

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

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# Outline I

## 1 Motivation

## 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

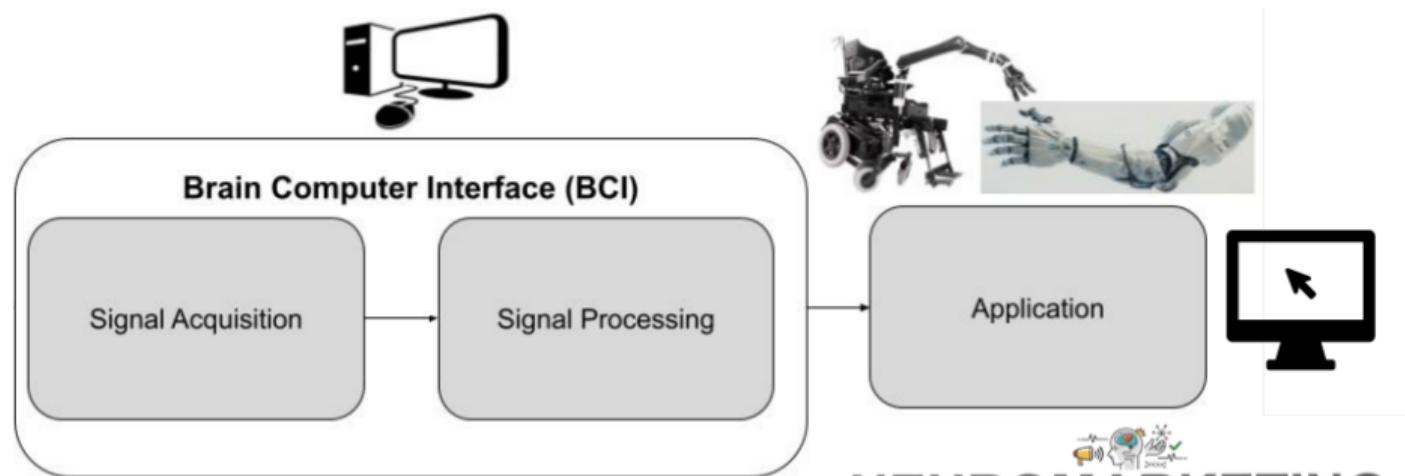
## 5 Outline and contributions

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# Brain computer interface (BCI)

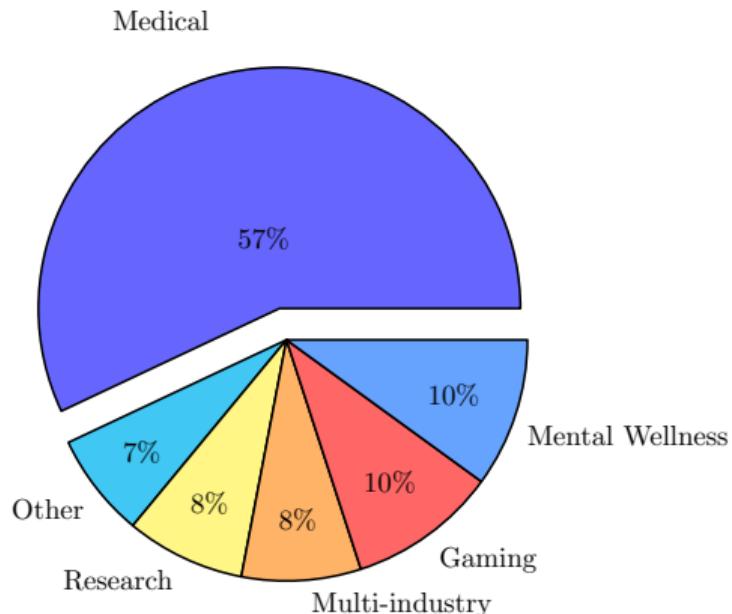
BCI provide people external world communication by translating brain signals [Khan et al., 2020]



**NEUROMARKETING**



# Brain computer interface (BCI)



- Over 150 companies specializing in BCI as of 2019.
- BCI market valued at 228 million in 2019, projected to reach 460 million by 2029 <sup>2</sup>.

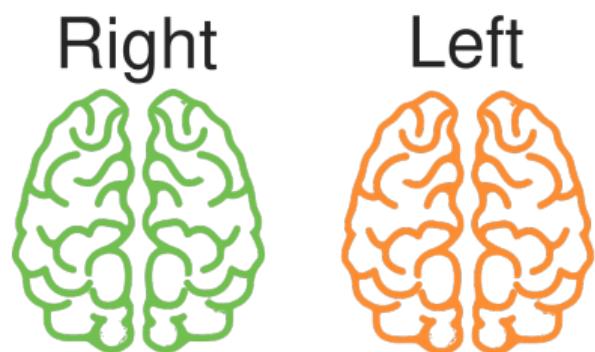
<sup>1</sup>Image: Adapted from The World Economic Forum 2024

<sup>2</sup>Global Brain Computer Interface Market Research Report 2023



# Motor Imagery (MI)

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



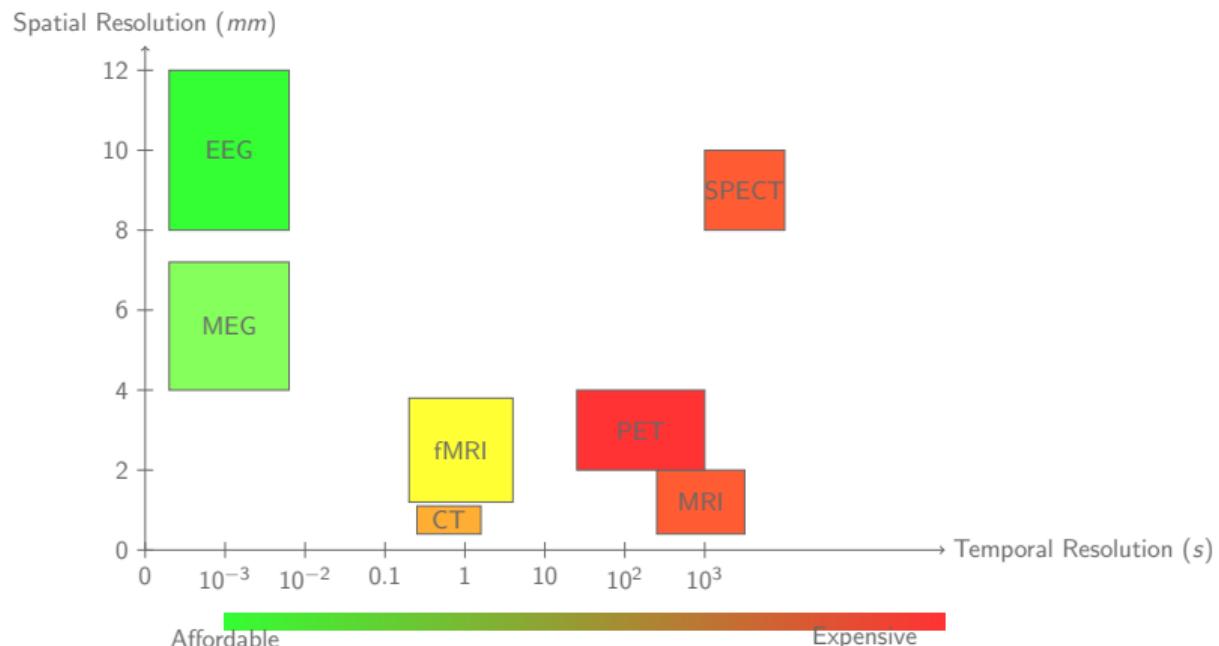
## Applications:

