Multimodal Integration of Motor Imagery Brain-Computer Interface (BCI) with Adaptive Virtual Reality(VR) Environments for Assistive Robotics

Presenters: Bihao.You, Yize Liu, Yun Zhang, Yutong Zhu, Zihan Yu

Supervisors: Dr. Rui Yang & Dr. Mengjie Huang

Time: 2025.10

Challenges in Complexity (EEG Channel Selection)

Inter-subject Variability:
- Significant differences in brain structure and functional connectivity across individuals.

Task-specific Requirements:
- Different MI tasks (e.g., left vs. right hand) rely on distinct brain regions.

Impact:
- These challenges make it difficult to select a fixed, small set of channels that work well across different individuals and tasks while maintaining high decoding accuracy.

Challenges in Signal Instability (Cognitive Load)

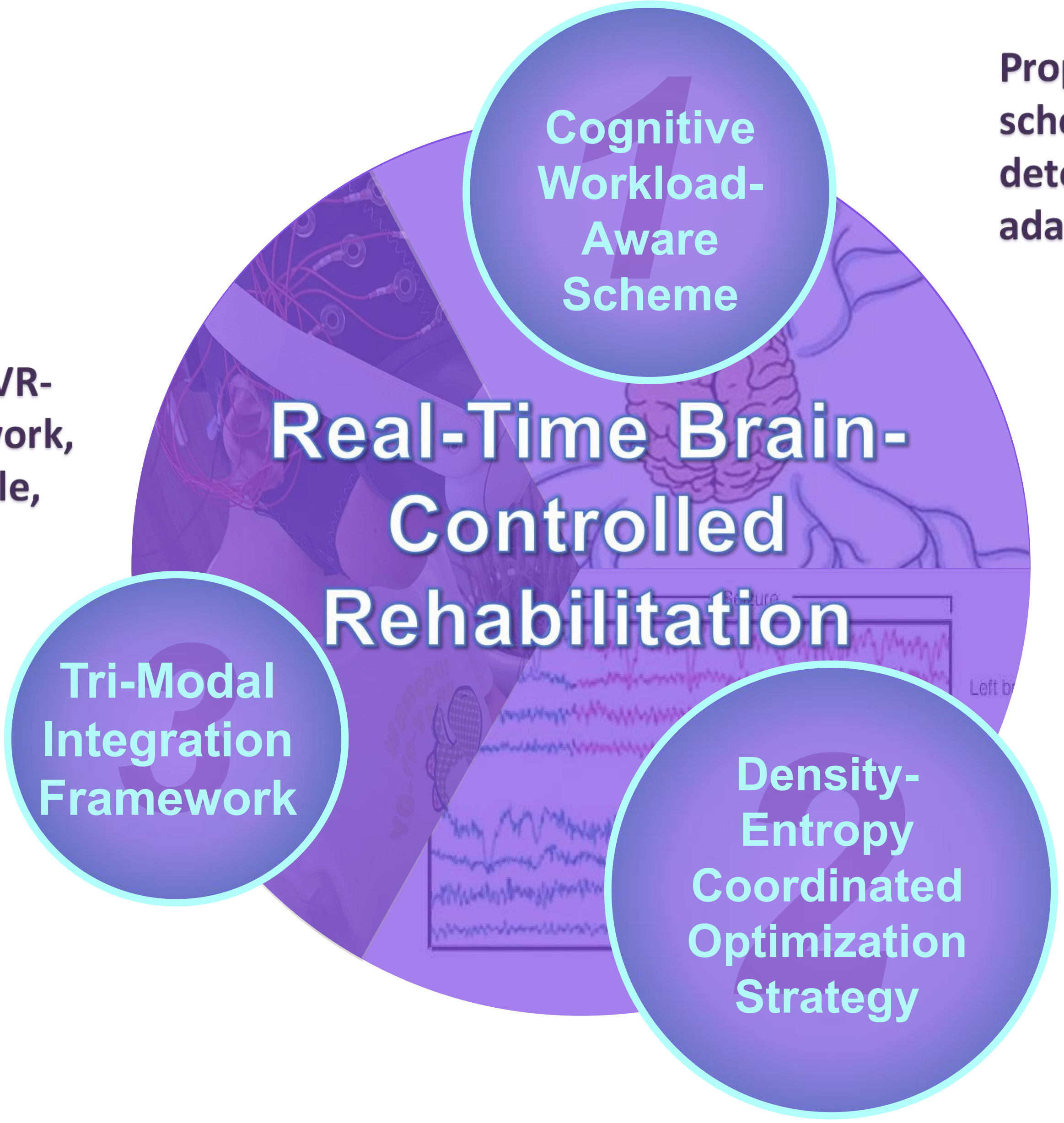
Signal Quality & Interference
- EEG signals are weak and easily corrupted by artifacts (EMG, EOG), reducing detection accuracy.

