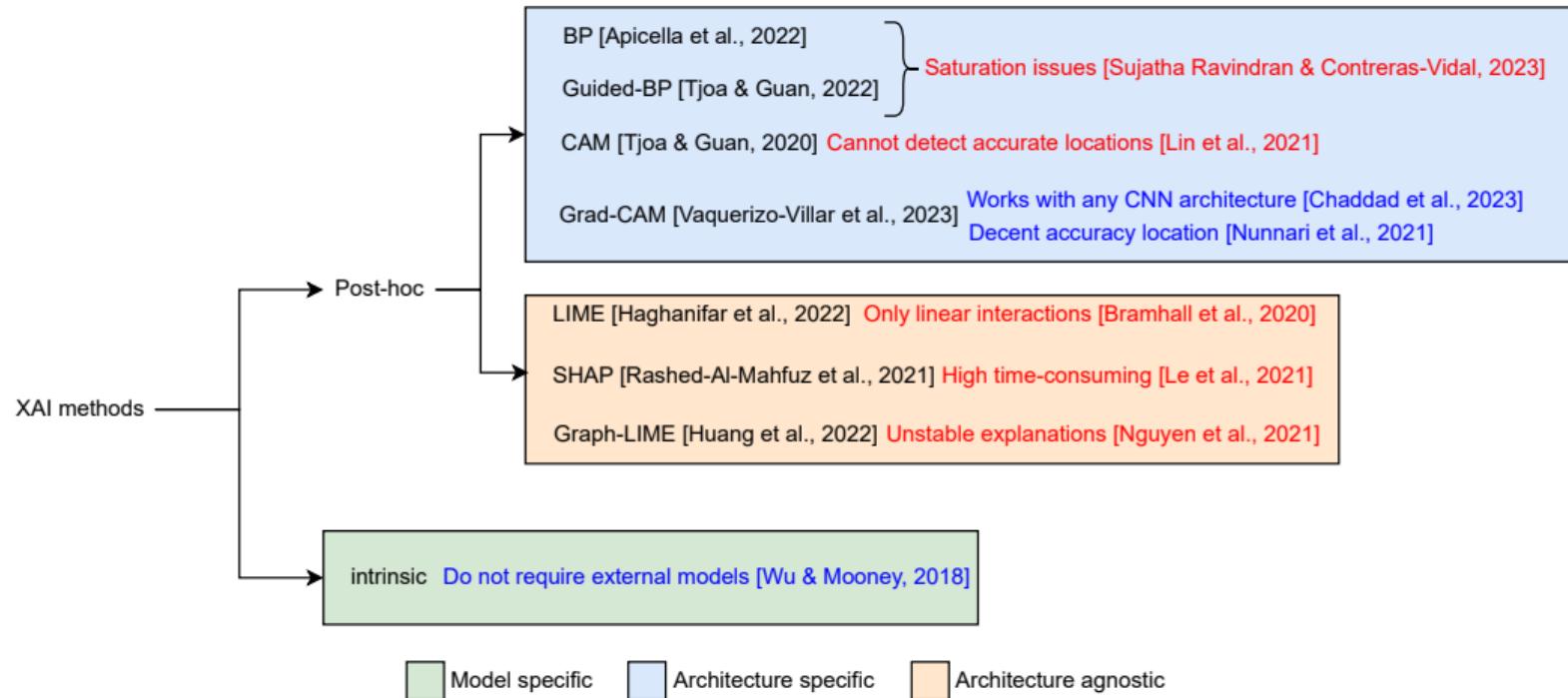
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# Interpretability Strategies in MI-BCI





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# General Objective

To develop a **single-trial indirect functional connectivity** framework, accompanied by **regularized deep learning** approaches, to extract pertinent subject-specific non-linear **spatio-temporal-frequency patterns** from non-stationary EEG data, improving the MI-BCI system's accuracy and **interpretability**.



# Specific Objectives

- 1 To develop a **single-trial indirect FC** for enhanced nonlinear feature extraction, preserving the spatio-temporal-frequency interpretability while favoring the **classification performance** in MI-BCI and avoiding spurious connectivities.
- 2 To extend the proposed single-trial FC within a **deep learning scheme** that handles artifacts and EEG representations, requiring **minimal preprocessing** efforts from raw signals.
- 3 To develop a **transparency and interpretability** strategy dedicated to MI-BCI classification that emphasizes spatial-temporal-spectral pattern domains, incorporating a **qualitative and quantitative** relevance analysis assessment.



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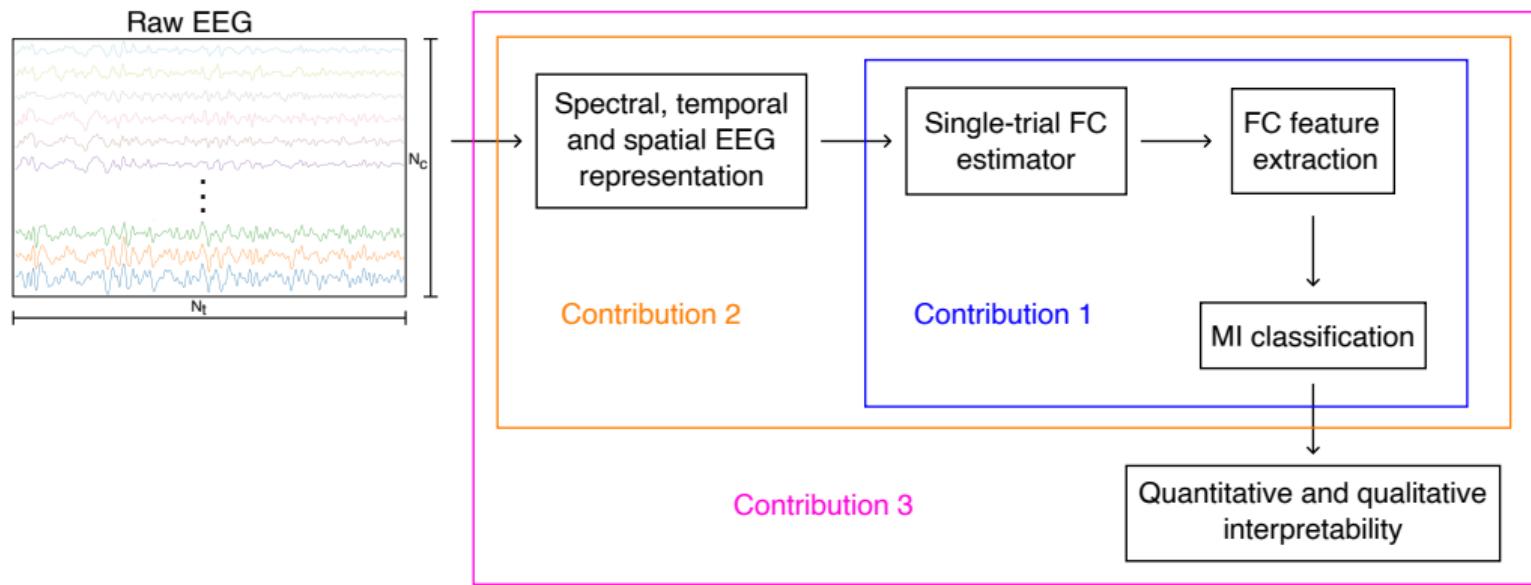
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# Contributions



Regularized DL-based **single-trial indirect FC** framework for extracting subject-specific **spatio-temporal-spectral patterns** to improve MI-BCI system's **accuracy** and **interpretability**.



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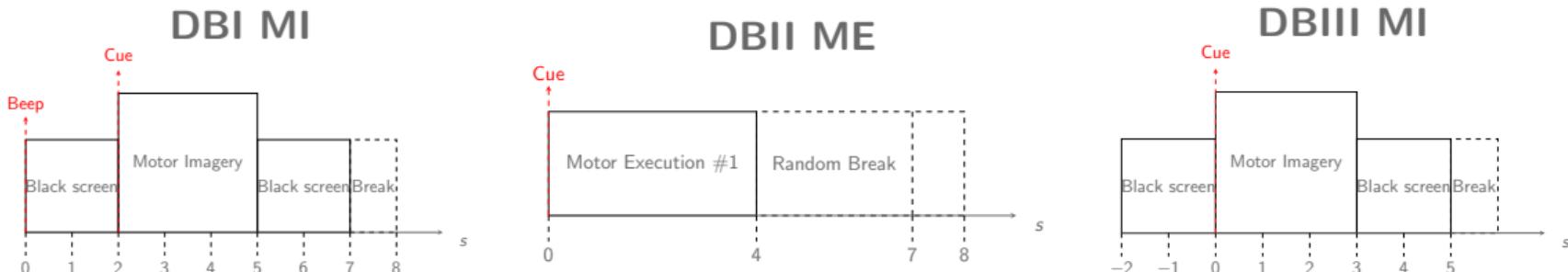
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# Datasets

Dataset	Subjects	Trials	Paradigm	Classes	Channels	Sampling rate
BCI Competition IV Dataset IIa (DBI MI) <sup>1</sup>	9	288	Motor imagery	2	22	250Hz
Gamma Motor Execution Database (DBII ME) <sup>2</sup>	14	260	Motor execution	2	44	500Hz
MI BCI EEG Giga Science Database (DBIII MI) <sup>3</sup>	50	200	Motor imagery	2	64	500Hz



<sup>1</sup><http://www.bbci.de/competition/iv>

<sup>2</sup><https://gin.g-node.org/robintibor/high-gamma-dataset>

<sup>3</sup><http://gigadb.org/dataset/100295>



# Outline II

## 7 Proposal and Results

- Single-Trial Kernel-based Functional Connectivity
- KCS-FCnet: Kernel Cross-Spectral Functional Connectivity Network
- IRKCS-FCnet: Interpretable Regularized Kernel Cross-Spectral Functional Connectivity Network

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# Single-Trial Kernel-based Functional Connectivity I

**1 Wiener-Khinchin's theorem** [Cohen, 1998]:

$$R_r^c(\tau) = \int_{\varpi \in \Omega} \exp(j2\pi\tau\varpi) dP_r^c(\varpi),$$

where  $P_r^c(\varpi) \in \mathbb{R}[0, 1]$  is the spectral distribution function.

**2 Bochner's theorem** [Bochner, 2020]:

$$\kappa_r^{cc'}(\Delta_x) = \int_{\varpi \in \Omega} \exp(j2\pi\Delta_x^\top \varpi) S_r^{cc'}(\varpi) d\varpi,$$

where  $\Delta_x = \mathbf{x}_r^c - \mathbf{x}_r^{c'}$  is the vector delay,  $\varpi \subseteq \Omega$  is the frequency domain that contains the bandwidth set of analysis  $\Omega$ , and  $S_r^{cc'}(\varpi)$  is the cross-spectral density.



