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The third N3BG Summer School 2025
Sofia, Bulgaria

From neuroscience and neural networks to AI machine consciousness with applications

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What is missing in the current AI revolution: The FAIR Project

Francesco Carlo Morabito

University Mediterranea of Reggio Calabria, Italy

President INNS

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What is the future of AI?

<u>Present scenario</u>:
Continuous growth of (huge) data requests
(e.g., in **healthcare**, improved *sensitivity* and *specificity* in diagnoses and prognosis estimation through increased database size; in **autonomous driving**, additional scenes and situations; **social applications**, see Meta in What’s Up)
Industry involvment

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What is the future of AI?

<u>Present scenario</u>:

Continuous improvement of energy consumption

The *carbon footprint* of AI is no longer negligible

Coping with AI environmental sustainability (*green AI*)

Green AI: AI research that yields novel results while taking into account the computational cost

Energy and water consumption

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What is the future of AI?

Present scenario:
Taking into account all the different stages of an AI system's lifecycle (e.g. data collection, data preprocessing, training, monitoring) including architecture and hardware deployment
High emphasis on the AI training phase, as the inference phase consumes a negligible fraction of enenrgy, but the inference phase is highly executed

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What is the future of AI?

<u>Present scenario</u>:
Continuous improvement of agents' capabilities (e.g. AGI), emotional AI and interpretation of the brain states by machines; possibility of interacting between humans and AI agents; collective intelligence through interactions among AI products

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What is the future of AI?

<u>Present scenario</u>:
Towards *machine consciousness*
What is consciousness, neuroscientists interpret it by neural circuits spiking and bending
Accuracy and transformational attention (retrospective extraction of patterns)
But *creativity*? It goes beyond schemes extracted from the past examples

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I will propose considerations with regard to some aspects of the future of AI

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Partenariato Esteso su Intelligenza Artificiale

Shared by Francesco Scarcello

Coordinator SPOKE 9

Schedule:

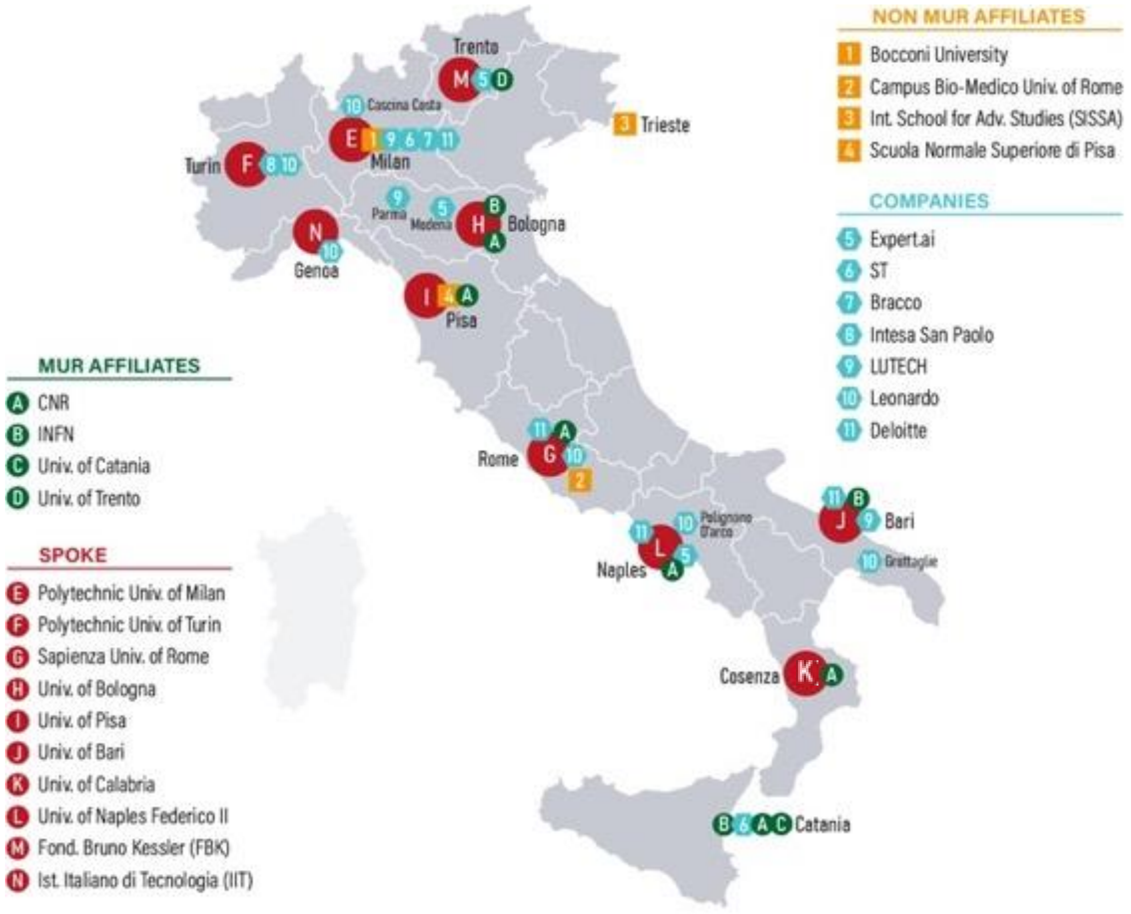
Future Artificial Intelligence Research

Università della Calabria

FAIR Scientific Partners

Some statistics

- A critical mass of 350 researchers
  - 3619 PM - at least 3 PM/year per researcher
  - 24.45% female - target to achieve: 40%
  - 42.30% southern researchers
  - 11.38 early stage researchers



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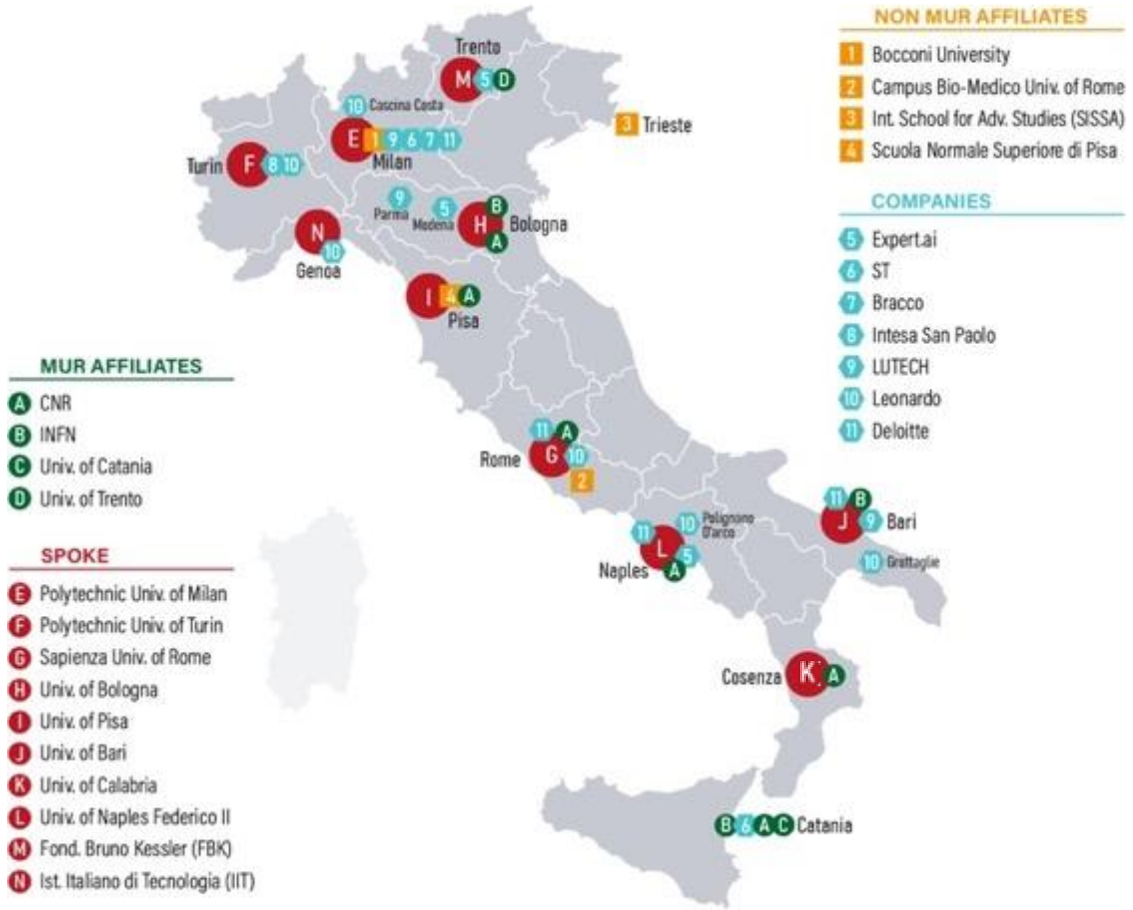


FAIR Foundation Members

12 PUBLIC INSTITUTIONS CONTROLLED BY MUR

Consiglio Nazionale delle Ricerche, INFN, Politecnico Milano 1863, Politecnico di Torino, Sapienza, Università di Trento, Università degli Studi di Napoli Federico II, Università degli Studi di Bari Aldo Moro, Università della Calabria, Università di Catania

Other 6 PUBLIC/PRIVATE INSTITUTIONS

Fondazione Bruno Kessler, IIT Istituto Italiano di Tecnologia, Bocconi, Campus Bio-Medico di Roma, Scuola Normale Superiore, SISSA

