NEURAL SIGNATURES OF DISTURBED DREAMS: AN EEG-BASED APPROACH FOR DETECTION AND ASSISTED DIAGNOSIS FOR NIGHTMARE DISORDER

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Introduction:

Nightmare disorder is characterized by repeated occurrences of extended, extremely dysphoric dreams that typically involve threats to survival, security, or self-esteem, often leading to abrupt awakenings with vivid recall and significant distress. It impacts quality of life by causing daytime fatigue, anxiety, and impaired functioning, particularly in vulnerable groups such as military veterans or survivors of abuse.

The absence of objective, automated diagnostic tools for nightmare disorder results in overreliance on subjective self-reports, which are susceptible to recall biases, stigma, and individual variability, impeding accurate identification, monitoring, and treatment of affected individuals. Current methods fail to distinguish between nightmare experiences and recall abilities, and do not leverage physiological markers like stage-specific power spectra or theta oscillations to provide reliable insights. This limitation hinders clinicians from detecting distinct EEG patterns in REM and NREM sleep, leading to delayed interventions and suboptimal therapeutic outcomes, particularly in high-risk populations such as trauma survivors.

This project introduces an **EEG-based computational framework to detect and classify nightmare disorder**, addressing the limitations of subjective reporting by identifying distinct neural patterns in both REM and NREM sleep. The model, built on a deep support vector data description (SVDD) architecture, is pretrained on sleep data from healthy sleep datasets, finetuned using dream data and calibrated with small real nightmare samples obtained by the **collaboration with Dr. Peter Simor (Lab Director, Budapest Laboratory of Sleep and Cognition).** It provides probabilistic nightmare scoring across sleep stages, enabling clinicians to visualize EEG spectrograms, frequency band contributions, and insights via an API-integrated dashboard.

Objectives:

1. To establish a standardized, physiology-driven method to identify nightmare-related neural activity, reducing reliance on self-reported symptoms.
2. To enhance diagnostic understanding by identifying distinct EEG patterns associated with nightmares through spectrogram analysis and anomaly detection.
3. To provide clinicians with visual and analytical tools that facilitate the interpretation of nightmare-related brain activity.
4. To develop a prototype tool that allows clinicians to upload sleep spectrograms and receive system-generated insights in an accessible format.

Methodology:

The project follows a structured workflow that combines sleep neuroscience, EEG signal processing, and anomaly-detection–based machine learning. First, based on the model performances in the steep stage classification and literature survey, a Deep SVDD model is **pretrained on large-scale sleep datasets** containing multiple REM and NREM stages. This step helps the model learn general patterns of normal sleep physiology, which is important because nightmare-related abnormalities vary across stages. The model is then **fine tuned on healthy dream EEG samples**, enabling it to capture the typical spectral characteristics and dynamics of normal dreaming, forming a baseline representation of “non-nightmare” activity.

To evaluate the system, **nightmare samples are obtained by the collaboration with Budapest Sleep Research Lab are used**. As they are in small number and we’re yet to obtain more samples, we constructed **synthetic nightmare-like samples** generated using frequency features repeatedly associated with nightmares in the samples, such as elevated beta/gamma arousal or irregular theta activity. This combined approach ensures reliable evaluation despite limited access to clinical nightmare EEG data.

The fine-tuned model then performs **anomaly detection**, measuring how much nightmare samples deviate from the learned dream baseline. Performance is assessed using Sensitivity, Specificity, Accuracy, Precision, F1-Score, and ROC-AUC, with separate analysis for REM and NREM to identify which stage reveals clearer nightmare signatures. For interpretability, the system highlights **physiological markers** commonly mentioned in nightmare research, such as slow-theta disruptions, hyperarousal rhythms, and deviations linked to impaired fear-extinction mechanisms.

To automate and streamline the workflow, a **backend API** is developed that allows clinicians to upload EEG spectrograms. The API handles preprocessing, anomaly detection, metric computation, and physiological interpretation, returning structured outputs ready for visualization. A **ReactJS-based frontend** dashboard provides an accessible interface where clinicians can upload data, view highlighted spectrogram regions, read interpretation summaries, and review past analyses.

