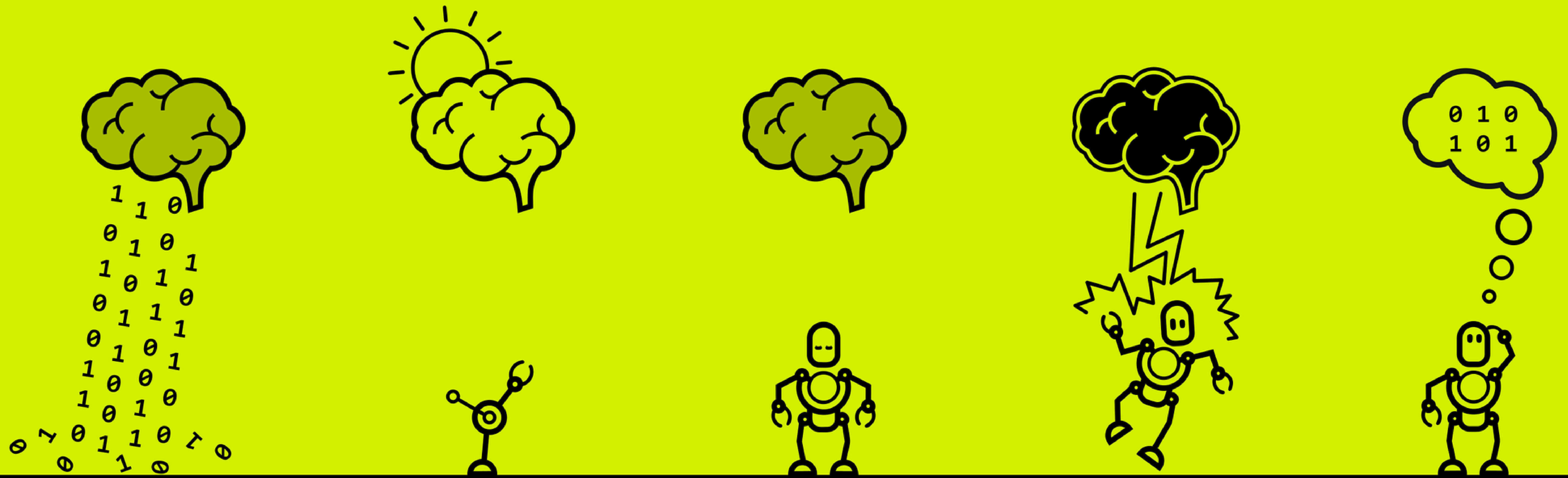

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THE BRAIN-COMPUTER INTERFACE DESIGNERS HACKATHON

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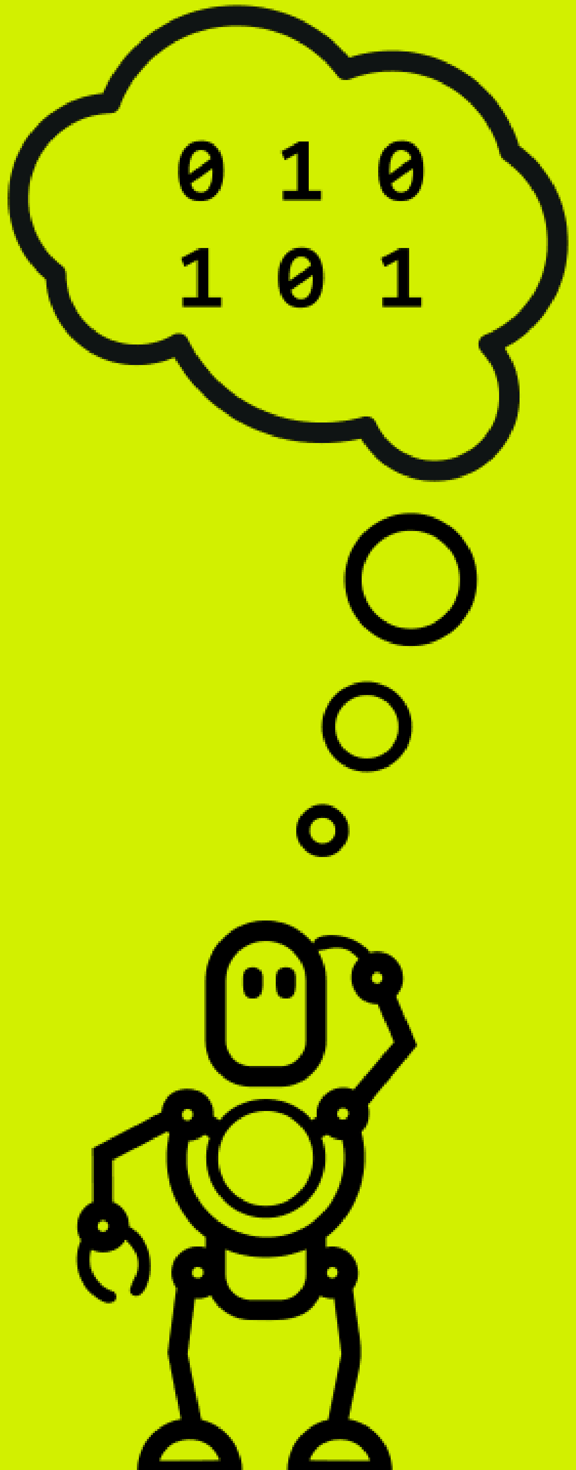
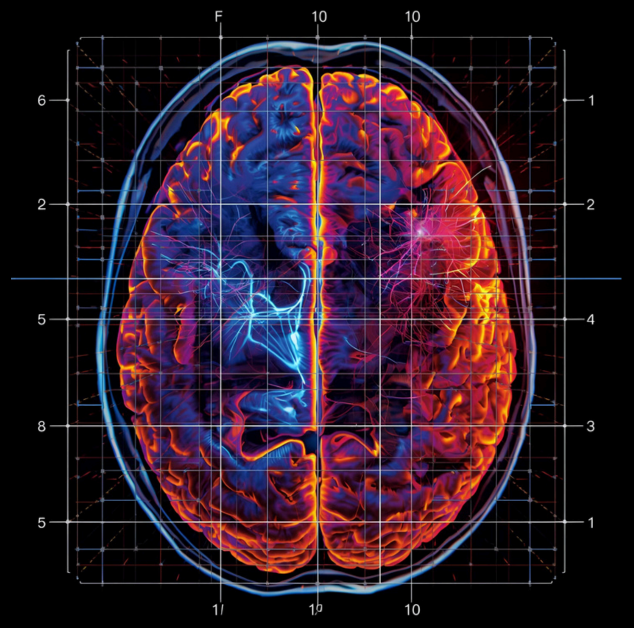
Bringing together neuroscience, machine learning, and creative engineering to explore how the brain sees the world.

Our TEAM NeuroPulse
— capturing the rhythm of thought





ECoG Video Watching Analysis

Dimitrios Georgiou[1] | Zomorodah MHD Izzat | Bakhit[2] | Laura Maria Höber[3] | Aryan Aghababaei[4] | Tasnim Helmy Elbahouty[5]

1. Data Scientist @ HSBC, AI Researcher @ KLIMAKA (suicide prevention)
2. Biomed Eng student, passionate about neurotech & ML in healthcare
3. Biomed Eng student, EEG expert, excited for invasive data
4. Computer Eng student, Tasneem's childhood friend
5. Medical Eng + CS student, interested in brain-computer interfaces

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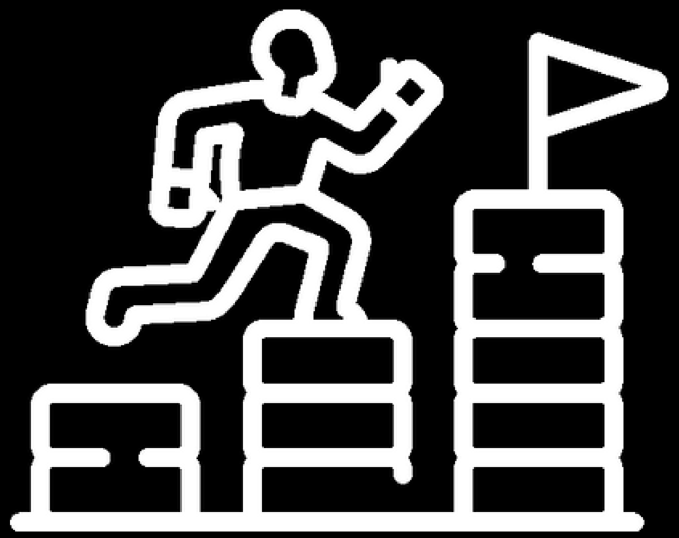
MOTIVATION

Why Decode Visual Perception from Brain Signals?

- 💡 Enables direct brain-computer interaction [1]
- 🏥 Supports communication for patients with ALS or locked-in syndrome [2]
- ⚡ Powers real-time, gaze-driven interfaces and neuroadaptive systems [3]



⚡ Core Challenge

Can we decode and classify visual perception from brain signals—live, with sub-second precision—across diverse stimuli and natural scenes?