7 COMPANIES

Bracco, Deloitte., expert.ai, Intesa Sanpaolo, Leonardo, Lutech, ST

2 Foundation members only

UNIMORE Università degli Studi di Modena e Reggio Emilia, cini

AI Foundational Aspects

FAIR's goal is to build AI systems capable of:

interacting and collaborating with humans;

perceiving and acting within **evolving contexts;**

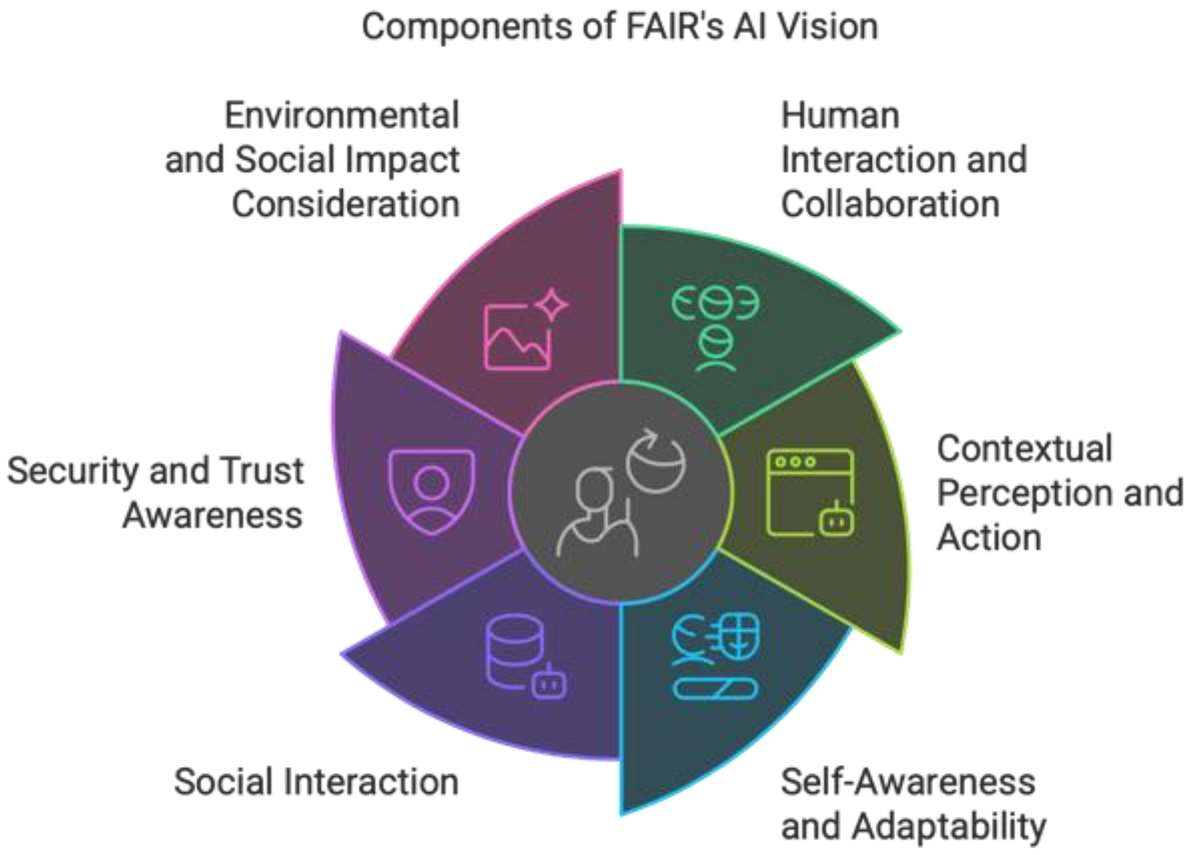
being aware of their own limitations and **able to adapt to new situations;**

interact appropriately in **complex social settings;**

being aware of their **perimeters of security and trust;**

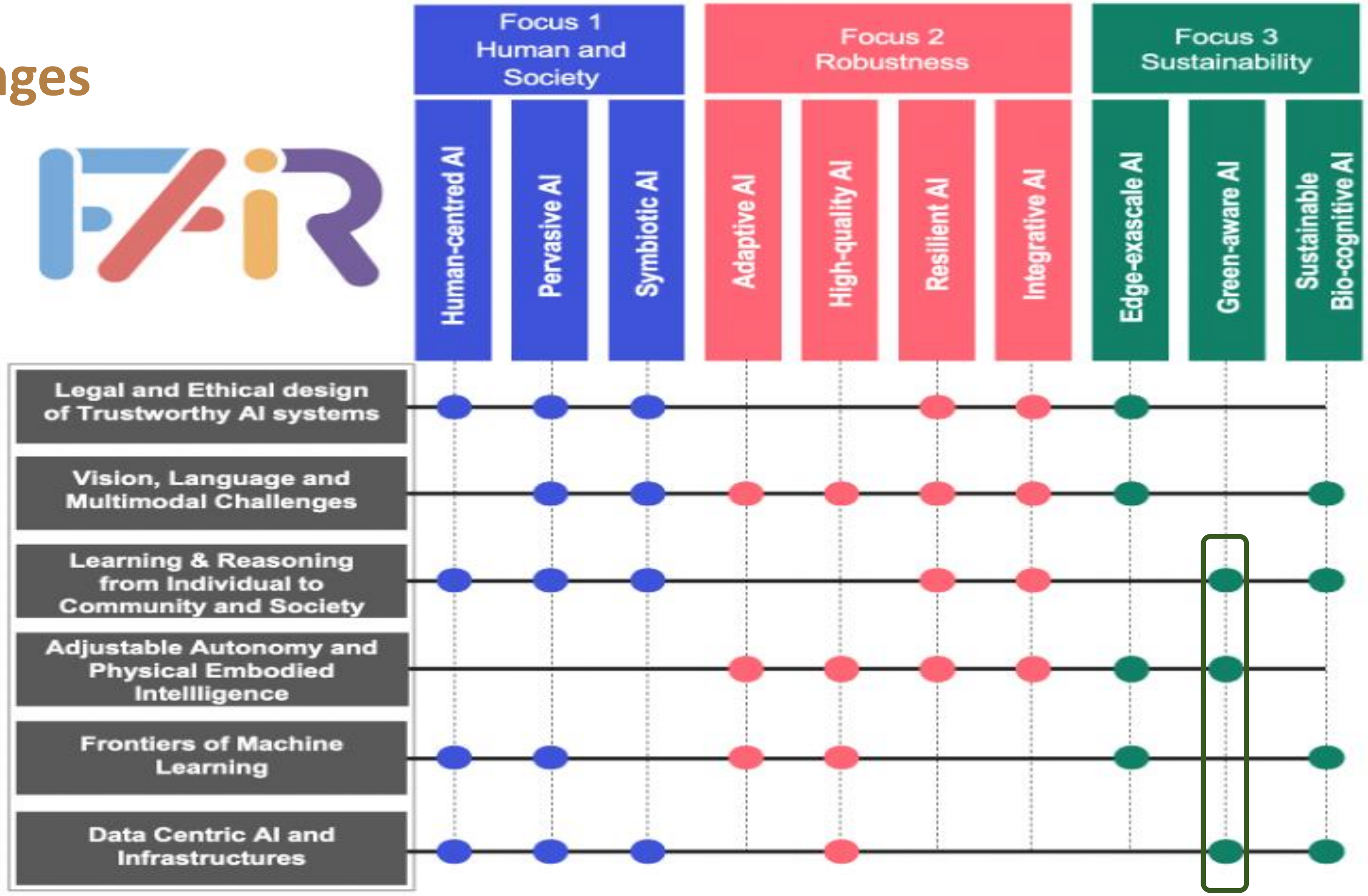
being attentive to the **environmental and social impact** that their implementation and execution may entail.

To achieve this goal, FAIR adopts a **multidisciplinary research approach** aimed at rethinking the AI foundations, involving, in addition to STEM researchers, lawyers, philosophers, social scientists, neuroscientists, psychologists, etc.



Transversal Projects

Inter-spoke research challenges



By Roy Schwartz, Jesse Dodge, Noah A. Smith, Oren Etzioni
Communications of the ACM, 63(12), 2020

Creating efficiency in AI research will decrease its carbon footprint and increase its inclusivity as deep learning study should not require the deepest pockets.

Green AI and AI for green

- AI must be greener
- AI applications for SDGs

SPOKE 9 –GREEN-AWARE AI

Università della Calabria,
Consiglio Nazionale delle Ricerche

- consider the “green dimension” by design
- foundational aspects of green-aware AI agents and systems

Assets

Leading research groups in

- Knowledge representation and Hybrid systems
- Algorithmic game theory, Multiagent systems, Computational social choice, Cooperative Game Theory
- High-performance computing
- Edge computing and Internet of Things
- Explainable AI, Argumentation, Outlier Detection
- Machine Learning (deep learning, federated learning, graph-neural networks)
- Social network analysis, social media analytics, graph mining
- Optimization (with applications to energy, battery design, and more)
- Robotics and smart materials, manufacturing

FAIR Ecosystem: Basic Research Activities

University	Project
Università degli Studi di Palermo	Models and Algorithms relying on knowledge Graphs for sustainable Development goals monitoring and Accomplishment - MAGDA
Università degli Studi dell'Aquila	Enhanced Network of Intelligent Agents for Building Livable Environments - ENABLE
Università degli Studi di Sassari	Smart Knowledge-driven Environmental and Territorial Monitoring - SKET-Monitor
Università degli Studi di Reggio Calabria	Green Deep Learning approaches to Clinical AI - NAEL
Università degli Studi Magna Graecia di Catanzaro	Machine Learning for Bioinformatics - FAIR-BIOINFORMATICS
Università degli Studi 'G. d'Annunzio' Chieti-Pescara	Existence, Complexity and efficiency of stable solutions in green-Oriented GAMES - EcoGames
Università del Salento - Università del Salento - Dip. matematica e fisica	Green-Aware MEchanismS - GAMES
Gran Sasso Science Institute	Graph Algorithms and MiNiIng for green agents - GAMING
Università degli Studi di Messina	Energy-efficient Computation of Graph Edit Distance - ECOGED
Università degli Studi 'G. d'Annunzio' Chieti-Pescara	Smart Knowledge: Enhancing Argumentation and Abstraction for Explanation and Analysis - SMARTK
Università di Salerno	Mechanism Design, Online Learning, Robust Optimization, and Sentiment Extraction Tools for Adjustable Green-Aware Agents - MORE-GREEN
Università Politecnica delle Marche	A Collaborative Ecosystem for Industry 5.0 - CE4I5.0
Università degli Studi di Brescia	Argumentation for Informed Decisions with applications to Energy Consumption and Edge Computing - AIDECC

Workpackages

1. Knowledge representation and reasoning
2. Interactions among green-aware agents
3. Green AI
4. Green-aware explainable AI
5. Adjustable green-aware AI
6. AI for green (pilots)

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WP9.3 GREEN AI

Shared by Domenico Talia

Schedule:

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WP 9.3 Green AI - Intro

- WP 9.3 investigates new **machine learning and AI algorithms** that are **able to deal with limited amounts of data and reduced computation resource**s for learning.
- This goal will be reached by **exploiting** available domain knowledge, **energy awareness techniques** and **estimation of** devices/computers **energy consumption**.
- WP 9.3 explores **combinations of symbolic and sub-symbolic approaches to solve problems** in contexts **where we need to save hardware/software resources and energy.**

WP 9.3 Green AI – Main Goals

- Work package 9.3 has five main objectives:
  - **Developing Machine Learning solutions for energy efficient data-intensive AI.**
  - **Designing energy-aware machine learning techniques.**
  - **Exploiting informed Machine Learning for Green AI.**
  - **Designing Green Deep Learning for Clinical AI.**
  - **Exploiting Machine Learning techniques for Bioinformatics**.