Finally, a **Visualization and Reporting Module** presents stage-specific anomaly hotspots, relevant frequency-band contributions, comparisons with healthy dream baselines, and severity indicators. This ensures that the system’s outputs are interpretable, clinically useful, and aligned with established sleep-science literature.

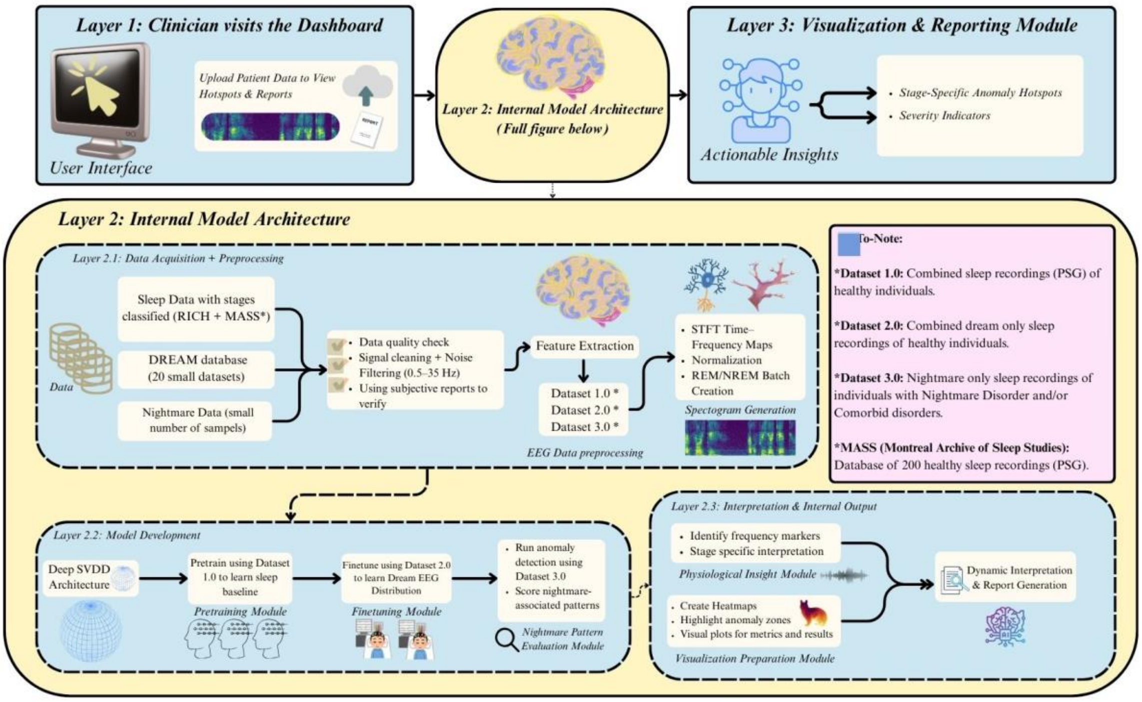

Figure 1.1: Architecture Diagram of the EEG-Based Nightmare Detection System

Result and Conclusion:

Validation showed strong performance: near-perfect within-domain discrimination (AUC ≈ 1.0), good cross-domain generalization (AUC 0.735–0.839), and robust handling of nightmares. The modular architecture and React.js and Next.js dashboard deliver spectrograms, probabilistic scores (0–100%), severity indicators, and interpretable reports.