# Single-Trial Kernel-based Functional Connectivity II

## 3 Cross-spectral distribution:

$$P_r^{cc'}(\varpi) = 2 \int_{\varpi \in \Omega} \mathcal{F} \left\{ \kappa(x_r^c, x_r^{c'}) \right\} d\varpi,$$

where the notation  $\mathcal{F}\{\cdot\}$  stands for the Fourier transform.

## 4 Kernel-based spectral distribution estimation:

$$\hat{P}_r^{cc'}(\mathbf{u}^{cc'}, \kappa_x(\cdot; \sigma)) = \sum_{n=1}^{N_f} \sum_{w_t=1}^{N_t} u_{nw_t}^{cc'} \kappa_x \left( x_{rnw_t}^c, x_{rnw_t}^{c'}; \sigma \right),$$

where  $\mathbf{u}^{cc'} \in \mathbb{R}^{N_f N_t}$  is the spatio-temporal-frequency relevance vector.



# Single-Trial Kernel-based Functional Connectivity III

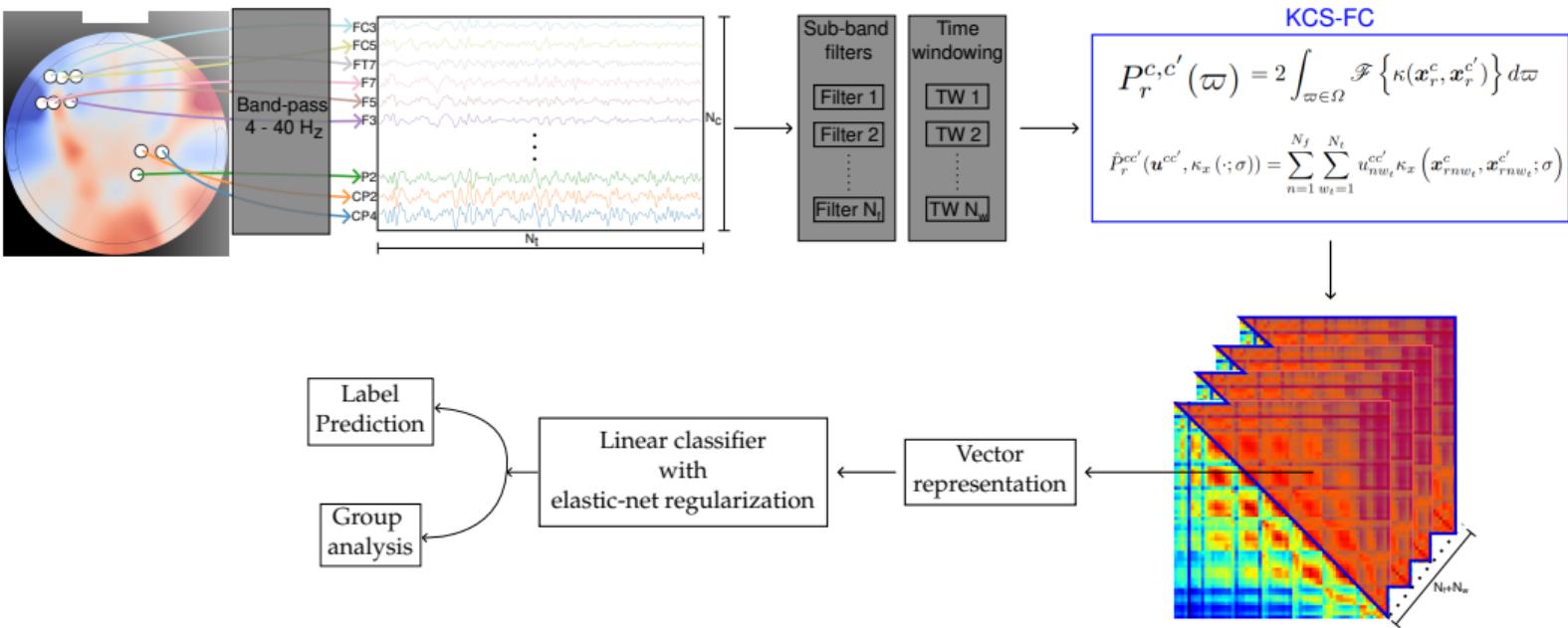
## 5 Supervised kernel-based spectral distribution estimation:

$$\mathbf{u}^* = \arg \min_{\mathbf{u}} \sum_{r=1}^R \left\| \sum_{c,c'=1}^{N_c} \hat{P}_r^{cc'}(\mathbf{u}^{cc'}, \kappa_x(\cdot; \sigma)) - y_r \right\|_2^2 + \alpha \sum_{c,c'=1}^{N_c} \|\mathbf{u}^{cc'}\|_1 + \frac{1-\alpha}{2} \sum_{c,c'=1}^{N_c} \|\mathbf{u}^{cc'}\|_2 \quad : \forall c < c',$$

where  $\alpha \in \mathbb{R}^+$  is the regularization hyperparameter,  $y_r$  is the label corresponding to the  $r$ -th trial, and  $\|\cdot\|_q$  is the  $\ell_q$ -norm.



# Single-Trial Kernel-based Functional Connectivity Proposal





# Experimental Set-up

- 1 Sliding window of length  $\tau = [0.5, 1.0, 1.5, 2.0]$  s, and overlap of 75%.
- 2 Frequency bands from 4 Hz to 40 Hz, window bandwidth of 4 Hz, and overlap of 50%.
- 3 Data split using 5-fold 80-20 scheme.
- 4 Gaussian kernel

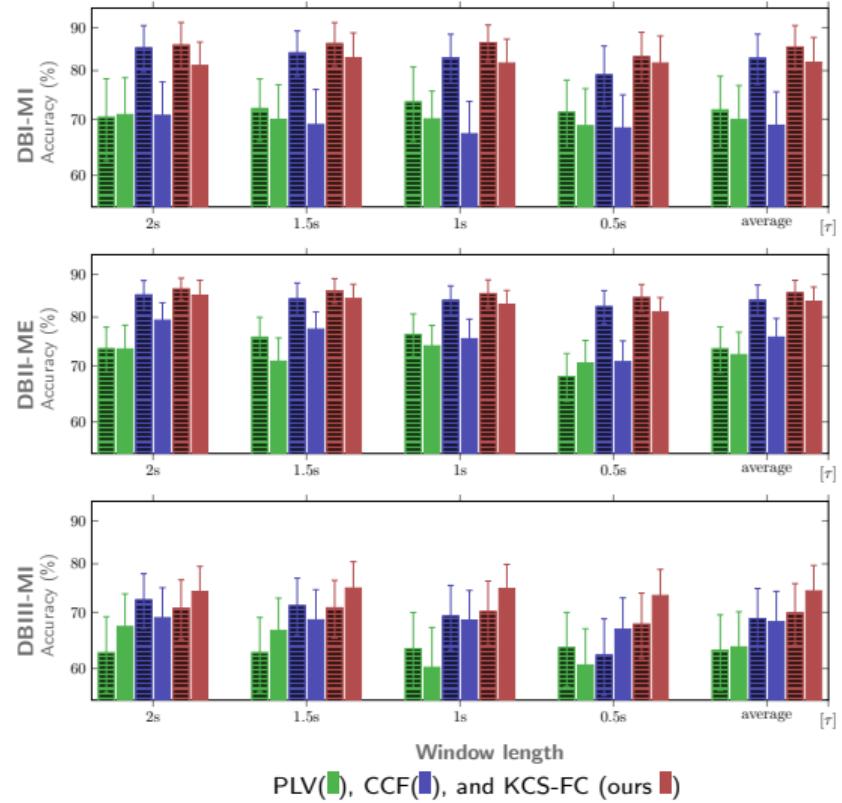
$$\kappa_x \left( \mathbf{x}_{rnw_t}^c, \mathbf{x}_{rnw_t}^{c'}; \sigma \right) = \exp \left( -\|\mathbf{x}_{rnw_t}^c - \mathbf{x}_{rnw_t}^{c'}\|_2^2 / 2\sigma^2 \right),$$

- 5 We compare our proposal with Cross-Correlation Coefficient (CCF) and Phase Lag Value (PLV)

$$\rho(\mathbf{x}_{rnw_t}^c, \mathbf{x}_{rnw_t}^{c'}) = \left\langle \mathbf{x}_{rnw_t}^c, \mathbf{x}_{rnw_t}^{c'} \right\rangle$$

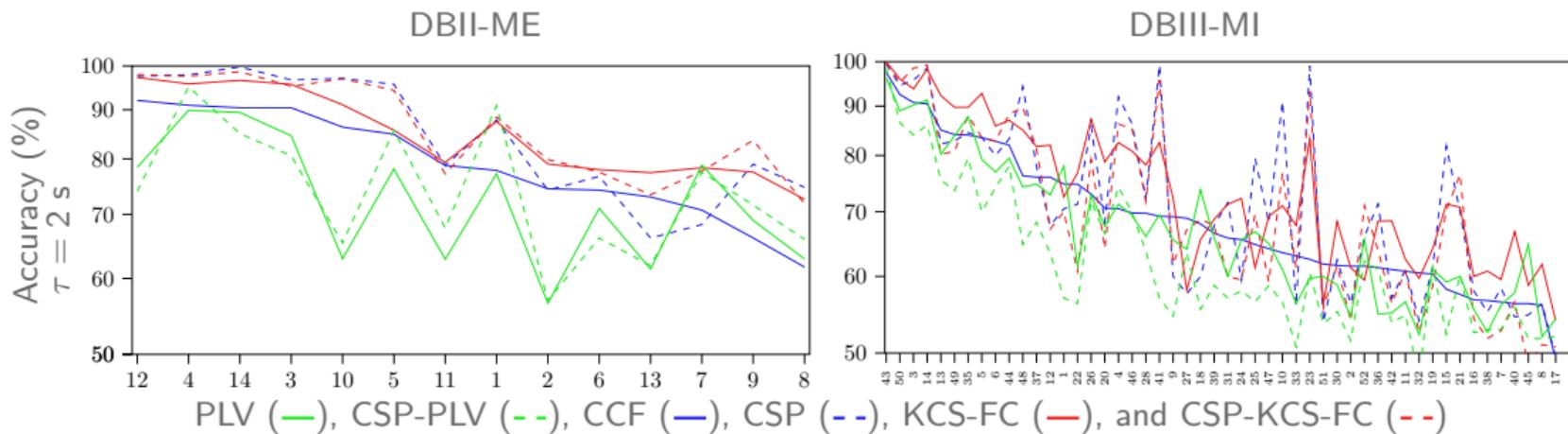
$$\Delta\phi(\mathbf{x}_{rnw_t}^c, \mathbf{x}_{rnw_t}^{c'}) = |\exp(j(\phi_{rnw_t}^c - \phi_{rnw_t}^{c'}))|$$

