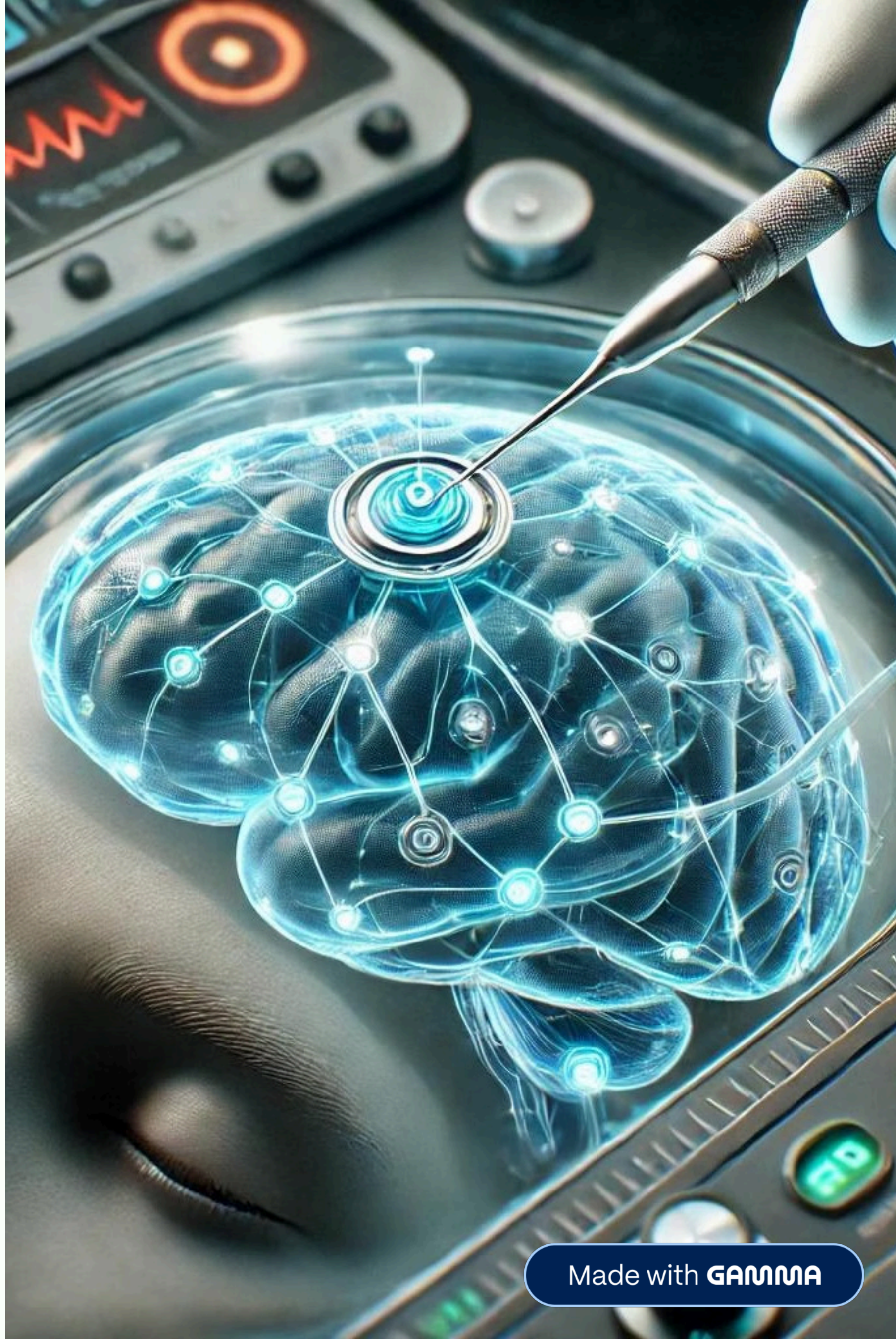
NEUROWHEEL



Project Overview

1

Motor Imagery BCI Focus

This project develops a high-performance Brain-Computer Interface (BCI) exclusively centered on the Motor Imagery (MI) paradigm. Users consciously imagine specific physical movements (e.g., left hand, right hand), allowing for direct control bypassing traditional muscle movement.

2

Neural Signal Processing

Mental rehearsal of movements elicits distinct changes in the brain's electrical activity. We specifically focus on Sensorimotor Rhythms, which are measured and analyzed using Electroencephalography (EEG).

3

Dataset & Methodology

Our approach utilizes existing high-quality benchmark PhysioNet datasets. These robust datasets are crucial for training and validating advanced machine learning models to ensure accuracy and reliability.

Project Vision

Hybrid BCI System

Developing a hybrid BCI system pushing the boundaries of current technology.

Empowering Lives

Empowering individuals with paralysis and motor impairments by providing them with advanced tools for communication and interaction, restoring independence.

