LEARNING CORTICAL ANOMALY THROUGH MASKED ENCODINGFOR UNSUPERVISED HETEROGENEITY MAPPING

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Code Available

Introduction

We introduces CAM (Cortical Anomaly Detection through Masked Image Modeling), a ***Self-Supervised*** framework designed for ***Unsupervised Detection*** of brain disorders using ***Cortical-surface features***. We employ this framework for the detection psychotic spectrum, achieving an AUC of 0.696 for Schizoaffective and 0.769 for Schizophreniform, without the need for any labels.

Dataset

OPN (training / val) [1]

Group	# Subjects	Age	Sex (M/F)
Healthy Control (HC)	1135	5-73	44%/56%

TOP (testing) [2]

Group	# Subjects	Age	Sex (M/F)
Healthy Control (HC)	290	18-59	54%/46%
Schizophrenia (SZ)	165	19-60	65%/35%
Bipolar Disorder (BD)	189	17-65	42%/58%
Schizoaffective (SA)	33	20-62	30%/70%
Schizophreniform (SZF)	22	19-45	50%/50%

Results

AUC of Unsupervised anomaly detection. C: Curvature, S: Sulcus, T: Thickness. *p-value < 0.05, **p-value < 0.01.

	IForest	GMM	VAE	DAE	CAM(C)	CAM(S)	CAM(T)
HC vs SZ	0.55	0.61*	0.60*	0.59	0.59	0.63*	0.67*
HC vs BD	0.50	0.54	0.58	0.58	0.57	0.55	0.63*
HC vs SA	0.61*	0.58	0.66*	0.66*	0.65*	0.64*	**0.70****
HC vs SZF	0.47	0.65*	0.71**	0.70**	0.62*	0.65*	**0.77****