Individual Variability
- Differences in cognitive ability and brain patterns hinder universal models.

Real-Time Trade-Off
- Accurate processing vs. fast response—complex algorithms cause delays, limiting adaptive support.

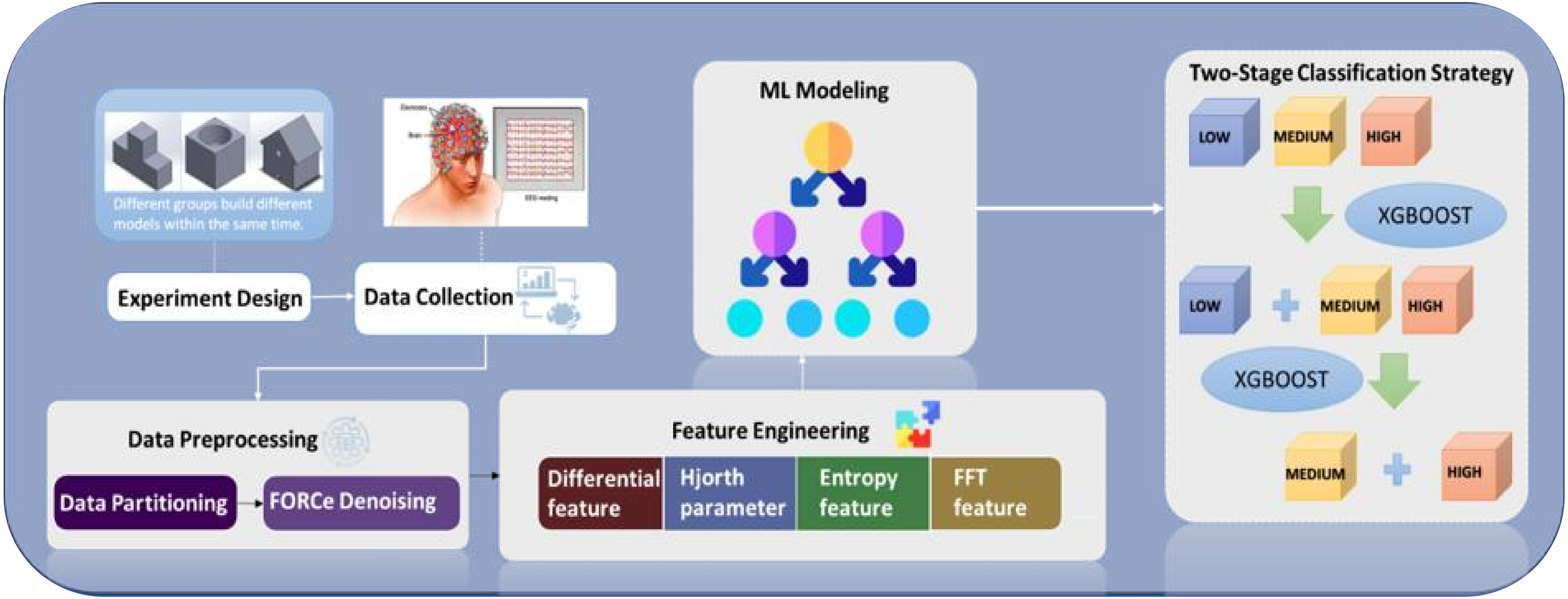
Propose a cognitive workload-aware scheme enabling three-level state detection and real-time VR difficulty adaptation, improving stability.

Establish a tri-modal BCI-VR-Robot Integration framework, forming a portable, reliable, and scalable platform for rehabilitation.



Develop a novel density-entropy coordinated optimization strategy to minimize electrode numbers, reducing setup and compute.

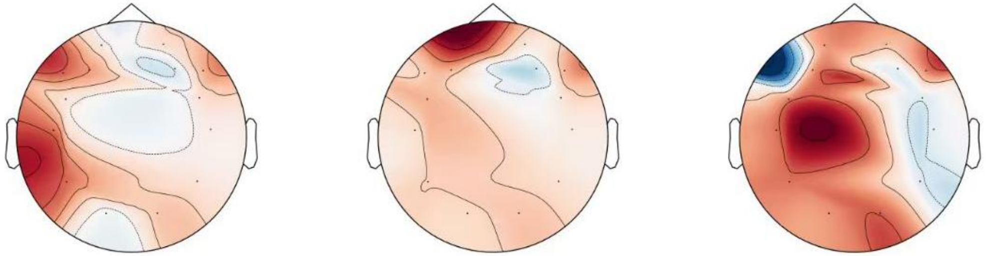
The Logic Frame of cognitive workload Detection Scheme