- 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].



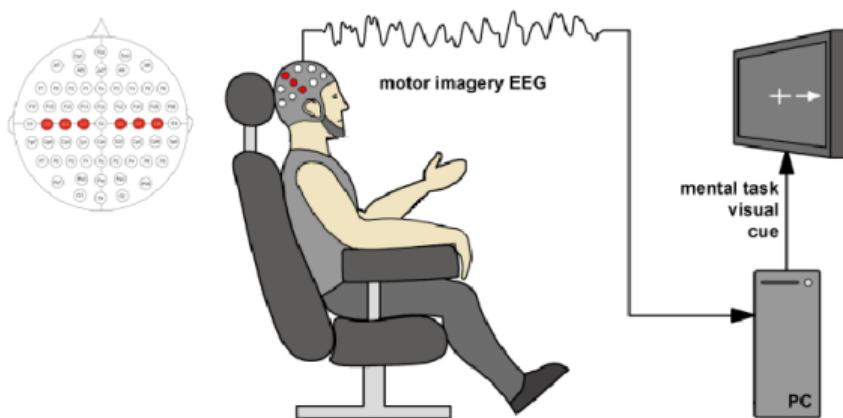
# Neuroimaging techniques

- 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]





# Experimental setup for MI-based BCIs



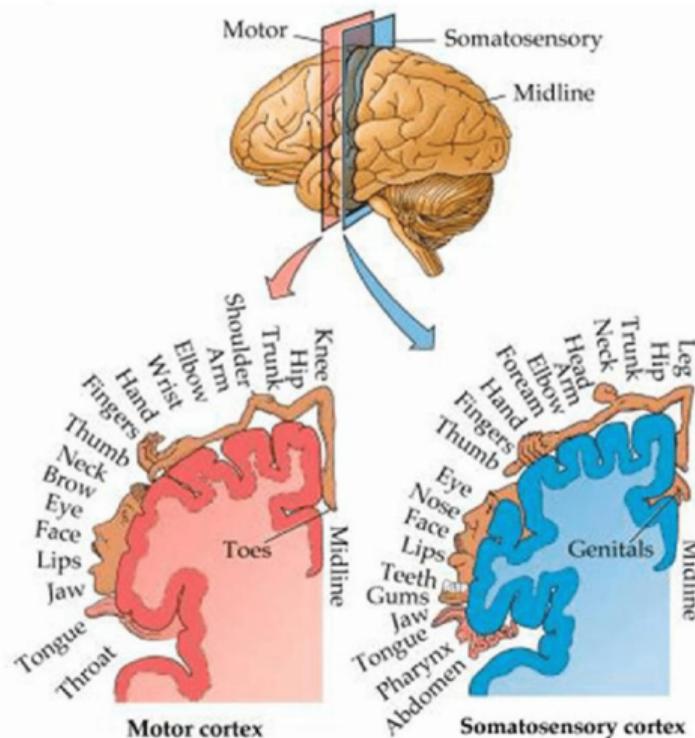
- EEG headsets are equipped with 1 to 256 electrodes [Grigorev et al., 2021].
- Visual cues are often used to guide MI tasks during EEG recordings [Hosseini et al., 2020].

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



# Sensorimotor rhythms (SMRs)

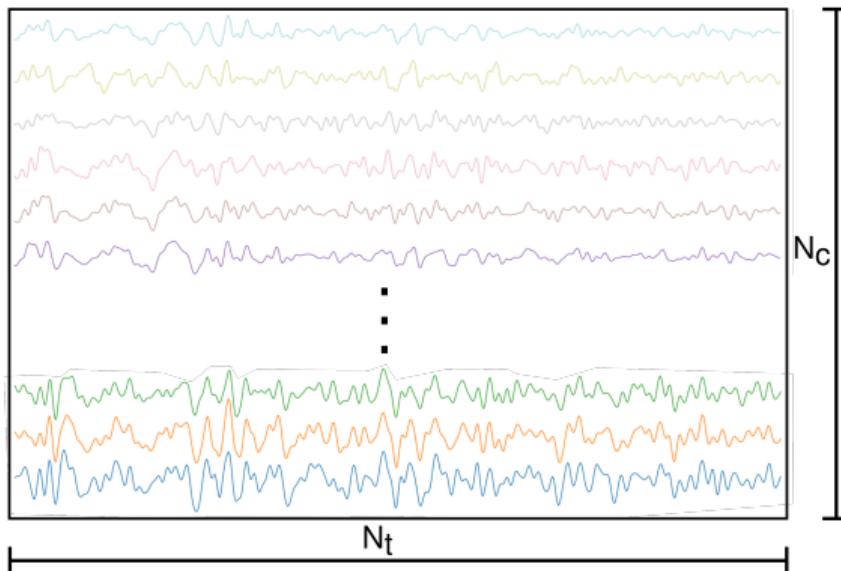
- EEG signals contains multiple electrical variations (rhythms)  
[Barrios et al., 2019].
- Sensorimotor Rhythms (SMRs) occur in the brain's sensorimotor cortex [Altaheri et al., 2023].
- SMRs contain spectral-spatio-temporal patterns of MI tasks [Li et al., 2019].



