MANIFOLDFORMER: GEOMETRIC DEEP LEARNING FOR NEURAL DYNAMICS ON RIEMANNIAN MANIFOLDS

Yihang Fu[⋆]   *Lifang He*[†]   *Qingyu Chen*[‡]

[⋆] Health Informatics, School of Public Health, Yale University, New Haven, USA
[†] Department of Computer Science and Engineering, Lehigh University, Bethlehem, USA
[‡] Department of Biomedical Informatics and Data Science, School of Medicine,
Yale University, New Haven, USA

ABSTRACT

Existing EEG foundation models mainly treat neural signals as generic time series in Euclidean space, ignoring the intrinsic geometric structure of neural dynamics that constrains brain activity to low-dimensional manifolds. This fundamental mismatch between model assumptions and neural geometry limits representation quality and cross-subject generalization. ManifoldFormer addresses this limitation through a novel geometric deep learning framework that explicitly learns neural manifold representations. The architecture integrates three key innovations: a Riemannian VAE for manifold embedding that preserves geometric structure, a geometric Transformer with geodesic-aware attention mechanisms operating directly on neural manifolds, and a dynamics predictor leveraging neural ODEs for manifold-constrained temporal evolution. Extensive evaluation across four public datasets demonstrates substantial improvements over state-of-the-art methods, with 4.6-4.8% higher accuracy and 6.2-10.2% higher Cohen's Kappa, while maintaining robust cross-subject generalization. The geometric approach reveals meaningful neural patterns consistent with neurophysiological principles, establishing geometric constraints as essential for effective EEG foundation models.

Index Terms— EEG foundation models, geometric deep learning, Riemannian manifolds, neural dynamics, brain-computer interfaces

1. INTRODUCTION

Electroencephalography (EEG) foundation models have achieved remarkable progress through large-scale self-supervised learning, yet they fundamentally treat neural signals as generic time series in Euclidean space. This approach ignores a crucial neurobiological principle: neural activity is constrained to low-dimensional dynamical manifolds that encode cognitive states and motor intentions. Existing architectures such as BENDR [1], EEGFormer [2], and CBraMod [3] employ standard attention mechanisms with Euclidean distance metrics, leading to a fundamental mismatch between model assumptions and the intrinsic geometry of neural dynamics. This

limitation severely restricts representation quality, hinders cross-subject transferability, and prevents models from capturing the smooth, continuous neural state transitions that characterize brain function.

We introduce ManifoldFormer, a novel architectural framework for EEG foundation models that explicitly models neural signals on Riemannian manifolds. The architecture integrates three cascaded innovations: a Riemannian variational autoencoder (VAE) that learns compact manifold embeddings while preserving local geometric structure through hypersphere and hyperbolic projections; a geometric Transformer that replaces replaces Euclidean attention with geodesic-aware mechanisms that compute attention weights using manifold distances; and a dynamics predictor that employs neural ODEs with manifold constraints to model smooth neural state evolution. This geometric formulation naturally accommodates the curved structure of neural state spaces, enables robust cross-subject alignment through Procrustes transformations, and captures the continuous dynamics underlying EEG signals. Extensive evaluation demonstrates substantial improvements across motor imagery and emotion recognition tasks, confirming that geometric constraints are essential for building effective neural foundation models.