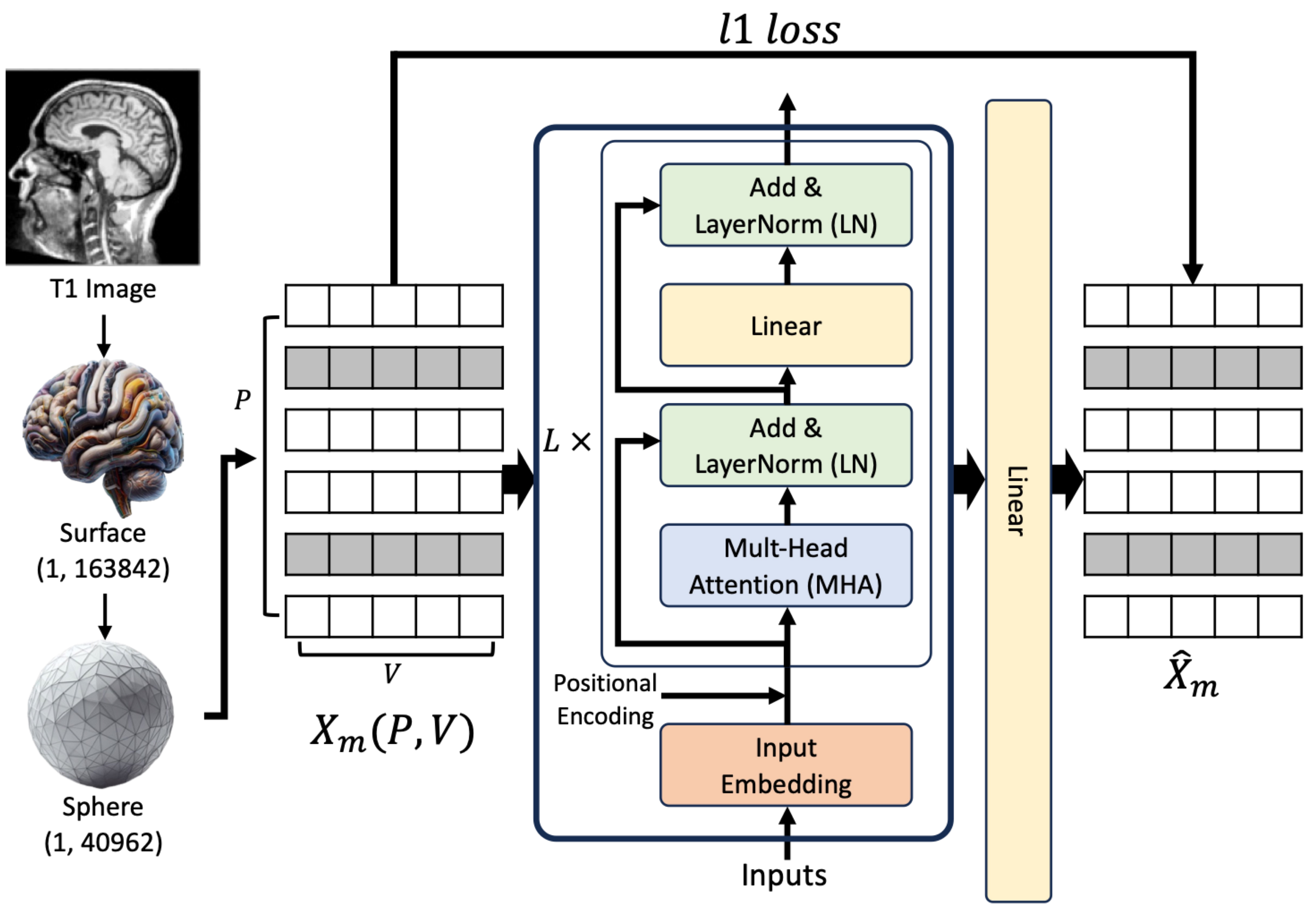
Analysis

ROIs identified by two-tailed Student's t-test (p-value < 0.01) utilizing CAM(T)'s anomaly scores.

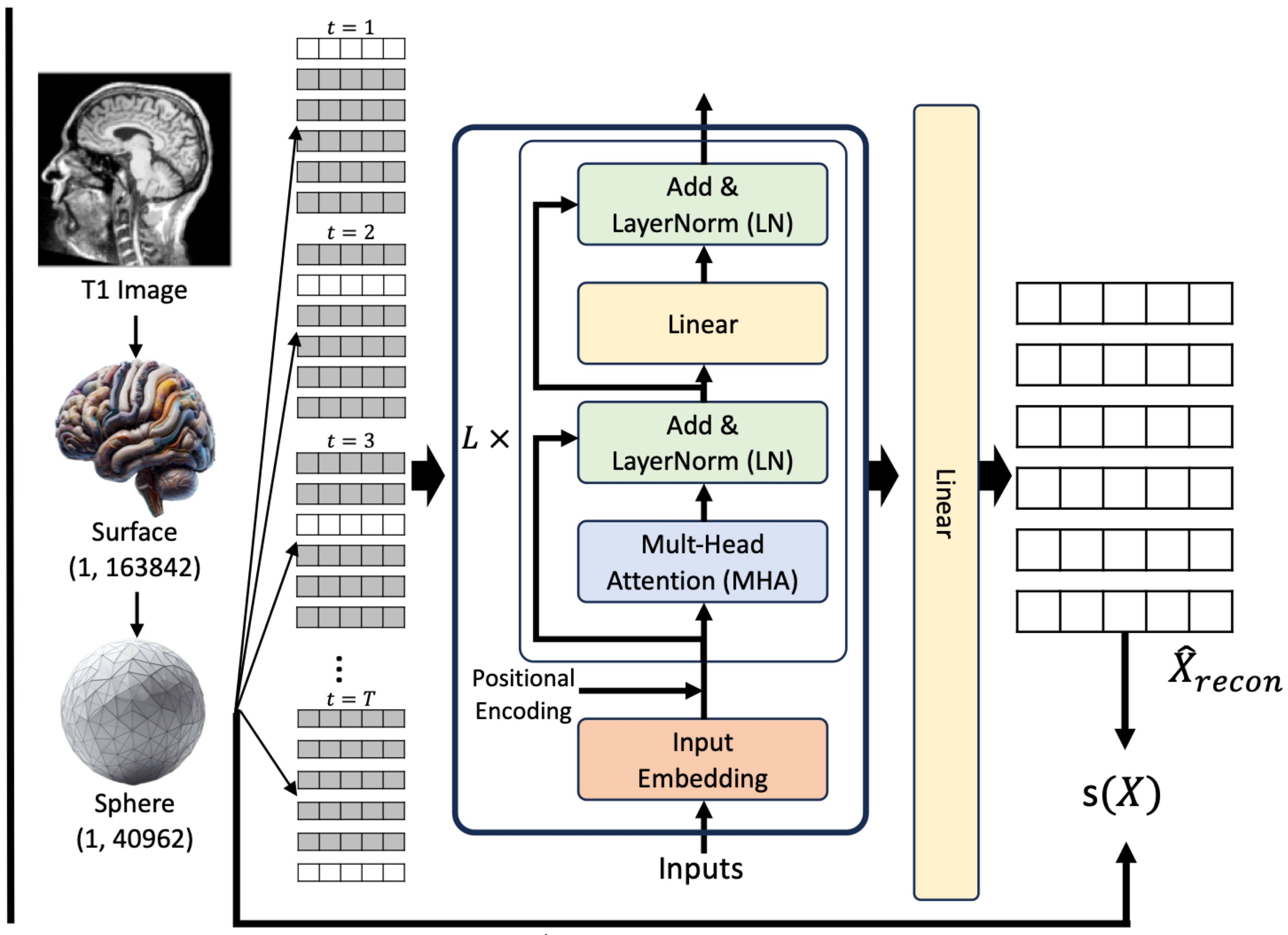
	ROIs
HC vs SA	Pars Triangularis (0.696)
HC vs SZF	Superior Frontal (0.769), Rostral Middle Frontal (0.750), Frontal Pole (0.693), Parsorbitalis (0.660)