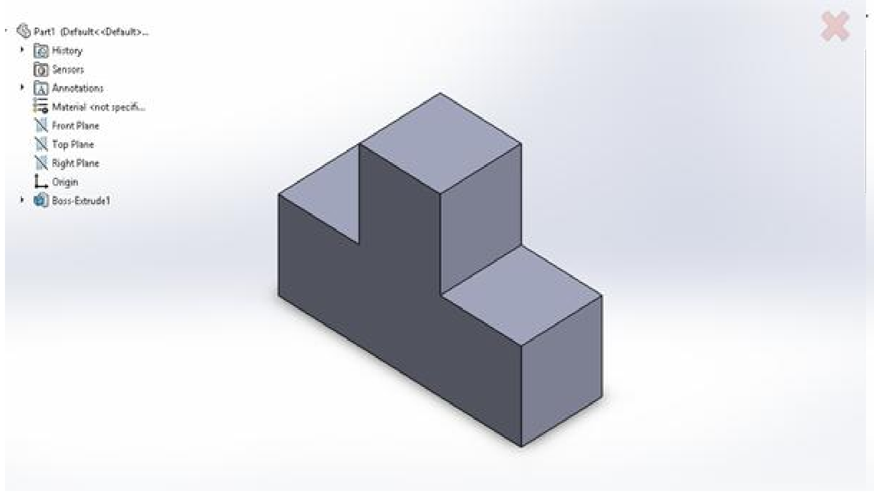
Data Collection

Task with 3 Different Cognition Levels

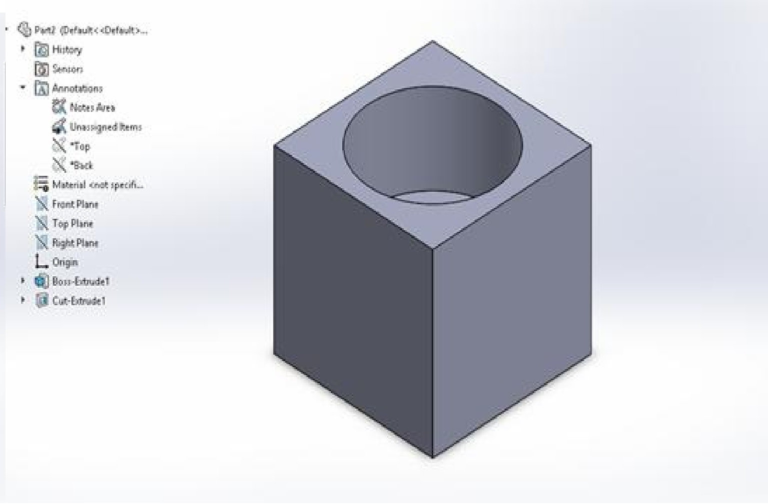
EEG Topographic Maps



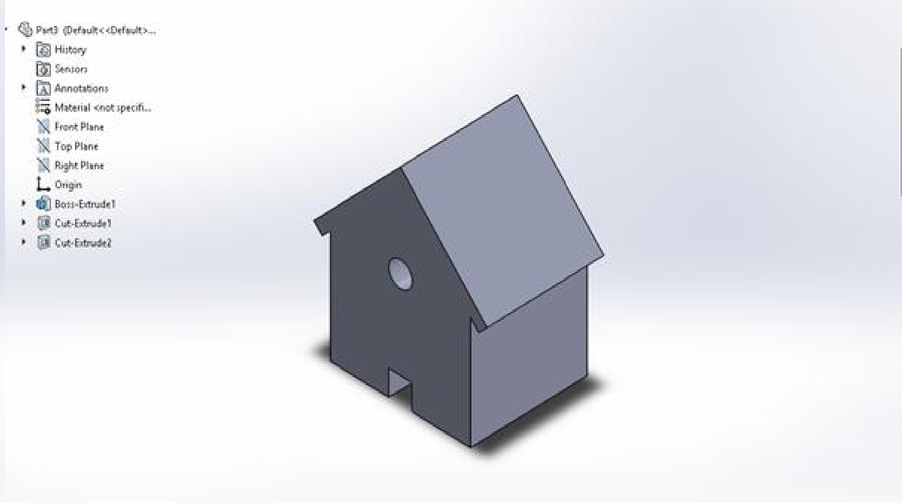
- Each subject was told to build **3 models of various complexity** with given time limit.
- Each Trial Included the following step
  a. The **first 5 seconds** of procedure was quiet, subject was **Idle**
  b. At the beginning of 6th second the subject started building the model.
  c. Finally, after given time limit and **5s idle time** after the experiment indicates the end of trial.
  d. Record their EEG signal