# Influence of Sliding Windows



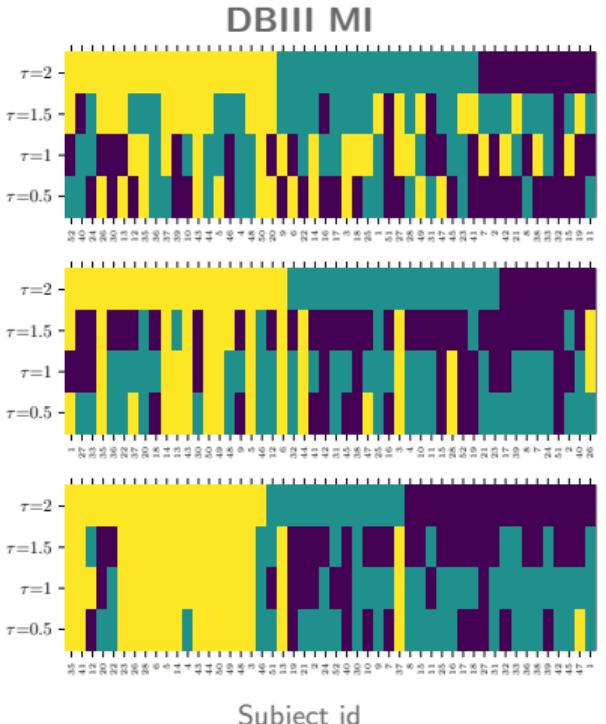
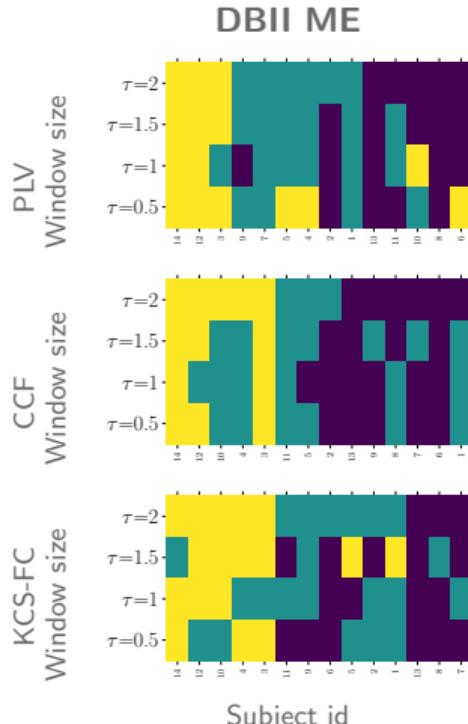
- Solid bars represent concatenated data; striped bars show CSP-filtered.
- DBIII-MI shows the highest subject variability, with all FC measures, especially PLV, dropping in accuracy.
- CSP filtering effectiveness depends more on the selected sliding window.
- PLV and CCF accuracy are sensitive to sliding window size, while KCS-FC (ours) remains consistent across  $\tau$ .

# Classifier Accuracy of Individuals



- CSP algorithm reduces the effectiveness of KCS-FC (ours) in handling subject variability.
- Both versions of the PLV algorithm achieve the lowest accuracy.
- KCS-FC (ours) ensures several subjects exceed the BCI-inefficiency threshold (below 60%).

# Interpretation of Subject Clusters

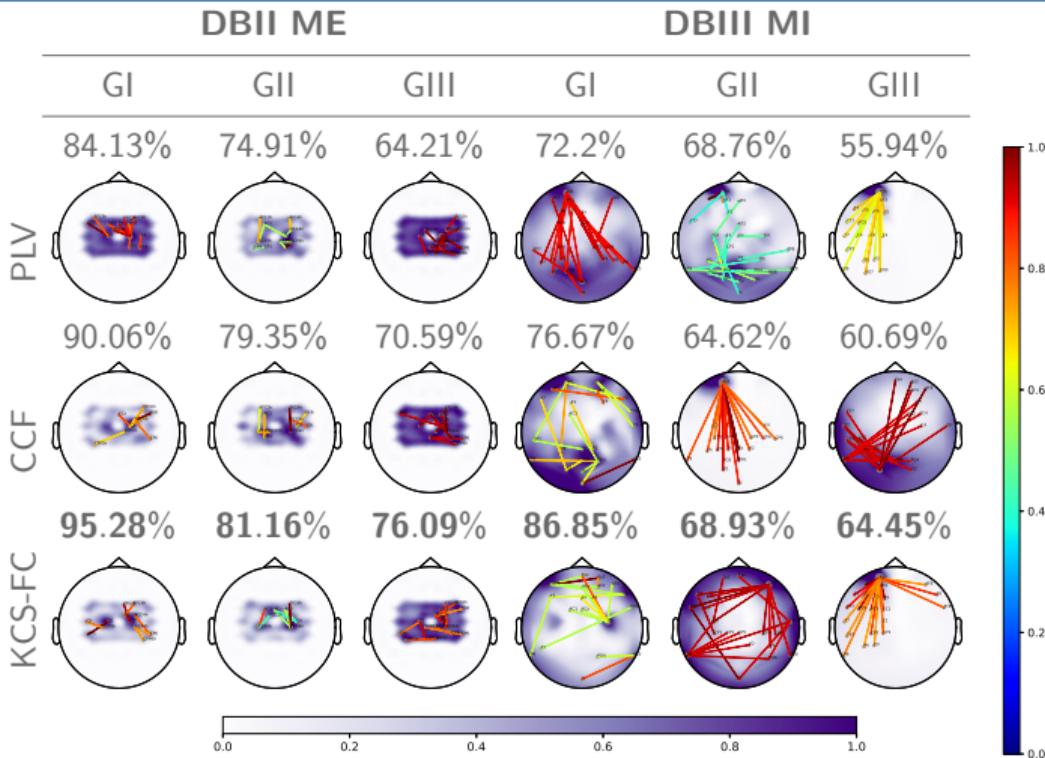


- Groups are ranked in decreasing order of accuracy: Group I (Yellow), Group II (Teal), Group III (Purple).
- Different window values cause frequent changes between groups for PLV and CCF measures.
- KCS-FC (ours) is less affected by different window values.



# Functional Connectivity Analysis

- PLV shows high background activity, CCF has fewer amplitudes, and KCS-FC shows localized activity over SMR hemispheres.
- GII and GIII generate abnormally connections over the frontal and occipital lobe.





# Classifier Accuracy Comparison of FC Approaches

Data	Time Window	Filter Band	Interpretation	Feature Extraction	Accuracy (%)
DBI-MI	✓	✓	✓	TSGSP [Zhang et al., 2018]	<b>82.50 ± 12.2</b>
	-	-	✓	STR connectivity [Rodrigues et al., 2019]	69.56±15.02
	✓	-	✓	Renyi's $\alpha$ -entropy [De La Pava Panche et al., 2019]	72.40 ± 6.50
	✓	✓	✓	Proposed KCS-FC	81.92 ± 9.44
DBIII-MI	-	✓	✓	CSP [Cho et al., 2017]	67.60 ± 13.17
	✓	✓	-	OPTICAL [Kumar et al., 2019]	68.19 ± 9.36
	-	-	✓	STR connectivity [Rodrigues et al., 2019]	62.00 ± 13.00
	✓	✓	✓	Proposed KCS-FC	<b>74.12 ± 12.13</b>

KCS-FC (ours) achieves competitive classifier performance compared to state-of-the-art FC strategies.



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# Kernel Cross-Spectral Functional Connectivity Network I

## 1 1-D convolutional feature extraction and Gaussian pairwise similarity:

$$\hat{P}_r(\mathbf{w}_f) = \tilde{K}(\cdot; \sigma) \circ \varphi(\mathbf{X}_r; \mathbf{w}_f),$$

where  $\tilde{K}(\tilde{\mathbf{X}}_r; \sigma) = [\mathbf{K}_{r1}, \mathbf{K}_{r2}, \dots, \mathbf{K}_{rf}, \dots, \mathbf{K}_{rN_f}]$  and  $\mathbf{K}_{rf}$  is defined as:

$$\mathbf{K}_{rf} = \begin{bmatrix} \kappa_x(\mathbf{x}_{rf}^1, \mathbf{x}_{rf}^1; \sigma) & \kappa_x(\mathbf{x}_{rf}^1, \mathbf{x}_{rf}^2; \sigma) & \cdots & \kappa_x(\mathbf{x}_{rf}^1, \mathbf{x}_{rf}^{N_c}; \sigma) \\ \kappa_x(\mathbf{x}_{rf}^2, \mathbf{x}_{rf}^1; \sigma) & \kappa_x(\mathbf{x}_{rf}^2, \mathbf{x}_{rf}^2; \sigma) & \cdots & \kappa_x(\mathbf{x}_{rf}^2, \mathbf{x}_{rf}^{N_c}; \sigma) \\ \vdots & \vdots & \ddots & \vdots \\ \kappa_x(\mathbf{x}_{rf}^{N_c}, \mathbf{x}_{rf}^1; \sigma) & \kappa_x(\mathbf{x}_{rf}^{N_c}, \mathbf{x}_{rf}^2; \sigma) & \cdots & \kappa_x(\mathbf{x}_{rf}^{N_c}, \mathbf{x}_{rf}^{N_c}; \sigma). \end{bmatrix}$$

## 2 Average functional connectivity measure:

$$\tilde{\mathbf{P}}_r = \text{AvgPooling}_f \left( \hat{P}_r(\mathbf{w}_f) \right),$$



# Kernel Cross-Spectral Functional Connectivity Network II

## 3 Vectorized version of $\tilde{P}_r$ :

$$\bar{\mathbf{p}}_r = \left[ \tilde{p}_r^{12}, \tilde{p}_r^{13}, \dots, \tilde{p}_r^{cc'}, \dots, \tilde{p}_r^{(N_c-1)N_c} \right]; \forall c < c',$$