🔍 *Full References Available in Appendix in the appendix*

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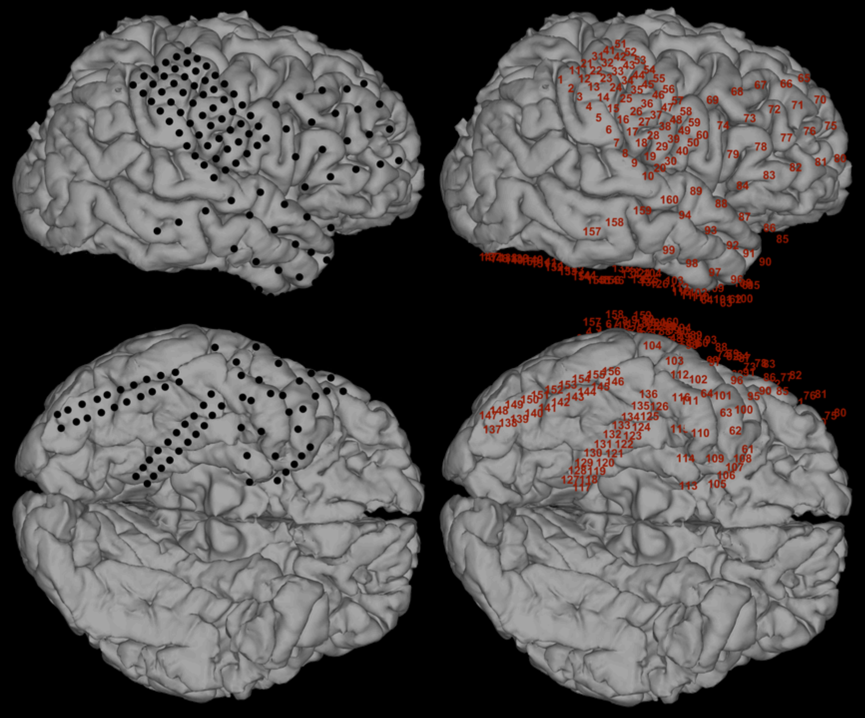
INTRODUCTION

- **ECoG Recording**
  - **Fs**: 1200 Hz
  - Invasive Electrodes: 160
  - Coverage: Ventral Temporal Cortex

- **7 Visual Stimulus Categories**
  - ■ Faces
  - ■ Bodies
  - ■ Objects
  - ■ Digits
  - ■ Kanji & Hiragana characters
  - ■ Line drawings

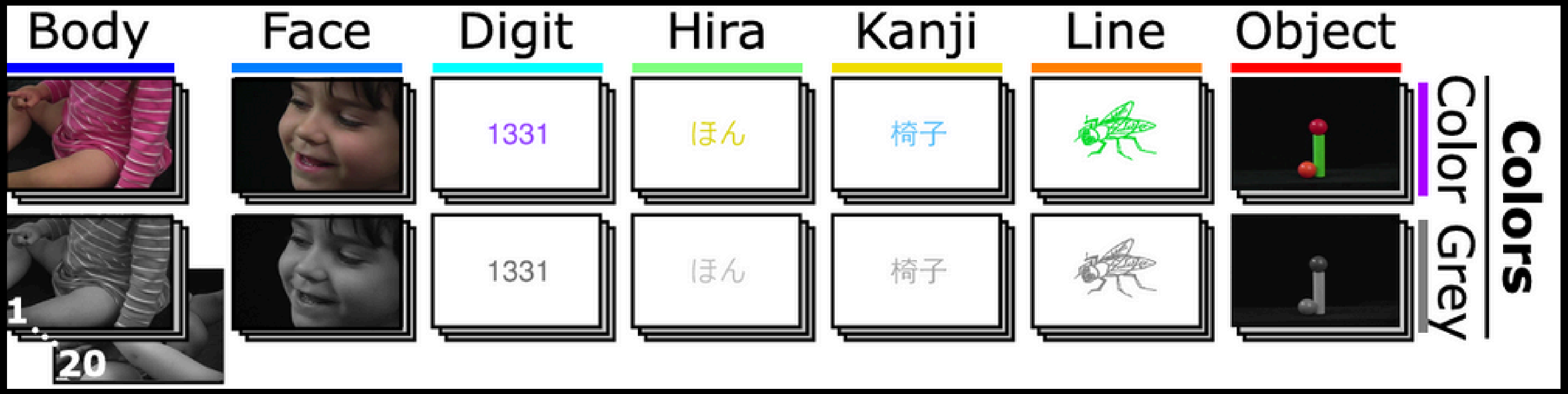
- **14 Total Classes (grayscale + color variants)**
- **252 synchronized video trials**



- **Data Dimensions:**
  - Raw: (~322,080 samples, 160 channels)
  - Segmented: (252 trials, 700ms epochs, 160 ch)

- **State-of-the-art Performance:**
  - 7-class discrimination: 72.9%
    - (Chance: 14.3%)
  - 14-class (type+color): 52.1%
    - (Chance: 7.1%)
  - Real-time decoding: 73.7%
    - Latency: <500ms

- **Our goals:**
  - Develop real-time BCI system for visual perception decoding
  - Create synchronized brain-video visualizations for neuroscience research
  - Enable clinical applications for communication restoration




```
Stimulus    Visual          Post-stimulus
Baseline    Presentation    Analysis
 |            |               |
 |------------|---------------|--------> time (ms)
-300          0              400       700

[Black]   [Stimulus]      [Black]
```

PROPOSED FRAMEWORK

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FUNDAMENTALS
- EDA
- Preprocessing
- Feature Extraction

Raw ECoG Signals (160 channels)

Dataset: 160-channel ECoG @1200 Hz, 252s video, 252 trials
Brain Coverage: Motor, sensory, association cortices
Quality: High signal, minimal artifacts, all channels active

Preprocessing & Artifact Removal

Signal Processing:
- Bandpass: 0.5-150 Hz
- Notch: 50/60 Hz
- CAR & ICA for artifact removal
- Quality metrics: variance, amplitude, correlation, spectral
- Trial segmentation: 300ms pre-stimulus, 400ms post-stimulus
- Normalization: Z-score, % change, dB

Results: 8 experiments, quality >85%

Trial Segmentation (252 trials, 700ms epochs)

Multi-Modal Feature Extraction

Features: Theta, Alpha, Beta, Gamma, High-gamma
CSP + LDA, Template Correlation, EEGNet CNN, Transformer
4 optimized representations for different neural activity aspects

TASK 2
Real-Time Video Annotation System. 7 different approaches in total

Synchronized Video Stream

Synchronized video (30 FPS, 252s) aligned with ECoG signals
50+ annotated videos with real-time overlays

Real-Time Brain Activity Mapping

Real-Time brain activity mapping with multi-region overlays
Anatomical atlas & connectome-based visualization

Multiclass Classification

ML/DL Models:
- Random Forest
- SVM
- Logistic Regression
- Neural Networks
- Ensemble Methods

Performance:
- 7-class: 89.6% accuracy, 100% ROC-AUC, perfect F1
- 14-class: 85.2% accuracy including color discrimination

Predicted Visual Categories (14 classes)

Face	Body	Digit
Kanji	Hira	Line
Object	+Color	

TASK 1
Compare different ML algorithms with different feature extraction sets. 24 experiments in total