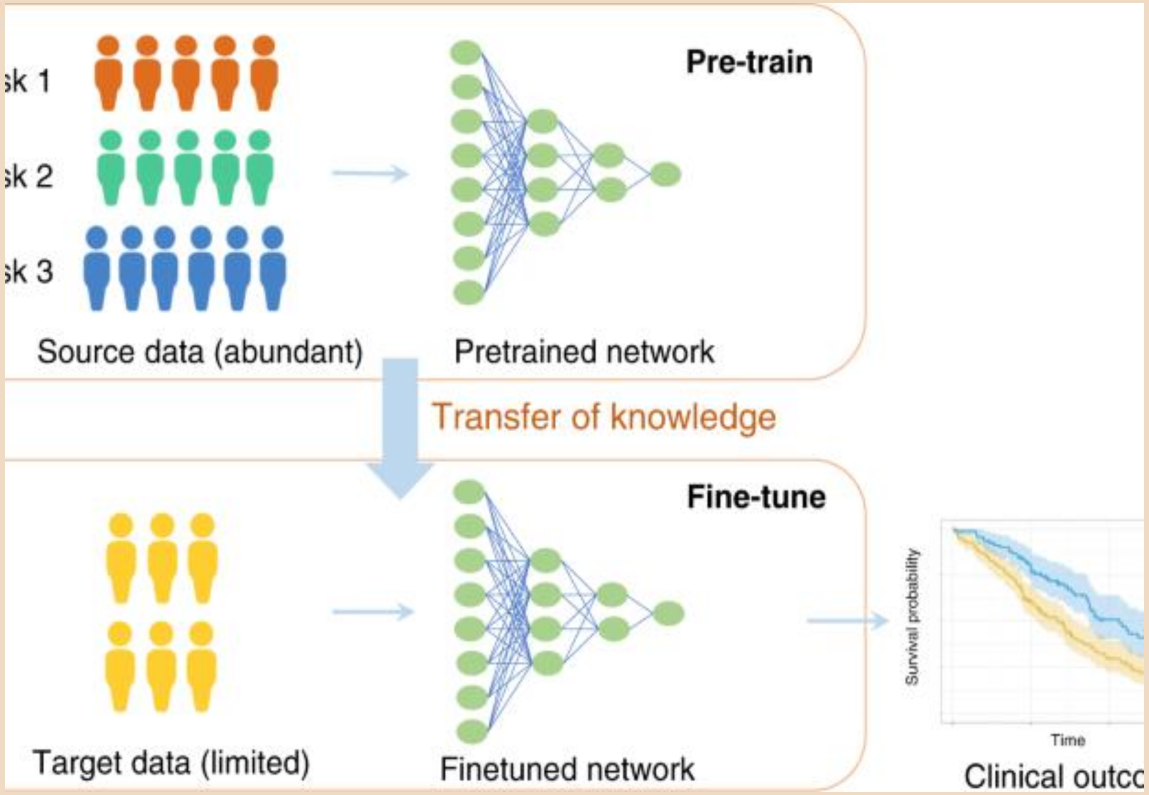
WP 9.3 Green AI – Tasks

- The Work Package 9.3 is organized in four tasks:
  - **Task 9.3.1 – Machine learning for energy efficient data analysis;**
  - **Task 9.3.2 – Informed machine learning for Green AI;**
  - **Task 9.3.3 – Green Deep Learning approaches to Clinical AI;** (UniRC)
  - **Task 9.3.4 – Machine learning for bioinformatics.** (UniCZ)

WP 9.3 Green AI – Talks

- **Towards Interpretable Energy Estimation for Edge AI Applications** (Riccardo Cantini)
- **Data/compute -efficient Machine Learning for Green AI** (Luigi Pontieri)
- **Meta-learning approaches for small-size clinical data** (Carlo Morabito)
- **Green-aware approaches for artificial Intelligence, bioinformatics and text mining** (Mario Cannataro)

Meta-learning approaches for small-size clinical data



Outline

- Green Deep Learning Approaches to Clinical AI (Objective 4 Call)
- FAIR BAC NAEL Project (UniRC), WP 9.3 Task 9.3.3
- Design, development, and deployment of algorithms in Clinical AI favouring both explainability and use of limited resources
- Synthetic, augmented, and clinicall databases
- Incorporation of signal processing to make partially data-driven models
- Explainability modules to reduce the impact of future ML/DL models
- Meta-learning strategies for reducing need of data (few-shot and MAML)

SPOKE 9 - GREEN AI –UNIRC

According to the proposed/approved activities and the related budget, in the period July 2024 – March 2025, we've carried out the following actions/researches:

1) Health data collection and pre-processing: both online available databases and clinical databases have been exploited; the former regards the **BCI-MI** and the **Parkinson Disease**; the latter have been obtained through a collaboration with the **GOM Reggio Calabria Hospital**; they are neurological data (EEG – CJD, AD, PNES, …) and imaging data (recto-colon cancer – pending ethical committee approval);
2) The pre-processing stages of the available data have been devoted to extract from them a collection of **time, frequency, and time-frequency features** in addition to some nonlinear parameters: this has been shown to help reduce the computational burden of the full data-driven model and to comply with medical/clinical interpretation (WP2).

3) We've developed novel algorithms that are energy-aware from one hand, and allowed us to learn relevant features in the form of **learned feature maps**; on the other hand, the algorithms are focusing on achieving good performance in classification and object detection in case of reduced cardinality of the available database (WP3).

4) Some techniques for **explainability and interpretability** in the sub-case of Green-AI models have been analyzed, also by considering the explainability for design (WP4).

5) The **deployment on Edge-AI** of the classification models is under study.

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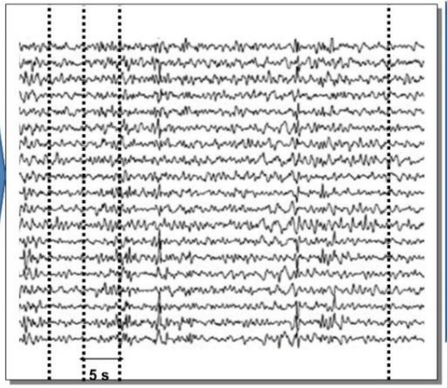
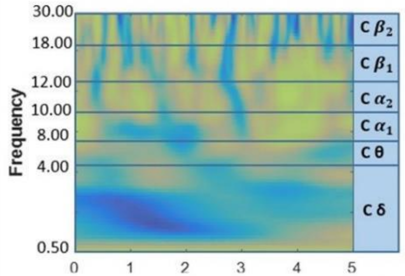
(1) EEG recording

(2) EEG signal windowing

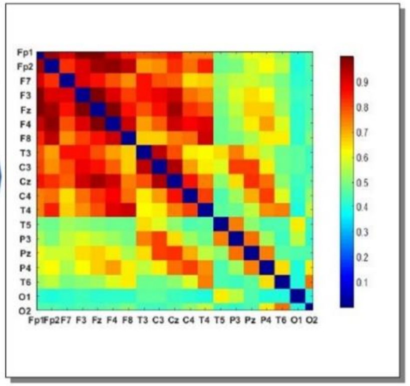


(3) Cxy Wavelet Coherence



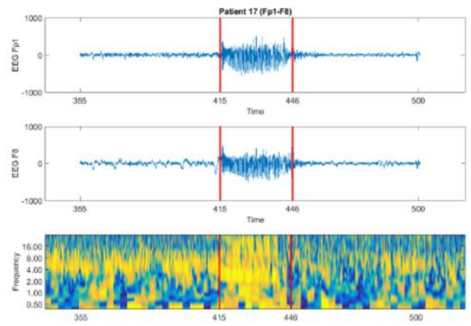
$$WC(a,b) = \frac{|S(CWT_x^*(a,b)CWT_y(a,b))|^2}{S(|CWT_x|^2)(a,b)S(|CWT_y|^2)}$$

