

# A Dual-Layer Normative Deviation System with Regime Mapping for Resting EEG

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## Abstract

Resting-state EEG biomarker research has produced many informative findings, but reproducible subject-level systems remain difficult to build across heterogeneous psychiatric and neurodevelopmental populations. A key limitation is that most approaches compress variation into a single scalar without separating magnitude of deviation from type of large-scale organization.

We present a dual-layer resting EEG framework that combines a multivariate Normative Deviation Index (NDI) with a Universal Architecture Score (UAS) and a joint regime map. The system was evaluated on a TDBRAIN-derived labeled cohort ( $N = 911$ ). A search-optimized multivariate feature panel was used to construct a covariance-aware deviation index relative to healthy reference structure. This produced strong scalar separation with  $AUC = 0.824$  for clinical versus healthy,  $AUC = 0.821$  for ADHD versus healthy, and  $AUC = 0.832$  for MDD versus healthy.

A reduced subject-level classifier benchmark was weaker ( $AUC$  0.67 to 0.74), indicating that the principal signal lies not only in feature values but in their multivariate organization relative to healthy structure. The second axis, UAS, captures large-scale cortical organization and is not itself a diagnostic scalar. When combined with NDI, the joint space partitions subjects into distinct regimes including compact healthy-like states, preserved-structure high-deviation states, structural-shift states, and reorganized states.

These results support a two-axis view of resting EEG variation in which magnitude of deviation and organization type are partially dissociable. The framework therefore shifts the biomarker problem from classification toward structured deviation mapping.

## 1 Introduction

Resting-state EEG has long been explored as a biomarker source due to its sensitivity to distributed neural dynamics. However, reproducibility across datasets remains limited [4, 5]. Many approaches rely on isolated feature shifts or generic classifiers, which do not fully capture system-level organization.

We instead separate two questions:

1. How far is a subject from healthy reference organization?
2. What kind of organization does the subject exhibit?

The first is captured by a multivariate deviation index (NDI), and the second by an architecture score (UAS). Their combination defines a regime map.

## 2 Methods

### 2.1 Data

The analysis uses processed resting-state EEG from a TDBRAIN-derived dataset [1]. The final cohort includes  $N = 911$  subjects spanning healthy, ADHD, MDD, and other clinical groups.

### 2.2 Feature construction

EEG signals were segmented into overlapping windows (3 seconds, 50% overlap). Spectral features were computed using Welch’s method [2]. Feature families included:

- spectral entropy
- spectral peak-gap structure
- temporal variability
- frontal-posterior organization
- asymmetry and homologous coupling
- entropy-gap coupling

### 2.3 Normative deviation index

A fixed-size feature panel was selected through search over candidate subsets. The deviation index was computed as a covariance-aware distance from the healthy reference distribution [3].

### 2.4 Architecture score

A complementary architecture score was constructed from interpretable structural components reflecting:

- central-versus-frontal/posterior balance
- homologous interhemispheric coordination
- posterior-frontal spectral structure

### 2.5 Regime mapping

Healthy-reference quantiles were used to partition the joint (UAS, NDI) space into regimes representing distinct modes of deviation and organization.