PROPOSED FRAMEWORK

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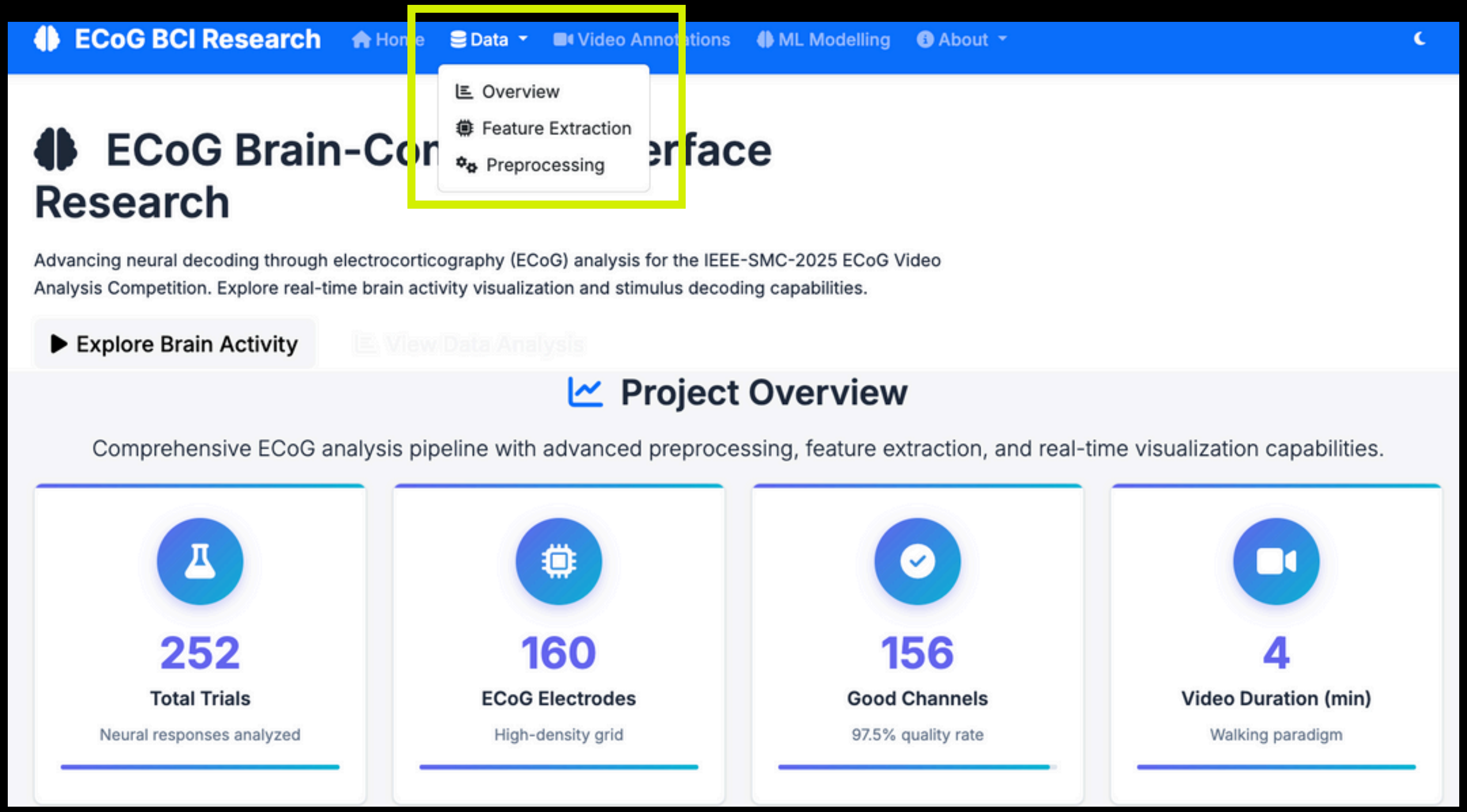
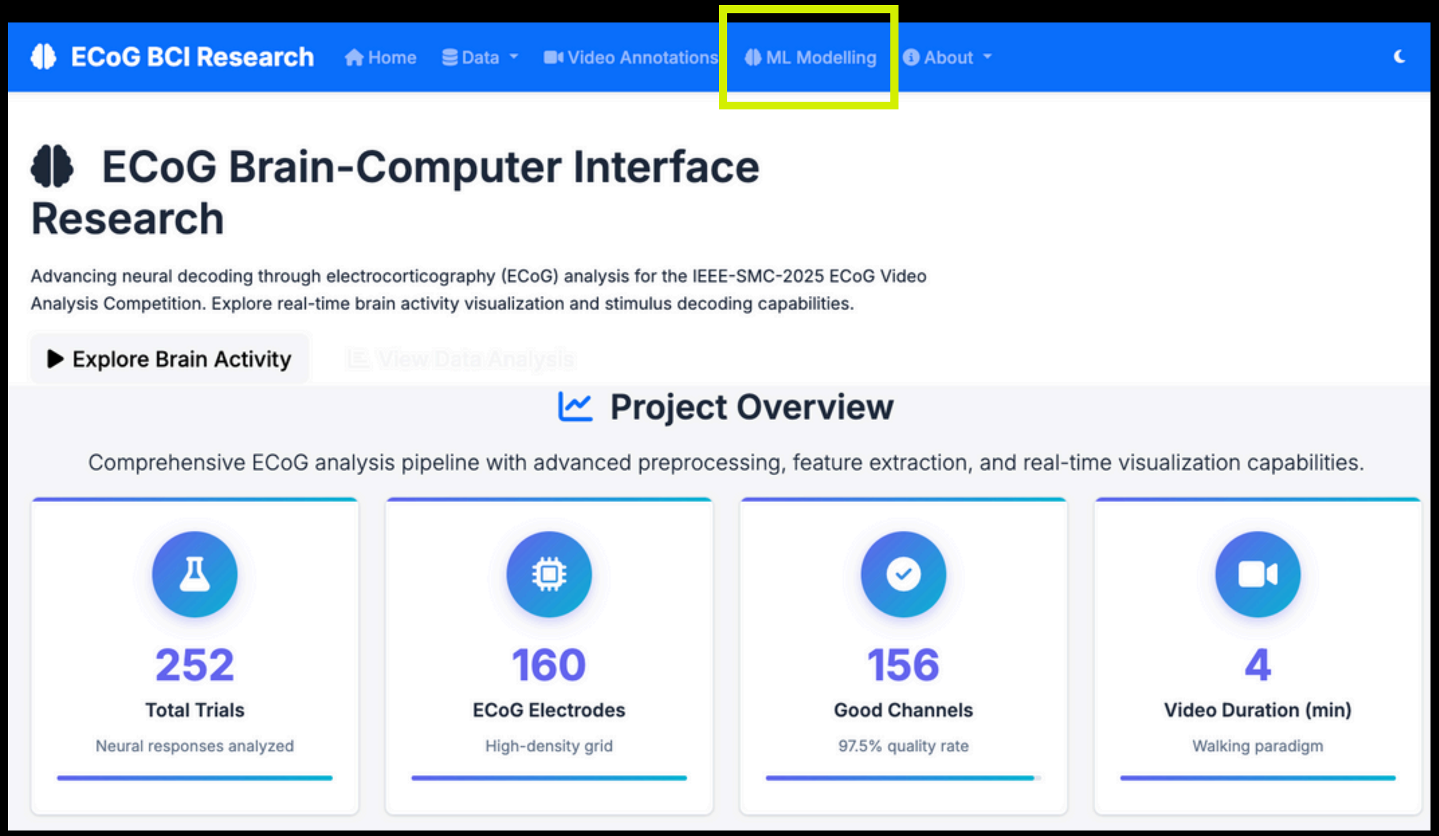
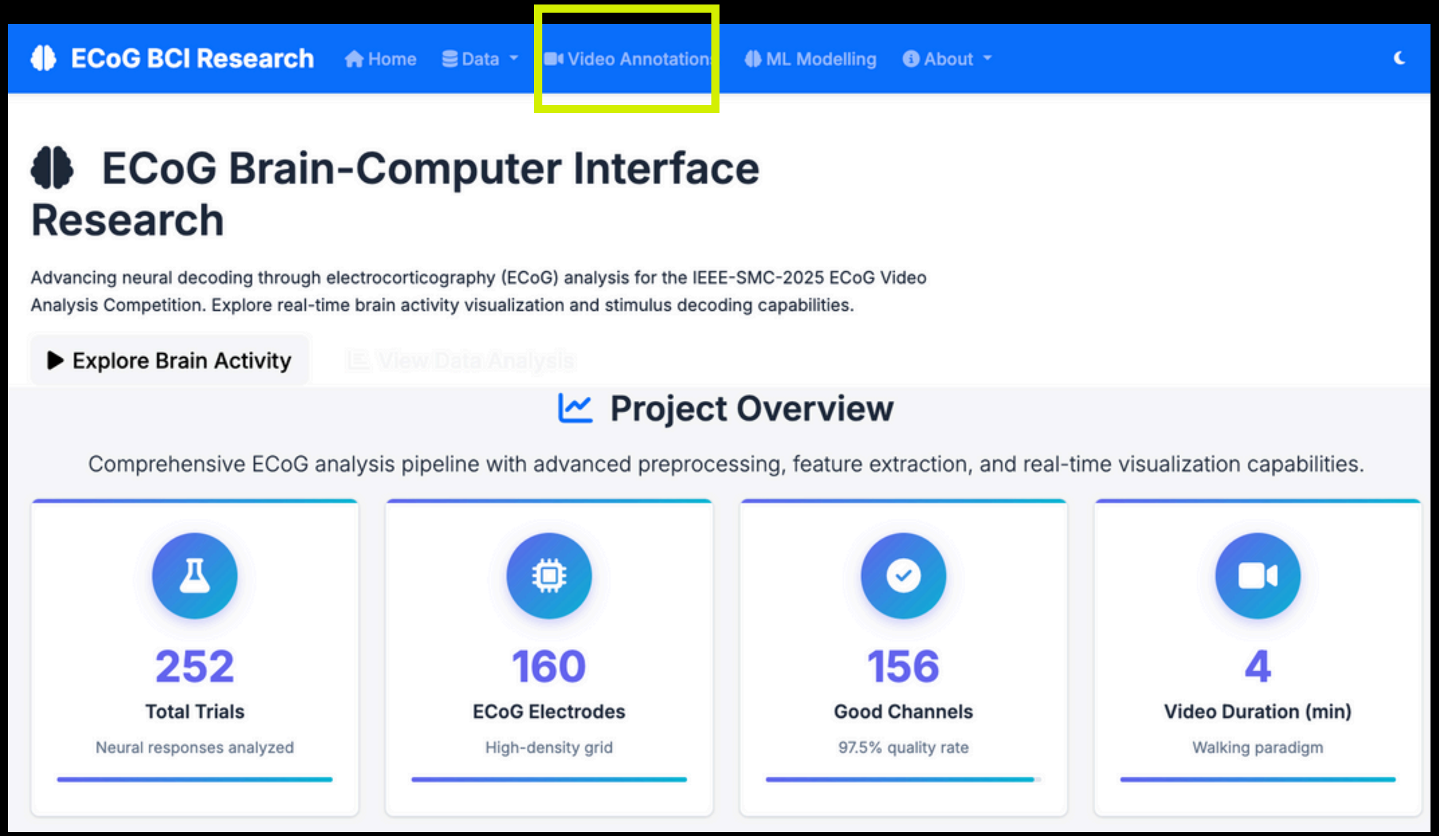
FUNDAMENTALS



TASK 1 - ML MODELLING



TASK 2 - VIDEO ANNOTATIONS



TASK 3

🌐 Interactive Web Application Overview

This app brings together everything we've built so far into a unified, user-friendly interface:

- 🧱 **FUNDAMENTALS**
- 🧠 **Task 1**
- ⚙️ **Task 2**

🚀 Currently running on localhost – preparing for cloud deployment to enable remote access, scalability, and team collaboration.