(4) Data processing



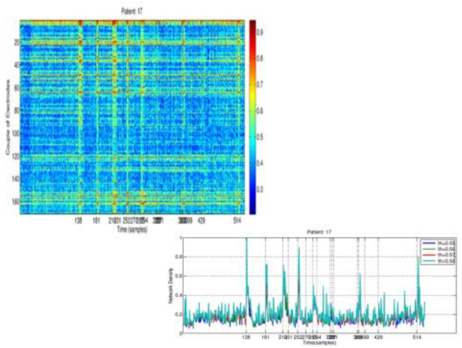
(1) EEG recording

(2) Cxy Wavelet Coherence



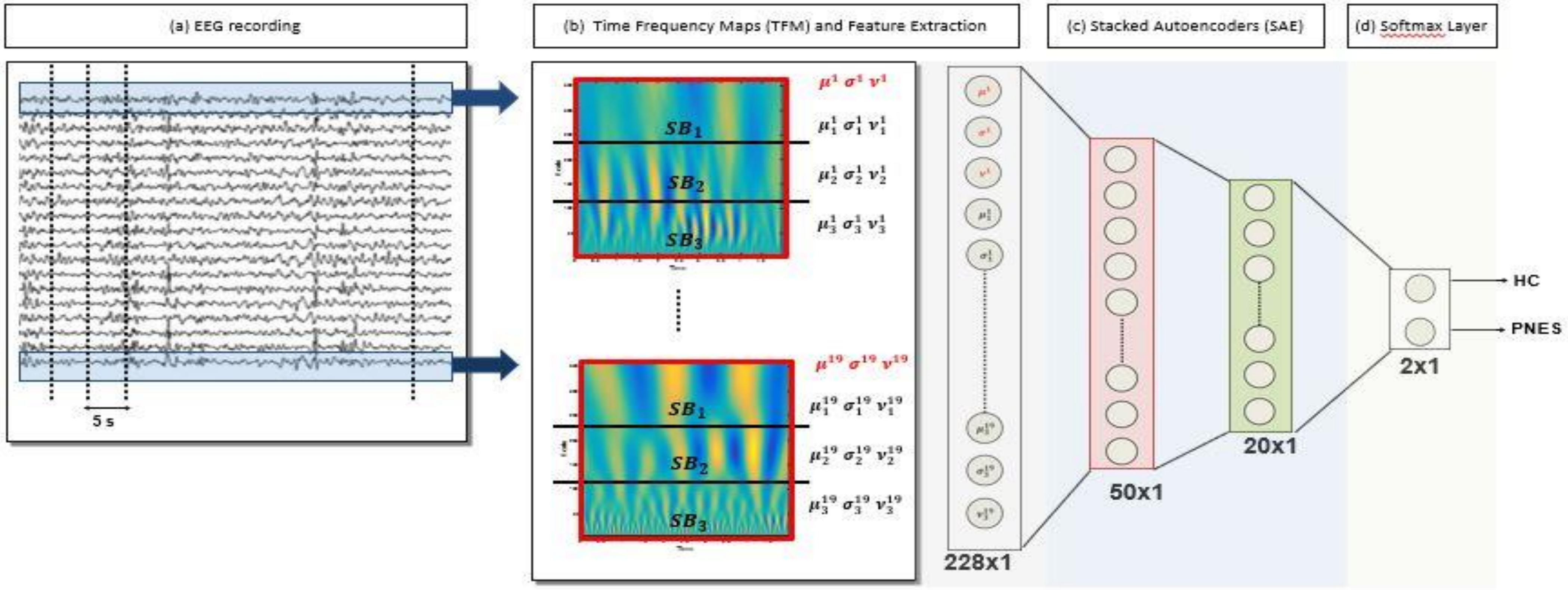
$$WC(a,b) = \frac{|S(CWT_x^*(a,b)CWT_y(a,b))|^2}{S(|CWT_x|^2)(a,b)S(|CWT_y|^2)}$$

(3) Data processing



$$ND_{th}(t) = \frac{AC_{th}(t)}{n*(n-1)/2}$$

Pre-processing of EEG Data



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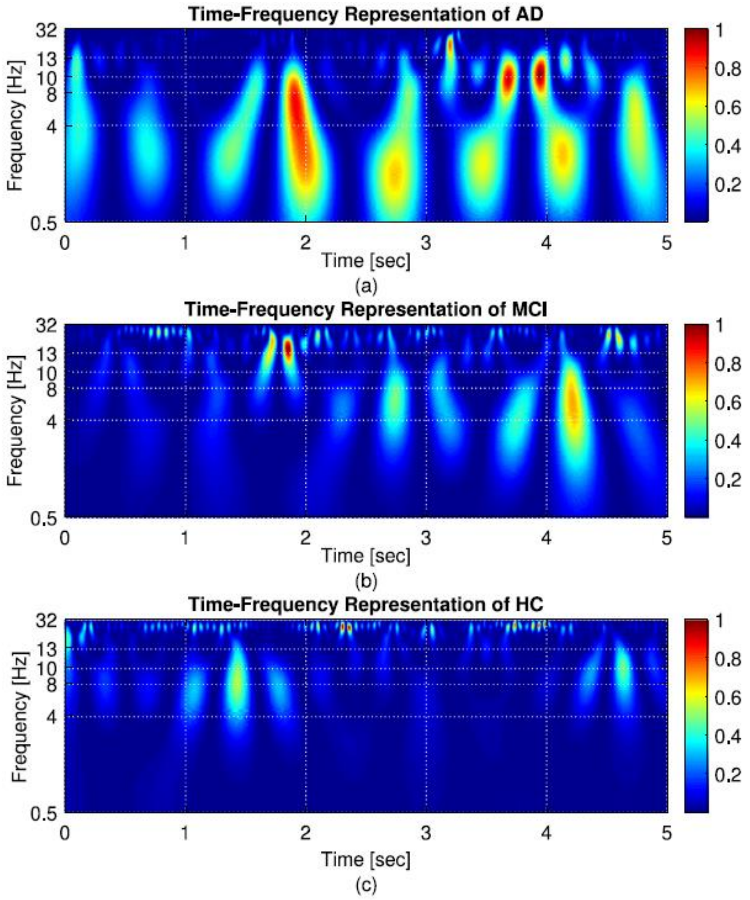
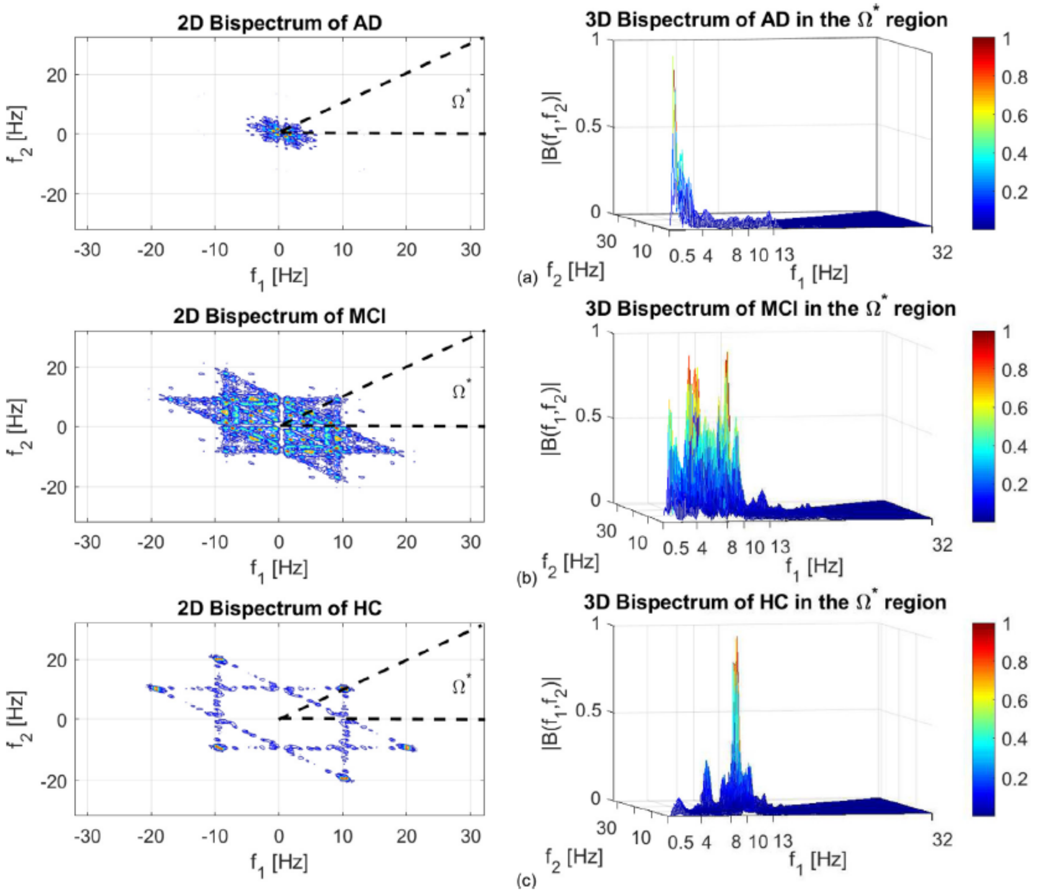
Combined Use of Time-Frequency Approach and Bispectrum Analysis