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



# MI-EEG feature extraction

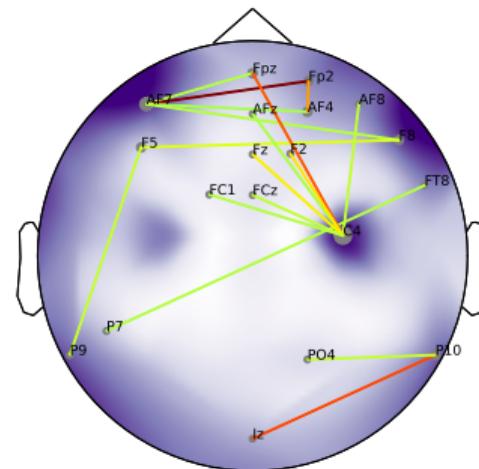


- High number of channels and sampling rate [Chevallier et al., 2024].
- Huge number of data points [Singh et al., 2021].
- Feature extraction strategies are required to reduce dimensionality [Ai et al., 2019].



# Single channel feature extraction

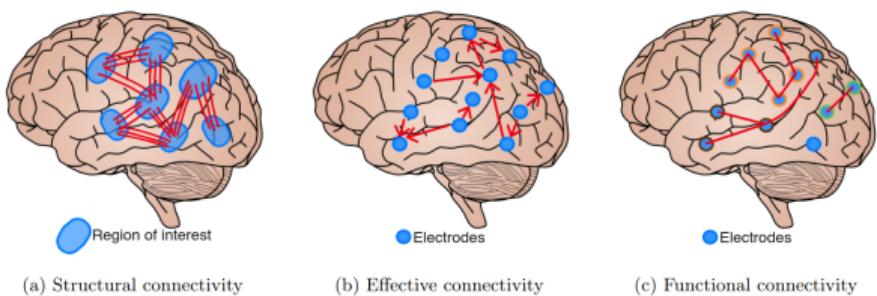
- Capture rhythms on specific EEG channels [Samuel et al., 2017].
- Time domain: statistical [Hamed et al., 2014], Hjorth [Yilmaz et al., 2018], etc.
- Spectral domain: Power spectral density [Oikonomou et al., 2017], Welch's periodogram [Roy et al., 2022], spectral entropy [Sarraf, 2017], etc.



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., 2022]

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 has been working on the design of ML and DL models to improve the performance and explainability of EEG-based MI-BCIs [Collazos-Huertas et al., 2023].

The screenshot displays the BCI Framework software interface, which includes:

- Code Editor (MAIN.py):** Shows Python code for a stream consumer. The code handles topics like "eeg" and "marker". It resamples and normalizes the EEG data, feeds it into a stream, and logs markers.
- Raw EEG Plot:** A multi-channel plot showing raw EEG data from channels Fp1, Fp2, T3, C3, C4, T4, O1, and O2 over time from -30 to 0 seconds.
- Electrodes Distribution:** A circular diagram showing the placement of electrodes on a head model, with labels for Fp1, Fp2, T3, C3, C4, T4, O1, and O2.
- Montage Selection:** A dropdown menu for selecting a montage, currently set to "montage\_1020".
- Project Management:** Sections for CONNECTION, RECORDS, ANNOTATIONS, and PROJECTS.
- Saved Montages:** A list of saved montages including "montage\_1020", "montage\_1010", "montage\_1000", and "montage\_0100".
- Status Bar:** Displays the last package streamed (60.51 ms ago), datasets (EEG (8,100) | AUX (3,100)), and system information (3:29:07 PM, 10/3/20).