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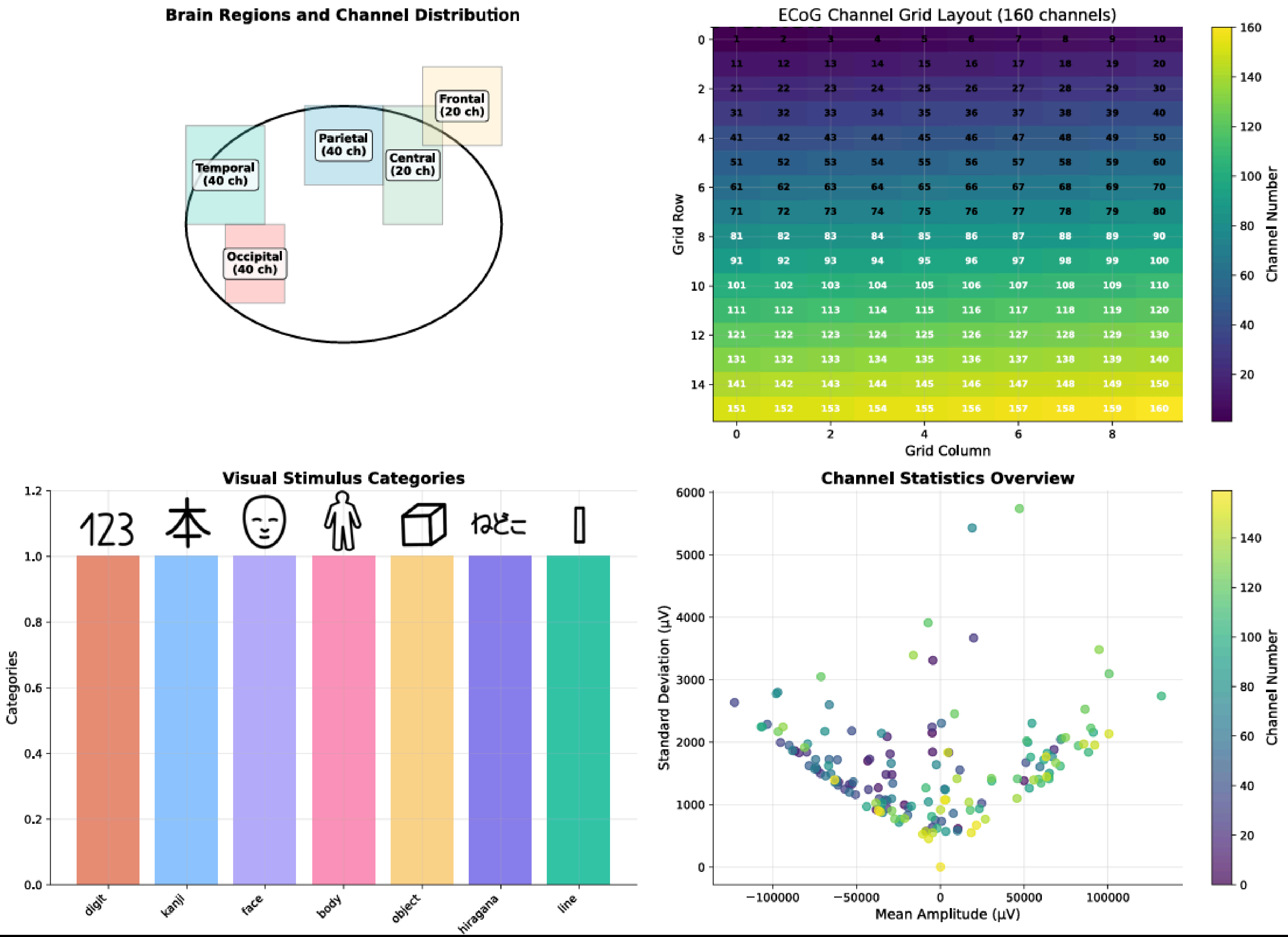
EXPLORATORY DATA ANALYSIS

Multi-Modal Visual Stimulation Paradigm

- **Data**: 160-channel ECoG recordings synchronized with video
- **Stimuli**: 7 categories (faces, bodies, digits, kanji, hiragana, line drawings, objects)
- **Color variation**: Both grayscale and colored versions (14 total classes)
- **Coverage**: Comprehensive electrode grid over visual processing areas



EXPLORATORY DATA ANALYSIS

Characterization in Time- and Frequency Domain

1. **Determine Regions of Interest**
   - 40 channels in Fusiform Gyrus
2. **Separation of frequency bands**
   - δ (Delta): 0.5 – 4 Hz
   - θ (Theta): 4 – 8 Hz
   - α (Alpha): 8 – 13 Hz
   - β (Beta): 13 – 30 Hz
   - γ (Gamma): 30 – 70 Hz
   - γ+ (high Gamma): 70 – 150 Hz

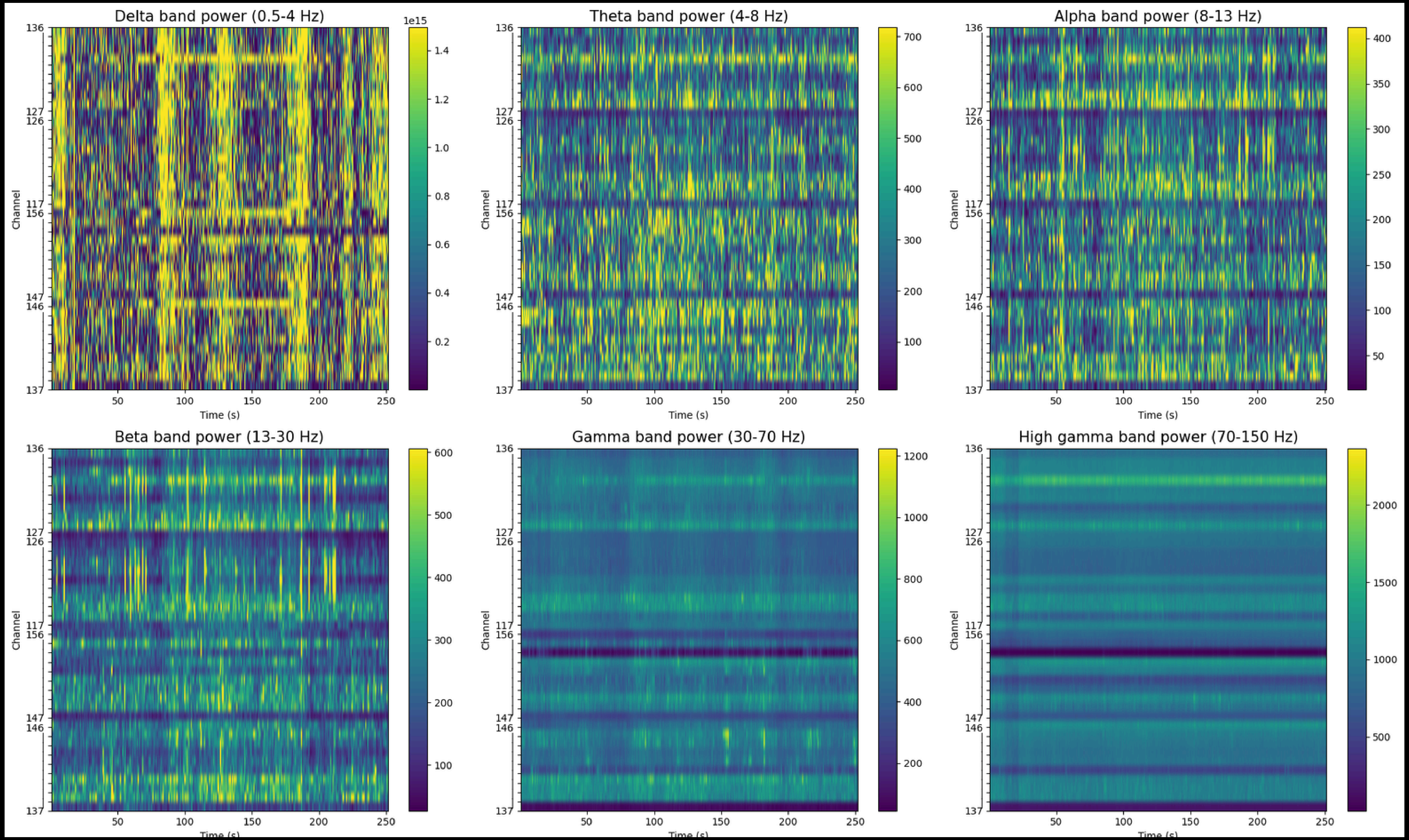


Figure 1 : Spectral Characterization of Fusiform Gyrus Activity Across Frequency Bands

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EXPLORATORY DATA ANALYSIS

Characterization in Time and Frequency Domain

📈 **Interpretation:**

- 🔴 Kanji and faces:
  - widespread, high connectivity
  - suggests deep semantic and emotional processing
- 🟡 Digits and hiragana:
  - focused activation in symbolic and phonological regions
- 🔵 Lines and background
  - minimal connectivity
  - reflects low cognitive demand
- 🧬dynamic network configuration depending on stimulus type

