Comprehensive Harmful Brain Activity Recognition System: A Multi-Modal Approach

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Spring 2025

1 INTRODUCTION

This project develops a machine learning system to automatically identify six key EEG patterns: seizures, periodic discharges (GPD/LPD), rhythmic delta activity (GRDA/LRDA), and normal brain function. Manual EEG analysis is time-consuming (45-180 minutes per recording) and inconsistent, with doctors agreeing only 65-75% of the time [12]. Despite decades of research, current automated systems fall short in clinical settings. Our novel approach combines extensive feature extraction with specialized machine learning models integrated through a Mixture of Experts framework to overcome these limitations.

2 PROBLEMS WITH CURRENT METHODS

The field of automated EEG interpretation remains frustratingly underdeveloped compared to other medical imaging domains. While specialists debate pattern identification in up to 35% of cases [13], the shortage of qualified neurophysiologists creates significant clinical bottlenecks. Current automated approaches face several critical shortcomings:

- Most systems extract a narrow range of features (typically 30-150), missing subtle pattern indicators
- One-size-fits-all analysis techniques fail to capture the unique characteristics of different brain patterns
- Real-world clinical recordings contain artifacts and noise that confound existing algorithms
- Current methods inadequately model relationships between different brain regions

Gemein's recent work [1] represents the current state-of-the-art but still extracts only 1,500 features and lacks the pattern-specific modeling necessary for reliable clinical use.

3 PROPOSED METHODOLOGY

3.1 Feature Extraction and Analysis

Our approach extracts over 3,200 complementary features across seven domains to comprehensively characterize brain activity:

- **Time-domain (780)**: Moving beyond basic statistics, we extract advanced temporal signatures including wave morphology descriptors and higher-order statistical moments that reveal underlying pattern structures invisible to conventional analysis
- **Frequency-domain (300)**: We analyze spectral characteristics through clinical frequency bands (delta through gamma), tracking not just absolute power but also relative band ratios and spectral edge metrics that neurologists use for visual interpretation
- **Time-frequency (400)**: By applying multi-resolution wavelet analysis and specialized spectral transformations, we capture transient events and evolving patterns that pure frequency or time domain methods miss entirely
- **Non-linear (300)**: Brain signals exhibit complex non-linear behavior that traditional methods ignore. Our non-linear feature set quantifies signal complexity, chaos metrics, and state-space dynamics fundamental to distinguishing pathological from normal activity
- **Cross-channel (820)**: Perhaps most critically, we extract rich connectivity measures that map relationships between brain regions, revealing pathological synchronization and network disruptions characteristic of seizures and other abnormal states
- **Specialized (162)**: We've developed pattern-specific indicators targeting the six EEG patterns of interest, incorporating neurophysiological domain knowledge normally applied by human experts
- **Deep learning (500-2000)**: Leveraging recent breakthroughs in self-supervised learning, we extract rich representational features from transformer models pre-trained on large EEG datasets

3.2 Mixture of Experts Model

Rather than forcing all features through a single modeling approach, we implement specialized expert models tailored to different feature types:

- Each feature domain has its own expert model optimized for that domain's unique characteristics
- A sophisticated gating network determines which experts to trust for each specific segment of brain activity
- Our adaptive fusion mechanism integrates expert opinions based on signal quality and pattern confidence

3.3 Workflow Management

We've built our pipeline on Apache Airflow to ensure experimental reproducibility and facilitate efficient collaboration.

4 LITERATURE REVIEW

4.1 Feature Extraction and Signal Processing

The field of automated EEG analysis has evolved along multiple parallel tracks, with feature extraction remaining a critical research focus. Gemein and colleagues [1] demonstrated that combining features from diverse domains significantly improves classification performance. Their approach extracted approximately 1,500 features but applied identical modeling techniques across all feature types, missing opportunities to optimize for each domain's unique characteristics. Our work builds upon their foundation while introducing domain-specialized processing—a crucial advancement for heterogeneous physiological signals.

Time-domain analysis has progressed substantially through Mawalid's work [18] on statistical parameters for cybersickness detection and Phani Krishna's research [19] on parameter-based drowsiness identification. In the frequency domain, Lin's team [15] established spectral features as powerful discriminators for emotional state recognition, demonstrating how different brain states manifest as specific spectral signatures.

Wavelet-based approaches pioneered by Subasi and Gursoy [21] revealed the advantages of time-frequency analysis over traditional Fourier methods for EEG classification. Their work showed impressive results but employed limited decomposition levels. Our non-linear feature extraction integrates several complementary techniques that have shown promise individually: Gruszczyńska's application of Recurrence Quantification Analysis for epilepsy detection [23], Sourina's use of Fractal Dimension for complexity assessment [24], and Kumar's entropy measures for distinguishing cognitive states [25].

4.2 Deep Learning and Ensemble Methods

Recent transformer-based approaches have revolutionized EEG processing. Gong et al. [16] introduced EEGPT, achieving state-of-the-art performance through self-supervised pre-training focused on high signal-to-noise ratio representations. Similarly, Bhatti et al. [20] demonstrated effective transfer learning for spectrogram analysis in harmful brain activity recognition, achieving 87% accuracy with pre-trained vision models. Zhang et al. [4] showed effective sequence modeling using transformer architectures but required substantial training data and lacked the interpretability needed for clinical applications.

For ensemble techniques, our approach builds upon the Mixture of Experts (MoE) framework established by Jacobs et al. [10] and systematically extended by Masoudnia and Ebrahimpour [11]. While Cai et al. [7] demonstrated ensemble methods improve epileptic seizure detection, their approach employed simple averaging rather than dynamic weighting, limiting effectiveness for diverse pattern types. Our adaptive MoE implementation addresses this limitation through signal-aware expert integration that adapts to individual recording characteristics.