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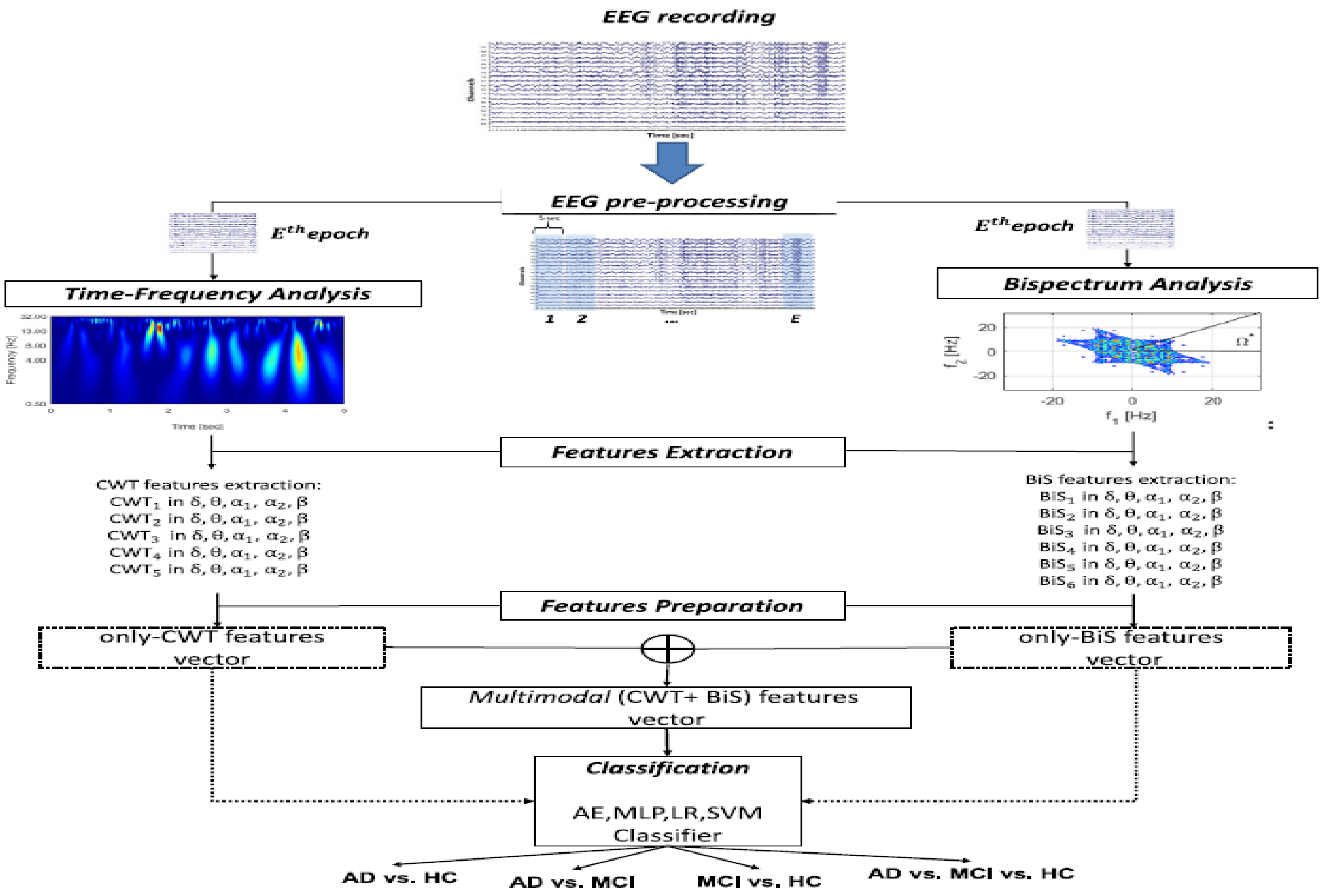
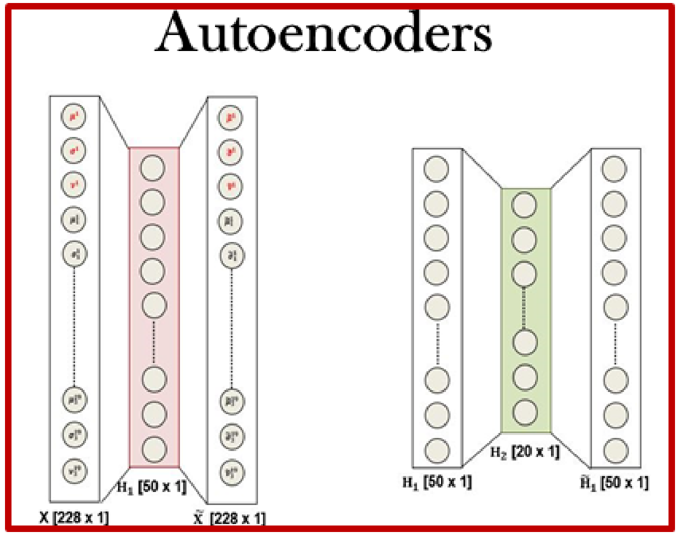
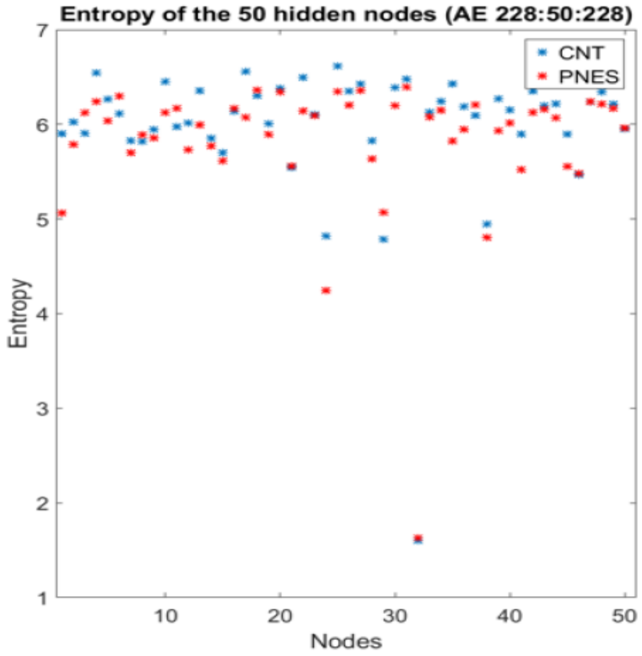
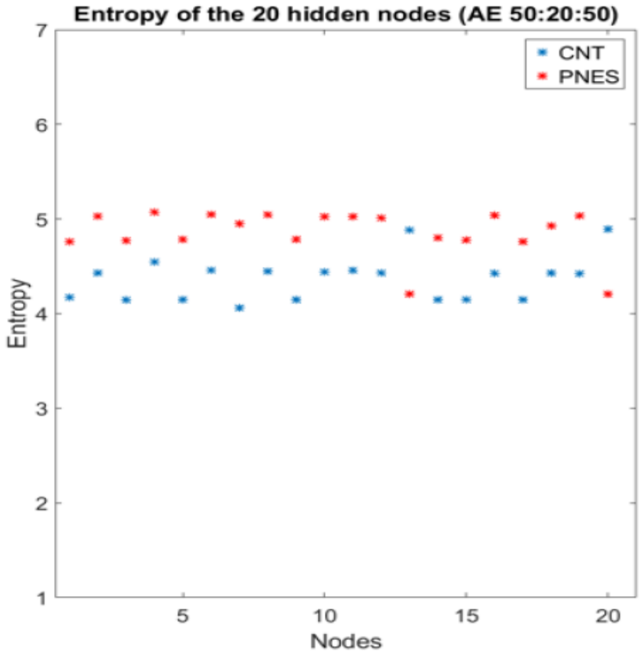


Entropy Reduction of Data in Autoencoders







Meta-Learning as a Learning-to-Learn Strategy

Novel methodologies needed for dealing with main problems raised from the actual use of AI in clinics, diagnostics and medicine: concepts of **Meta-Learning** and **Explainability**/Interpretability of AI

- Paucity/scarcity of available data
- Data imbalanced
- Domain adaptation
- Inter-subject and intra-subject variability
- Privacy and Federated Learning
- Fusion of data/diagnostic modalities

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Meta-Learning for EEG data

The usefulness of the Meta Learning approaches in addressing inter-subject variability is its ability to achieve significantly improved accuracy in classifying labels for unseen subjects.

This is accomplished through a feature extractor that enables efficient training via task-specific adaptation, allowing for precise adjustments to the decision boundary and effectively addressing subject variability in EEG signal processing (classification of pathologies, early detection of dementia onset, …).

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Meta-Learning for EEG data

The effectiveness of this framework is supported by experimental results demonstrating its reliability across various datasets and backbone networks.

The performance have been shown to be comparable with more complex models, overcoming inter-subject variability, and consistently showed statistically significant improvements over the DeepConvNet baseline, highlighting its strength in diverse datasets.

MAML approach have been also tested with different dropout rates

MAML (Model-Agnostic Meta-Learning)

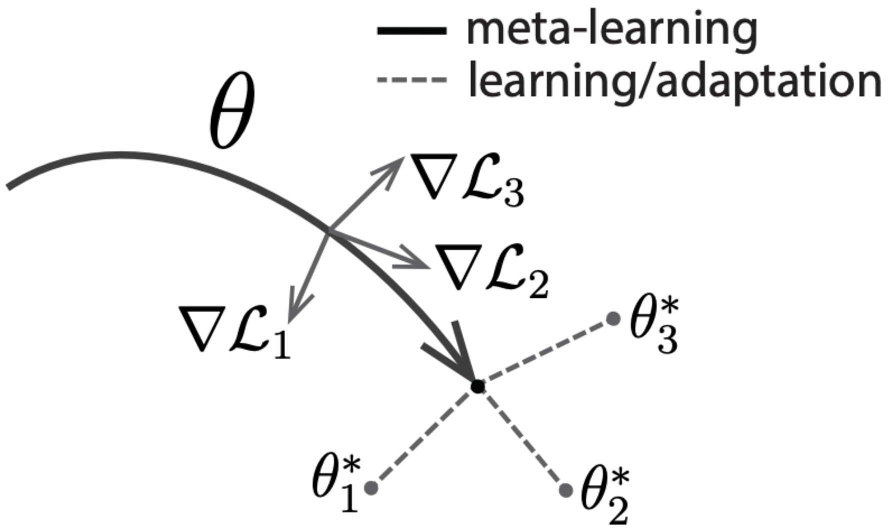

Figure 1. Diagram of our model-agnostic meta-learning algorithm (MAML), which optimizes for a representation θ that can quickly adapt to new tasks.