Bridging Cognition & Digital

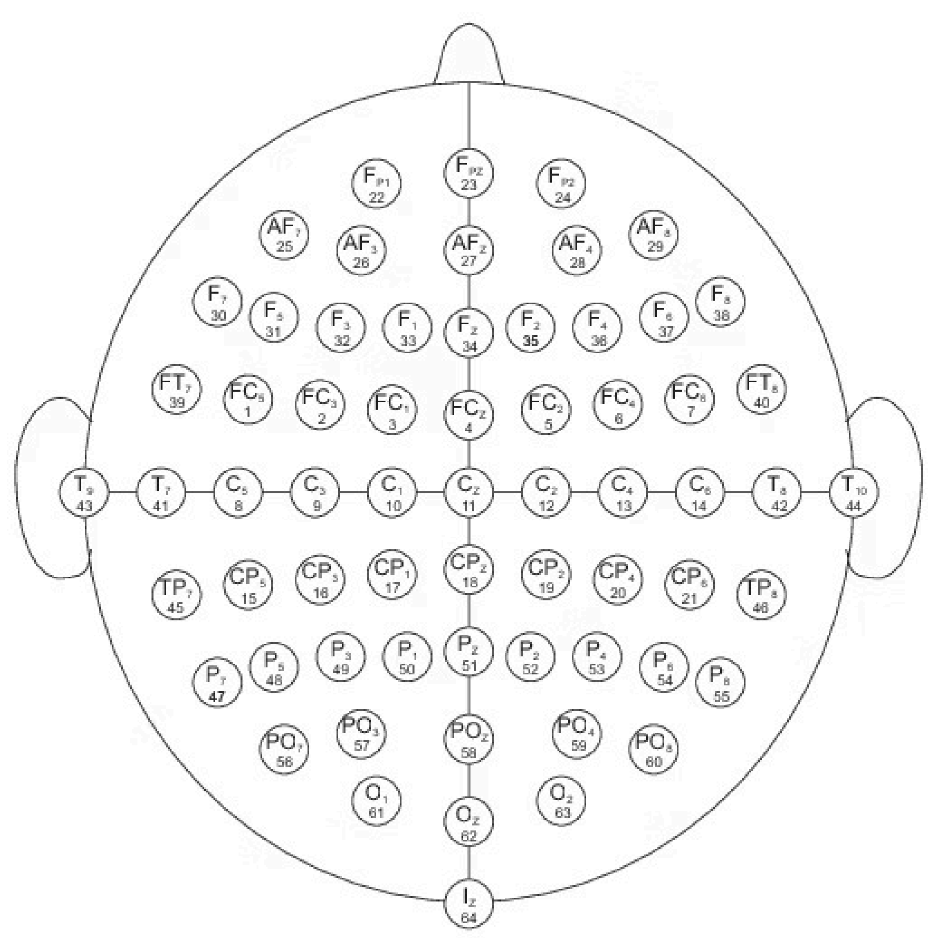
Breaking barriers between human cognition and digital interaction, fostering a deeper connection and control over the digital world with thought alone.

Session Records

Run	Description	Category
R01	Eyes open (baseline)	Rest
R02	Eyes closed (baseline)	Rest
R03	Move left fist	Motor execution
R04	Move right fist	Motor execution
R05	Move both fists	Motor execution
R06	Move both feet	Motor execution
R07	Imagine left fist	Motor imagery
R08	Imagine right fist	Motor imagery
R09	Imagine both fists	Motor imagery
R10	Imagine both feet	Motor imagery
R11	**Repeat of R03** (move left fist again)	Motor execution
R12	**Repeat of R04** (move right fist again)	Motor execution
R13	**Repeat of R07** (imagine left fist again)	Motor imagery
R14	**Repeat of R08** (imagine right fist again)	Motor imagery

EEG Channel Locations and Functions

Channel	Brain Region	Main Function / What It Measures
Fp1, Fpz, Fp2	Frontopolar (front of forehead)	Detects eye movement, attention, and frontal brain activity.
Af7, Af3, Afz, Af4, Af8	Anterior Frontal	Measures decision-making, focus, and emotional responses.
F7, F5, F3, F1, Fz, F2, F4, F6, F8	Frontal	Involved in thinking, reasoning, and motor control.
Fc5, Fc3, Fc1, Fcz, Fc2, Fc4, Fc6	Fronto-Central	Between frontal and central – involved in planning movement.
C5, C3, C1, Cz, C2, C4, C6	Central	Main motor and sensory areas (movement and touch).
Cp5, Cp3, Cp1, Cpz, Cp2, Cp4, Cp6	Centro-Parietal	Combines movement and sensory processing information.
Ft7, Ft8	Fronto-Temporal	Speech and auditory processing (language areas).
T7, T8, T9, T10	Temporal	Hearing, speech, and memory processing.
Tp7, Tp8	Temporo-Parietal	Integration of visual and auditory information.
P7, P5, P3, P1, Pz, P2, P4, P6, P8	Parietal	Sensory processing, attention, and spatial orientation.
Po7, Po3, Poz, Po4, Po8	Parieto-Occipital	Combines vision and spatial perception.
O1, Oz, O2	Occipital	Main visual processing region (vision and light perception).
Iz	Inion (back of head)	Reference near occipital area; vision-related.