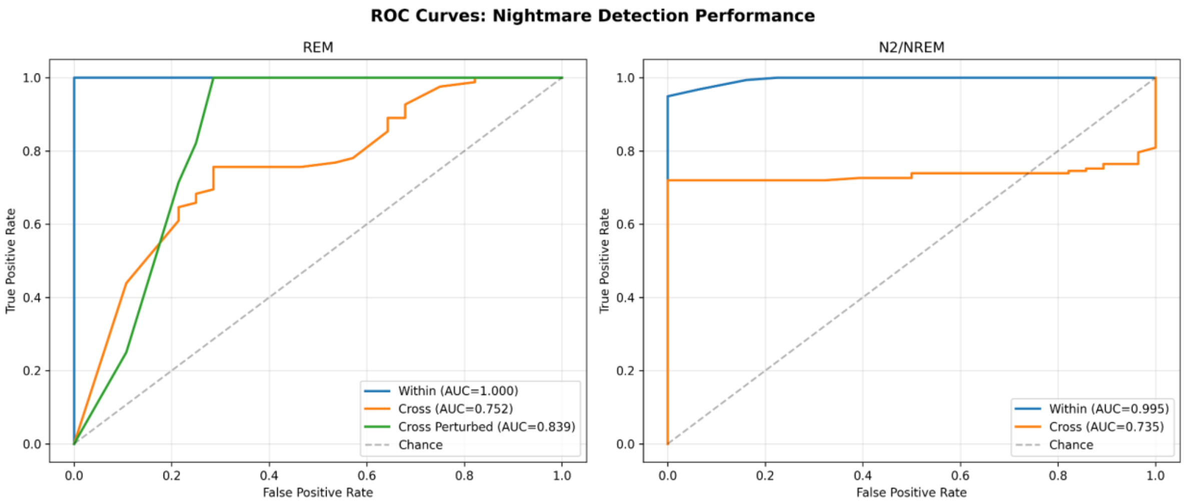

Figure 1.2: ROC Curves: Nightmare Detection Performance

The ROC curves demonstrate the model's ability to discriminate nightmare from normal dream EEG across REM and N2/NREM stages. These curves highlight excellent within-domain performance and reasonable cross-domain generalization, with perturbation robustness validating the synthetic calibration approach.

Confusion matrices summarize classification outcomes at the 85th percentile threshold, balancing sensitivity and specificity. Overall, the model achieves high within-