Level 1: Low

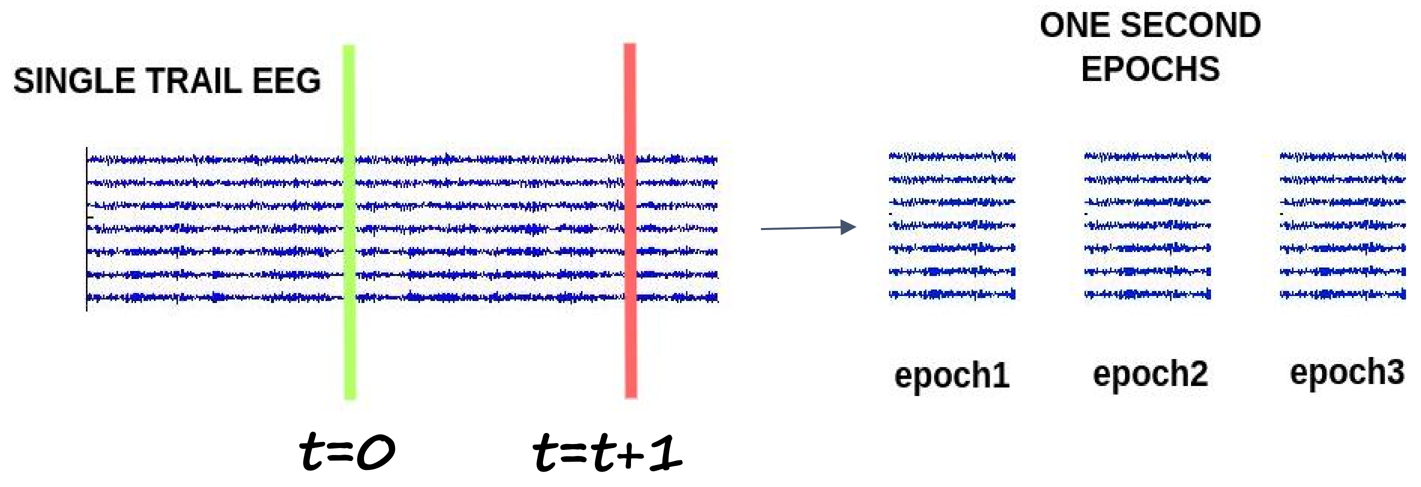


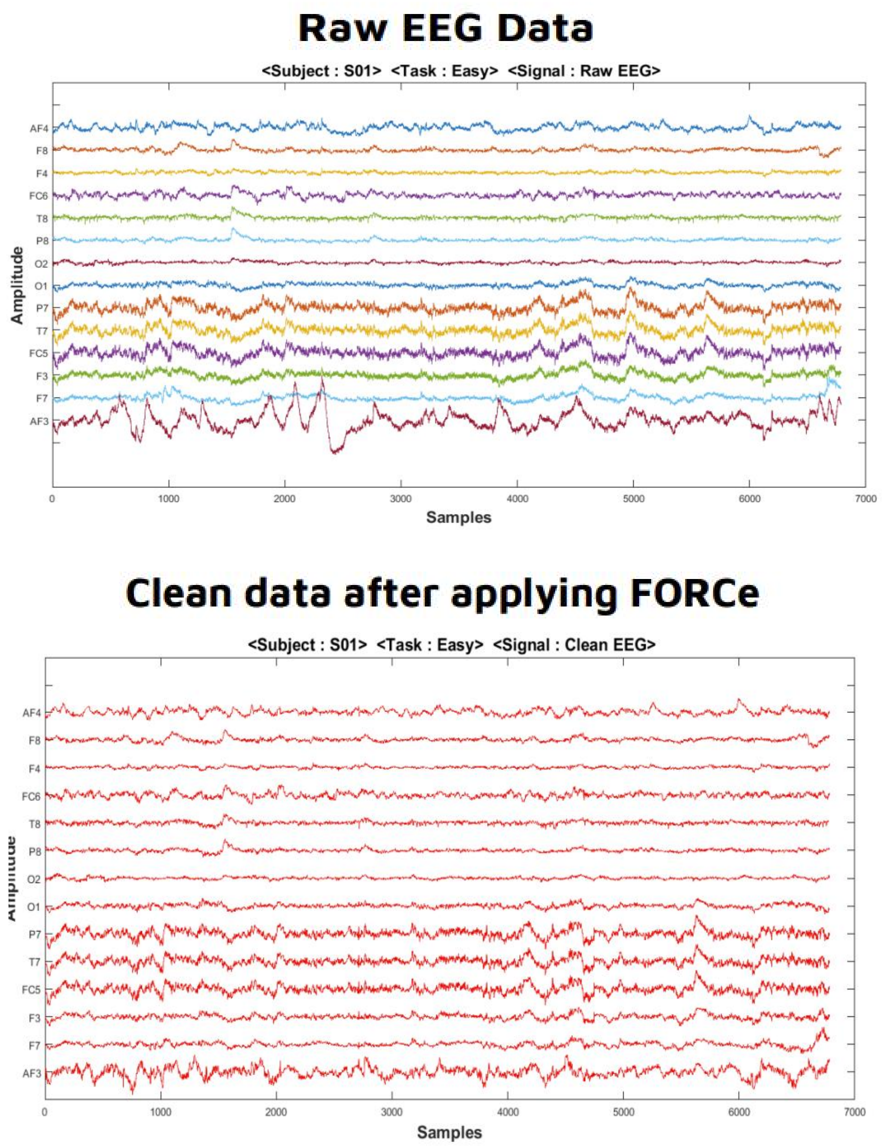
Level 2: Medium



Level 3: High

Data Preprocessing: Data Partitioning, FORCe Denoising





65 Features: COEFF OF VARIATION, SKEWNESS, KURTOSIS, Fractal dimension, 1st DIFF MEAN, 1st DIFF MAX, MEAN ABS XCORR EEG-EEG…

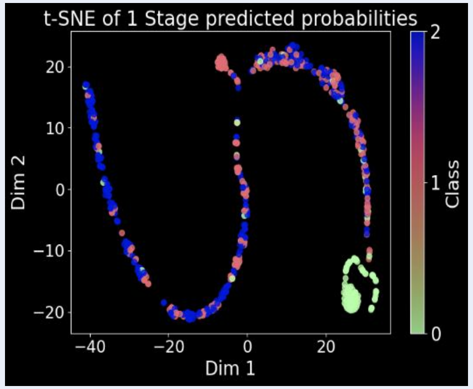
3 Feature Selection Methods to select top best features :

- Tree-based feature selection (Extra Trees Classifier)
- Extreme Gradient Boosting (XGBoost)
- Correlation Matrix

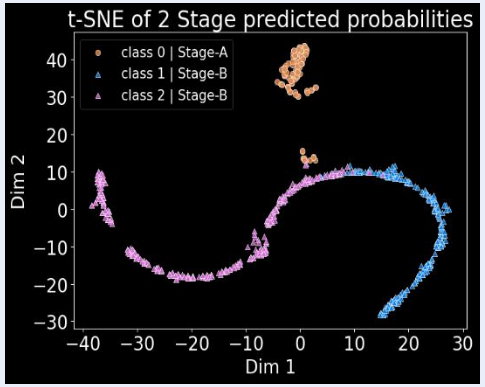
Result & Visualization

Applied Machine Learning Classifier	Accuracy using all features	Time taken with all features	Accuracy using selected features	Time taken using selected features