## 3 Results

### 3.1 Scalar deviation performance

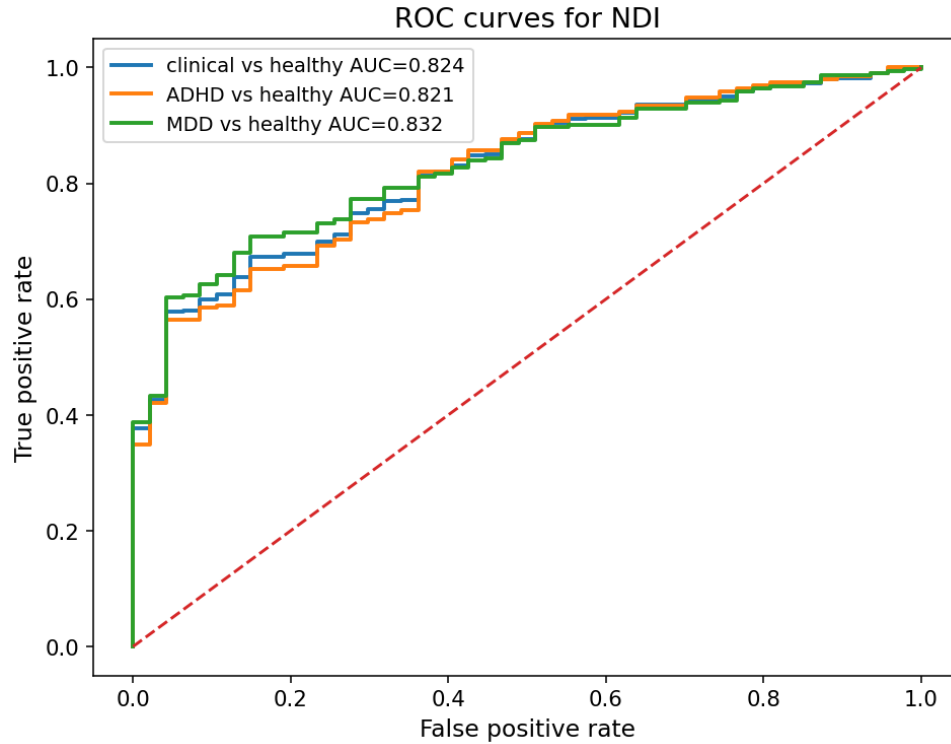


Figure 1: ROC performance of the Normative Deviation Index across the primary contrasts.

The deviation index achieved:

- Clinical vs healthy:  $AUC = 0.824$
- ADHD vs healthy:  $AUC = 0.821$
- MDD vs healthy:  $AUC = 0.832$

### 3.2 Comparison to reduced models

Reduced subject-level classifiers achieved lower performance ( $AUC$  0.67 to 0.74), indicating that multivariate structure is critical.

### 3.3 NDI distribution

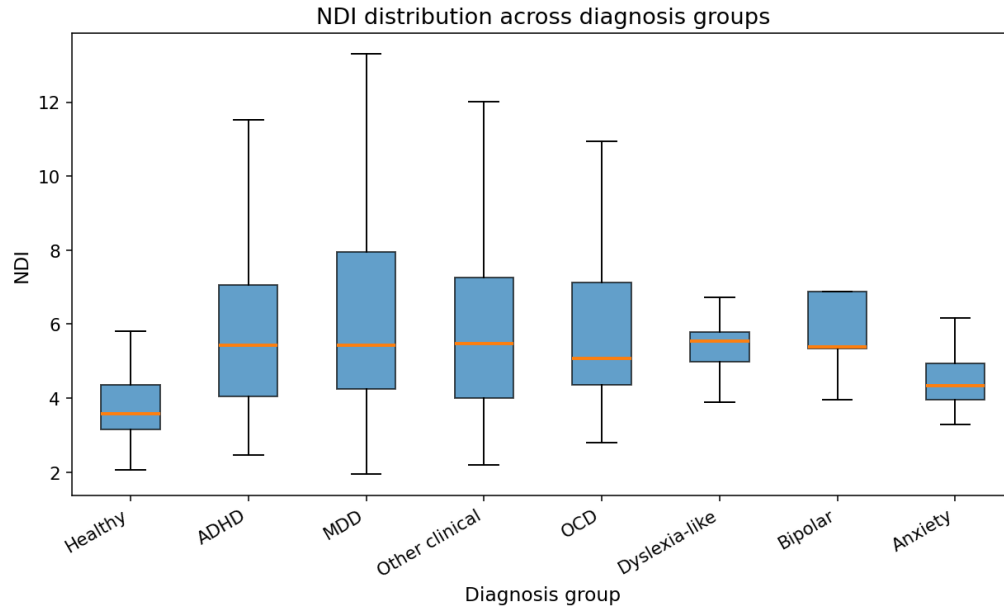


Figure 2: Distribution of the Normative Deviation Index across diagnosis groups. Healthy subjects cluster at lower values, while clinical groups show broader and shifted distributions.