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Meta-Learning for EEG data

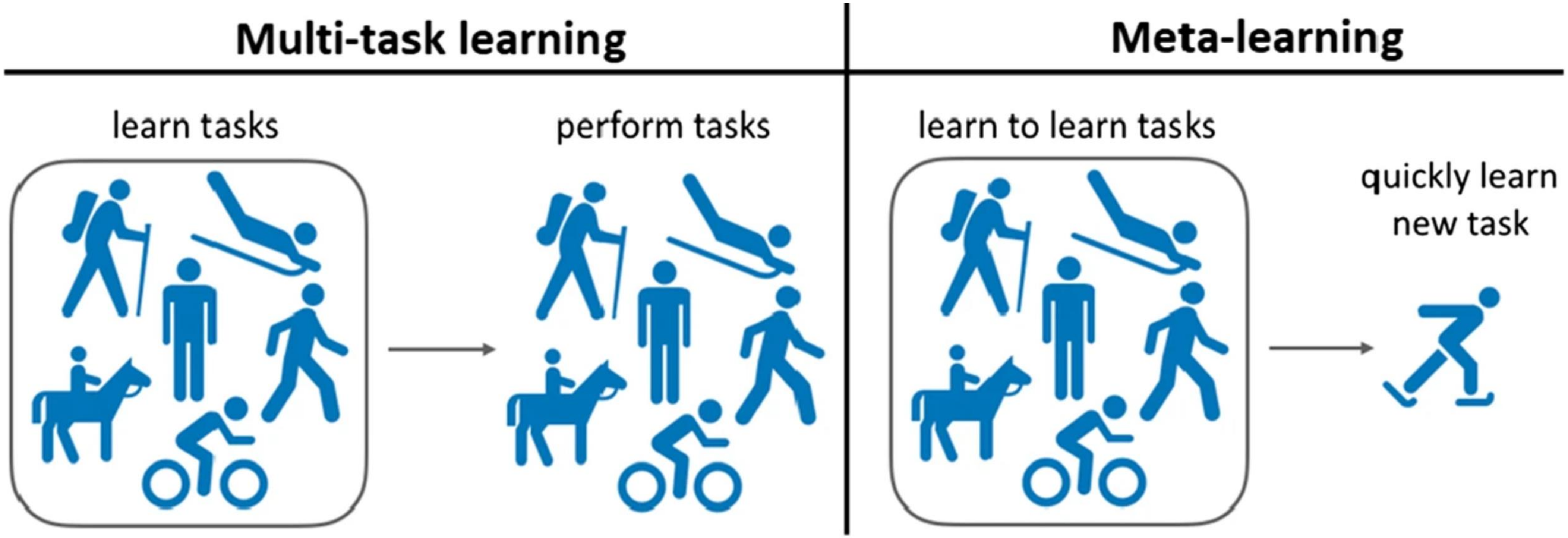
Developing an efficient and generalizable method for inter-subject recognition from EEG is an emerging and challenging problem in neurology.

Human subjects usually have heterogeneous EEG characteristics and variable brain activities during resting styate and cognitive task actions that challenge the recognition algorithms from achieving high inter-subject classification accuracy.

A model-agnostic meta-learning algorithm (MAML) allows to learn an adaptable and generalizable EEG-based decoder at the subject's population level.

This learning algorithms include a pre-training step and an adaptation step.

Specifically, the meta-decoder first learns on **diverse known subjects** and then further adapts it to **unknown subjects** with one-shot adaptation.


Multi-task learning
Meta-learning
learn tasks
perform tasks
learn to learn tasks
quickly learn
new task

Few-Shot Learning

Meta Learning

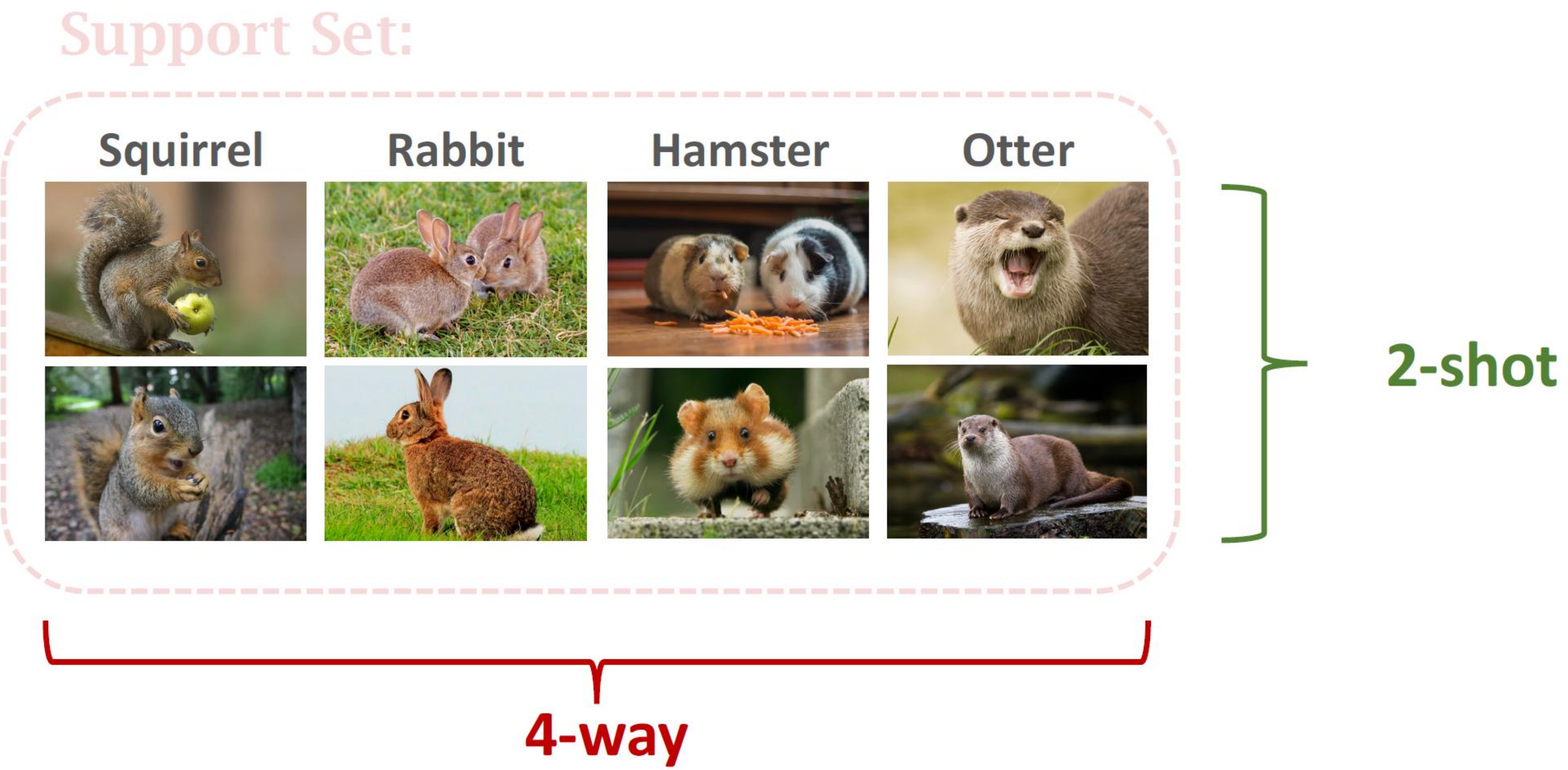
Few-Shot Learning

Give him the cards:

Fox | Squirrel | Rabbit | Hamster | Otter | Beaver

Few-Shot Learning

k-way *n*-shot Support Set



Few-Shot Learning: Basic idea

- First, learn a similarity function from large-scale training dataset.

Few-Shot Learning: Basic idea

- First, learn a similarity function from large-scale training dataset.
- Then, apply the similarity function for prediction.
  - Compare the query with every sample in the support set.
  - Find the sample with the highest similarity score.

Support Set:

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Few-Shot Learning: Basic idea

What is in the image?

Query:

sim = 0.2	sim = 0.1	sim = 0.03	sim = 0.05	sim = 0.7	sim = 0.5
Greyhound	Bulldog	Armadillo	Pangolin	Otter	Beaver
					