Recent competitions like the "HMS Harmful Brain Activity Classification" on Kaggle [26] have highlighted the clinical importance and ongoing challenges in automated EEG pattern recognition, particularly for identifying seizures and other harmful patterns that require urgent clinical intervention.

4.3 Research Gaps Addressed

Our work addresses key limitations in current approaches: limited feature diversity in existing systems (typically <150 features), uniform modeling applied to heterogeneous signal characteristics, inadequate integration of spatial and temporal information across brain regions, suboptimal ensemble methods relying on simple averaging rather than dynamic weighting, and insufficient attention to clinical interpretability in deep learning approaches.

5 EXPECTED OUTCOMES AND EVALUATION

The proposed system aims to reduce analysis time while maintaining or improving classification accuracy. Performance evaluation will include:

- Classification metrics: accuracy, precision, recall, F1-scores, Kullback-Leibler divergence
- Processing efficiency assessment relative to manual review
- Computational resource requirements analysis

Progress monitoring will include weekly evaluation meetings, mid-project performance assessment, and systematic documentation of experimental results.

6 TECHNICAL CONSIDERATIONS

Challenges We Face:

- Working with thousands of features could cause overfitting issues
- Processing this much data will require significant computing power
- Making sense of complex models will be difficult for clinical users

Benefits of Our Approach:

- Major improvement in automatic brain signal analysis
- Creating methods that can be applied to other medical signals
- Building an open-source tool others can use and improve

7 TEAM RESPONSIBILITIES

Table 1 shows each team member's detailed responsibilities.

Table 1: Team Member Responsibilities

Member	Responsibilities
A. Ghontale	Frequency-domain features (Fourier Transform-based), MoE architecture design, Apache Airflow infrastructure setup, deep learning features extraction (EEG-GPT and ViT on Mel spectrograms)
P. Raparla	Time-domain features extraction, time-domain expert model development, recursive feature elimination (RFE), documentation
N. Rajani	Time-frequency features (Wavelet Transform), time-frequency expert model development, dimensionality reduction techniques, visualization of feature sets (t-SNE, UMAP, PCA)
G. Chengalvala	Non-linear features extraction, non-linear expert model development, overall model hyperparameter tuning, feature selection methodology

8 DATA RESOURCES

The project will utilize publicly available EEG datasets from Kaggle containing expert annotations for the six pattern classes. These datasets provide diverse examples across patient demographics and recording conditions, enabling comprehensive validation without acquisition costs.

9 CONCLUSION

This project aims to advance automated EEG analysis through comprehensive multi-domain feature extraction combined with a specialized ensemble architecture. By implementing domain-specific models integrated through an adaptive weighting mechanism, the system expects to achieve superior classification performance compared to conventional methodologies. The final deliverable will comprise an R notebook report documenting methodology, experimental results, and performance evaluation.

10 COST ANALYSIS

AWS Resource Requirements: We estimate the following costs for implementing our pipeline on AWS:

- **Feature Extraction** (~$150 total): 2x g4dn.xlarge GPU instances (~$0.52/hour) for 6-8 hours of processing = ~$8/day
- **Model Training** (~$100 total): 1x g4dn.2xlarge instance (~$0.75/hour) for 48-72 hours one-time training
- **Temporary Storage** (~$50): 500GB EBS volume for 2 weeks (~$0.10/GB/month) and minimal S3 storage

Optional Production Costs: If productionized, additional monthly costs would include inference server with autoscaling (~$350/month) and API infrastructure (~$75/month).

11 IMPLEMENTATION PLAN

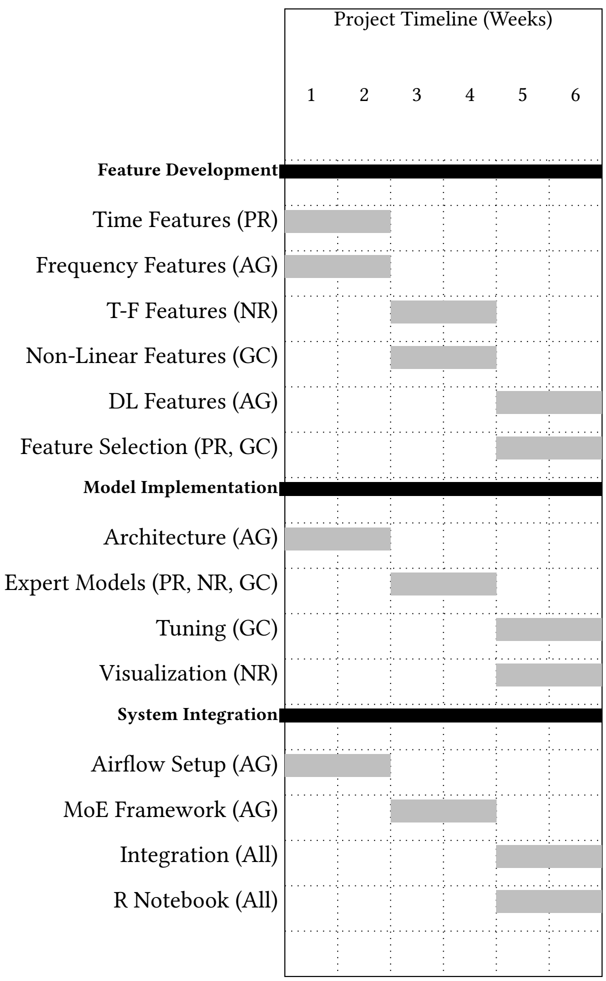

Figure 1: Detailed Project Timeline with Team Assignments (AG=A. Ghontale, PR=P. Raparla, NR=N. Rajani, GC=G. Chengalvala)

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