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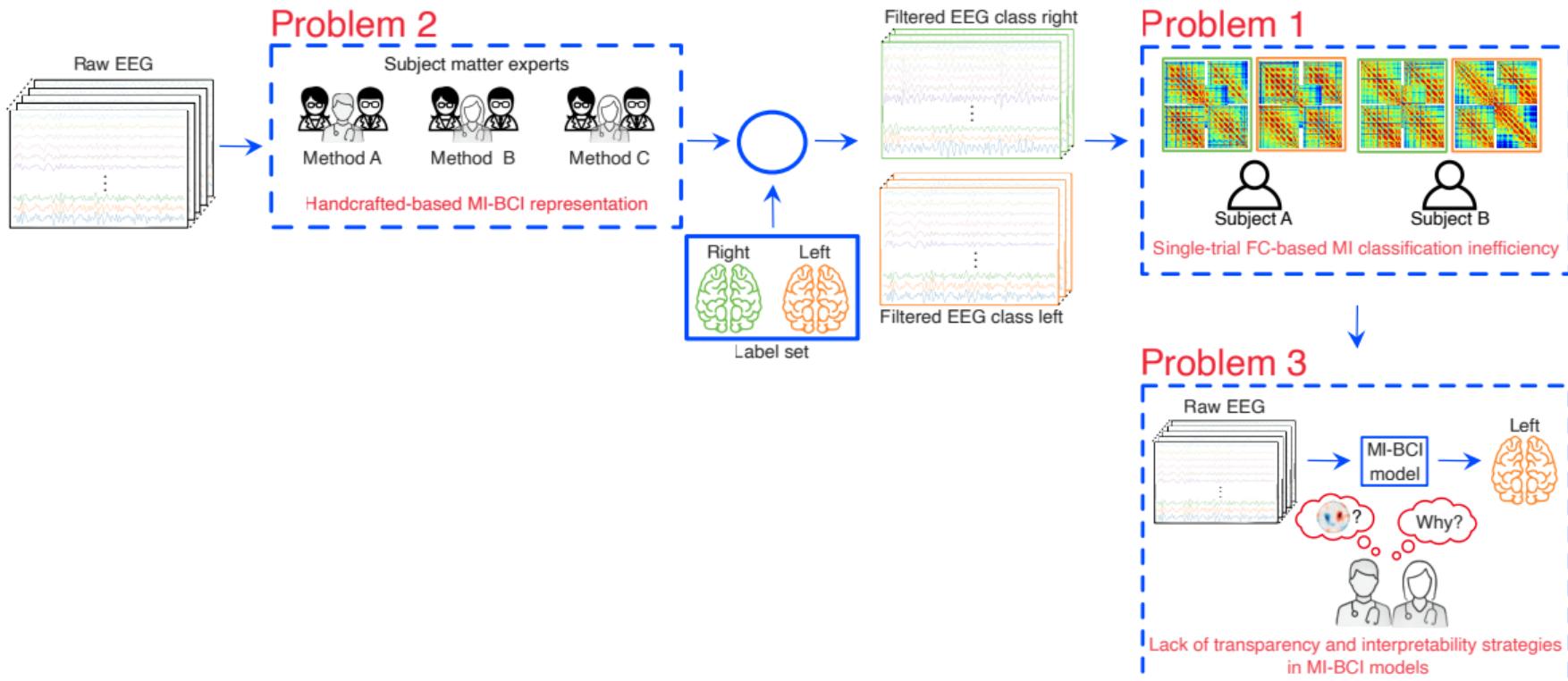
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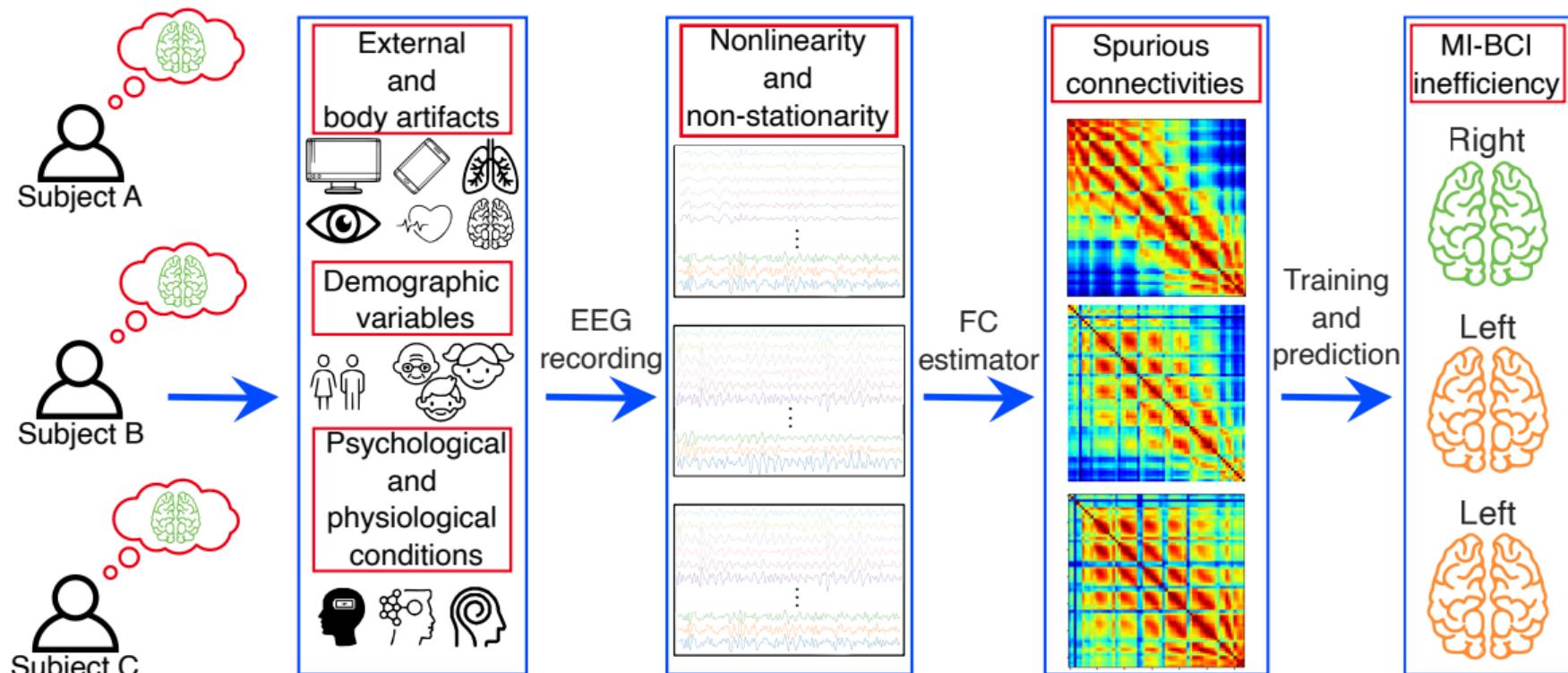