Formulation

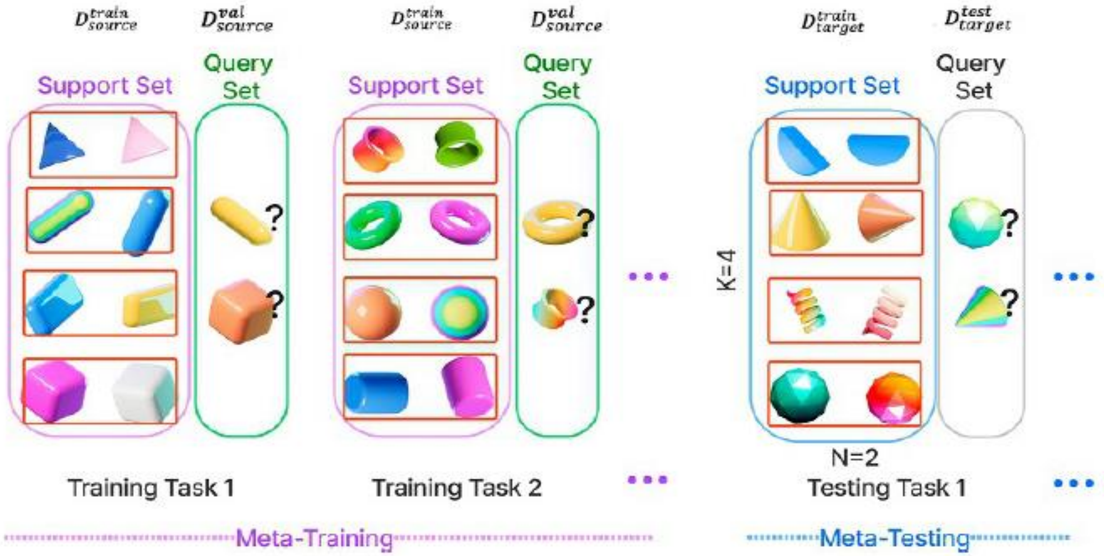


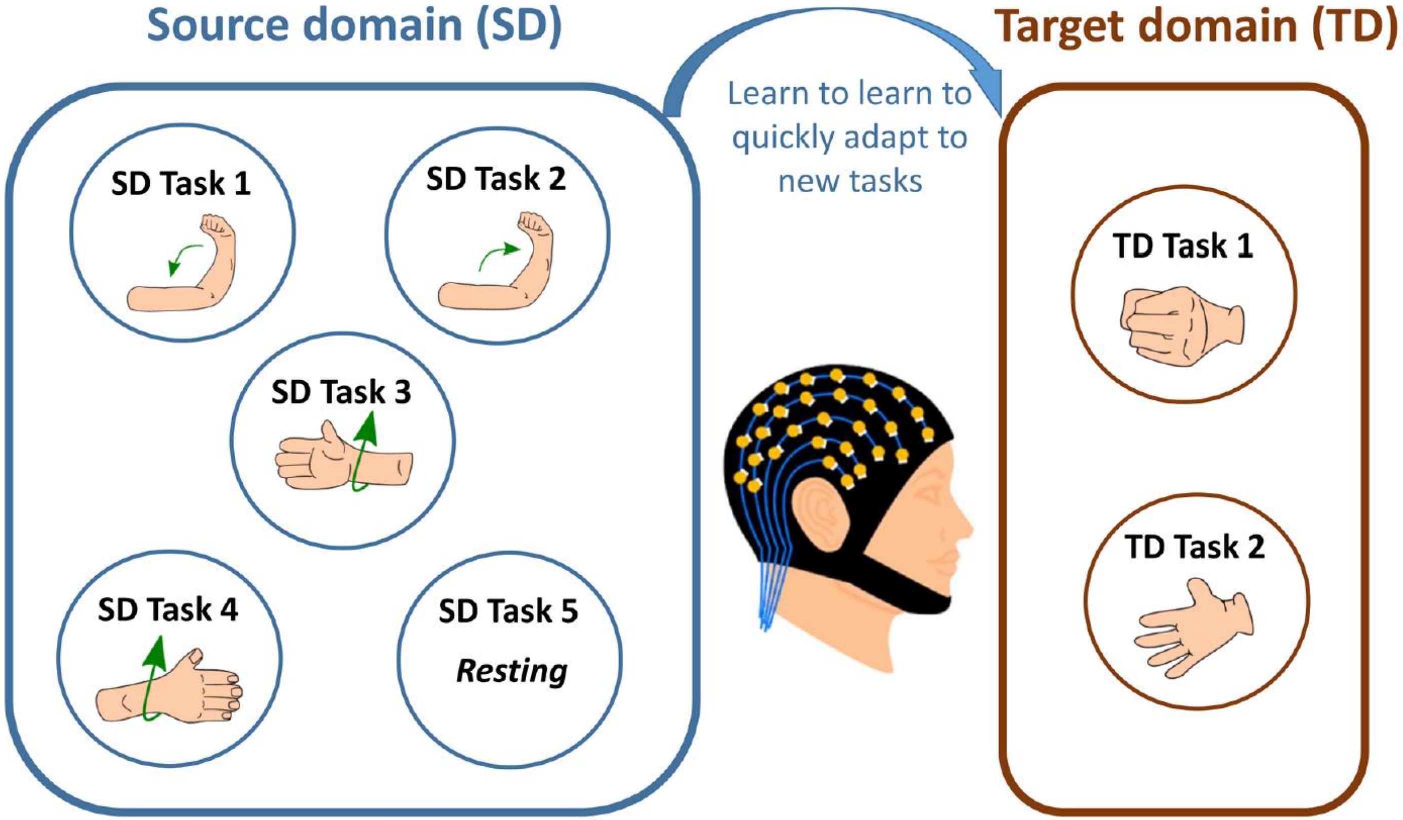
FIG. 1.1 Visualization of task sets in meta-training and meta-testing. Illustration of a four-way two-shot image classification task.

$$\omega^{*} = \arg\min_{\omega} \sum_{i=1}^{S} \mathcal{L}^{meta}\left(\theta^{*\,(i)}(\omega), \omega, D_{source}^{val\ (i)}\right) \quad (1.2)$$

$$\theta^{*\,(i)}(\omega) = \arg\min_{\theta} \mathcal{L}^{task}\left(\theta, \omega, D_{source}^{train\ (i)}\right) \quad (1.3)$$

Few-Shot Learning for EEG analysis

GOAL: To develop and train a model to classify some tasks (source domain tasks) from EEG signals and then adapt the model, with a few-shot learning approach, to classify new tasks (target domain tasks) using a few EEG samples

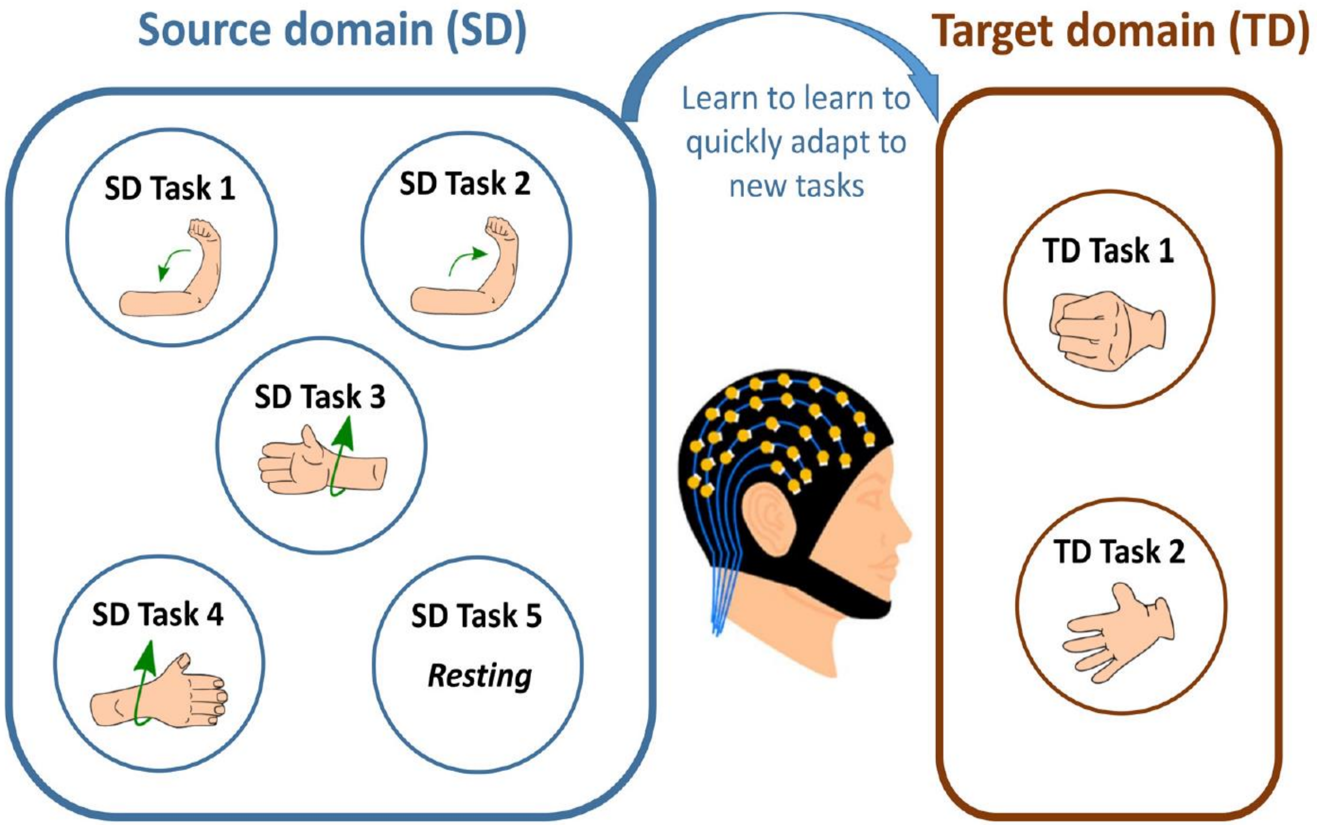


Few-Shot Learning in EEG analysis

Concise representation of the **two phases** of the proposed method:

(1) The aim is to train the proposed model to classify the samples of the **source domain**, thus to discriminate the preparatory phases of complex sub-movements of the same limb, in this study: elbow flexion (EF, source domain task 1), elbow extension (EE, source domain task 2), forearm supination (SU, source domain task 3), forearm pronation (PR, source domain task 4), resting (RE, source domain task 5);

(2) **Adaptation** of the pre-trained model for the recognition of new tasks in the target domain: hand close (HC, target domain task 1), hand open (HO, target domain task 2).



Dataset description

- ✓ The public collection of EEG signals and motion data acquired during experiments of motor imagery/execution, available at **http://bnci-horizon-2020.eu/database/data-sets**, was adopted.
- ✓ EEG signals were collected by means of 59 active EEG electrodes and four 16-channel amplifiers (g.tec medical engineering GmbH, Austria). Right mastoid was the reference channel and AFz electrode was the ground channel.
- ✓ EEG signals were band-pass filtered between 0.01 Hz and 200 Hz (by means of a 8-th Chebyshev filter), notch filtered at 50 Hz and sampled at 512 Hz.
- ✓ Motion data were collected through a glove equipped with motion sensors.
- ✓ Every participant performed cue-based movements of the right upper limb starting from a neutral position (lower arm in a neutral rotation and extended to 120 degree with the hand half open).
- ✓ Each experiment consisted in the execution of 60 trials for every sub-movement of the right upper limb, namely: elbow extension (EE), elbow flexion (EF), forearm pronation (PR), forearm supination (SU), hand close (HC), hand open (HO). Trials where the subject was asked to remain in a resting state (RE), performing no motor preparation, were also conducted.