1.1. EEG Foundation Models and Architectural Innovations

Recent EEG foundation models have achieved breakthrough performance through large-scale self-supervised pre-training on heterogeneous datasets. For example, FoME [4] introduced adaptive temporal-lateral attention scaling trained on 1.7TB of diverse EEG data, while EEGFormer [5] employed vector quantization for interpretable discrete representations. More recent developments have explored alternative architectures: EEGMamba [6] leveraged state space models for improved sequence modeling, CBraMod [3] captured heterogeneous spatial-temporal dependencies using criss-cross transformers with parallel attention mechanisms, and the Large Cognition Model [7] integrated temporal and spectral attention to enhance generalization.
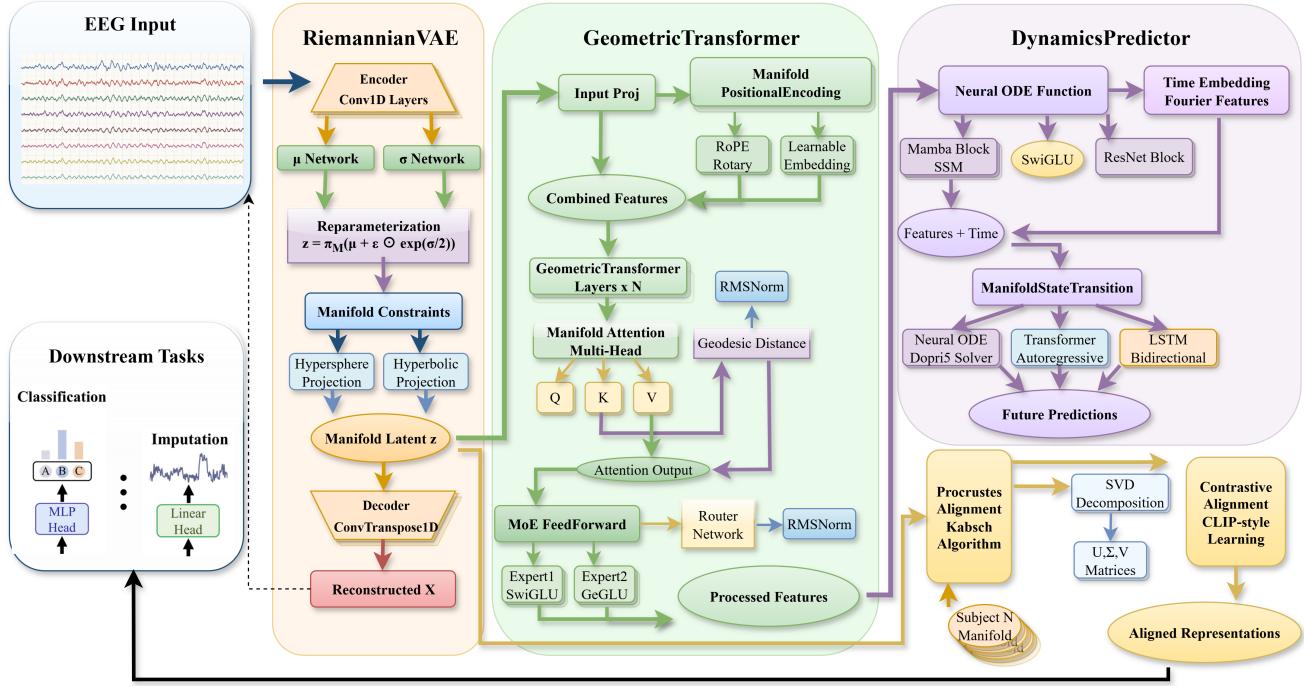
Fig. 1. ManifoldFormer architecture overview showing the three-stage pipeline from EEG input to manifold learning and dynamics prediction.

Earlier foundation models established important precedents. BrainBERT [8] adapted transformers for stereoelectroencephalographic data, LaBraM [9] introduced neural tokenization, and Neuro-GPT [10] demonstrated the potential of generative pre-training. These works laid the groundwork for adapting large-scale architectures to EEG signals. Subsequent innovations emphasized EEG-specific structural characteristics. TimesNet [11] introduced temporal 2D-variation modeling for time series analysis.

1.2. Self-Supervised and Representation Learning Approaches

Self-supervised learning has emerged as the dominant paradigm for EEG foundation models, addressing the scarcity of labeled data through pretext tasks. For example, BENDR [12] adapted Wav2Vec 2.0 for contrastive learning on raw EEG signals. Such approaches demonstrated the effectiveness of self-supervised objectives in learning generalizable representations across diverse EEG datasets and experimental paradigms.