From Sensor to Action

Signal Acquisition

- Raw EEG

Preprocessing

- Bandwidth Filter: (0.5 - 50 Hz)
- Notch Filter: (50 Hz and 60 Hz)
- Filtering channels
- Referencing
- ICA (Independent Component Analysis)

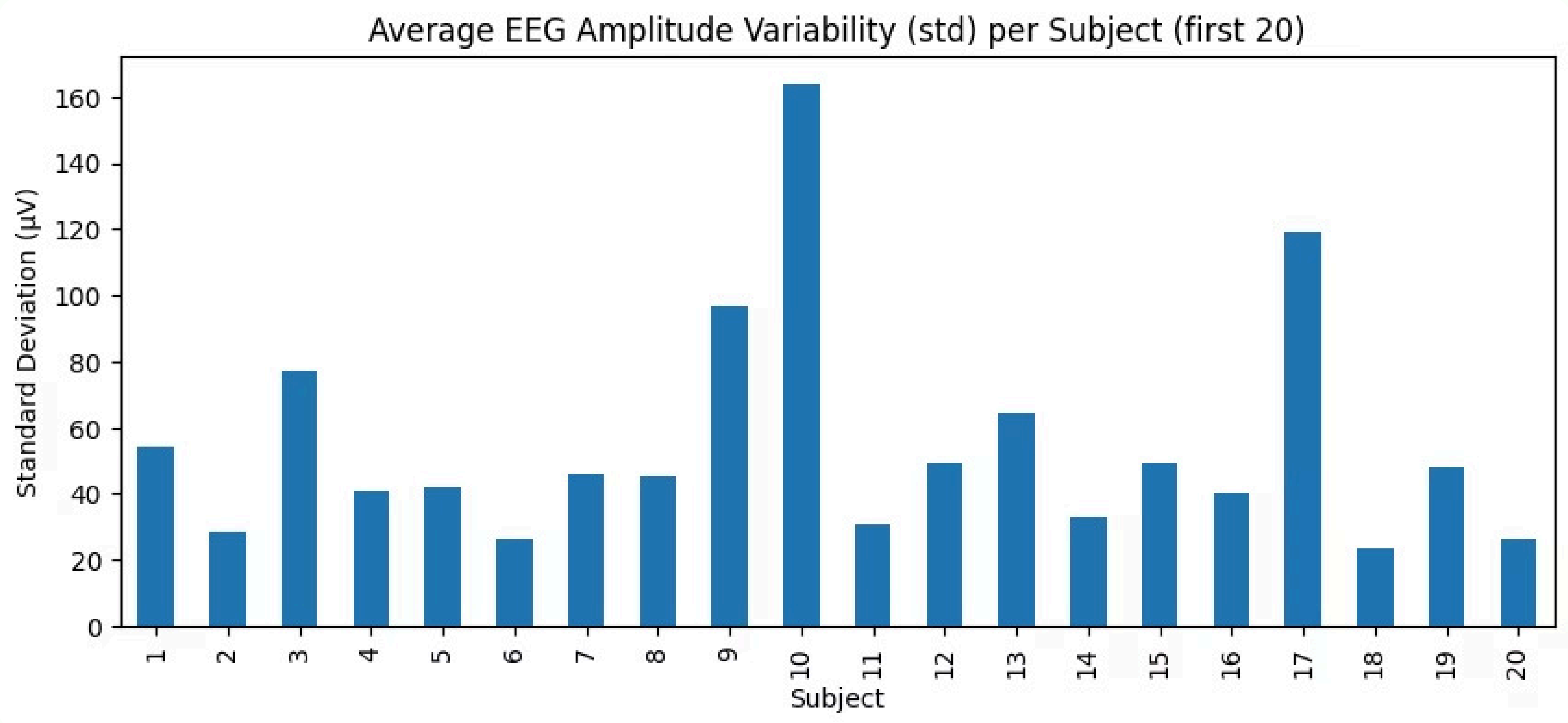
Epoching & Labeling

- Left
- Right
- Forward
- Stop

This labeled data is prepared as the training dataset

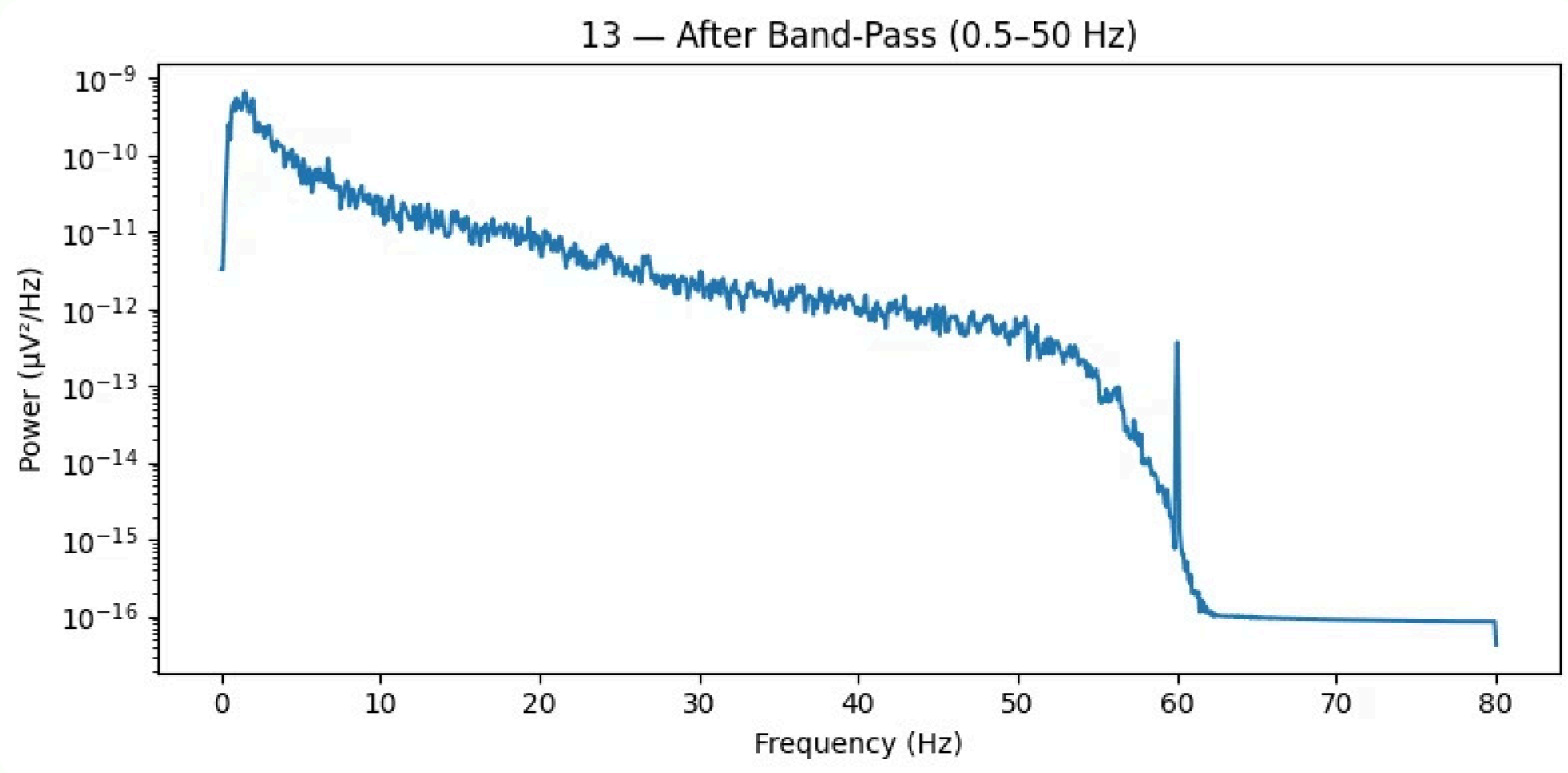
Model Training

- EEGNET
- MIREPNET

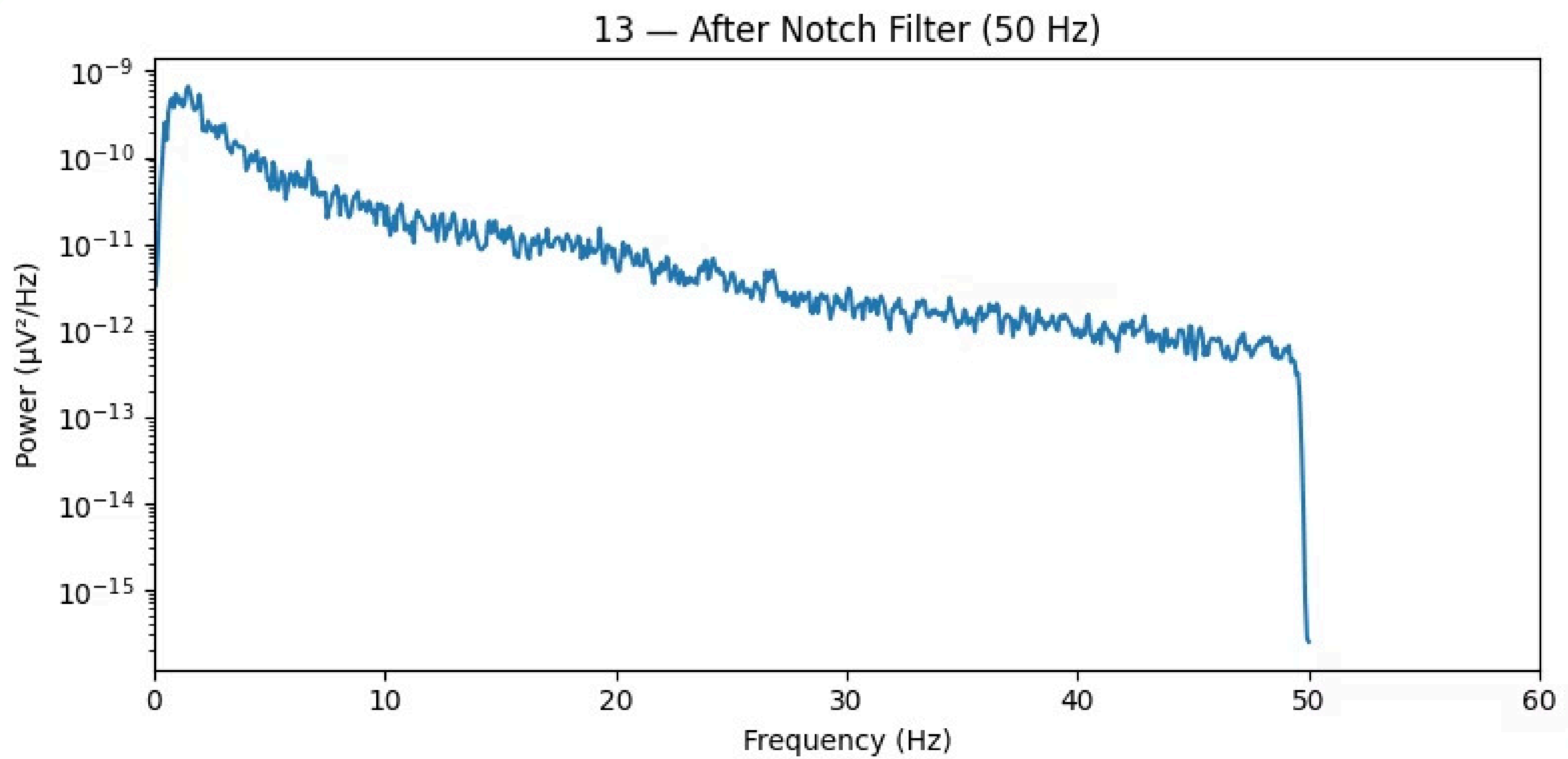


High variation indicates noise

Values above 100 are likely noise channels or runnings



Frequency spectrum after applying the 0.5–50 Hz band-pass filter



Frequency spectrum after removing 50 Hz noise using a notch filter

EEGNet(Baseline Model)

Preparation Steps:-

- EEG preprocessing (filtering, epoching, normlization)
- Train/val split
- Apply class weights or augmentation if needed

EEGNet Overview:-

- compact CNN for EEG
- Depthwise + Separable convolutions
- 3 main convolutional blocks
- Designed for small datasets & BCI tasks

EEGNet Results

Initial accuracy: 0.43 (overfitting)

Applied class weights —> handle imbalance

Applied Mixup augmentation —> improves generalization

Final accuracy: 0.58

MIRepNet Preparation

Preparation Steps:-

- Replicate MIRepNet paper preprocessing
- Normalize per channel