### 3.4 Dual-layer regime structure

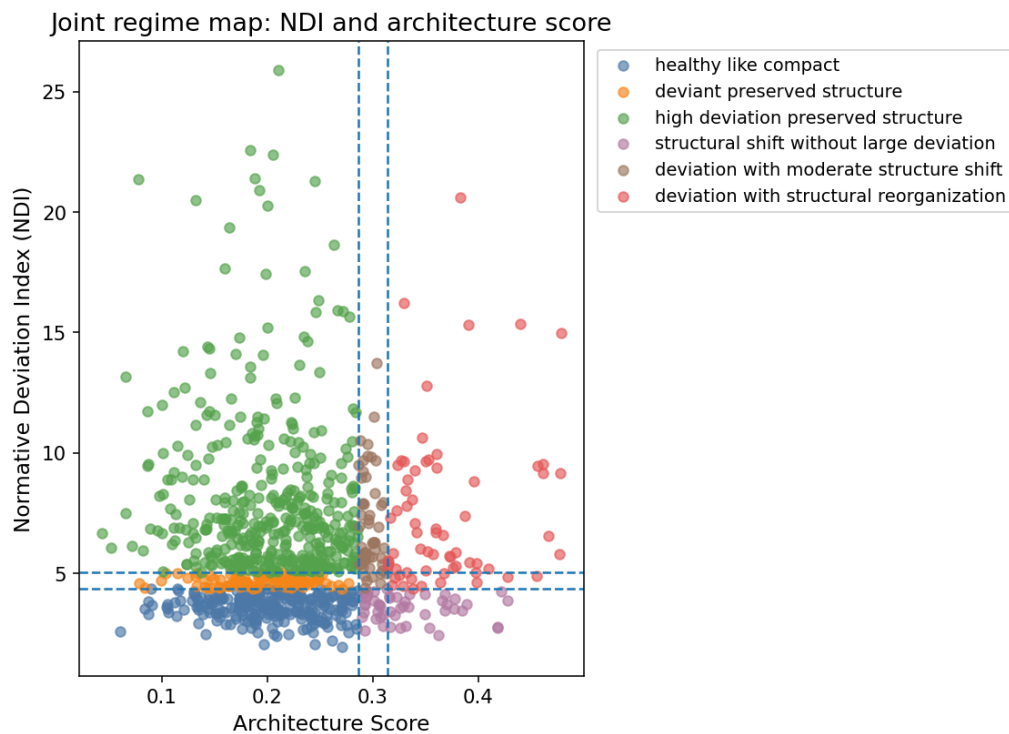


Figure 3: Joint regime map of deviation and organization. The horizontal axis represents architecture score and the vertical axis represents the Normative Deviation Index. Dashed lines indicate healthy-reference quantile boundaries used for regime partitioning.

The joint space separates into multiple regimes, including:

- compact healthy-like organization
- preserved-structure deviation
- structural shift without large deviation
- structural reorganization

### 3.5 Regime composition

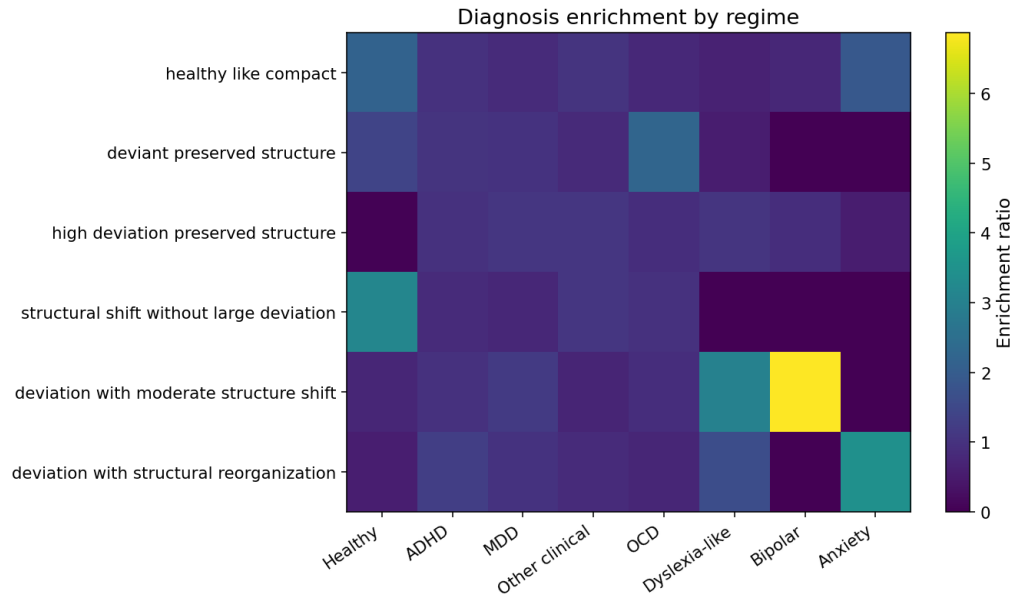


Figure 4: Diagnosis enrichment across the regime map. Values represent enrichment relative to overall diagnosis prevalence, showing that regimes are not reducible to diagnostic labels alone.