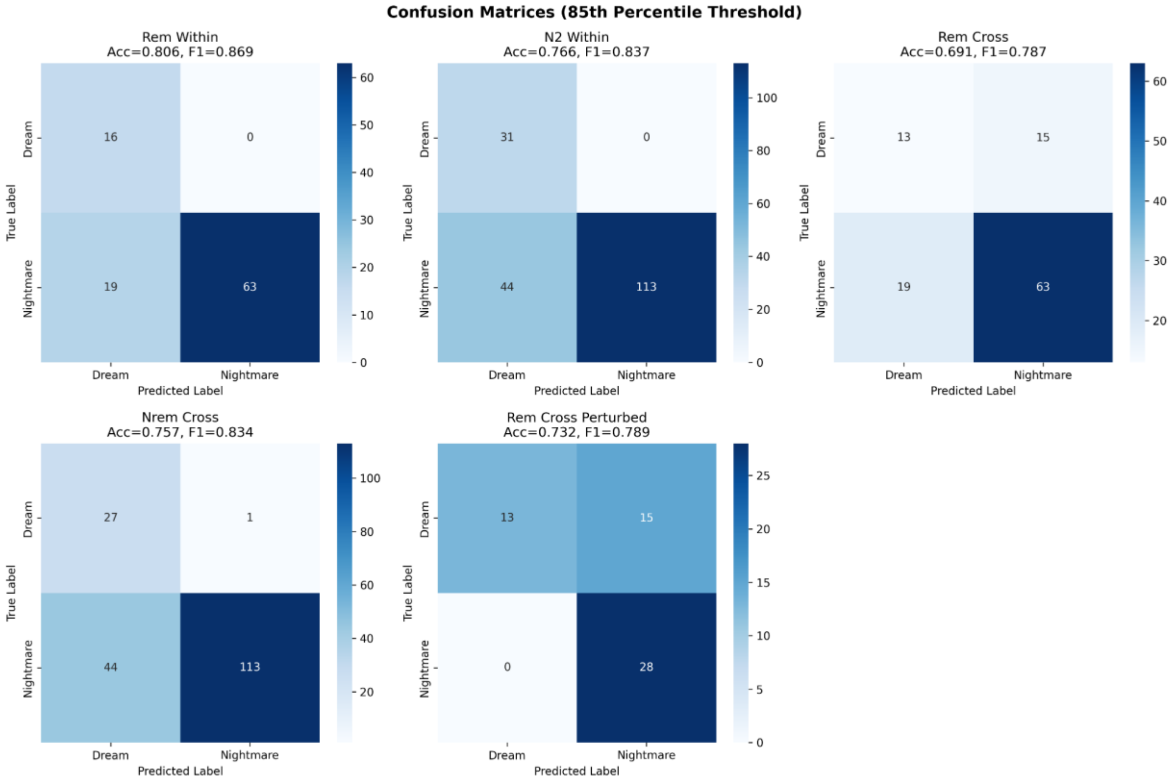

Figure 1.3: Confusion Matrices: Nightmare Detection Performance

domain accuracy and strong F1 scores, with good cross-domain robustness and excellent handling of synthetic perturbations, supporting its potential for reliable nightmare detection across sleep stages.

To conclude, our project successfully developed and evaluated an EEG-based system for detecting neural markers associated with nightmare disorder using a frequency-aware Deep SVDD model. The system processes N2 and REM sleep EEG signals in a stage-specific manner to identify deviations indicative of nightmares, providing clinicians with interpretable tools for diagnosis and monitoring.

Project Outcome & Industry Relevance:

Project outcomes include:

- A trained, empirically validated, Stage-Aware EEG-Based Deep Learning Model for Nightmare Detection
- Objective and Clinician-Readable Nightmare Severity Metrics as quantifiable outputs for interpretation
- Identification and Interpretation of Nightmare-Related Electrophysiological Markers, grounded in established sleep and nightmare literature.
- Comparative Performance Evidence Across Sleep Stages for nightmare detection, supported by sensitivity, specificity, ROC–AUC, and related metrics.

In context of industry relevance, our project is highly relevant to clinical institutions, sleep research centers, and mental health services, as it provides an objective, physiology based tool for detecting neural signatures associated with nightmare disorder. Such a system addresses a major gap in sleep medicine where diagnosis currently depends almost entirely on subjective self-reports, which are known to be unreliable due to recall bias, stigma, and under reporting (especially in PTSD and trauma-exposed populations). The system can be extended to support longitudinal monitoring, enabling clinicians to evaluate treatment progress in therapies such as Imagery Rehearsal Therapy (IRT). This capability makes it valuable for hospitals, psychiatric institutions, sleep clinics, and telemedicine-based mental health programs.

Working Model VS Simulation Study:

The project is primarily intended to be a simulation, that enables users to upload eeg recordings from PSG (Polysomnography) in npy format to get the nightmare disorder analysis. The clinician-facing dashboard is built with React.js for interactive UI components and Next.js for server-side rendering, routing, and API integration. This provides a responsive interface for EEG upload, stage selection (N2/REM), real-time result display, and visualization of spectrograms, heatmaps, and reports. The repository containing codebase for the project can be found here: https://github.com/Pavana-karanth/Nightmare_Detection

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Future Scope:

The future scope of this project includes:

1. Utilising more Nightmare samples that will be shared by the Budapest Sleep Research Lab and iteratively improve the model performance and validate the model.
2. Comparing the current Deep SVDD approach against alternative one-class or anomaly detection models (e.g., Isolation Forest, Autoencoders, etc) to quantify performance differences in nightmare deviation detection.
3. Longitudinal monitoring — tracking patient progress over multiple nights and assessing treatment response (e.g., gamma reduction post-therapy) can help extensively in clinical aspect.
4. Enhancing LLM integration with more grounded, literature-backed information on nightmare phenotypes could improve interpretive reports.
5. Integrating multi-modal physiological signals, such as electrooculogram (EOG), electromyogram (EMG), and heart rate variability (HRV) from electrocardiogram (ECG), to enrich anomaly detection. This would strengthen clinical adoption by providing transparent links between EEG features and physiological interpretations.