- Segment into fixed-length windows
- One-hot labels for 4 classes

MIRepNet overview:-

Pretrained EEG representation learning model

Transformer-like + CNN blocks

Learns motor imagery features

Originally trained on 3-class PhysioNet

Differences (EEGNet vs MIRepNet)

EEGNet

- Small CNN
- End-to-End training
- Good for small data
- 3-layer architecture

MIRepNet

- Pretrained representation model
- Deeper , more complex
- Needs matching preprocessing
- Originally trained on 3 classes

Using MIRepNet

Without fine-tuning

(Frozen backbone)

acc = 0.48

Fine-tuning

(unfreeze layers)

acc = 0.46

Applying MIRepNet's own preprocessing

acc = 0.55

Limitation: pretrained on 3-class PhysioNet (LH/RH/Feet)

Our dataset: 4 classes –> mismatch –> lower accuracy

EEG-Based Emergency Stop System

Initial Research on P300

I started by studying the P300 signal, as it is one of the most commonly used signals in BCI research

I downloaded multiple datasets and experimented with different models to build an EEG-based Emergency Stop System for a wheelchair

After reviewing several research papers, I reached important conclusions:-

1- The jaw-clench signal is the strongest and most reliable

2- Next comes eye movement

And finally, P300

Since our goal is to build a system that is simple, fast, and requires minimal equipment, we chose eye-movement signals

Eye activity can be captured direclty from FP1/FP2 using the Vizzanet device without attaching additional sensors to the users

Choosing the Eye-Blink EEG Dataset

I searched extensively for datasets focused on eye movements until I found a suitable eye-blink EEG dataset

The experiment behind the dataset was designed to measure attention, and it was performed across three scenarios:

1- Participants performing different actions	2- Participants watching boring contents	3- Participants watching normal content

I selected the action scenario, because it contains clear and distinguishable signals :

1 = Blink

0 & 2 = Normal activity

During Preprocessing:-

Class 1 was kept as the blink class

All other values were merged into a single non-blink class

–>This simplifies the task into a clean binary classification problem

Model Experiments

CNN Model

I initially experimented with a standard CNN.

After multiple improvements, the model achieved around 77% accuracy (r1).

However, there were two major issues:

The model was too heavy for low-power devices.

Inference was slow, which is unacceptable for an emergency stop system.

EEGNet

I then moved to EEGNet, a lightweight architecture designed for EEG.