# Problem statement



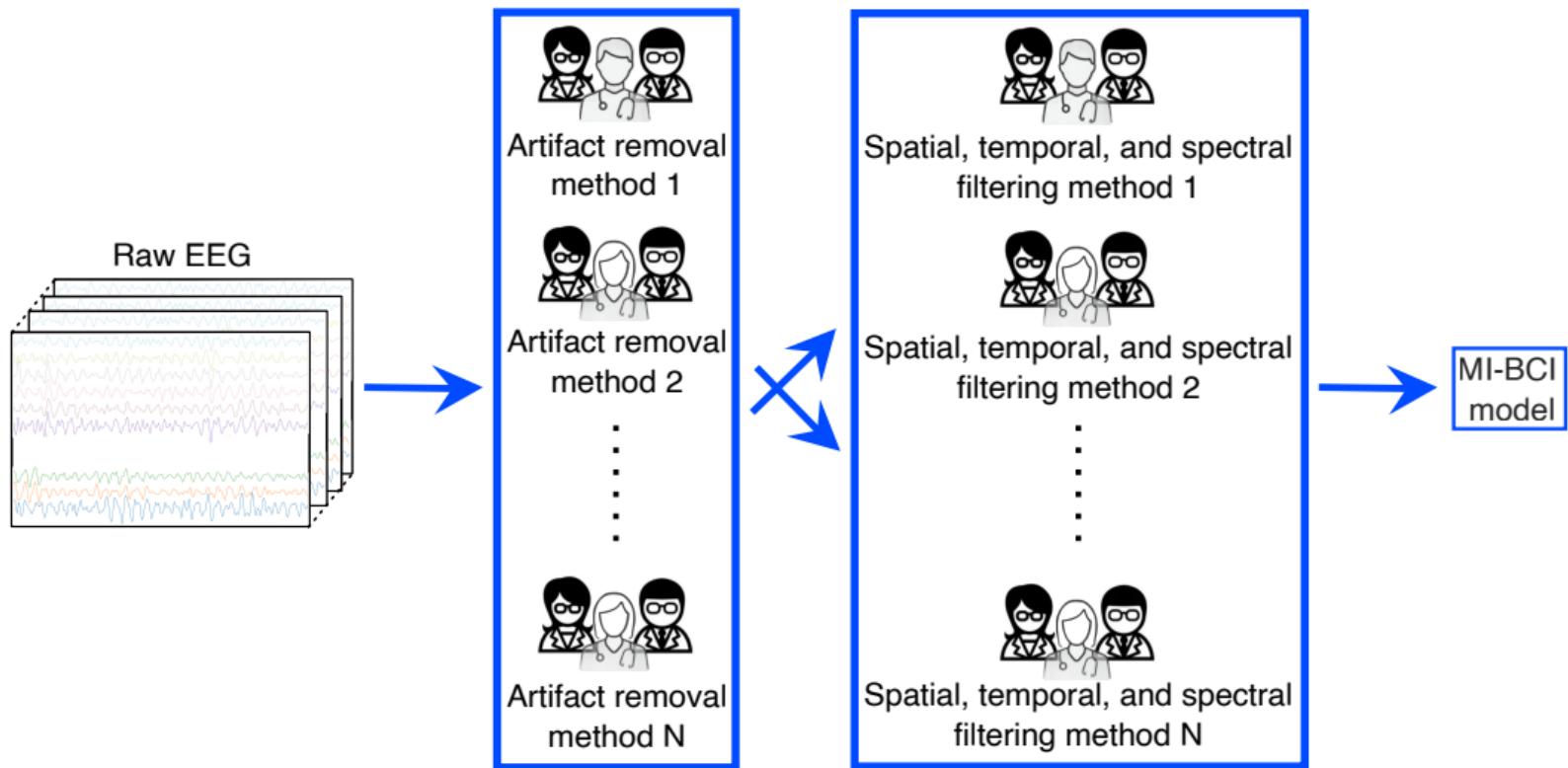


# Single-Trial FC MI Classification Inefficiency



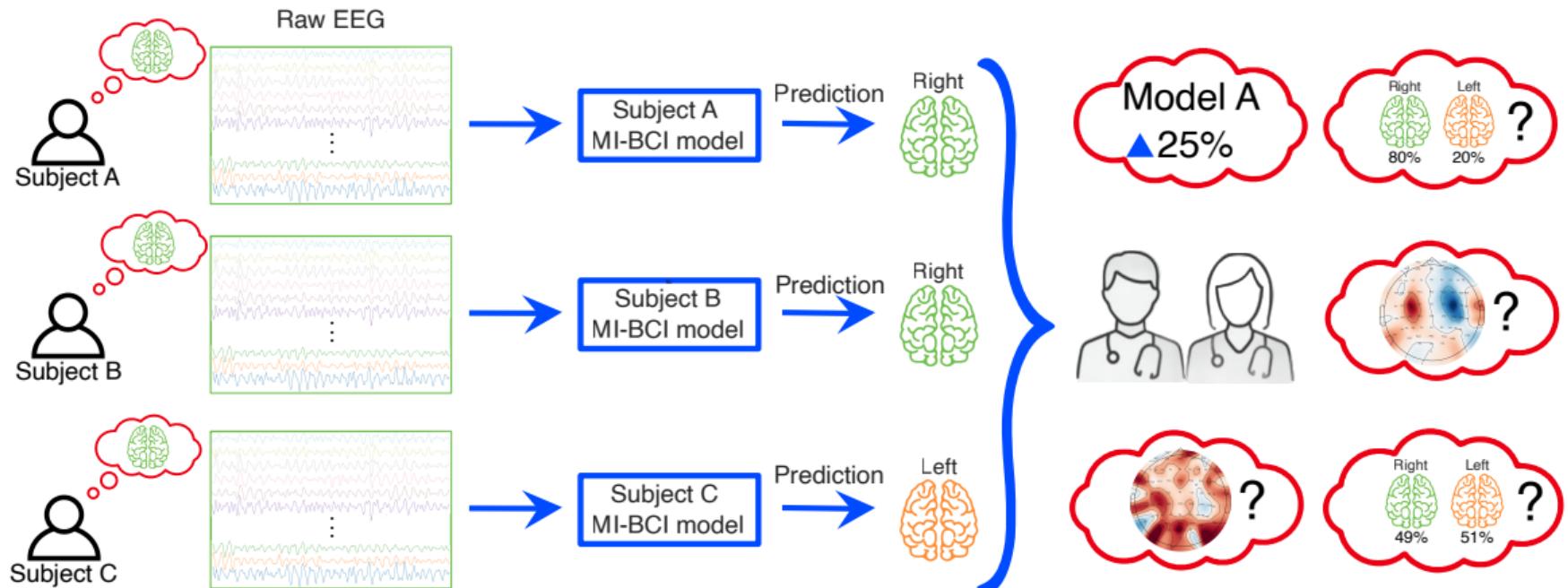


# Handcrafted-based Subject-Specific EEG-based MI-BCI Representation





# Lack of Transparency and Interpretability Strategies in MI-BCI





# 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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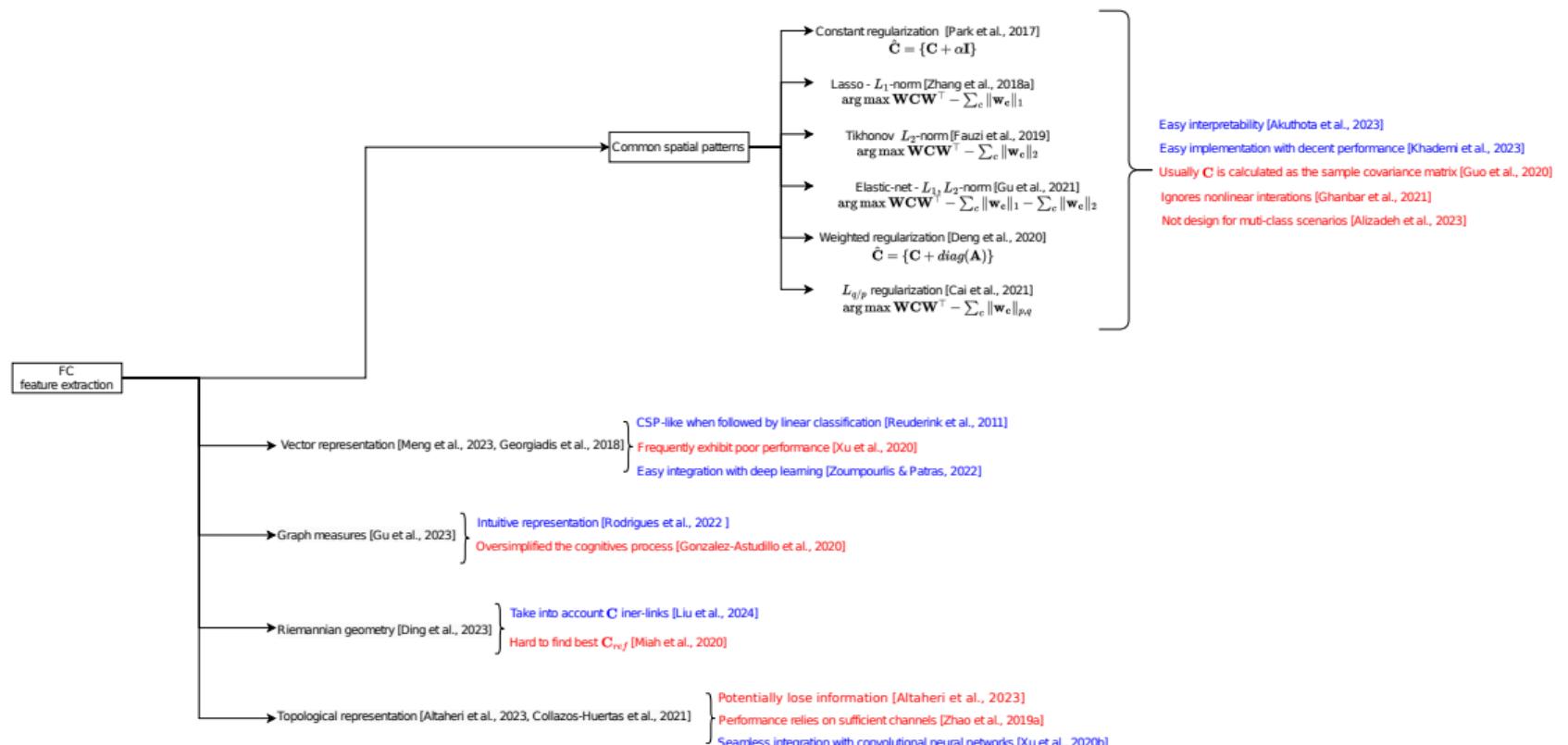
# Functional Connectivity Estimators