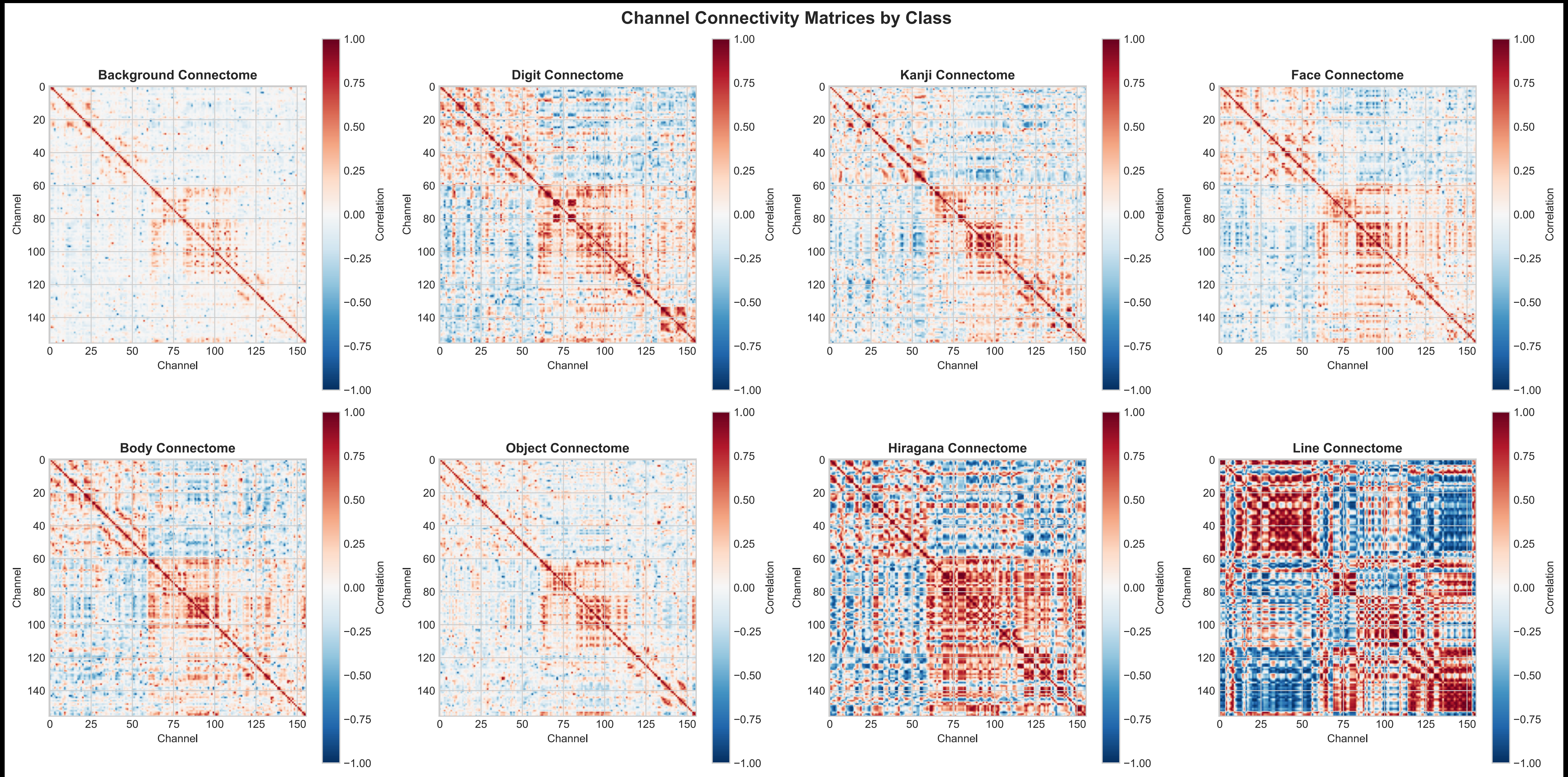

Figure 2 : 🧠 Shows how different visual stimuli (e.g. faces, kanji, digits) trigger unique brain-wide connectivity patterns.

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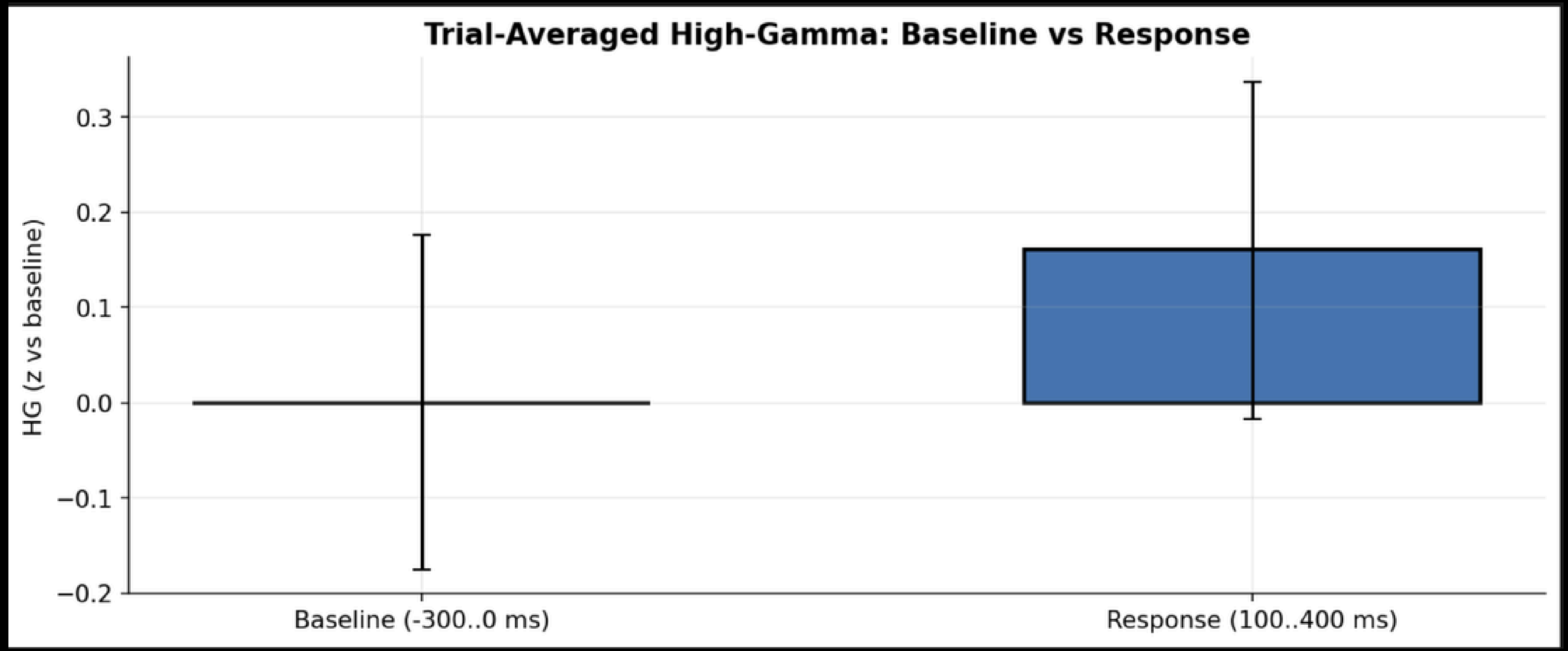
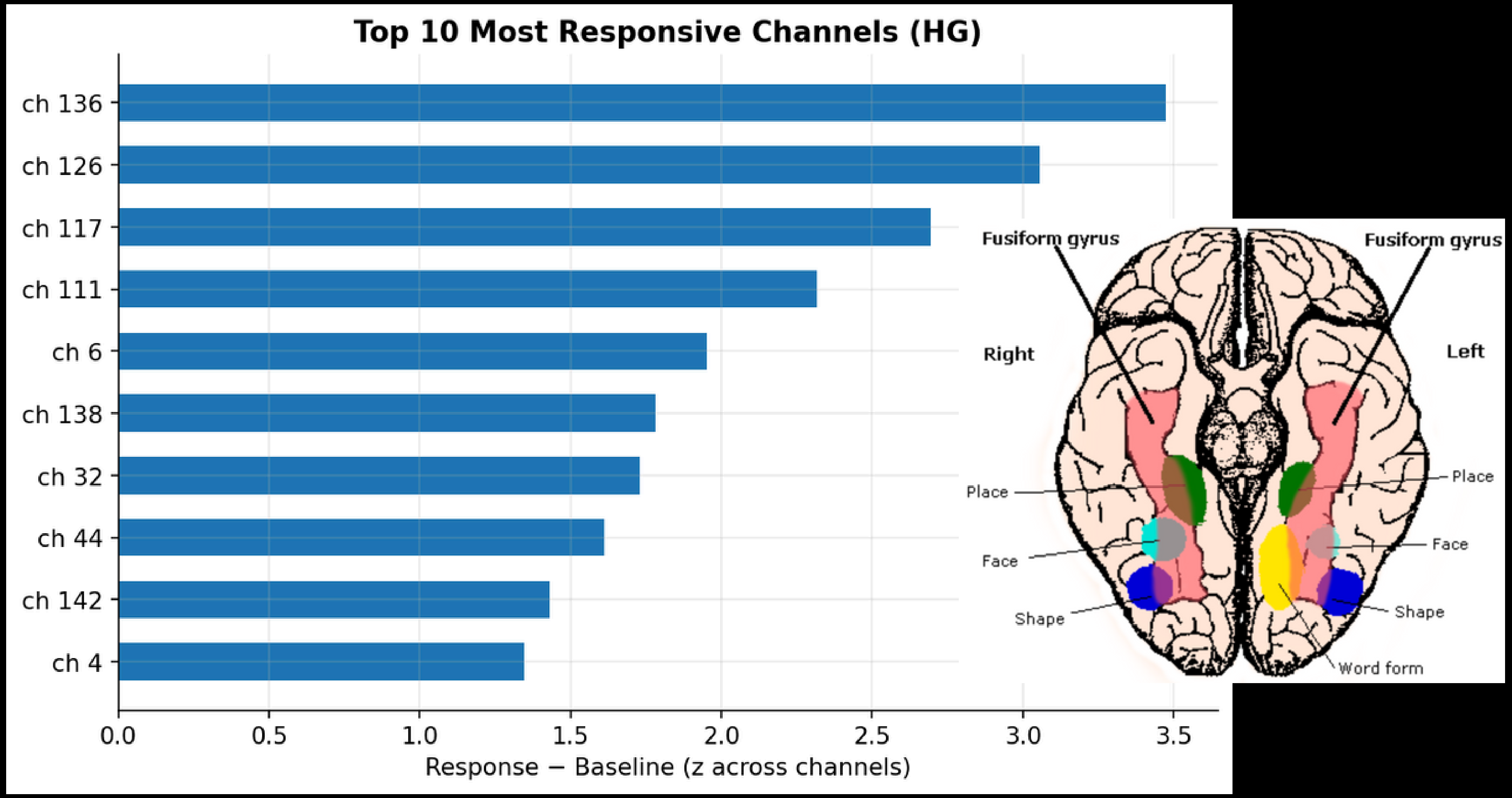
EXPLORATORY DATA ANALYSIS