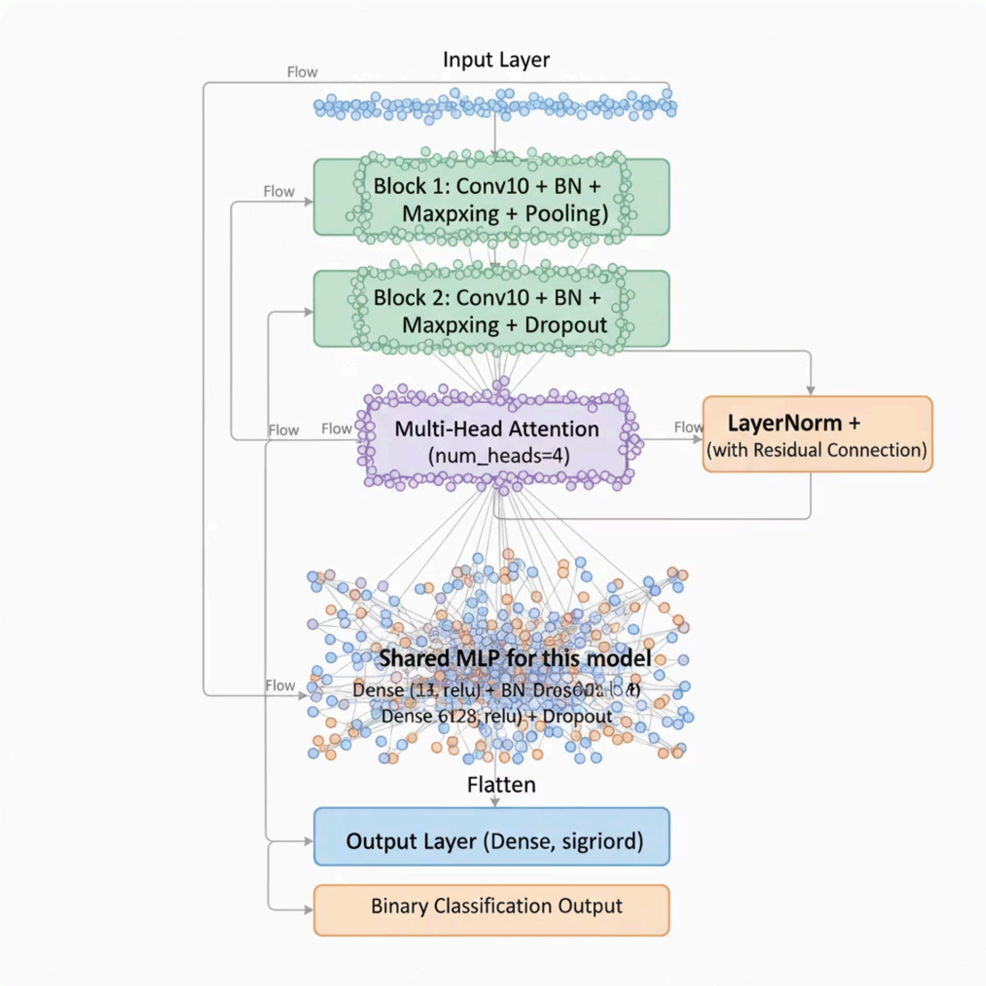
The results:

Much faster than CNN

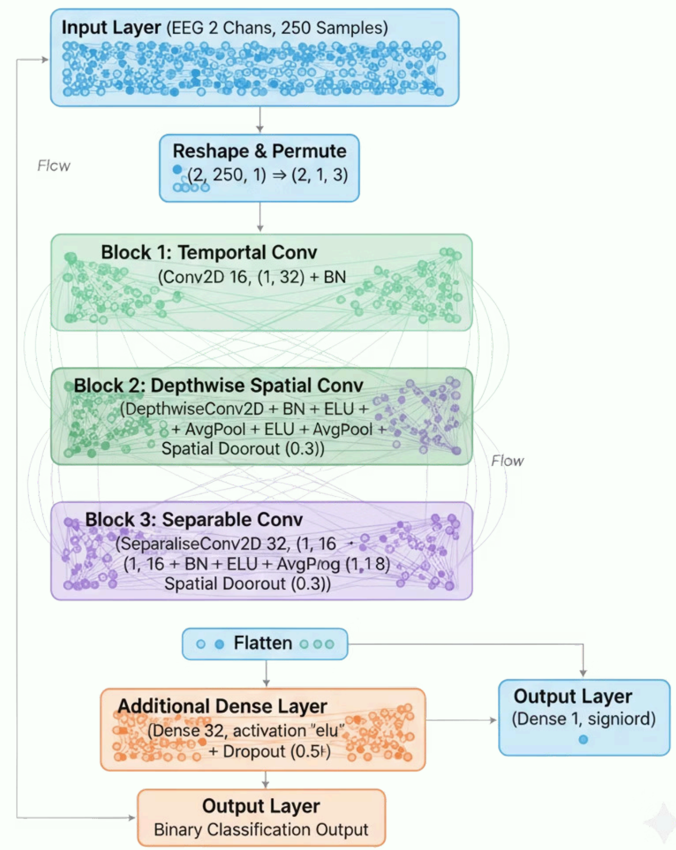
Slightly lower accuracy, but significantly better for real-time use

CNN vs EEGNet

CNN



EEGNet



EEGNet_Optimized

I optimized and tuned EEGNet to fit our dataset and classification needs.