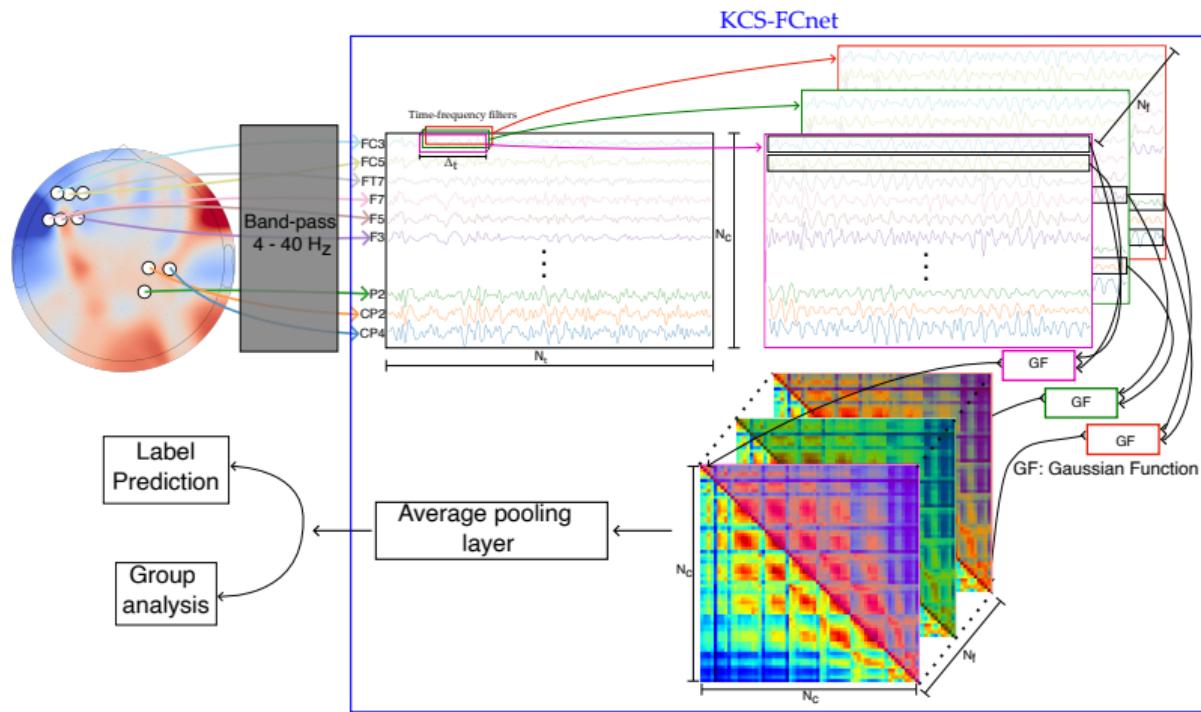
## 4 Optimization problem:

$$\Theta^* = \arg \min_{\Theta} \mathbb{E}_r \{ \mathcal{L}(\mathbf{y}_r, \hat{\mathbf{y}}_r | \Theta); \forall r \in \{1, 2, \dots, R\} \},$$

where  $\mathcal{L}\{\cdot\}$  is a given loss function (i.e., cross-entropy) and  $\hat{\mathbf{y}}_r = \text{softmax}(\mathbf{V}\bar{\mathbf{p}}_r + \mathbf{b})$



# Kernel Cross-Spectral Functional Connectivity Network Proposal





# Kernel Cross-Spectral Functional Connectivity Network Architecture

Layer	Output Dimension	Params.
Input	$N_c \times N_t \times 1$	.
Conv2D	$N_c \times (N_t - \Delta_t + 1) \times N_f$	max norm = 2.0, kernel size = $(1, \Delta_t)$ Stride size = $(1, 1)$ , Bias = False
BatchNormalization	$N_c \times (N_t - \Delta_t + 1) \times N_f$	.
ELU activation		
KCS-FCblock	$N_f \times (N_c \cdot (N_c - 1)/2) \times 1$	.
AveragePooling2D	$1 \times (N_c \cdot (N_c - 1)/2) \times 1$	.
BatchNormalization	$1 \times (N_c \cdot (N_c - 1)/2) \times 1$	.
ELU activation		
Flatten	$N_c \cdot (N_c - 1)/2$	.
Dropout	$N_c \cdot (N_c - 1)/2$	Dropout rate = 0.5
Dense	$N_y$	max norm = 0.5
Softmax		



# Experimental Set-up

## 1 Raw EEG Preprocessing:

- Database used DBIII MI
- Downsampling from 512 Hz to 128 Hz.
- Filtering from 4 Hz to 40 Hz.
- Records clipped from 0.5 s to 2.5 s post cue.

## 2 KCS-FCnet Training [Lawhern et al., 2018, Schirrmeister et al., 2017]:

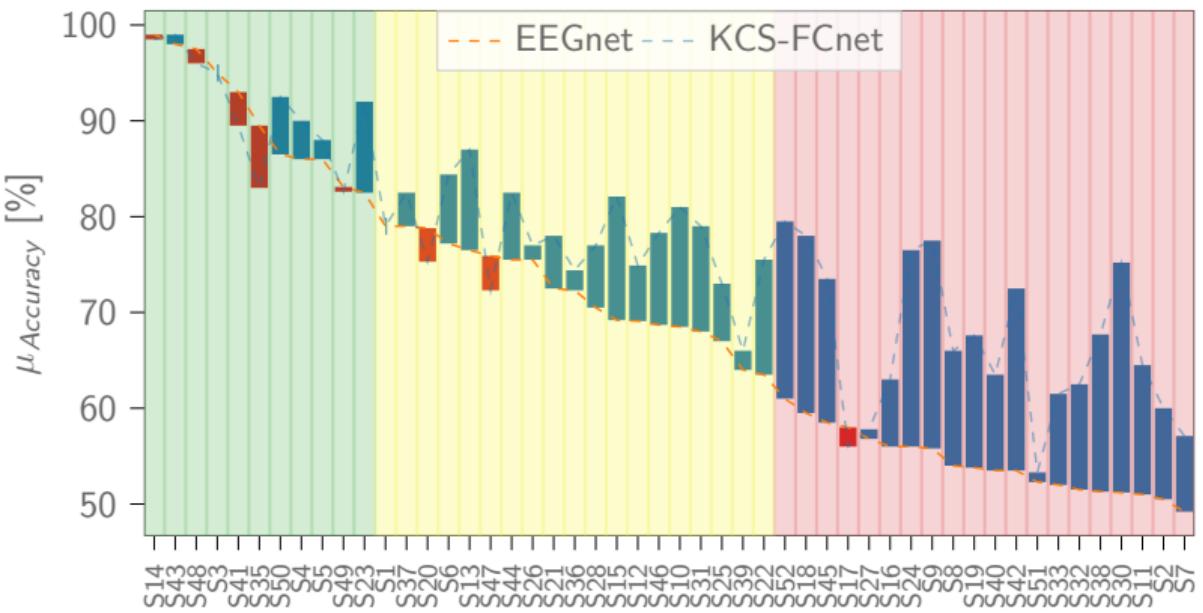
- Data split using 5-fold 80-20 scheme.
- 1-D convolutional kernel length set to 20
- Number of filters were searched within the set  $\{2, 3, 4\}$
- Gaussian kernel  $\sigma = \zeta \text{Median}(\mathbf{D})$  with  $\mathbf{D}$  being the distance matrix.

## 3 Group-Level Analysis:

- Scaled scoring matrix with subjects and accuracy, Cohen's kappa, AUC.
- Cluster subjects in three groups based on base line EEGnet.
- PCA was used to reduce the dimensions to two, enabling us to plot it.



# Subject Dependent and Group Analysis Results I

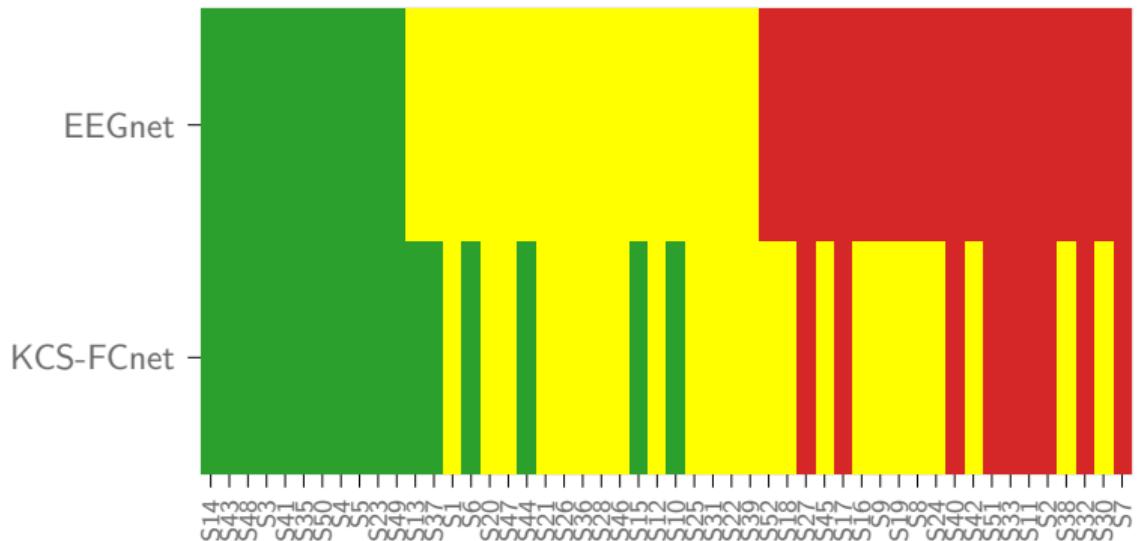


- KCS-FCnet (ours) shows strong impact on subjects in the third group.
- Seven subjects experienced a decrease in accuracy.
- 47 subjects experience an increase of more than five points in accuracy.



# Subject Dependent and Group Analysis Results II

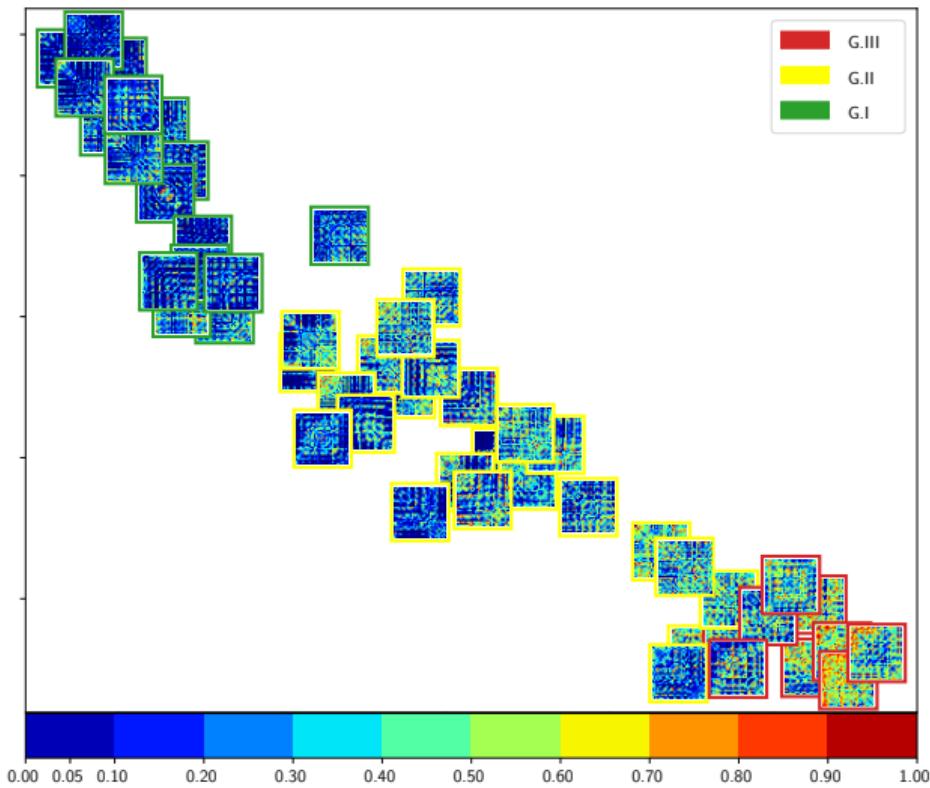
- Eleven subjects significantly improved their performance, transitioning to the GII cluster, while nine remained in GIII and six advanced to GI.
- Subjects initially in the best group retained their status.
- Our proposal boosts GII accuracy by 5.6% and GIII by 12.4%.