Foundation architectures have also incorporated domain-specific design principles. EEGNet [13] introduced compact convolutional networks tailored for brain-computer interfaces, and more advanced techniques, such as Transformer architectures [14] have been successfully adapted for EEG analysis. These approaches enable scalable learning from massive unla-

beled datasets while preserving the unique characteristics of neural signals.

2. METHODOLOGY

The proposed ManifoldFormer framework (Figure 1) addresses the core limitation of existing EEG foundation models by learning neural manifold representations rather than operating directly in the sensor space. The architecture comprises three cascaded components: a Riemannian VAE for manifold embedding, a geometric Transformer for manifold-aware processing, and a dynamics predictor for modeling neural state evolution. Together, these components enable principled geometric deep learning that aligns with the intrinsic structure of neural dynamics.

2.1. Riemannian Variational Autoencoder

Given a multi-channel EEG input $\mathbf{X} \in \mathbb{R}^{C \times T}$, where C is the number of channels and T is the sequence length, the Riemannian Variational Autoencoder (VAE) maps signals into a latent manifold $\mathcal{M}$ that preserves geometric structure.

The encoder produces two outputs through separate sub-networks: the mean vector $\boldsymbol{\mu} \in \mathbb{R}^d$ (via the μ-network) and the log-variance vector $\boldsymbol{\sigma} \in \mathbb{R}^d$ (via the σ-network). A latent vector $\mathbf{z}$ is then obtained via the reparameterization:

$$\mathbf{z} = \Pi_{\mathcal{M}}(\boldsymbol{\mu} + \boldsymbol{\epsilon} \odot \exp(\boldsymbol{\sigma}/2)), \tag{1}$$

where $\boldsymbol{\epsilon} \sim \mathcal{N}(0, I)$ is Gaussian noise and $\odot$ denotes element-wise multiplication. The operator $\Pi_{\mathcal{M}}(\cdot)$ enforces manifold constraints, ensuring that the latent vector $\mathbf{z}$ lies on the chosen manifold: **Hypersphere projection** where vectors are normalized to unit length so that $\mathbf{z}$ lies on the unit sphere $\mathbb{S}^{d-1}$, or **Hyperbolic projection** where vectors are mapped into the Poincaré ball, ensuring $\|\mathbf{z}\| < 1$ and distances follow hyperbolic geometry.

This formulation guarantees that latent embeddings $\mathbf{z}$ reside in the neural manifold $\mathcal{M}$, providing more faithful representations of EEG dynamics compared to unconstrained Euclidean embeddings.

2.2. Geometric Transformer

The geometric Transformer operates directly on the manifold $\mathcal{M}$ using geodesic-aware attention mechanisms. Rather than relying on Euclidean distances, it computes attention weights based on geodesic structure:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}} - \lambda \mathbf{D}_{geo}\right)\mathbf{V} \tag{2}$$

where $\mathbf{D}_{geo}$ represents geodesic distances on $\mathcal{M}$ and λ controls geometric regularization. Following the attention mechanism, a Mixture-of-Experts (MoE) feed-forward network is applied. The router network dynamically selects between nonlinear experts such as SwiGLU and GeGLU.

2.3. Dynamics Predictor

Neural state evolution is modeled using Neural ODEs [15] with manifold-constrained dynamics:

$$\frac{d\mathbf{z}(t)}{dt} = f_\theta(\mathbf{z}(t), t, \mathbf{c}(t)), \tag{3}$$

$$\hat{\mathbf{z}}_{t+1}^{\text{ode}} = \text{ODESolver}_{\text{Dopri5}}(\mathbf{z}_t, f_\theta), \tag{4}$$

$$\mathbf{z}_{t+1} = \hat{\mathbf{z}}_{t+1}^{\text{ode}} \oplus \text{Tf}_{\text{auto}}(\mathbf{z}_{\leq t}) \oplus \text{LSTM}_{\text{bi}}(\mathbf{z}_{\leq t}), \tag{5}$$

where $\mathbf{c}(t)$ aggregates contextual features from Fourier time embeddings, Mamba SSM outputs, and ResNet representations. The operator $\oplus$ denotes direct concatenation, producing an augmented hidden representation that jointly leverages continuous-time latent dynamics captured by the ODE, as well as sequential dependencies modeled by the Transformer and bidirectional LSTM encoders.