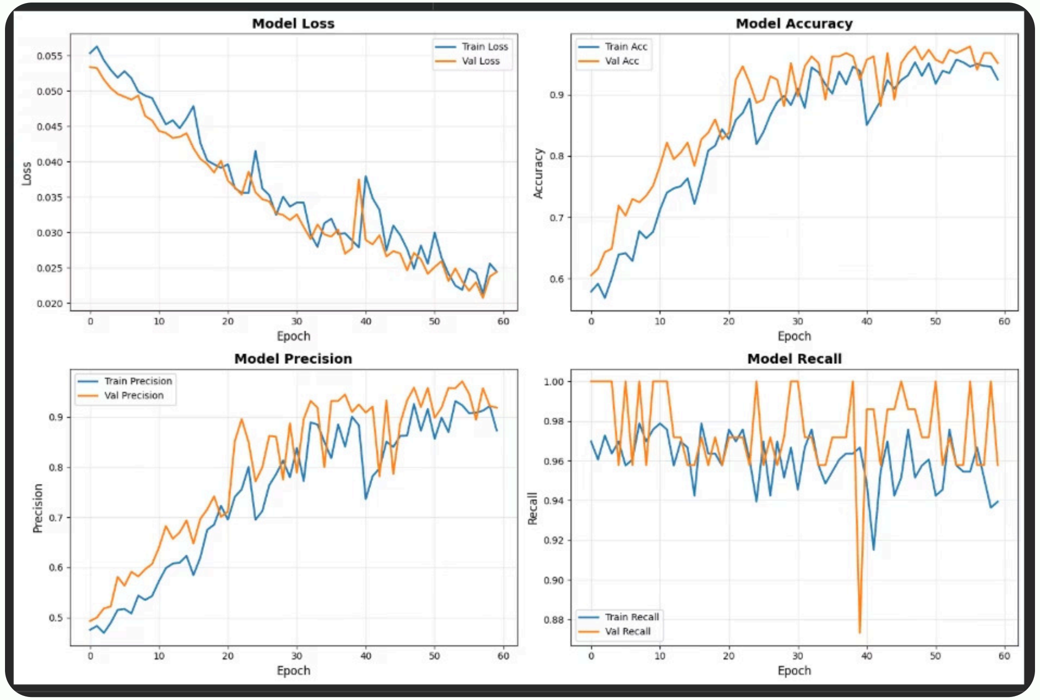
The improved model, EEGNet_Optimized, achieved:

a. Very high accuracy: ~99%
b. Fast inference time
c. Better performance balance between speed and accuracy