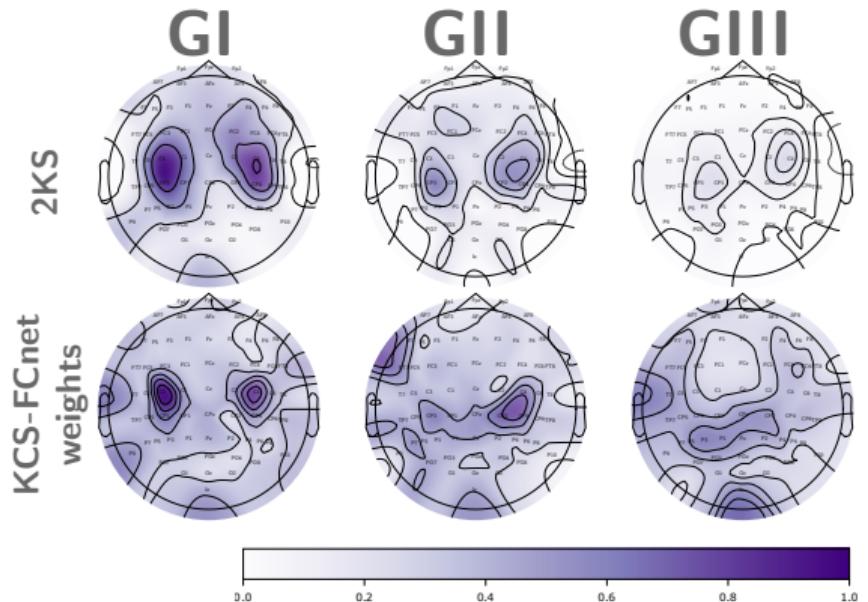
# Functional Connectivity Analysis I

- Two-sample Kolmogorov–Smirnov (2KS) test for MI separability.
- Lower p-values indicate higher class separability and more informative results.
- For GIII, most class PDFs are indistinguishable.





# Functional Connectivity Analysis II

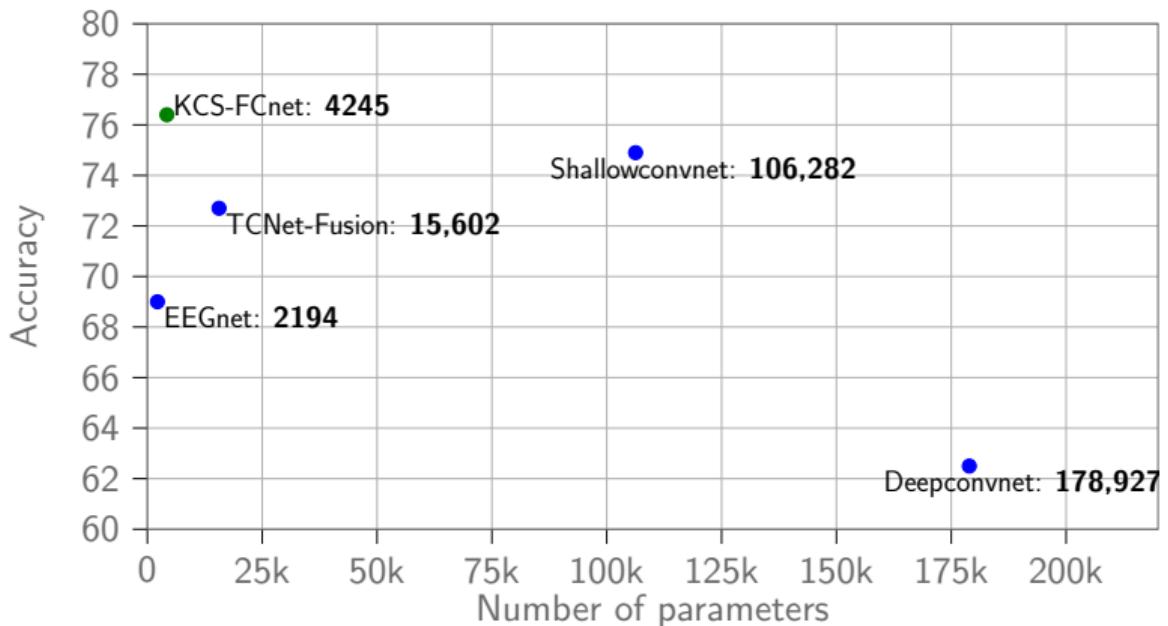


- GI shows similar results for both approaches.
- In GII, weighting approach highlights relevance around C4, while 2KS highlights C3 and C4.
- For GIII, the 2KS test reveals some importance around C3 and C4, whereas the weight-based approach lacks a clear pattern.



# Classifier Accuracy Comparison of DL Approaches

- A higher number of trainable parameters does not guarantee better classification accuracy.
- KCS-FCNet outperforms ShallowConvNet while using 25 times fewer parameters.





# Outline II

## 7 Proposal and Results

- Single-Trial Kernel-based Functional Connectivity
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# Interpretable Regularized Kernel Cross-Spectral FC Network I

## 1 Parzen density estimation:

$$\hat{\zeta}(\chi) = \frac{1}{N_c} \sum_{c=1}^{N_c} \kappa(\chi, x^c; \sigma),$$

## 2 Renyi's entropy $\alpha = 2$ :

$$\begin{aligned} H_2(\chi) &= -\log \left( \int_{\chi} \hat{\zeta}(\chi)^2 d\zeta \right) \\ &= -\log \left( \frac{1}{N_c^2} \sum_{c,c'=1}^{N_c} \kappa(x^c, x^{c'}; \sigma) \right). \end{aligned}$$



# Interpretable Regularized Kernel Cross-Spectral FC Network II

## 3 Concept extended to function composition:

$$\hat{\zeta}(\chi) = \frac{1}{N_c} \sum_{c=1}^{N_c} \kappa_x(\chi, \cdot; \sigma) \circ \varphi(\mathbf{x}^c; \mathbf{w}_f),$$

where  $\varphi(\cdot; \mathbf{w}_f)$  is a 1-D convolutional layer.

## 4 Optimization problem with Renyi's-based regularization:

$$\Theta^* = \arg \min_{\Theta} \mathbb{E}_r \left\{ \mathcal{L}(\mathbf{y}_r, \hat{\mathbf{y}}_r | \Theta) - \rho H(\tilde{\mathbf{P}}_r; \mathbf{w}_f, \sigma) \right\}; \forall r \in \{1, 2, \dots, R\},$$

where

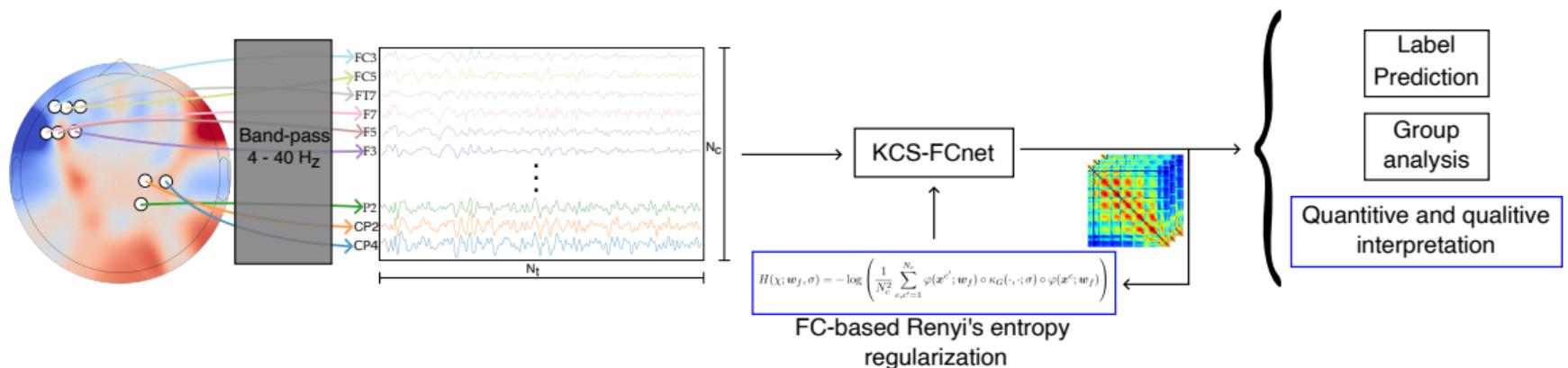
$$H(\tilde{\mathbf{P}}_r; \mathbf{w}_f, \sigma) = -\log \left( \frac{1}{N_c^2} \sum_{c,c'=1}^{N_c} \kappa_x(\cdot, \cdot; \sigma) \circ (\tilde{p}_r^{c'}(\mathbf{w}_f), \tilde{p}_r^c(\mathbf{w}_f)) \right).$$

---

<sup>1</sup>[Yu et al., 2019, Giraldo et al., 2014]