SVM	82.24%	1.041 s	70.56%	0.198 s
KNN	86.13%	0.456 s	75.08%	0.044 s
MLP	84.73%	1.937 s	71.81%	1.339 s
XGBoost	**88.01%**	**0.359 s**	**83.33%**	**0.046 s**
GaussianNB	57.32%	0.019 s	53.74%	0.007 s
Decision Tree	79.44%	0.121 s	73.21%	0.018 s

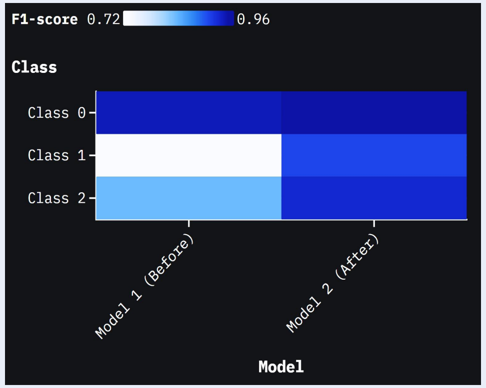
XGBoost achieved a highest accuracy of **83.33%** in classifying three workload levels. By further introducing a ***two-stage classification strategy***, the overall accuracy increased to **89.01%**, while the F1-scores for medium and high workload classes improved by about **12%**. t-SNE visualization further confirmed that this hierarchical approach yielded clearer separation among cognitive workload clusters.