2.4. Multi-Scale Geometric Learning

The self-supervised objective enforces geometric consistency across multiple scales:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{recon}} + \alpha \mathcal{L}_{\text{geo}} + \beta \mathcal{L}_{\text{align}}, \tag{6}$$

$$\mathcal{L}_{\text{geo}} = \sum_{i,j} \left\| |\mathbf{z}_i - \mathbf{z}_j|_{\mathcal{M}} - |\mathbf{x}_i - \mathbf{x}_j|_2 \right\|^2, \tag{7}$$

$$\mathcal{L}_{\text{align}} = -\sum_i \log \frac{\exp(\text{sim}(\mathbf{z}_i^{(1)}, \mathbf{z}_i^{(2)})/\tau)}{\sum_j \exp(\text{sim}(\mathbf{z}_i^{(1)}, \mathbf{z}_j^{(2)})/\tau)}. \tag{8}$$

Here, $\mathcal{L}_{\text{recon}}$ is the reconstruction loss from the Riemannian VAE. The geometric consistency term $\mathcal{L}_{\text{geo}}$ preserves local neighborhood structure by matching distances in latent space $\mathcal{M}$ with Euclidean distances in the input space, while $\mathcal{L}_{\text{align}}$ enables cross-subject knowledge transfer. For alignment, we adopt Procrustes mapping via the Kabsch algorithm with SVD decomposition.

3. EXPERIMENTS

3.1. Experimental Setup

ManifoldFormer is evaluated on four public EEG datasets: BCIC-2A [16] (9 subjects, 4-class motor imagery), BCIC-2B [17] (9 subjects, 2-class motor imagery), SEED [18] (15 subjects, 3-class emotion recognition), and PhysioNet-MI [19] (109 subjects, motor tasks). All data undergo standard preprocessing: 4-second segmentation, average re-referencing, 200Hz resampling, and 0.5-45Hz bandpass filtering.

ManifoldFormer uses PyTorch implementation with Riemannian VAE (latent dimension 128), Geometric Transformer (8 layers, 256 dimensions), and Neural ODE dynamics predictor. Training employs three stages: VAE pretraining (50 epochs), Transformer training (100 epochs), and end-to-end fine-tuning (50 epochs) using AdamW optimizer with learning rate lr = 1e-4. We compare against six baselines: EEGNet [20], DeepConvNet [21], BENDR [1], EEG-Transformer [22], BIOT [23], and CBraMod [3]. All experiments use 5-fold cross-validation with subject-independent splits.

3.2. Results and Ablation Study

The results are presented in Table 1, where ManifoldFormer consistently outperforms baseline methods across all datasets. The geometric manifold approach achieves 4.6-4.8% higher accuracy and 6.2-10.2% Cohen's Kappa improvements, demonstrating superior neural pattern recognition.