Different diagnostic groups occupy distinct regions of the regime map.

### 3.6 Dual-layer subject landscape

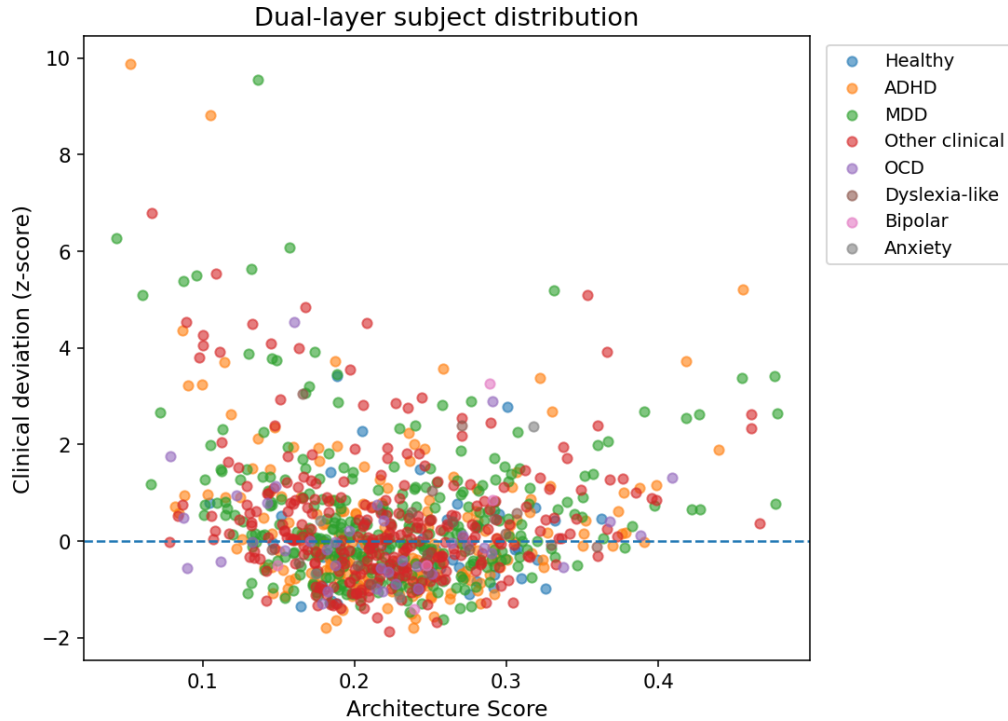


Figure 5: Dual-layer subject distribution in structure-deviation space. This view highlights that architecture score and clinical deviation are related but not identical dimensions.

As shown in Figures 3 to 5, subjects with comparable deviation magnitudes can occupy different structural regimes, while structural shifts can also appear without strong scalar elevation.

## 4 Discussion

The results show that resting EEG variation is not fully captured by a single scalar. Instead, two partially independent axes emerge:

- magnitude of deviation from healthy reference
- type of cortical organization

This explains why similar scalar deviations can correspond to different structural states, and why some subjects show structural shifts without strong scalar displacement.

The weaker performance of reduced classifiers suggests that the key signal lies in multivariate organization rather than individual features.

## 5 Conclusion

We present a dual-layer EEG biomarker framework combining:

- a multivariate deviation index
- an architecture score
- a regime-based interpretation

This reframes resting EEG analysis as structured deviation mapping rather than classification.

## References

## References

- [1] van Dijk et al. (2022). TDBRAIN dataset. *Scientific Data*.
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- [3] Mahalanobis, P. (1936). Generalized distance. *PNAS India*.
- [4] Newson & Thiagarajan (2019). EEG in psychiatry. *Frontiers*.
- [5] Wu et al. (2021). EEG for depression detection. *Biosensors*.