Cognition Cluster (Before)

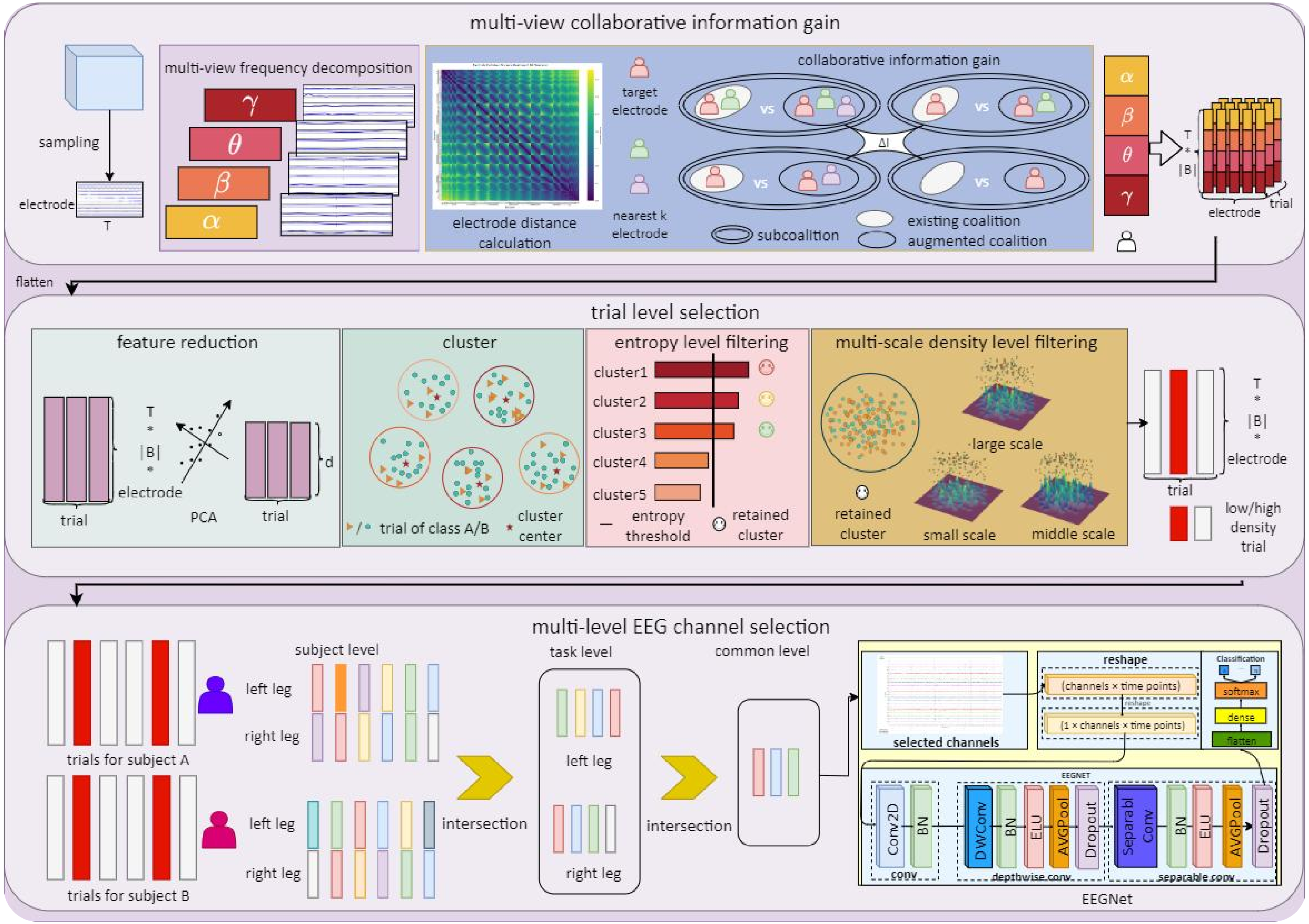


Cognition Cluster (After)



F1 Score Change in 3 Classes

The Proposed CHDECS Framework



The **principle** of proposed *Collaborative Hierarchical Density-Entropy Aware Channel Selection* (CHDECS) are:

A Novel Density-Entropy Collaborative Optimization Strategy:
This hard sample-driven approach employs dual density-entropy thresholds to force the model to concentrate on challenging samples near decision boundaries, thereby enhancing discriminative power for robust channel selection.

A Multi-Level Joint Optimization Framework:
A three-tiered framework (task, subject, and group levels) is designed to balance specificity and generalizability in channel selection.

Multi-View Collaborative Information Gain (MVIG):
A novel metric to quantify the individual and collaborative importance of EEG channels across frequency bands, effectively capturing complex inter-channel interactions.