Method

Self-supervised Masked Training



Iterative Masked Anomaly Detection



$$\mathcal{L}(\theta, \phi) = \frac{1}{|M|} \sum_{m \in M} |\hat{\mathbf{X}}_m - \mathbf{X}_m|_1$$

Algorithm 1 Iterative Masked Anomaly Detection

Require: Data samples $\mathbf{X}$, encoder f_θ, iteration count T=10
Ensure: Anomaly score $s(\mathbf{X})$.

patch_size ← total number of patches in $\mathbf{X}$
step ← int(patch_size/T)
start ← 0
end ← step
for $t = 1$ to T **do**
  Mask patches from start to end in $\mathbf{X}$ to obtain $\mathbf{X}_m^t$
  Obtain reconstructions: $\hat{\mathbf{x}}_m^t \leftarrow g\phi(f_\theta(\mathbf{X}_m^t))$
  start ← end
  end ← start + step
end for
$\hat{\mathbf{X}}_{\text{recon}} \leftarrow [\hat{\mathbf{x}}_m^1, \hat{\mathbf{x}}_m^2, ..., \hat{\mathbf{x}}_m^T]$
Compute the anomaly score: $s(\mathbf{X}) = ||\mathbf{X} - \hat{\mathbf{X}}_{\text{recon}}||_1$.

Conclusion

We demonstrate a scalable approach for anomaly detection of complex brain disorders based on cortical abnormalities.

Reference

[1] Christopher J Markiewicz , et al., "The openneuro resource for sharing of neuroscience data," eLife, vol. 10, pp. e71774, oct 2021.
[2] Kristina C Sk˚atun , et al., "Global brain connectivity alterations in patients with schizophrenia and bipolar spectrum disorders," Journal of Psychiatry and Neuroscience, vol. 41, no. 5, pp. 331–341, 2016.
[3] Thomas Wolfers, et al., "Replicating extensive brain structural heterogeneity in individuals with schizophrenia and bipolar disorder," Human brain mapping, vol. 42, no. 8, pp. 2546–2555, 2021.