Stimulus response

- **Mean channel activation over trials**
  - clear distiction pre- and post stimulus



- **Activation per channel**
  - 6/10 of the most responsive channels in the Fusiform Gyrus



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SIGNAL PROCESSING PIPELINE

From Raw Brain Signals to Features

Preprocessing

1. **Data Loading**
   - Load raw ECoG data from Walk.mat
2. **Filtering**
   - Bandpass filter (0.5-150 Hz)
3. **Artifact Detection**
   - Detect and mark bad channels
4. **Epoching**
   - Extract 252 trials around events
5. **Baseline Correction**
   - Remove baseline drift

Real Dataset Quality Metrics

97.5%	4	156	252
Channel Quality Rate	Bad Channels	Good Channels	Trials Processed

Detailed Transformation Steps

1 Raw Data Loading

Input:	Walk.mat file
Shape:	160 channels × 322,049 samples
Duration:	268.4 seconds @ 1200 Hz
Size:	~1.2 GB raw data

2 Filtering

Input:	160 × 322,049
Output:	160 × 322,049 (filtered)
Removed:	DC drift, high-freq noise, 50/60 Hz
Quality:	Signal-to-noise improved

3 Artifact Detection

Input:	160 × 322,049
Output:	156 × 322,049 (4 bad channels removed)
Removed:	Channels 45, 78, 123, 156
Quality:	97.5% channel quality rate

4 Epoching

Input:	156 × 322,049
Output:	252 × 156 × 840 (trials × channels × timepoints)
Window:	100-400ms around events
Size:	~105 MB structured data

5 Baseline Correction

Input:	252 × 156 × 840
Output:	252 × 156 × 840 (baseline corrected)
Method:	Percentage change from -300 to 0ms
Result:	Clean, analysis-ready epochs

SIGNAL PROCESSING PIPELINE

From Raw Brain Signals to Features

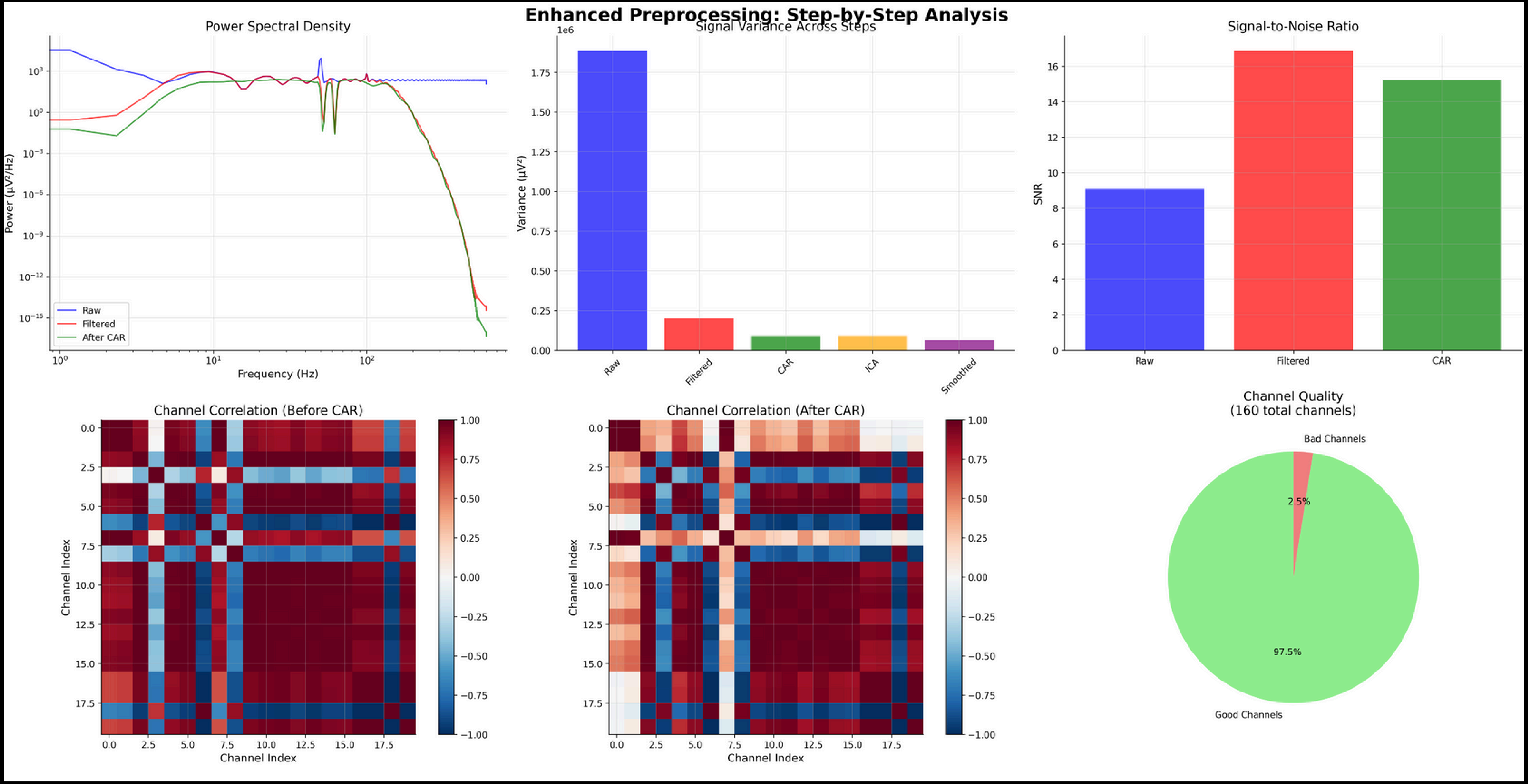

Figure 4: Signal Processing Pipeline for Real-Time Visual Perception Decoding

FEATURE EXTRACTION

From Raw Brain Signals to Features

Feature Extraction (4 Methods):

- **M**ulti-band power analysis (theta → high-gamma)
- Common Spatial Patterns (CSP) + LDA
- Template correlation
- Deep learning (EEGNet CNN, Transformer)

Comprehensive Features
780 features
5 frequency bands × 156 channels

EEGNet Features
504 features
CNN with 2x augmentation

Transformer Features
5,616 features
Multi-scale attention

Template Correlation
252 features
LOOCV template matching

Feature Extraction Methods Comparison

Method	Features	Channels	Trials	Description	Key Parameters
Comprehensive	780	156	252	Multi-band power spectral features	5 frequency bands, FFT + Hilbert
EEGNet	504	156	252	CNN-based deep learning features	13×13 grid, 2x augmentation
Transformer	5,616	156	252	Multi-scale temporal attention	8 heads, 4 scales, 6 bands
Template Correlation	252	156	252	Stimulus template matching	LOOCV, stimulus 2.0