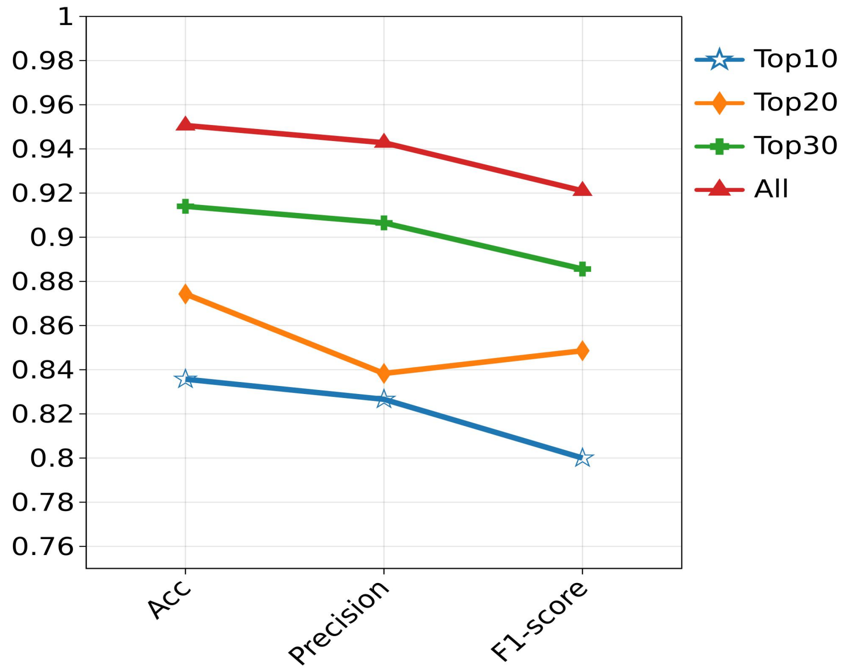
Task-Level Channel Ranking Score (TLCRS):
A comprehensive scoring mechanism that integrates information from time, frequency, and energy domains to evaluate channel significance.

Dataset & Preprocess & Result

Overview:
- Name: BCIC-III-IVa
- Subjects: 5 healthy subjects (aa, al, av, aw, ay)
- Task: Binary MI classification (right hand vs. right foot)

Experimental Design:
- Trials: 280 trials per subject
- Sampling Rate: 100 Hz
- Electrodes: 118 channels (10/20 international system)

Preprocess:
- Bandpass filter (5–40 Hz)
- Independent Component Analysis (ICA)



We compared the performance of our CHDECS-selected top 10, 20, and 30 channels against using all channels (left figure). **Our method is capable of cutting setup burden and computational cost while preserving decoding quality.**

Goal
- Close the loop from EEG motor imagery
- VR task
- Assistive robot motion with cognitive-load aware adaptation.

Scenarios
- Seated/standing leg-raise
- walking
- ball-kicking tasks.

Current Solutions:
- VR addresses the issue of varying abilities in people's imagination of movement

Channel Selection
- Channel selection resolves the slow decoding speed of motor imagery

VR Headset — Meta Quest 3
- Present the task context and visual cues.
- As a difficulty-adaptive host: Dynamically adjust the target size/distance, obstacle density, and rhythm based on the workload and success rate.
- Provide immediate feedback to the subjects to enhance immersion and compliance.

EEG CAP — Emotiv EPOC Flex
- Collect brain rhythms related to movement imagery, and use a small number of key channels selected by CHDECS for MI classification and cognitive workload estimation.
- As the "sensor core" of the closed loop: it not only provides the intention but also the status.

Assistive Robot — MileBot Max
- Provide hip joint flexion and extension assistance, synchronized with the subject's gait phase, converting "brain-VR intention" into actual lower limb movements and proprioceptive feedback.
- Linking with the difficulty of VR: Reduce the assistance when the challenge needs to be increased; increase the assistance when the difficulty is too high.

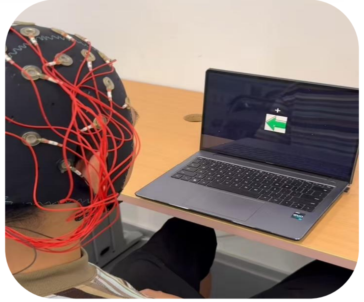
Architecture

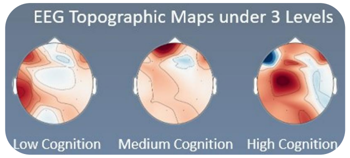
EEG Acquisition (EPOC Flex)

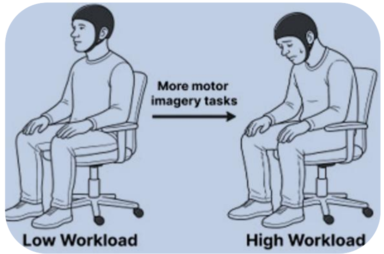
Preprocessing (band-pass/feature)