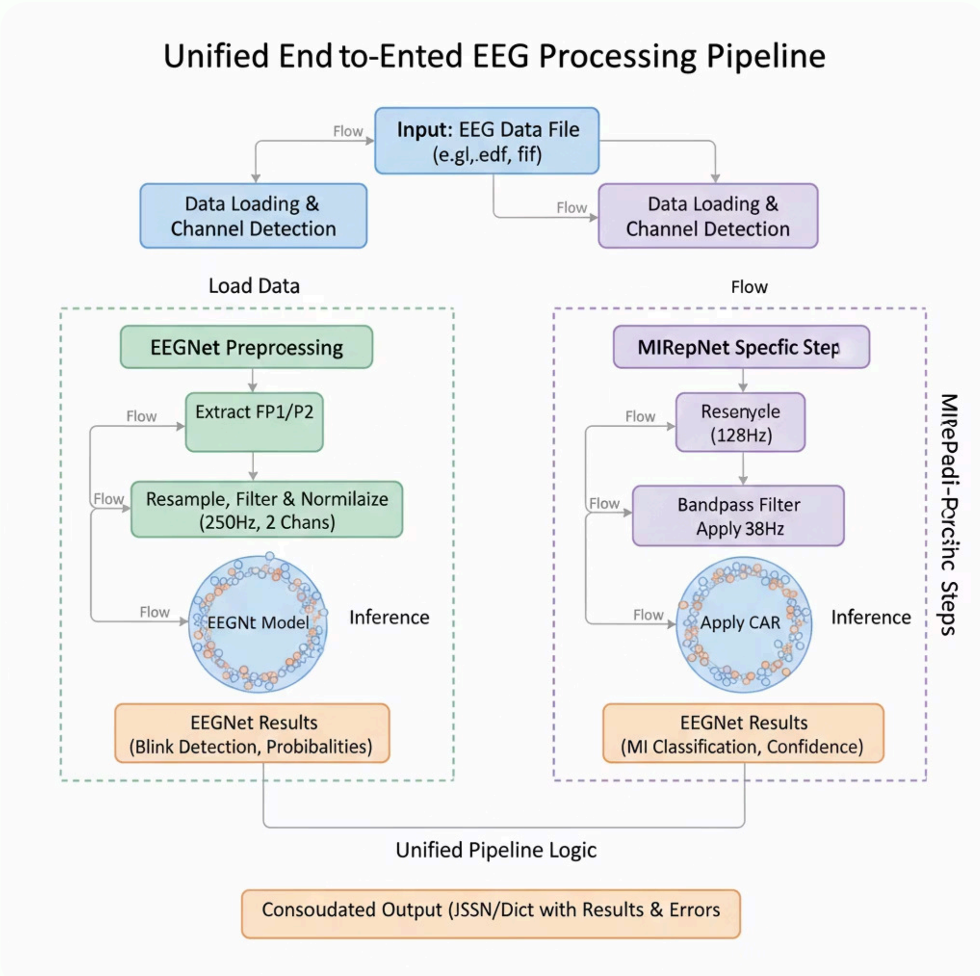
Final Outcome

Instant response time suitable for emergency scenarios

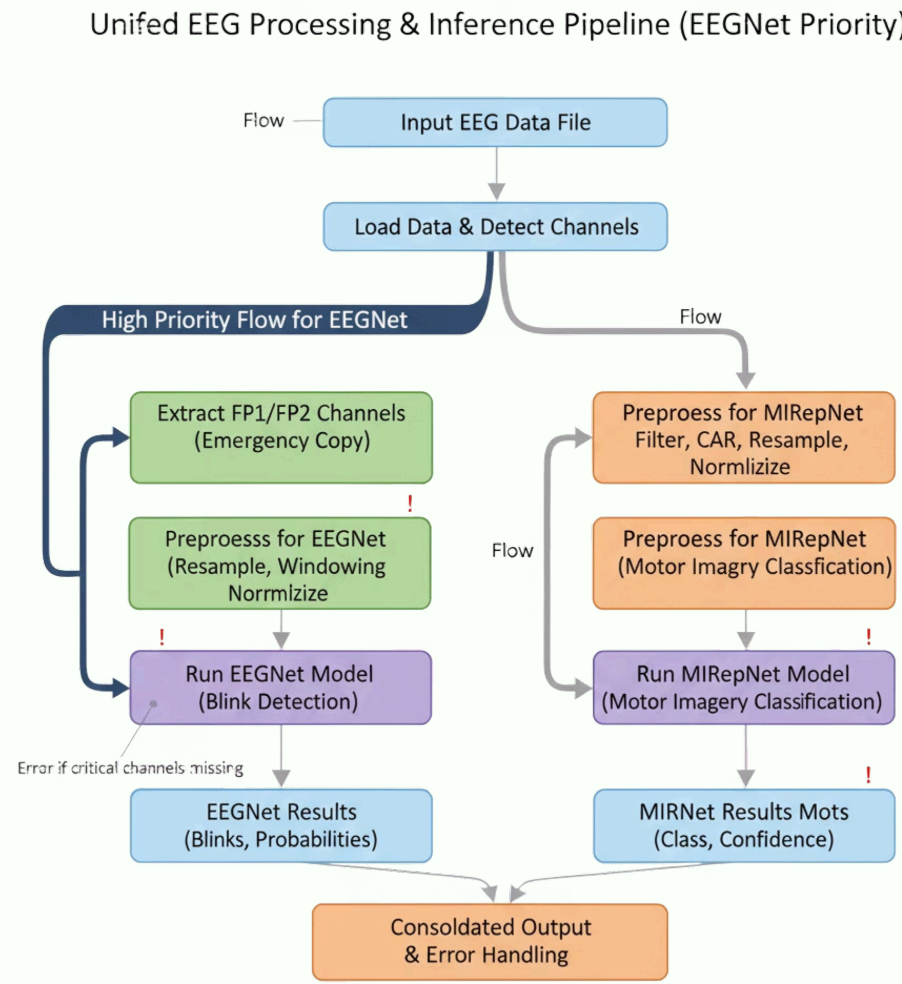
High accuracy (≈99%)



Pipeline



Unified End to-Ented EEG Processing Pipeline
Input: EEG Data File (e.gl,.edf, fif)
Flow
Data Loading & Channel Detection
Flow
Data Loading & Channel Detection
Load Data
Flow
EEGNet Preprocessing
Extract FP1/P2
Flow
Resample, Filter & Normilaize (250Hz, 2 Chans)
Flow
EEGNt Model
Flow
Inference
EEGNet Results (Blink Detection, Probibalities)
MIRepNet Specfic Step
Resenycle (128Hz)
Flow
Bandpass Filter Apply 38Hz
Flow
Apply CAR
Flow
Inference
EEGNet Results (MI Classification, Confidence)
MIrePadi-Porcinc Steps
Unified Pipeline Logic
Consoudated Output (JSSN/Dict with Results & Errors



Unifed EEG Processing & Inference Pipeline (EEGNet Priority)
Flow
Input EEG Data File
Load Data & Detect Channels
High Priority Flow for EEGNet
Flow
Extract FP1/FP2 Channels (Emergency Copy)
Preprocess for MIRepNet Filter, CAR, Resample, Normlizize
Preprocesss for EEGNet (Resample, Windowing Normlzize
Flow
Preprocess for MIRepNet (Motor Imagry Classfication)
Run EEGNet Model (Blink Detection)
Run MIRepNet Model (Motor Imagery Classification)
Error if critical channels missing
EEGNet Results (Blinks, Probabilities)
MIRNet Results Mots (Class, Confidence)
Consoldated Output & Error Handling

Deployment

- Deployed the machine learning model using Streamlit, enabling an interactive and user-friendly web application.
- Implemented and deployed a full Streamlit application for real-time model inference.

[Tray 🧐]

Thank you for your time.

Your attention means a lot.

Team

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