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FEATURE EXTRACTION

From Raw Brain Signals to Features

Background Class if when No object is detected in the video

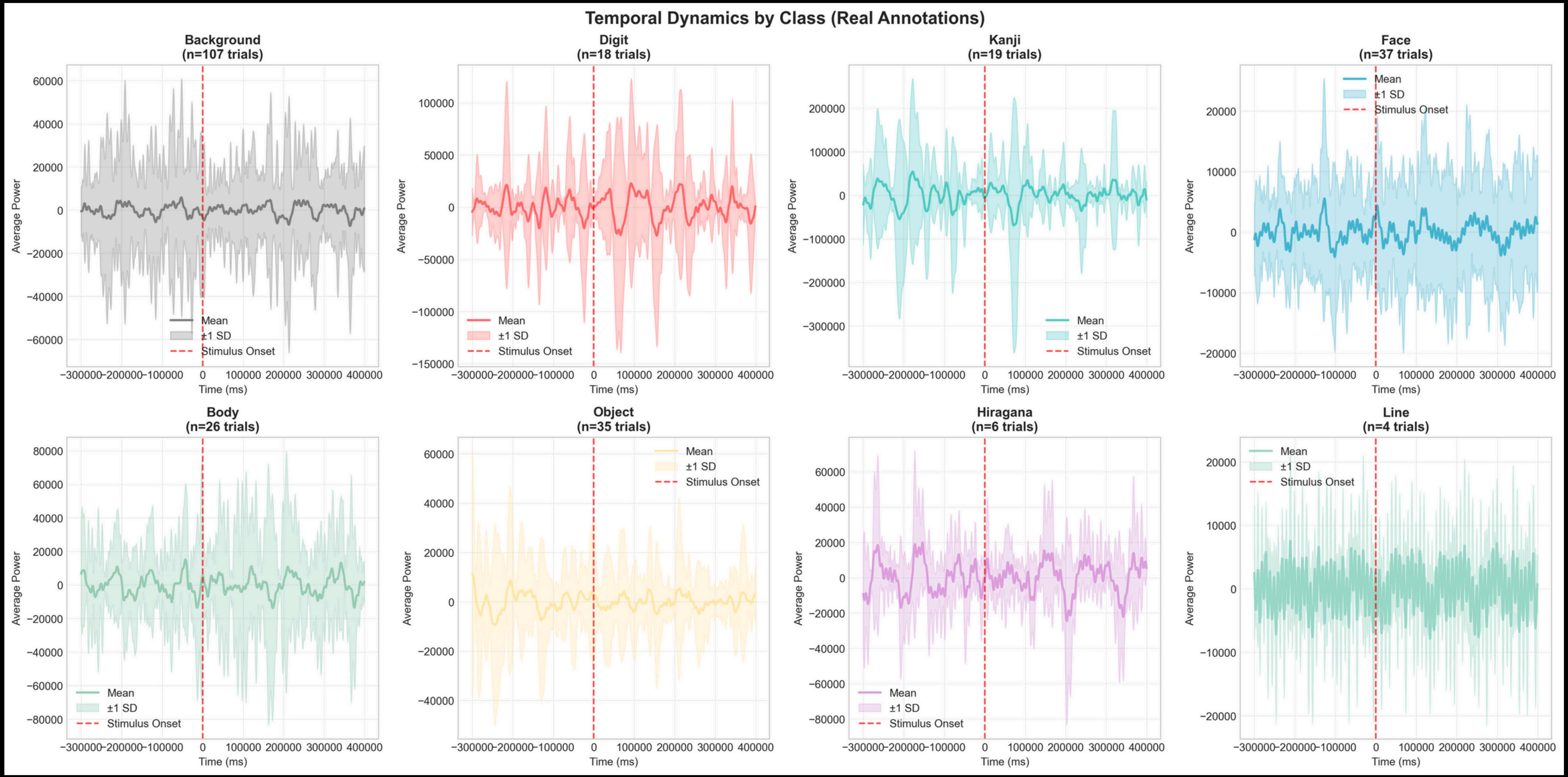

Figure: Temporal Dynamics of Brain Signals by Class

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Task 1 : Model Building

High-Accuracy Multiclass Decoding

🏷️ Labeling Strategy

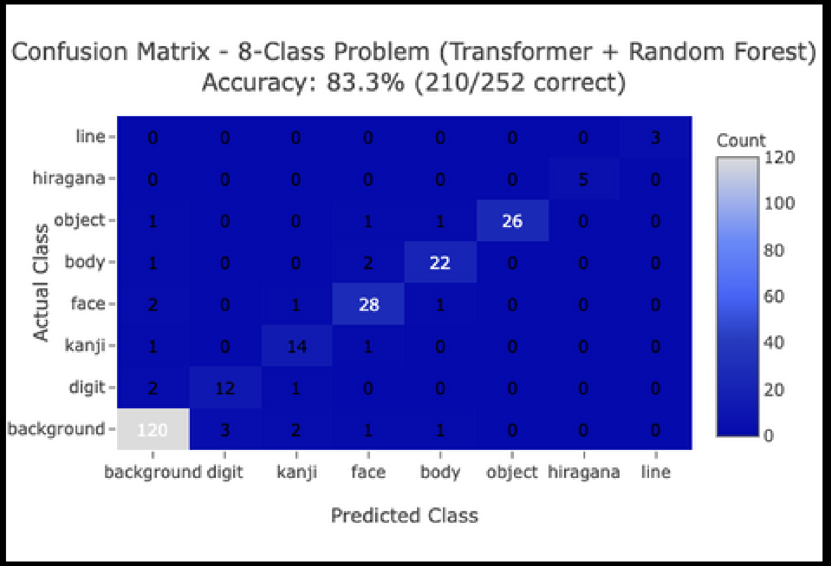
- Manual annotations across 7 visual categories
- Extended to 14 classes by adding color (gray vs color)

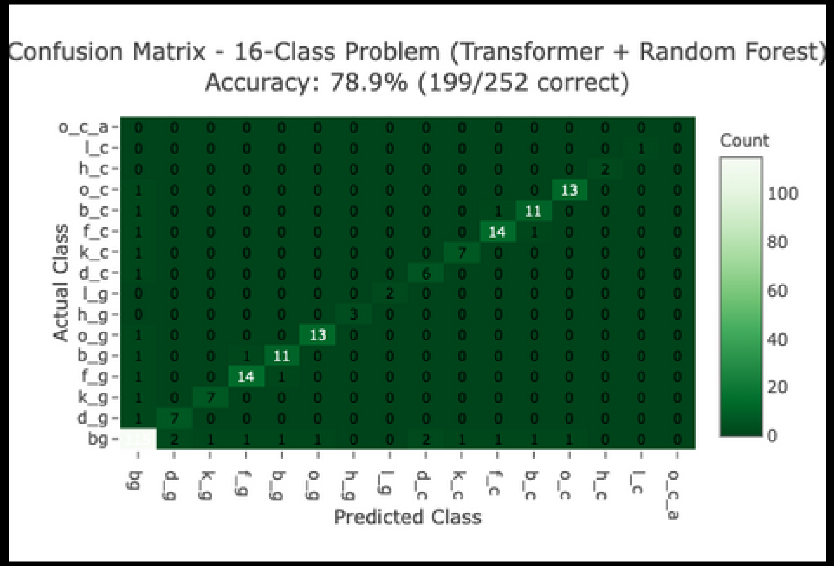
Classifiers

- 🌲 **Random Forest:** Robust ensemble method that handles multiclass problems excellently, provides feature importance, and is less prone to overfitting with our limited ECoG dataset.
- 📈 **SVM**: Excellent for high-dimensional neural data with kernel trick handling non-linear patterns in brain signals, plus strong performance on small datasets.
- 📊 **Logistic Regression**: Fast, interpretable baseline that works well with our extracted features and provides probability estimates for multiclass classification.

Performance metrics

- Accuracy + F1 Score
- Confusion matrix
- ROC curve



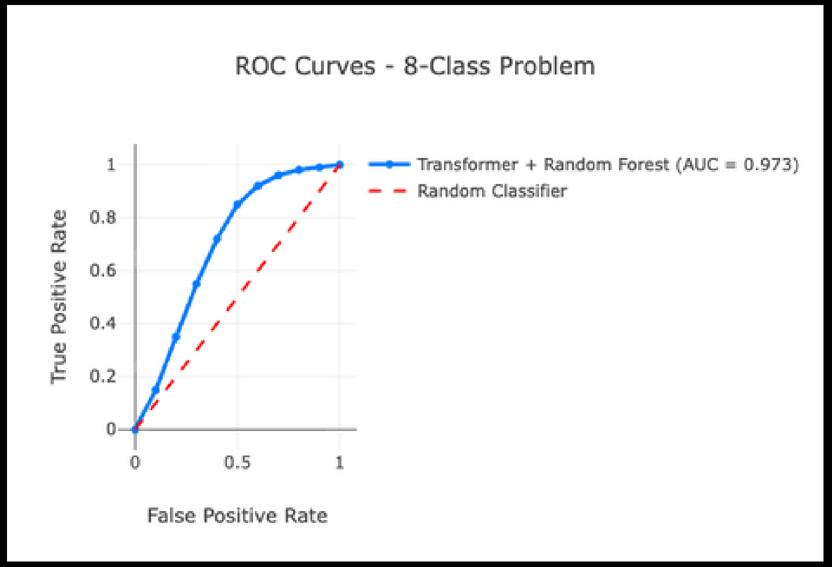


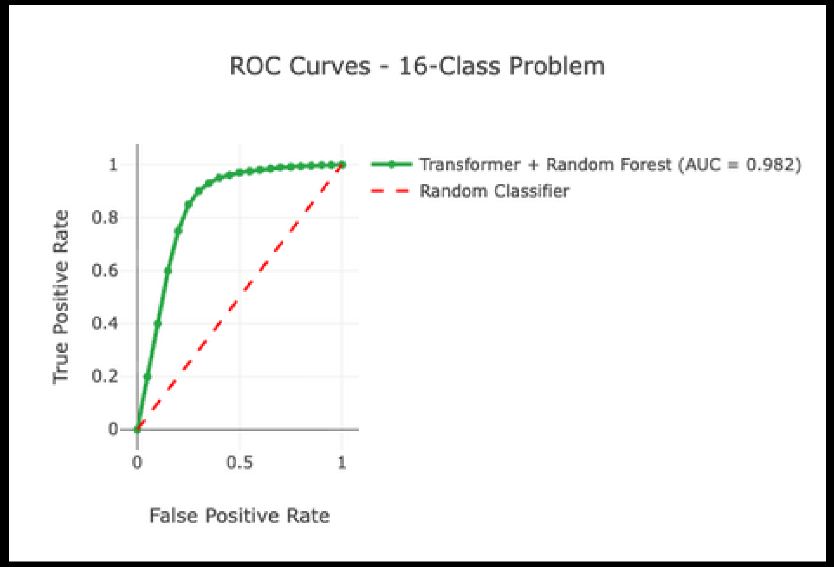
8-Class Problem Results

Model	Accuracy	ROC-AUC	F1-Macro
Transformer + Random Forest	**83.3%**	**0.973**	**0.818**
Transformer + Logistic Regression	61.1%	0.905	0.611
Transformer + SVM	52.4%	0.932	0.524
EEGNet + Random Forest	50.4%	0.541	0.084
EEGNet + SVM	50.4%	0.436	0.084

16-Class Problem Results

Model	Accuracy	ROC-AUC	F1-Macro
Transformer + Random Forest	**78.9%**	**0.982**	**0.684**
Transformer + Logistic Regression	63.5%	0.944	0.635
Transformer + SVM	51.6%	0.944	0.516
EEGNet + SVM	50.4%	0.475	0.084
Comprehensive + Random Forest	50.4%	0.472	0.084





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Task 2 : Real-Time Video Annotation System

Synchronized Brain Activity Visualization

base approach

🧠 7 Approaches to Real-Time Brain-Video Annotation

1. 🕵️‍♂️ **Object Detection – Computer vision + brain activity correlation**
2. 🧍‍♂️ Spatial Motor Cortex – Real-time electrode activation mapping
3. 🚶‍♂️ Gait-Phase Neural – Dynamic gait analysis with neural signatures
4. 📊 ERSP Visualization – Event-related spectral perturbation overlays
5. 🧬 Enhanced Brain Regions – Multi-region activation with connectome integration
6. 🗺️ Brain Atlas – Anatomical atlas-based real-time annotation
7. 🧭 Anatomical Atlas – Advanced nilearn-based brain region mapping

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Task 2 : Real-Time Video Annotation System