	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] SL [Gonzalez-Astudillo et al., 2021]	PLI [Siviero et al., 2023] PLV [Cattai et al., 2021] WPLI [Gonzalez-Astudillo et al., 2020]	Nonlinear
Directed	Cross-corr [Roy et al., 2022] GC [Rezaei & Shalbaf, 2023]	DTF [Rezaei & Shalbaf, 2023] PDC [Gaxiola-Tirado et al., 2017]	Linear
	TE [Rezaei & Shalbaf, 2023]		Nonlinear

 High sensitive    Sensitive    Less sensitive    Robust



## Feature Extraction from FC





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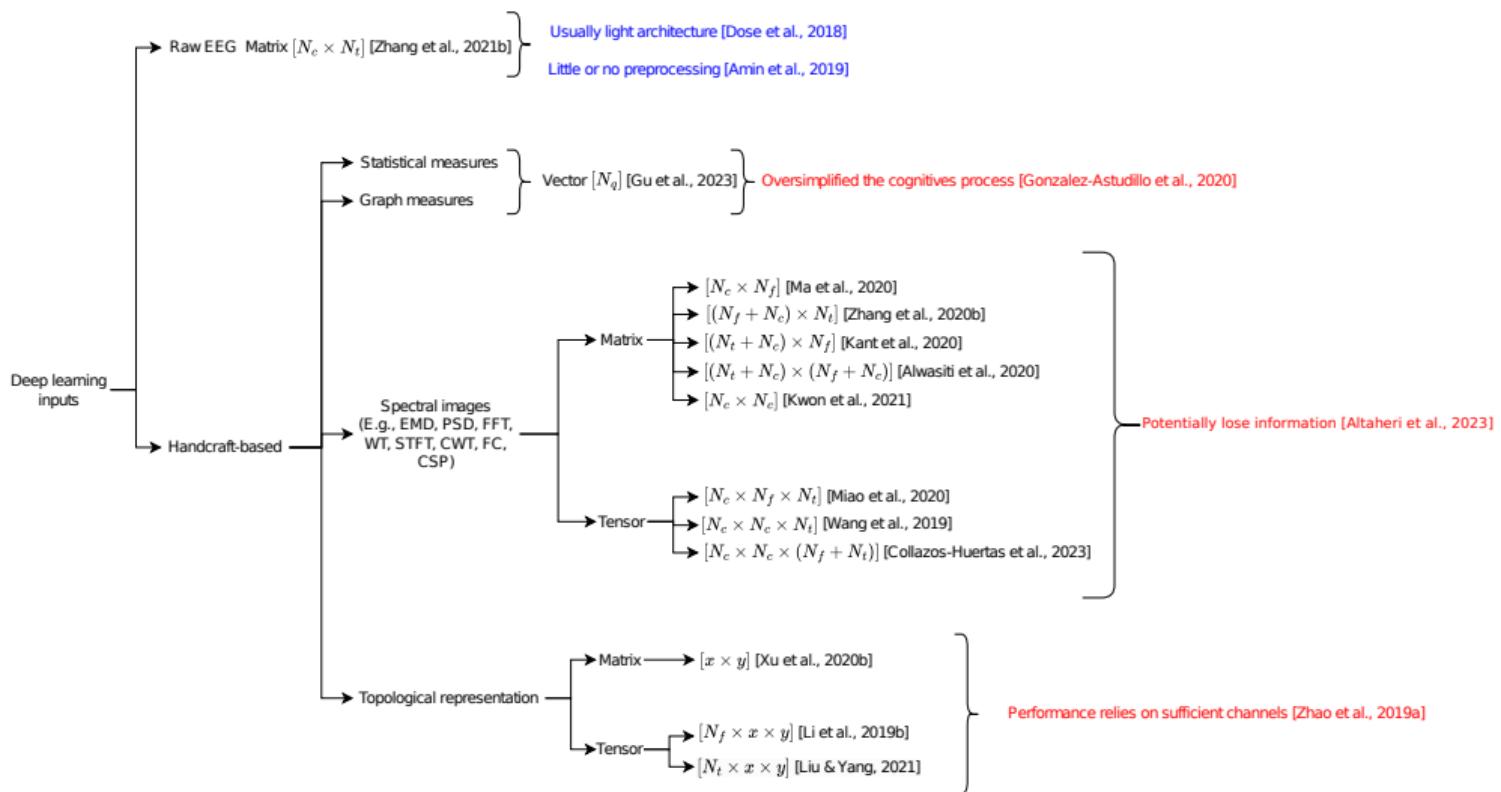
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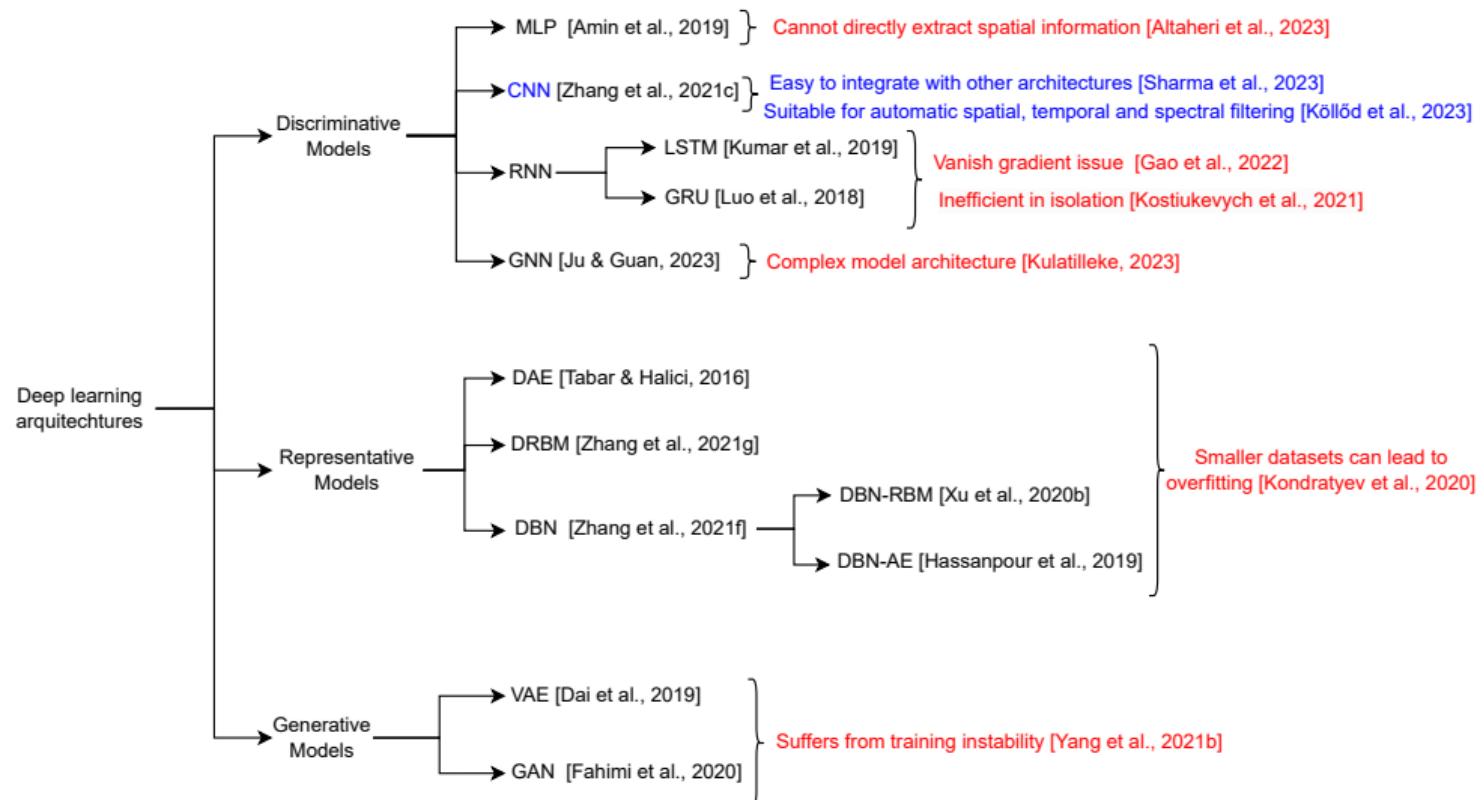


