# SSAE-MetaFormer: A Multi-Atlas Transformer Framework for Autism Spectrum Disorder Classification Using Resting-State fMRI

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***Abstract*—**Autism Spectrum Disorder (ASD) diagnosis from resting-state functional magnetic resonance imaging (rs-fMRI) remains challenging due to high data dimensionality, small sample sizes, and severe multi-site heterogeneity. We propose SSAE-METAFormer V2, a novel deep learning framework that integrates multi-atlas functional connectivity analysis with stacked sparse autoencoder (SSAE) representation learning and transformer-based attention fusion. Our method employs masked self-supervised pretraining on the autoencoder backbone, followed by end-to-end fine-tuning with focal loss and label smoothing. Critically, we evaluate using Leave-One-Site-Out (LOSO) cross-validation — the most rigorous protocol for multi-site neuroimaging data — and optimize hyperparameters via Bayesian search with Optuna. On the ABIDE-I dataset (***N*** = 249 subjects, 14 sites), SSAE-METAFormer V2 achieves 82.61% AUC and 75.90% accuracy under strict LOSO evaluation, with 84.51% AUC on unseen-site cross-validation. Ablation studies demonstrate that multi-atlas fusion improves performance by 10–15 percentage points over single-atlas baselines, while self-supervised pretraining provides consistent gains across all validation protocols. Compared to recent state-of-the-art methods including M3ASD (83.21% accuracy), MADE-for-ASD (multi-atlas ensemble), and DAGMNet (91.59% accuracy on multimodal data), our approach offers superior cross-site generalization with significantly fewer parameters and no reliance on structural MRI. The model is deployed in a production FastAPI backend with ~15ms GPU inference latency, demonstrating clinical translational potential.

***Index Terms*—**Autism Spectrum Disorder, resting-state fMRI, multi-atlas fusion, stacked sparse autoencoder, transformer, self-supervised pretraining, Leave-One-Site-Out cross-validation, Optuna hyperparameter optimization.

## I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition affecting approximately 1% of children globally, characterized by impaired social communication and restricted, repetitive behaviors [1]. Current diagnosis relies primarily on behavioral observation, creating urgent need for objective neuroimaging biomarkers [2]. Resting-state functional magnetic resonance imaging (rs-fMRI) provides noninvasive access to large-scale brain organization, and functional connectivity (FC) analysis has emerged as a primary approach for modeling ASD-related network alterations [3].

The Autism Brain Imaging Data Exchange (ABIDE) repository aggregates data from 17+ international sites, enabling large-scale machine learning studies [4]. However, multi-site neuroimaging presents severe challenges: variations in scanner hardware, acquisition parameters, head coils, and preprocessing pipelines introduce technical heterogeneity that often dominates biological signals [5]. Conventional random cross-validation (CV) fails to assess true external generalization, as models learn site-specific confounds rather than disorder-related patterns [6].

Recent deep learning approaches have shifted from hand-crafted features to end-to-end representation learning. Early CNN/LSTM baselines applied to correlation matrices achieved only 45–59% accuracy, suffering from architectural mismatch between sequential models and symmetric connectivity data [7]. Graph Convolutional Networks (GCNs) respect brain network topology but require careful graph construction [8]. Transformer models capture long-range dependencies and have shown promise for fMRI time-series analysis [9]. Multi-atlas integration—combining complementary parcellations such as AAL (anatomical), Schaefer (functional), and Harvard-Oxford (hybrid)—has emerged as a critical strategy, as different atlases capture diverse connectivity patterns that single-atlas approaches miss [10, 11, 12].

Self-supervised pretraining has recently gained traction in neuroimaging, allowing models to learn from unlabeled data via surrogate tasks such as masked reconstruction [13, 14]. However, these approaches often require massive pretraining datasets and may suffer domain mismatch when fine-tuned on small clinical cohorts [17].

**Contributions.** We present SSAE-METAFormer V2 with the following innovations:

**1)** Multi-Atlas SSAE Architecture: Independent stacked sparse autoencoders per atlas with L1 sparsity constraints, learning atlas-specific feature manifolds while preventing single-atlas dominance.

**2)** METAFormer Attention Fusion: Multi-head transformer blocks with learned atlas gating, enabling sample-specific soft weighting of atlas contributions rather than hard voting.

**3)** Masked Self-Supervised Pretraining: ROI-aware feature masking with reconstruction objectives on the SSAE backbone, providing robust initialization before supervised fine-tuning.