MI decoding (lifting legs left and right) + cognitive load assessment

Difficulty Adaptive System: Target size, distance, rhythm, task complexity





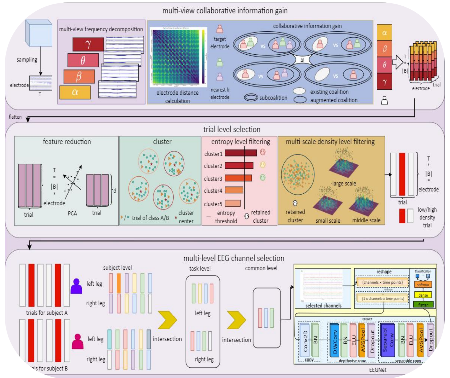


CHDES: channel selection

Robot Controller: Step Frequency, Ampliude, Phase Synchronization

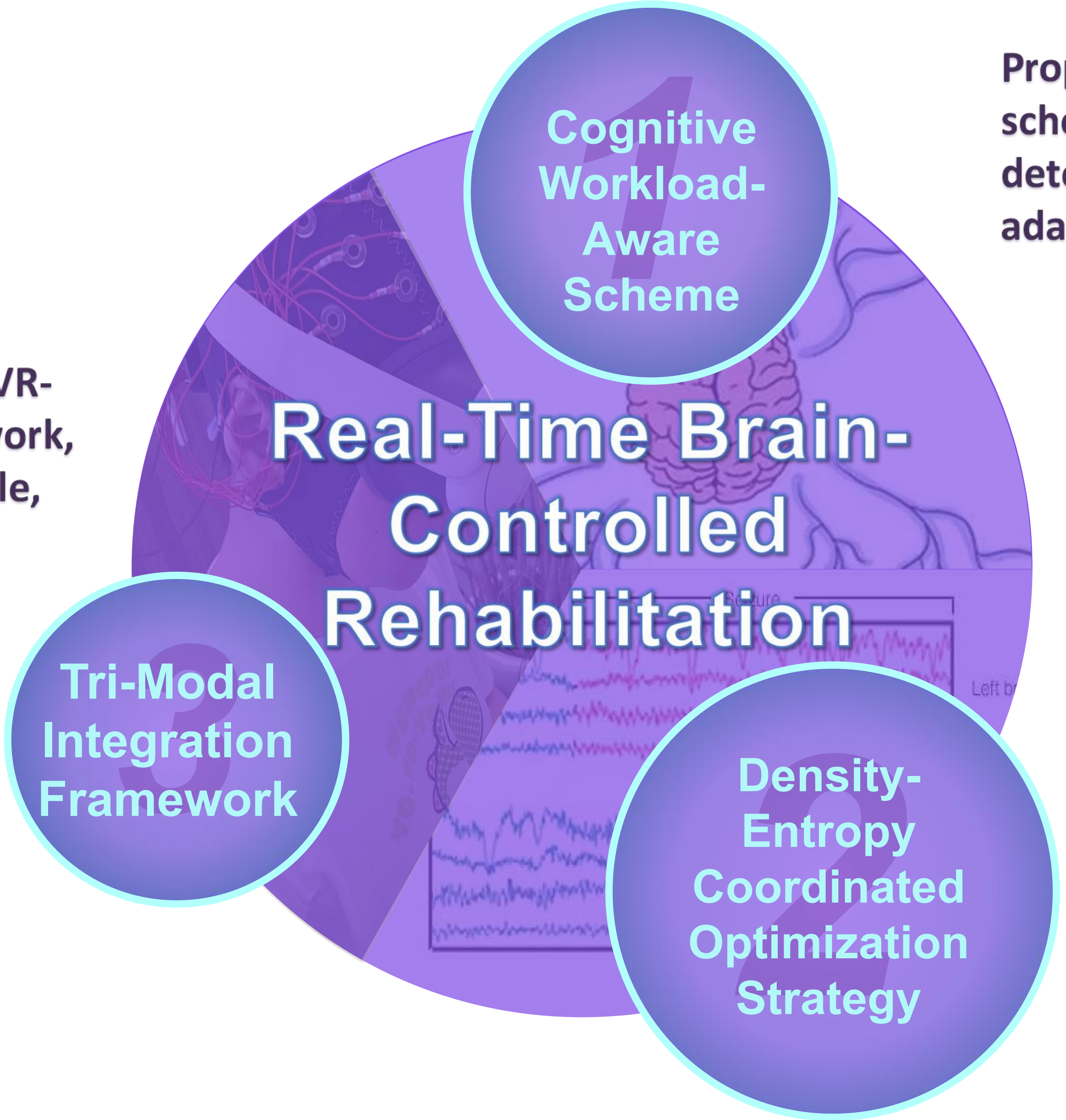
Multimodal feedback: Vision(VR), proprioception(Robot), performance indicators

Log and Security Monitoring



Propose a cognitive workload-aware scheme enabling three-level state detection and real-time VR difficulty adaptation, improving stability.

Establish a tri-modal BCI-VR-Robot Integration framework, forming a portable, reliable, and scalable platform for rehabilitation.



Develop a novel density-entropy coordinated optimization strategy to minimize electrode numbers, reducing setup and compute.