# Input Formulation in Deep Learning





# Deep Learning Architectures





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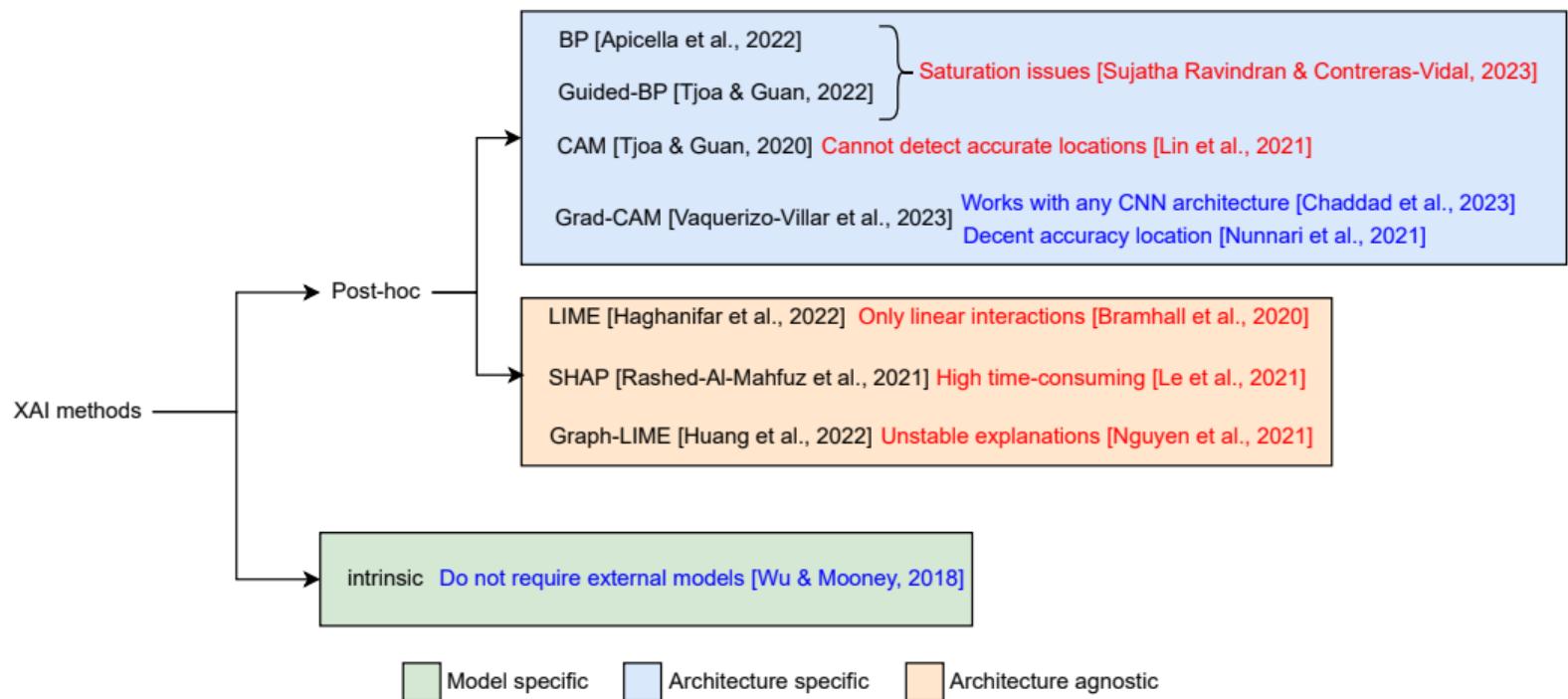
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# Interpretability Strategies in MI-BCI