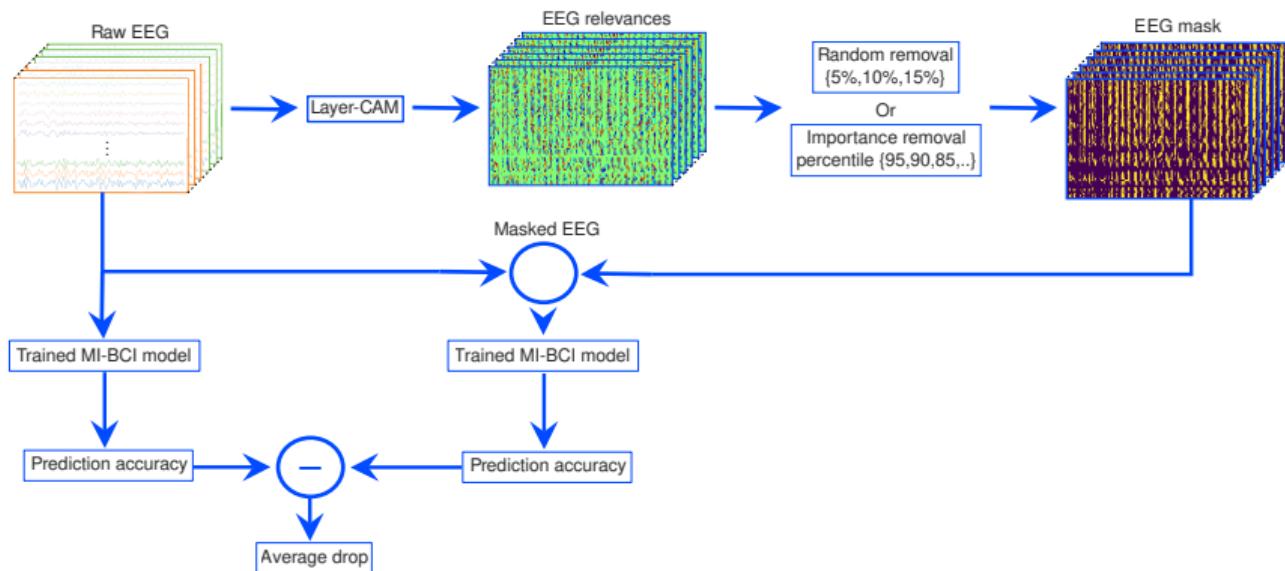


# Interpretable Regularized KCS-FCnet Proposal I





# Interpretable Regularized KCS-FCnet Proposal II



Quantitative average drop interpretation comparison



# Experimental set-up

## 1 Raw EEG Preprocessing:

- Database used DBIII MI
- Downsampling from 512 Hz to 128 Hz.
- Filtering from 4 Hz to 40 Hz.

## 2 IRKCS-FCnet Training [Lawhern et al., 2018, Schirrmeister et al., 2017]:

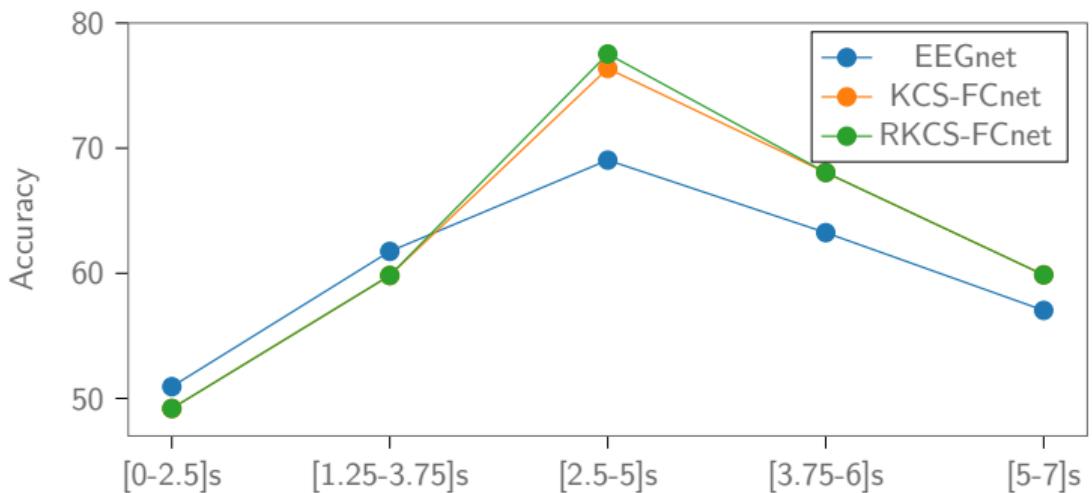
- Data split using 5-fold 80-20 scheme.
- 1-D convolutional kernel length set to 20.
- Number of filters were taken from the best results within the original model.
- Gaussian kernel  $\sigma = \varsigma \text{Median}(\mathbf{D})$  with  $\mathbf{D}$  being the distance matrix and  $\varsigma$  a trainable parameter.
- Regularization hyperparameter  $\rho$  is searched within the set  $\{0, 0.2, 0.5, 0.7, 1, 5, 10\}$ .

## 3 Group-Level Analysis:

- Scaled scoring matrix with subjects and accuracy, Cohen's kappa, AUC.
- Cluster subjects in three groups based on base line EEGnet.
- PCA was used to reduce the dimensions to two, enabling us to plot it.



# Model Level Analysis I

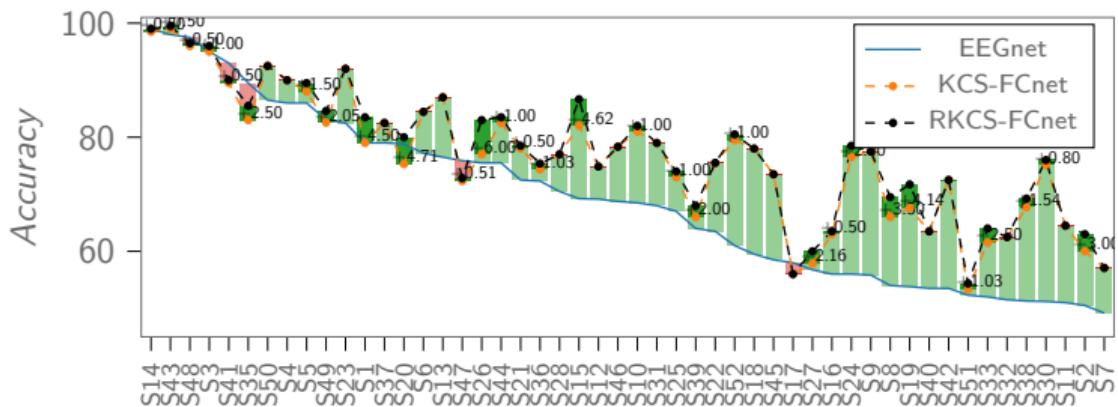


- Average performance comparison at different time windows.
- All three models show reduced accuracy with no or insufficient MI information.
- All models achieve peak accuracy in the [2.5 - 5]s window.



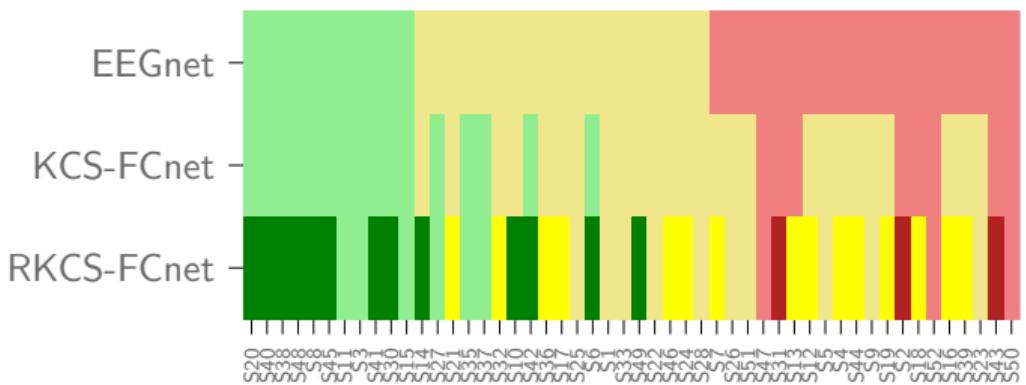
# Model Level Analysis II

- Regularized version consistently performs at least as well as, or better than, the plain version.
- Accuracy boost of more than four percentage points observed for subjects 1, 20, 26, and 15.
- Increases in accuracy were not significant in subjects already achieving more than 80% accuracy.





# Group Level Analysis I

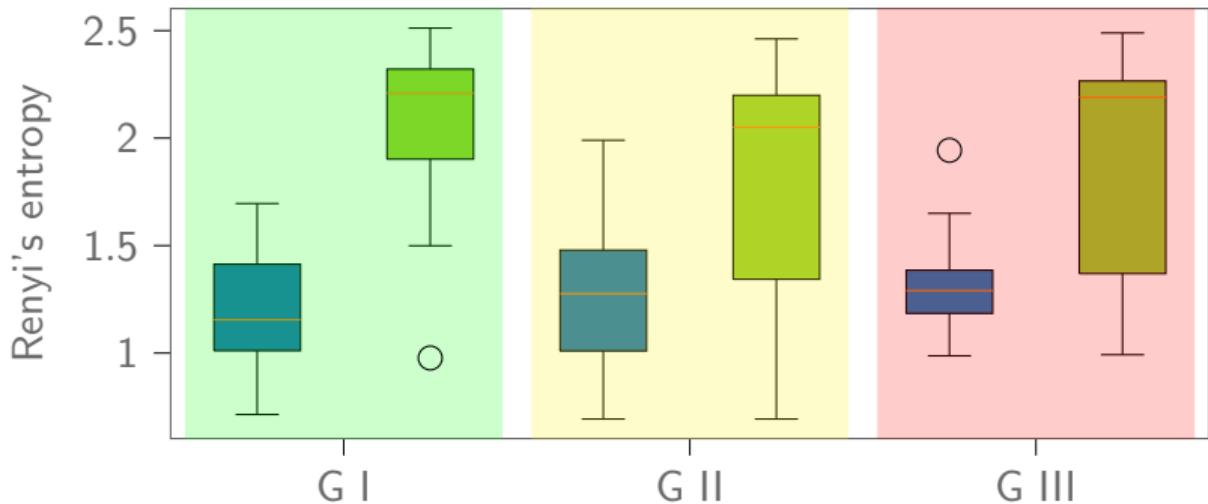


- Light-colored symbols mark subjects who remain with same accuracy.
- Subjects 14, 10, and 49 are promoted from the intermediate to the best group.
- Subjects 13 and 18 moved up from the worst to the intermediate Group
- Accuracy improvement of GII from 72.15% in EEGnet to nearly 80% in IRKCS-FCnet (ours).



# Group Level Analysis II

- IRKCS-FCnet (ours) consistently shows higher entropy values across all groups.
- Except for one, all samples exceed 1.5 in G I for IRKCS-FCnet (ours).
- Best-performing subjects may rely on fewer connections to achieve high accuracy.