Ablation results (Table 2) show that the Riemannian VAE provides the largest performance gain (4.6% of accuracy and 6.2% of Cohen's Kappa on BCIC-2A), confirming the importance of manifold learning. The Geometric Transformer contributes an additional 4.2% accuracy, and the Neural ODE dynamics add 3.5%. Importantly, their combined effect exceeds the sum of individual contributions, indicating strong synergy among components.
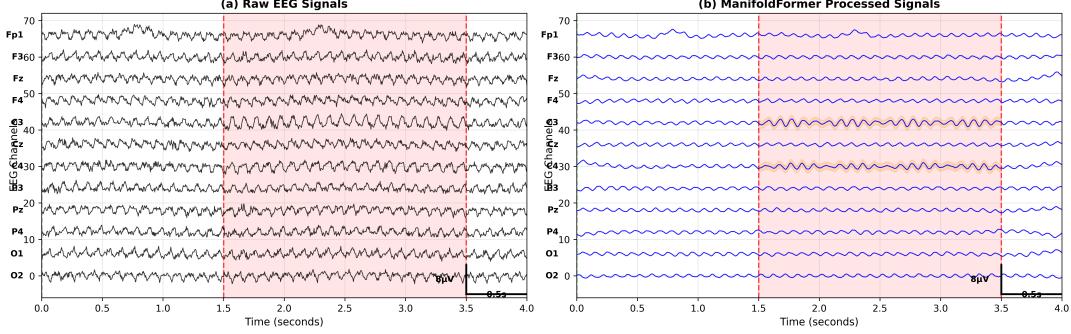
Fig. 2. EEG signal processing comparison during a motor imagery task from the SEED dataset. (a) Raw EEG signals with artifacts and noise. (b) ManifoldFormer-processed signals showing enhanced motor patterns (highlighted regions) in the sensorimotor channels C3 and C4, while preserving overall neural structure.

Table 1. Performance comparison across datasets, reporting Accuracy / Cohen's Kappa. ManifoldFormer consistently outperforms all baseline methods. Best results are highlighted in bold.

Method	BCIC-2A	BCIC-2B	SEED	PhysioNet-MI
EEGNet	0.542 / 0.389	0.698 / 0.396	0.634 / 0.451	0.598 / 0.464
DeepConvNet	0.567 / 0.423	0.715 / 0.430	0.652 / 0.478	0.621 / 0.495
BENDR	0.590 / 0.453	0.732 / 0.464	0.671 / 0.507	0.647 / 0.529
EEG-Transformer	0.614 / 0.485	0.749 / 0.498	0.688 / 0.532	0.663 / 0.551
BIOT	0.628 / 0.504	0.761 / 0.522	0.704 / 0.556	0.679 / 0.572
CBraMod	0.641 / 0.521	0.773 / 0.546	0.717 / 0.576	0.691 / 0.588
ManifoldFormer	**0.687 / 0.583**	**0.821 / 0.642**	**0.763 / 0.631**	**0.724 / 0.615**

Table 2. Ablation study on key components (Accuracy).

Without	BCIC-2A	SEED	PhysioNet-MI
RieVAE	0.631±0.015	0.718±0.013	0.680±0.014
GeoTf	0.645±0.013	0.735±0.012	0.695±0.013
DynPred	0.652±0.014	0.741±0.011	0.703±0.012
GeoAtten	0.661±0.013	0.748±0.012	0.710±0.013
ProAlign	0.673±0.012	0.755±0.011	0.717±0.012
Full Model	**0.687±0.012**	**0.763±0.011**	**0.724±0.013**

3.3. Qualitative Results

Figure 2 demonstrates ManifoldFormer's processing capabilities. Raw signals contain typical artifacts and noise, while processed signals show enhanced motor patterns in sensorimotor channels C_3 and C_4 during motor imagery periods. The learned manifold representations capture meaningful neural geometry with smooth state transitions and neurophysiologically relevant attention patterns, validating the geometric approach's effectiveness for EEG understanding.

4. CONCLUSION

ManifoldFormer introduces geometric deep learning as a new paradigm for EEG foundation models by modeling neural signals on Riemannian manifolds. Its three-component design, including Riemannian VAE, Geometric Transformer, and Neu-

ral ODE dynamics, achieves consistent improvements across diverse EEG tasks. These results demonstrate that incorporating geometric constraints is critical for capturing the intrinsic structure of neural dynamics and opens promising directions for future neuroscience and machine learning research. Our work opens new avenues for geometric approaches in neuroscience applications and establishes manifold learning as an essential component for building robust, interpretable brain-computer interface systems.

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