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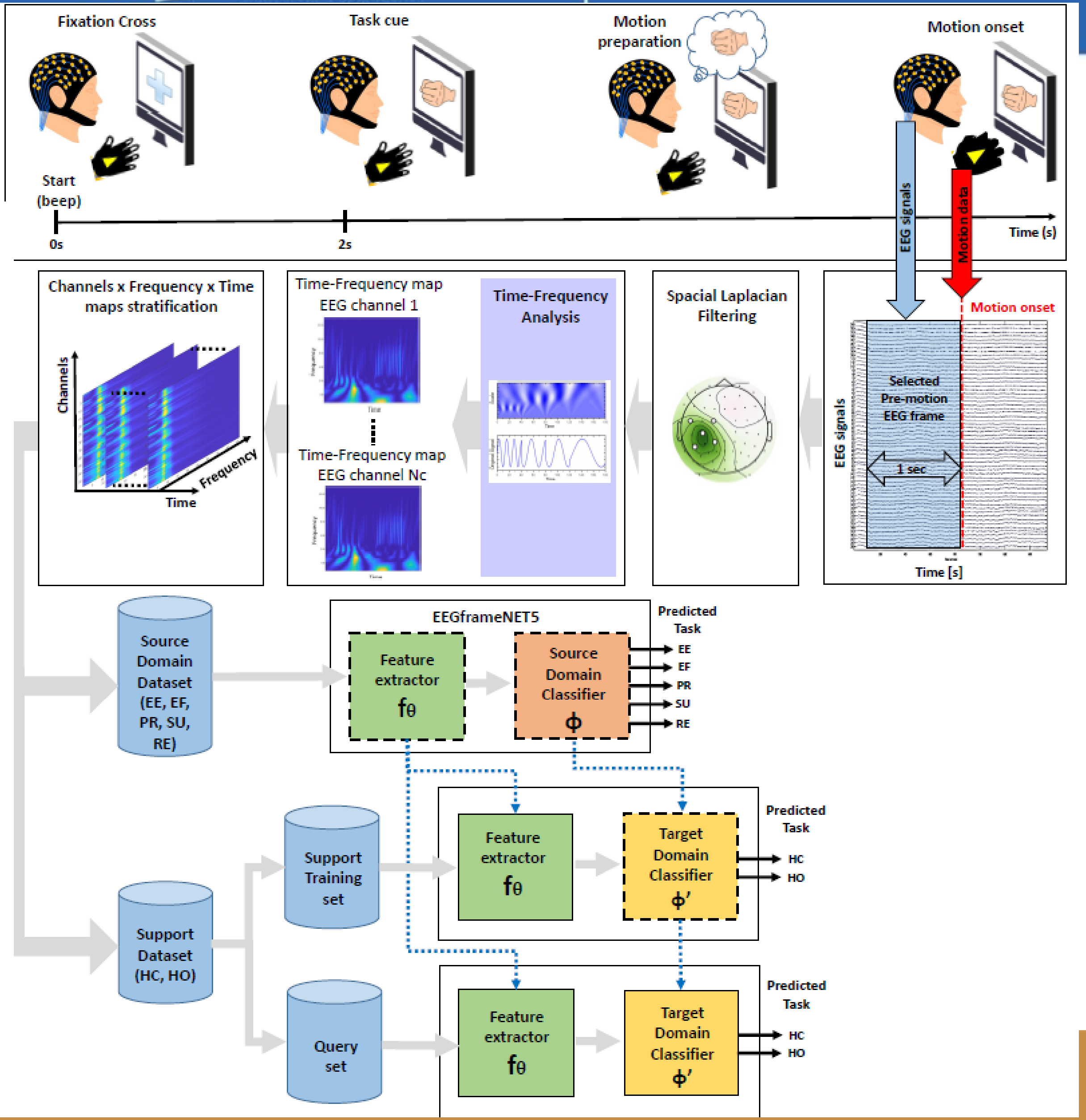
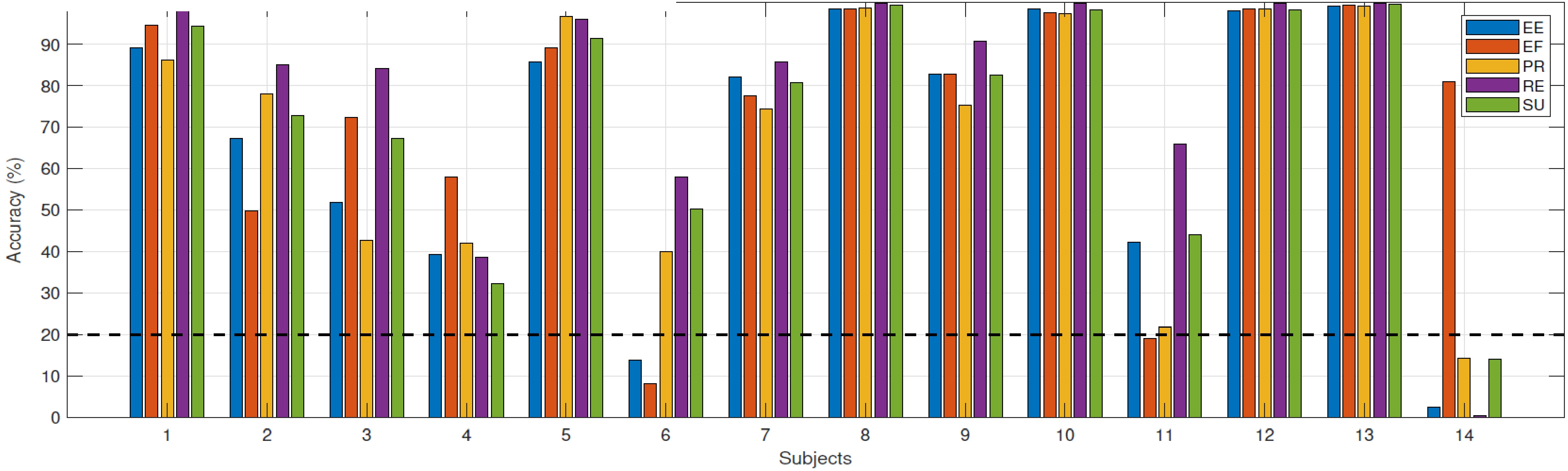
The proposed method

The EEG segments preceding the onset of motion are selected, labeled and stored in a dataset.
EEGs are spatially filtered by means of Laplacian, then time-frequency analysis is conducted by means of CWT. The time-frequency maps are stratified in channels frequency time volumes, then the channels frequency frame are labeled and stored. Two separate datasets are generated, the **source domain dataset** and the **support dataset**.
A custom CNN model **EEGframeNET5** is trained over the source domain dataset to perform the 5-way classification over the source domain dataset.
The support dataset is divided into support training set and query set. The support training set is used to fine-tune the last layer of the classifier to classify the tasks of the target domain.
The adapted system is then validated using the **query set**.

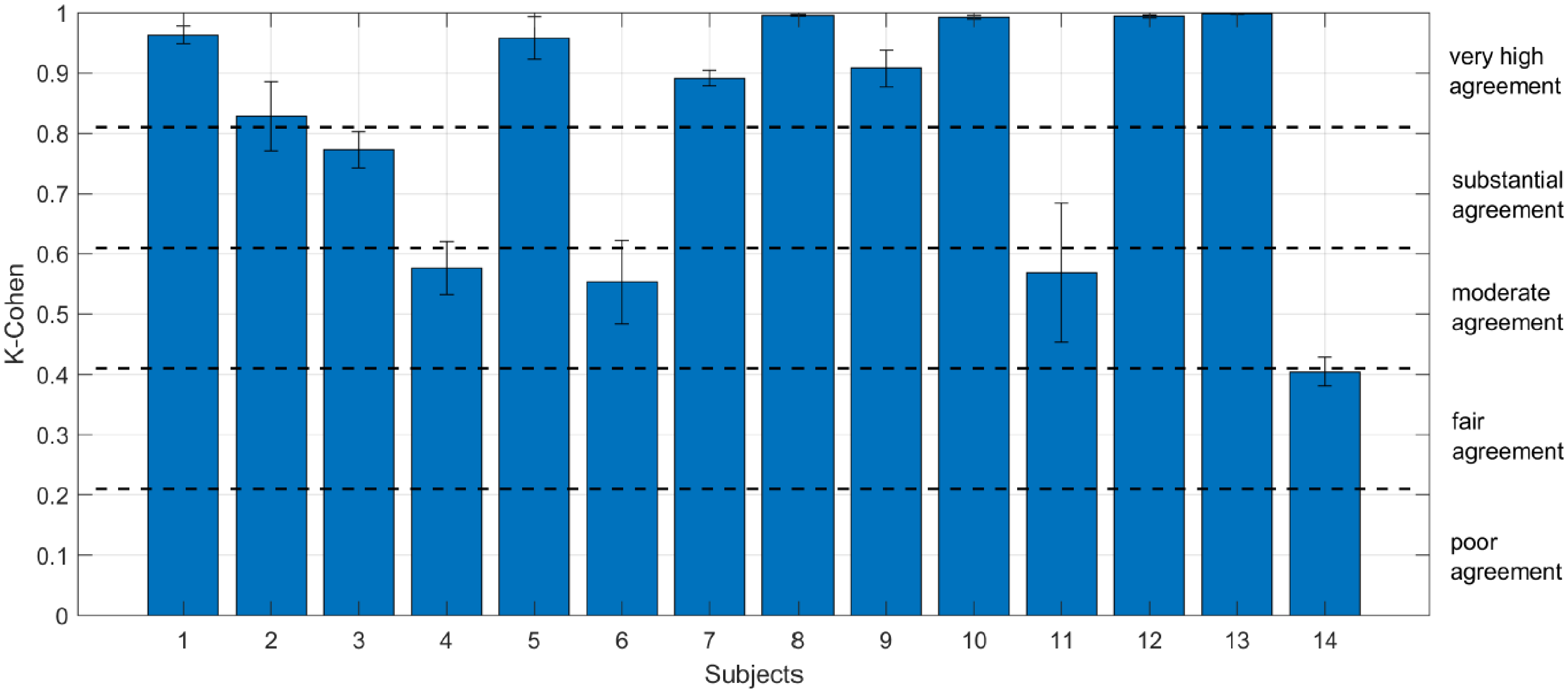


Results



Average Accuracy achieved over the large scale dataset in the 5-way classification (EE, EF, PR, SU, RE), subject by subject, class by class. Accuracy is represented as vertical bars, the horizontal dashed line marks the chance level.

Results



Average **K-Cohen** achieved over the source domain dataset in the 5-way classification (EE, EF, PR, SU, RE), subject by subject. K-Cohen is represented as vertical bars, horizontal dashed lines mark the level of agreement level between the predicted class and the target class. K-Cohen agreement levels are typically divided in the following ranges: poor, fair, moderate, substantial and very high.

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Concluding Remarks and Future Developments

- Generation and sharing of Green-AI models with reduced resources
- Design and comparison of different Meta-Learning strategies
- Agreement with GOM for making available databases
- Deployment on the Edge of ML/DL processing systems
- Dissemination at workshops WIRN and IJCNN 2025


THANKS