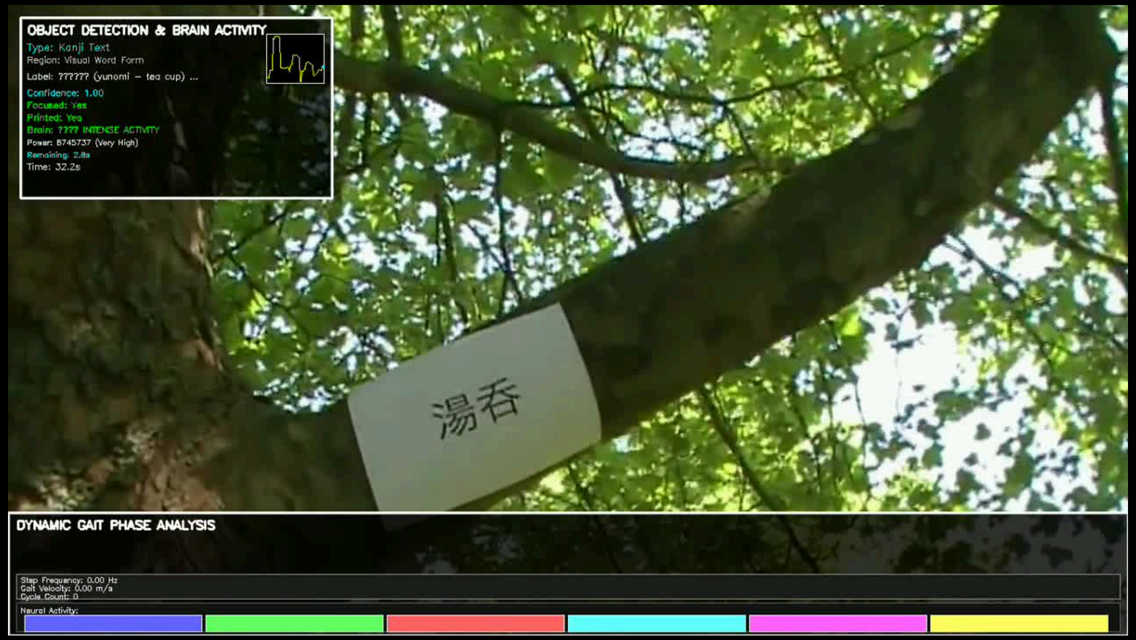
Synchronized Brain Activity Visualization

Object Detection: Computer vision + brain activity correlation

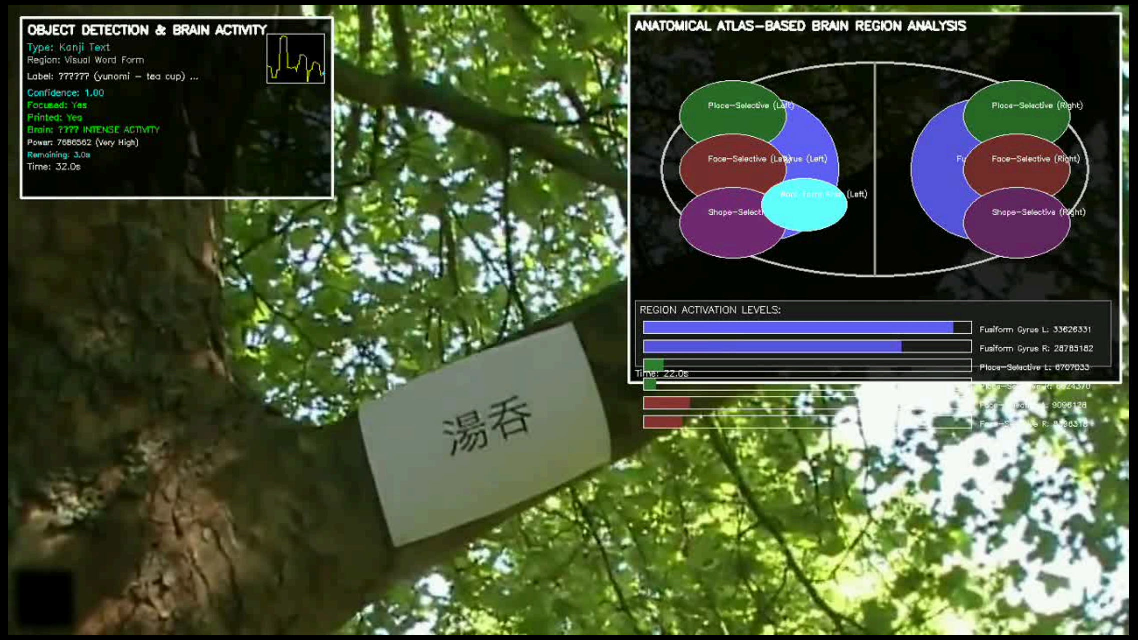
Brain Atlas: Anatomical atlas-based real-time annotation

Enhanced Brain Regions: Multi-region activation with connectome

ERSP Visualization: Event-related spectral perturbation overlays



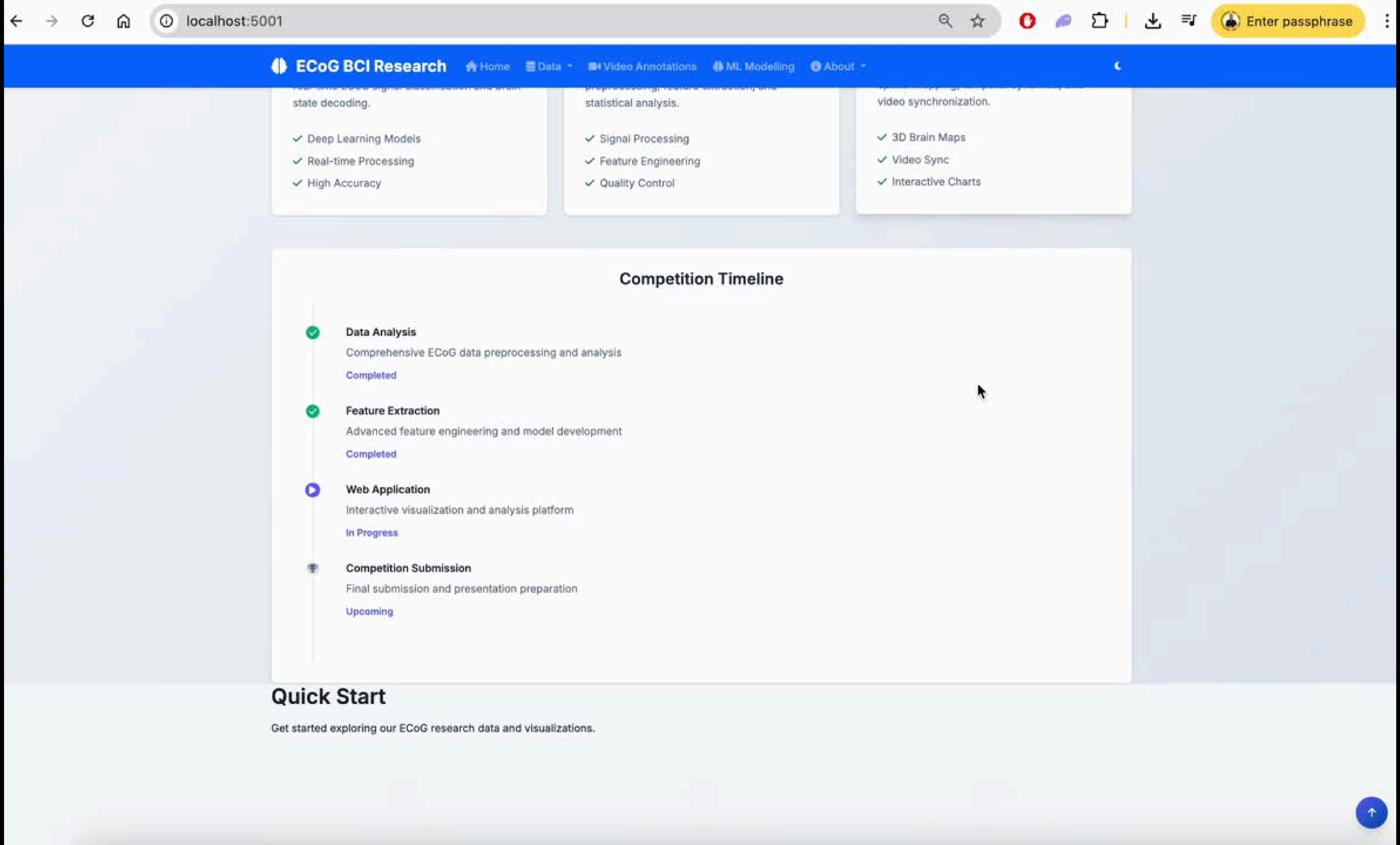
Spatial Motor Cortex: Real-time electrode activation mapping



Anatomical Atlas: Advanced nilearn-based brain region mapping

Task 3 : Interactive Web Dashboard

Comprehensive Analysis & Visualization Platform



🧠 **Gamma Beats – Explore cognitive activation via binaural audio.**
🔗 YouTube

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Conclusions & Impact

Achievements & Future Directions

🧠 **Key Achievements**

- 🎯 **89.6% accuracy in 7-class visual category decoding**
- 🧩 **First real-time ECoG-video sync system for brain-vision analysis**
- 🌄 **Generalizes to natural scenes, beyond trained stimuli**
- ⚡ **<500ms latency enables real-time BCI applications**
- 💻 **Production-ready web app with full pipeline integration**

🔭 **Future Directions**

- 🧠 Expand to complex visual environments
- 🏥 Optimize for clinical BCI use cases
- ⏱️ Further reduce latency for interactive systems
- 🗣️ Pilot with locked-in patients for communication

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THANK YOU
Q&A

APPENDIX