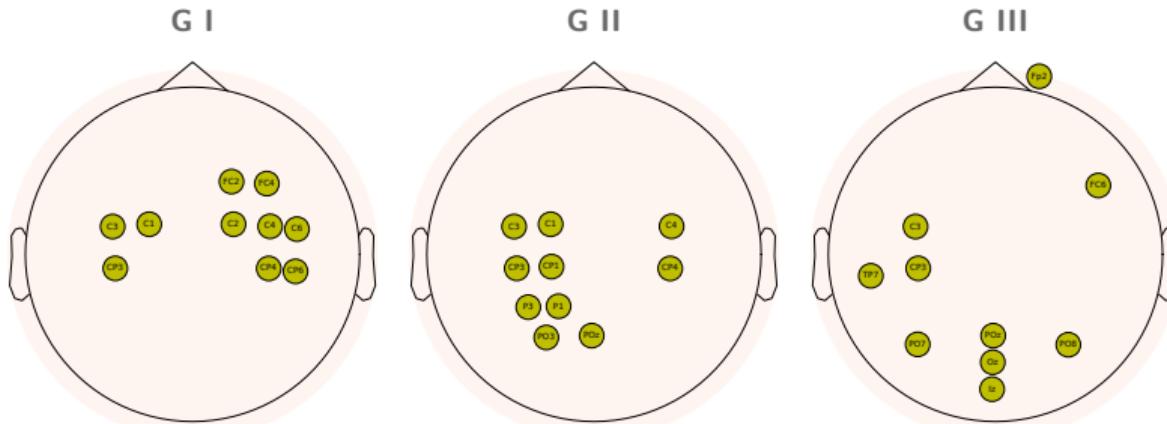
# Post-Hoc Interpretability

Strategy	Group	25%	20%	15%	10%	5%
KCS-FCnet	G I	40.51	37.93	35.97	30.25	17.12
	G II	40.10	39.00	36.46	28.60	17.72
	G III	39.05	36.98	31.99	25.28	15.02
RKCS-FCnet	G I	44.80	39.21	37.79	30.55	22.46
	G II	41.08	40.01	36.77	27.28	18.84
	G III	39.65	37.30	33.12	27.10	16.80

- The highest difference per group is indicated by (green) for G I, (yellow) for G II, and (red) for G III.
- Plain model drops 17.12 accuracy points, while the regularized model drops 22.46 points for 5% case.
- As feature removal increases, the accuracy drop discrepancy diminishes, plateauing around 40% from 15% to 25% removal.



# Intrinsic Interpretability I



- Ten most relevant channels for each group based on the last layer weights of IRKCS-FCnet.
- For GI, the best-performing group, most channels are located in the sensorimotor cortex (CP3, CP4, CP6), central sulcus (C1, C2, C3, C4, C6), and motor cortex (FC2, FC4).
- In GII, 60% of the most relevant channels are located in the motor-related brain area, while in GIII, this value drops to only 30%.



# Intrinsic Interpretability II

- In GI, the spectrum is stable, with power concentrated between 10 and 14 Hz, consistent with studies showing MI present on Mu rhythm (8–13 Hz) [Al-Saegh et al., 2021, Hobson and Bishop, 2017, Llanos et al., 2013].

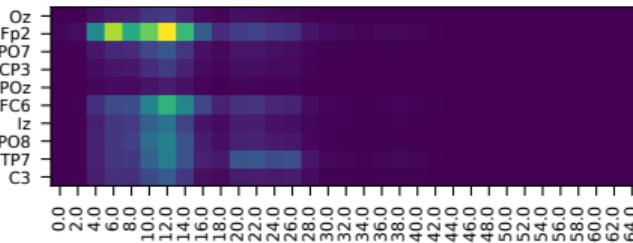
GI



GII



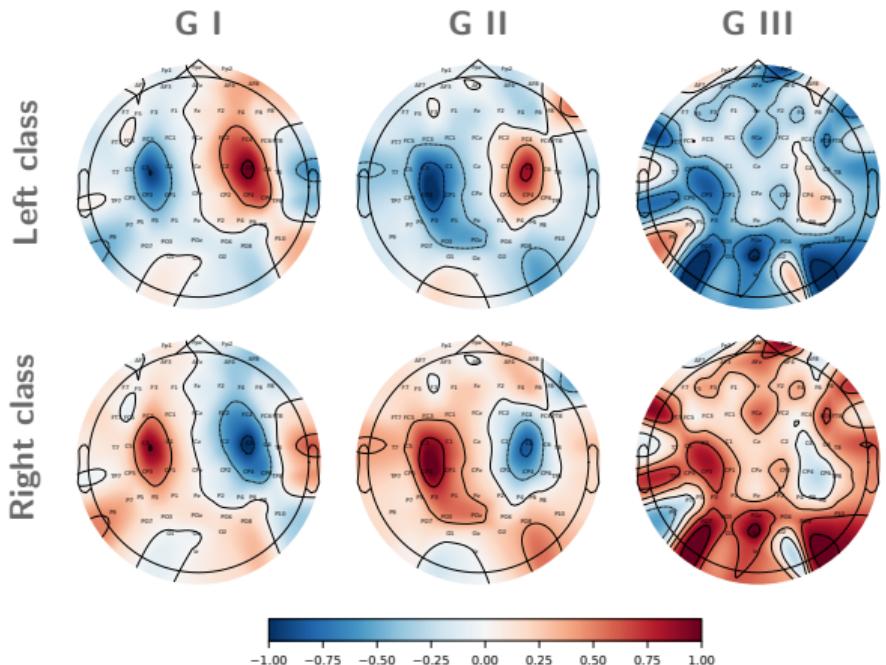
GIII



- GII shows a similar pattern, but the spectral power is slightly skewed to the right.
- In GIII, the Fp2 channel dominates spectral power, indicating significant artifact introduction [Han et al., 2023].



# Intrinsic Interpretability III



- For GI and GII, positive values are seen in the contralateral region while negative for the ipsilateral region [Van der Lubbe et al., 2021].
- GIII exhibits intriguing behavior, showing only faint significance in the contralateral region.
- GIII also displays numerous activations outside motor-related areas, likely due to artifact interference.



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# Conclusions I

- The proposed **single-trial KCS-FC** achieves **competitive classifier performance** while maintaining FC **interpretability** (Objective 1).
- **KCS-FCnet** automatically extracts **spatio-temporal-spectral feature** maps, outperforming other end-to-end architectures. Slightly more complex than EEGnet, it offers **greater accuracy**, especially compared to models with 25 times more parameters (Objective 2).
- The **IRKCS-FCnet** is an **intrinsically interpretable model**, providing valuable insights into spatial connections for MI tasks, particularly emphasizing the **contralateral nature of motor-related** neurological states within the brain network (Objective 3).



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# Future work I

- Extracting more information from time lags, rather than relying solely on instantaneous relationships, could help address volume conduction issues [Uribe et al., 2019, Bakhshali et al., 2020, De La Pava Panche et al., 2019].
- The current method's reliance on pairwise relationships may overlook the influence of a third channel, suggesting the potential benefits of more complex multivariate approaches that account for information from other electrodes [Vidaurre et al., 2023].



## Future work II

- Incorporate Riemannian geometry to capture the internal relationships between different channels in the FC matrix's feature extraction process [Carrara and Papadopoulou, 2023].
- To compare with state-of-the-art methods we employ a 5-fold cross-validation (80-20 split) for our proposals, which may lead to hyperparameter overfitting. Future work could explore subject-independent or cross-dataset approaches to mitigate this risk [Wei et al., 2023]..



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# Academic Products

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- 2 García-Murillo, D.G.; Álvarez-Meza, A.M.; Castellanos-Dominguez, C.G. KCS-FCnet: Kernel Cross-Spectral Functional Connectivity Network for EEG-Based Motor Imagery Classification. *Diagnostics* 2023, 13, 1122. <https://doi.org/10.3390/diagnostics13061122> (Q2-A2)
- 3 García-Murillo, D.G.; Álvarez-Meza, A.M.; Castellanos-Dominguez, C.G. IRKCS-FCnet: Interpretable Regularized Kernel Cross-Spectral Functional Connectivity Network with Qualitative and Quantitative Post-Hoc and Intrinsic Explainability (Sent)
- 4 Github repository containing all notebooks used in this study IRKCS-FCnet repository



# Acknowledgements

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Group	KCS-FCnet vs. Random	RKCS-FCnet vs. Random
G I	0.00077*	0.00230*
G II	0.00368*	0.00434*
G III	0.00108*	0.00074*

Strategy	Group	25%	20%	15%	10%	5%
KCS-FCnet	G I	40.51	37.93	35.97	30.25	17.12
	G II	40.10	39.00	36.46	28.60	17.72
	G III	39.05	36.98	31.99	25.28	15.02
RKCS-FCnet	G I	44.80	39.21	37.79	30.55	22.46
	G II	41.08	40.01	36.77	27.28	18.84
	G III	39.65	37.30	33.12	27.10	16.80

- The accuracy drop upon important feature removal in both models is statistically different from the random drop.
- Plain model drops 17.12 accuracy points, while the regularized model drops 22.46 points, a difference of over 5 points.
- As feature removal increases, the accuracy drop discrepancy diminishes, plateauing around 40% from 15% to 25% removal.



# Group Level Analysis II

Strategy	G I	G II	G III
EEGnet	$90.55 \pm 5.88$	$72.15 \pm 4.87$	$54.27 \pm 3.21$
KCS-FCnet	$91.46 \pm 5.31$	$77.85 \pm 4.76$	$66.66 \pm 7.88$
IRKCS-FCnet	<b><math>92.28 \pm 4.79</math></b>	<b><math>79.26 \pm 4.93</math></b>	<b><math>67.77 \pm 7.83</math></b>

- The standard deviation for the regularized version decreases by over one percentage point, indicating enhanced performance consistency.
- Accuracy improvement of GII from 72.15% in EEGnet to nearly 80% in IRKCS-FCnet (ours).



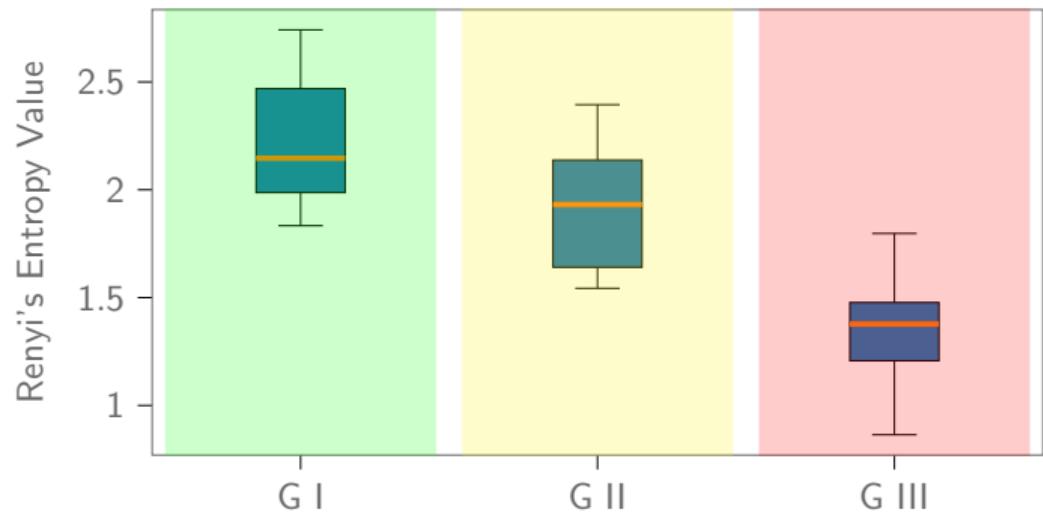
# Classifier Accuracy Comparison of DL Approaches I

Approach	Accuracy	Kappa	AUC
Deepconvnet [Schirrmeister et al., 2017]	$62.5 \pm 13.0$	$24.5 \pm 25.9$	$68.9 \pm 17.8$
EEGnet [Lawhern et al., 2018]	$69.0 \pm 14.6$	$38.0 \pm 29.1$	$75.4 \pm 16.6$
TCNet-Fusion [Musallam et al., 2021]	$72.7 \pm 14.0$	$45.0 \pm 28.2$	$79.6 \pm 15.9$
Shallowconvnet [Schirrmeister et al., 2017]	$74.9 \pm 13.9$	$49.5 \pm 27.8$	$79.9 \pm 15.1$
KCS-FCnet	$76.4 \pm 11.3$	$52.6 \pm 22.7$	$82.2 \pm 12.2$

- DeepConvNet performs the worst, making it unsuitable for high intra-class variability.
- KCS-FCNet (ours) achieves the highest scores with the lowest standard deviation.