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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, necessitating 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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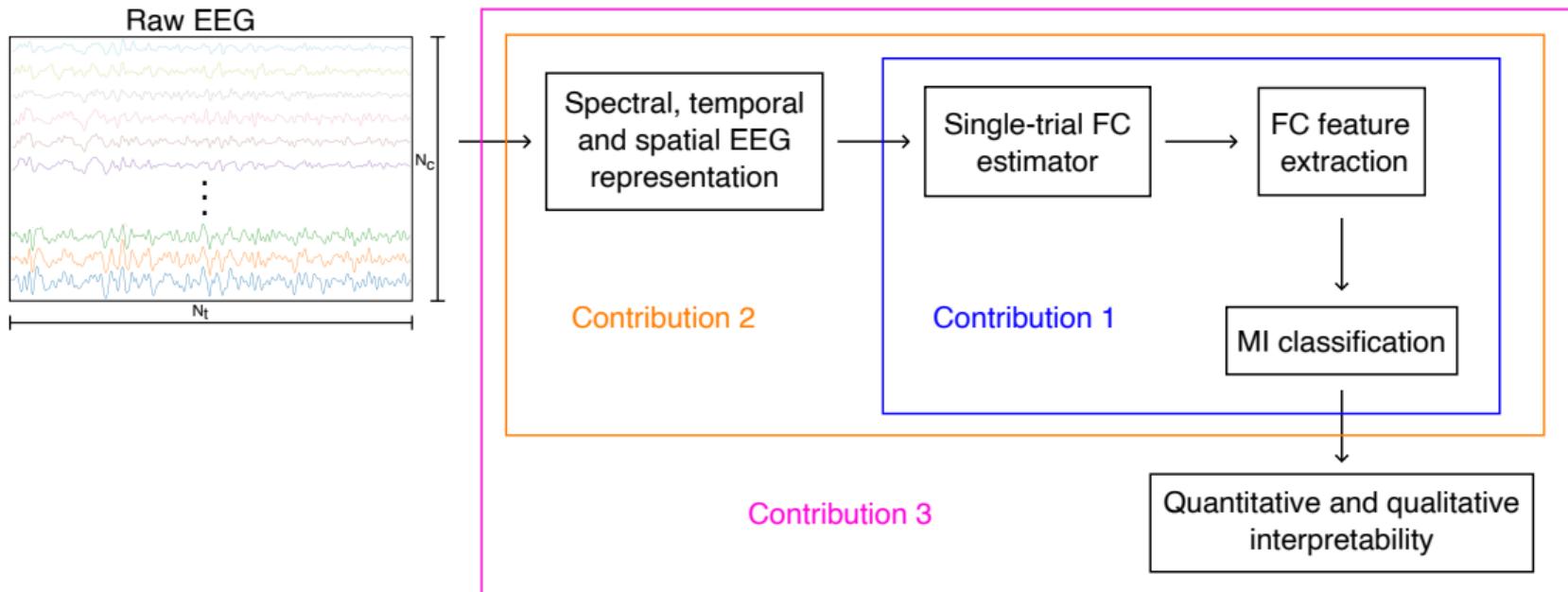
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# Outline and contributions





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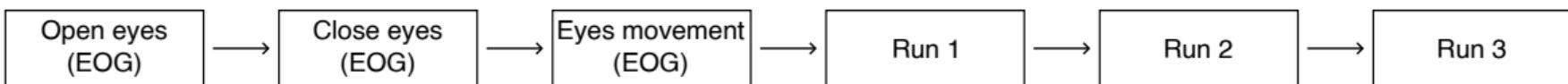
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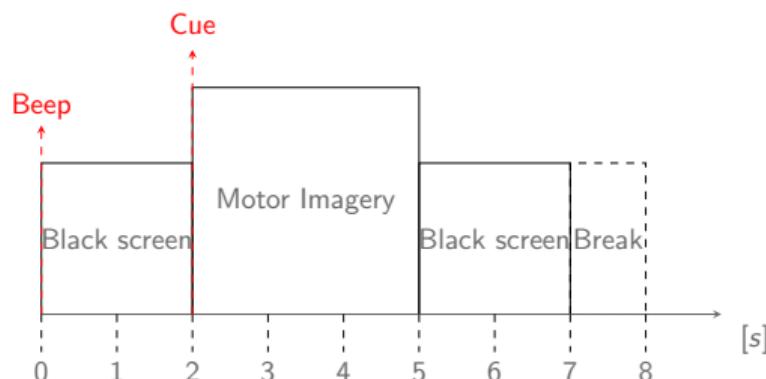


# BCI Competition IV Dataset IIa - DBI MI

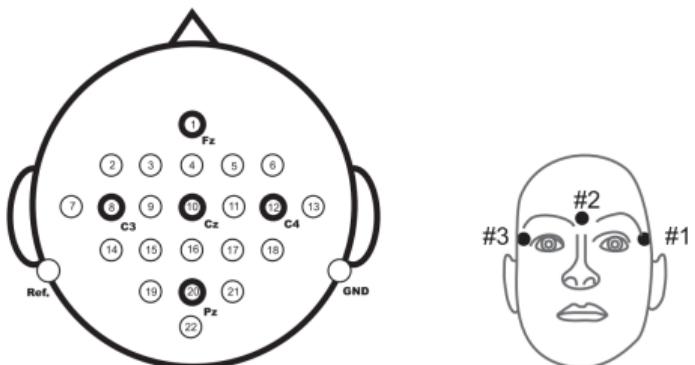
## One-day data collection



Acquisition protocol



Electrode montage





# Gamma Motor Execution Database—DBII ME

b

# MI BCI EEG Giga Science Database - DBIII MI



C



# Outline II

## 7 Proposal and Results

- Single-Trial Kernel-based Functional Connectivity for Enhanced Feature Extraction in EEG-based MI-BCI
- KCS-FCnet: Kernel Cross-Spectral Functional Connectivity Network for Automatic EEG Representation in MI-BCI
- IRKCS-FCnet: Interpretable Regularized Kernel Cross-Spectral Functional Connectivity Network with Qualitative and Quantitative Post-Hoc and Intrinsic Explainability

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