# Functional Connectivity Analysis II

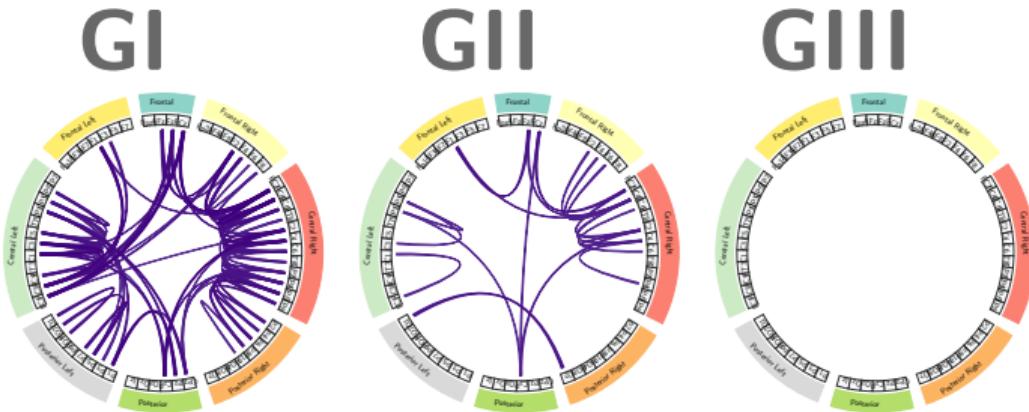


- The Rényi's entropy  $\alpha = 2$  quantifies the interpretability performance from 2KS test matrices.
- Higher entropy values indicates a higher class distribution separability.
- Groups that perform better show higher entropy values.



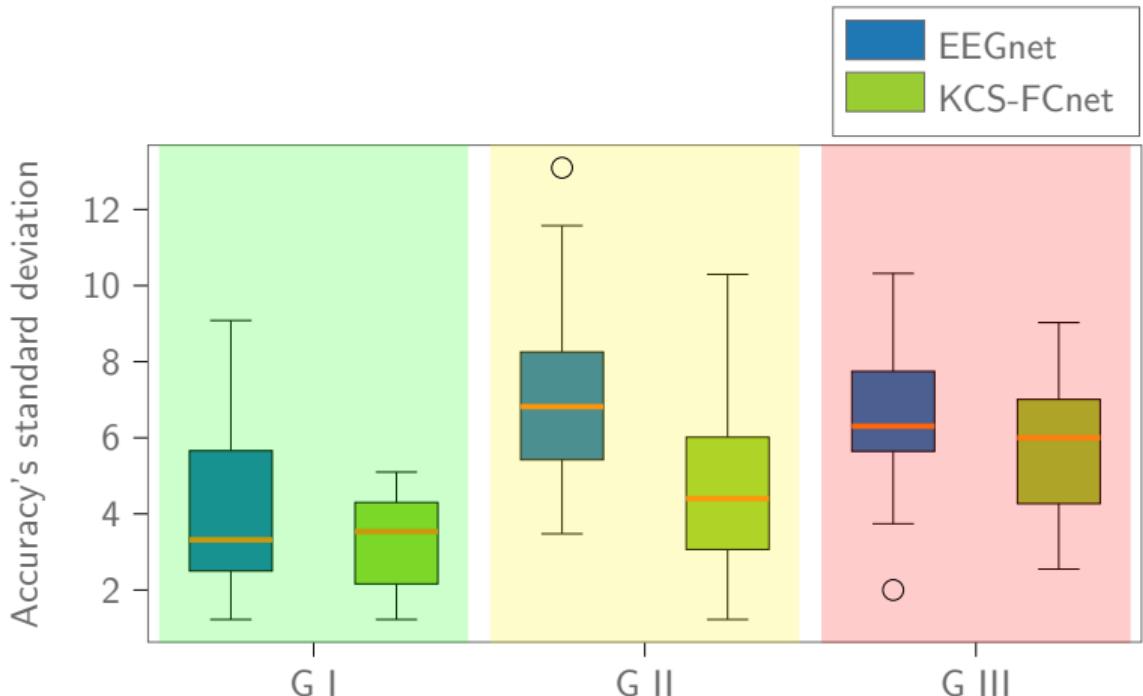
# Functional Connectivity Analysis III

- Relevant connections identified from 2KS test matrices.
- In GI, most relevant connections are found in motor-related areas.
- In GII lacks relevant connections.





# Subject Dependent and Group Analysis Results IV



- For GI, KCS-FCnet (ours) reduces variability.
- For GII, KCS-FCnet (ours) lowers standard deviation, with similar variability proportion.
- For GIII, both approaches behave similarly.



# Subject Dependent and Group Analysis Results III

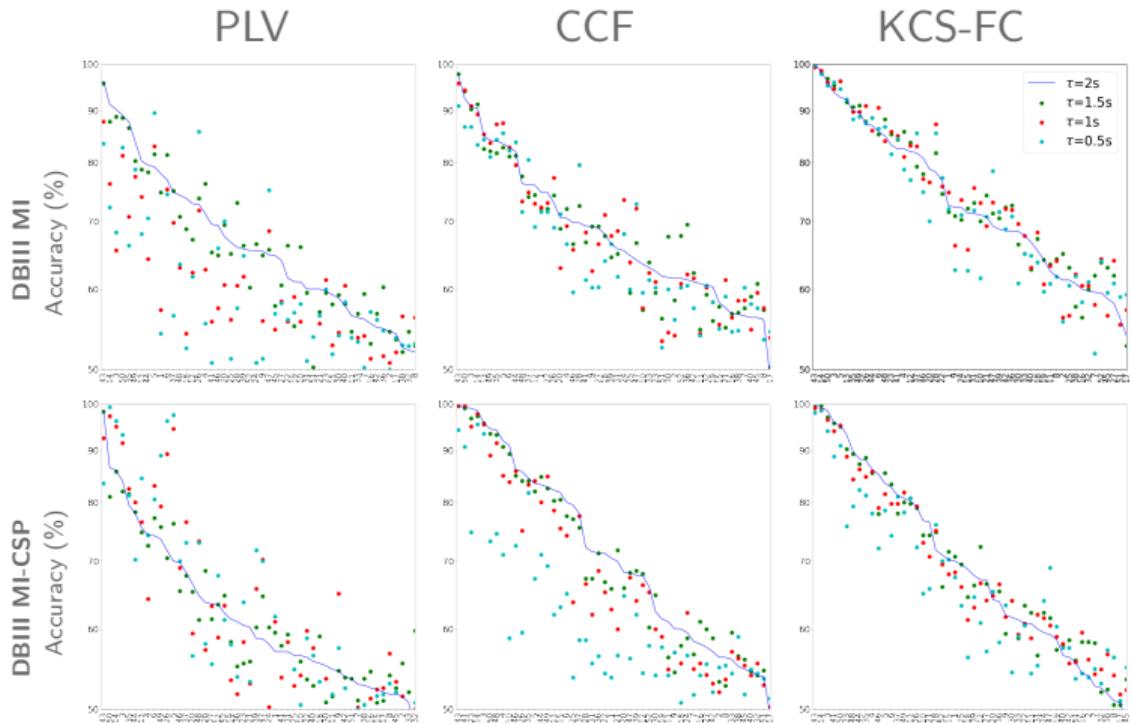
Approach	Group	Accuracy	KCS-FCnet Gain
EEGnet	G I	$90.6 \pm 4.3$	.
	G II	$72.2 \pm 7.3$	.
	G III	$54.3 \pm 6.6$	.
KCS-FCnet	G I	$91.5 \pm 3.3$	<b>0.9</b>
	G II	$77.8 \pm 4.7$	<b>5.6</b>
	G III	$66.7 \pm 5.6$	<b>12.4</b>

Our proposal not only outperforms EEGnet in terms of accuracy but also reduces the variability for all clusters.



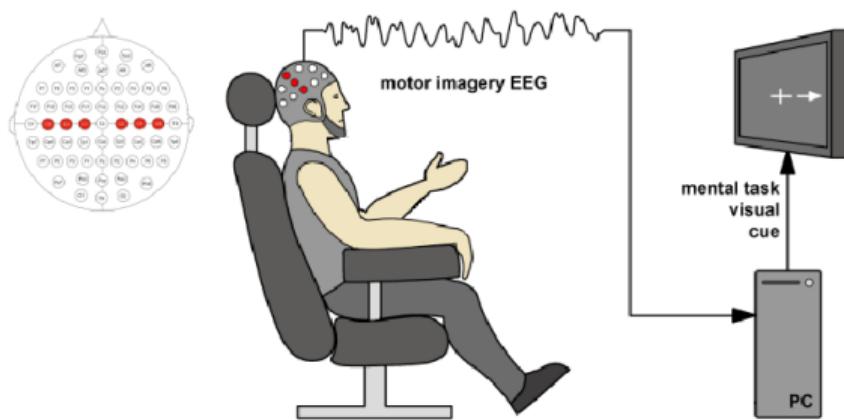
# Impact of Prior CSP Filtering

- PLV shows high variance and low accuracy.
- CSP accuracy drops at  $\tau = 0.5$  due to its reliance on FC estimation, where less information leads to poorer estimates.
- KCS-FC (ours) outperforms other FC measures, with less variance in accuracy across subjects.





# Experimental Setup for MI-based BCIs



- EEG headsets are equipped with 1 to 256 electrodes [Grigorev et al., 2021].
- Visual cues are often used to guide MI tasks during EEG recordings [Hosseini et al., 2020].

<sup>1</sup>Image: Adapted from [Grigorev et al., 2021]