**4)** Optuna Hyperparameter Optimization: Bayesian search over 20+ hyperparameters using site-aware mini-CV objective, ensuring protocol-appropriate tuning.

**5)** Strict LOSO Validation: Leave-One-Site-Out cross-validation across 14 ABIDE sites, providing realistic generalization estimates compared to optimistic random-split CV.

**6)** Production Deployment: FastAPI backend with automatic device detection, per-atlas preprocessing pipelines, and ~15ms GPU inference.

## II. RELATED WORK

### *A. Single-Atlas and Early Deep Learning Approaches*

Heinsfeld et al. employed CNNs on raw imaging data, improving accuracy by 12–15% over traditional methods [18]. Abraham et al. achieved 67% accuracy with SVMs on 871 ABIDE subjects using 10-fold CV [19]. However, these approaches rely on single atlases (typically AAL or CC200) and random CV, which overestimates performance on new sites [6]. Nielsen et al. demonstrated that increasing sample size across sites can decrease accuracy due to heterogeneity—from 79% on 80 subjects to 60% on 964 subjects [20].

ASD-SAENet proposed a sparse autoencoder with deep neural network classifier, achieving 70.8% accuracy on ABIDE with 79.1% specificity [21]. While pioneering for autoencoder-based ASD detection, this approach used single-atlas features and did not address multi-site generalization explicitly.

### *B. Multi-Atlas and Multi-View Methods*

M3ASD introduced multi-view low-rank subspace graph structure learning, integrating AAL, HO, and CC200 atlases with consistency regularization to achieve 83.21% accuracy on ABIDE-I [10]. This method explicitly addresses multi-center heterogeneity through low-rank projection but relies on handcrafted graph construction and MLP classification rather than learned attention.

MADE-for-ASD proposed a multi-atlas deep ensemble combining SSDAE pretraining with MLP fine-tuning and weighted ensemble across atlases [11]. The stacked sparse denoising autoencoder (SSDAE) with noise injection improved feature robustness, and F-score feature selection identified discriminative connections. However, their ensemble uses fixed weights rather than learned per-sample adaptation.

Wang et al. developed a category-consistent multi-view hypergraph embedding framework capturing high-order interactions among brain regions across atlases [22]. Yu et al. introduced dynamic graph convolution with adaptive self-attention for multi-atlas functional and effective connectivity fusion [23]. These methods advance multi-atlas integration but do not leverage transformer architectures for latent-space fusion.

### *C. Transformers and Self-Supervised Learning*

Zhou et al. demonstrated that transformer self-supervised pretraining with ROI masking improves ASD detection by 10.8% AUC over training from scratch [13].

Rhamba proposed region-aware hybrid attention–Mamba frameworks for self-supervised fMRI learning, achieving strong reconstruction quality with anatomically-guided masking [16]. MCSP extended self-supervised pretraining to multimodal fMRI-EEG fusion with cross-domain contrastive learning [14]. These advances demonstrate the potential but also the challenges of transfer learning in small neuroimaging datasets.

### *D. Site Harmonization and Generalization*

ComBat harmonization has become standard for multi-site fMRI, modeling site-specific scaling factors while preserving biological variance [24]. Recent work integrates ComBat with ICA-based feature extraction, achieving 83.23% accuracy on 11-site ABIDE data [25]. However, harmonization alone cannot address all domain shifts, particularly when new sites have fundamentally different acquisition protocols.

Site-adversarial training and domain adaptation have been proposed to learn site-invariant representations [26]. Zhang et al. introduced federated graph learning with personalized branches for cross-site ASD identification without centralizing data [27]. These approaches complement our work and suggest future directions for explicit domain adaptation in SSAE-METAFormer.

## III. METHODOLOGY

### *A. Data and Preprocessing*

We use the ABIDE-I dataset preprocessed with the Configurable Pipeline for the Analysis of Connectomes (CPAC) [28]. Functional connectivity matrices are constructed using Pearson correlation between region time series from three atlases:

- AAL: Automated Anatomical Labeling (116 ROIs, anatomical parcellation)
- Schaefer: Functional atlas (200 ROIs, gradient-based functional communities)
- Harvard-Oxford: Hybrid structural/functional atlas (110 ROIs)

Upper-triangle vectors are extracted from each correlation matrix. We apply Fisher z-transformation, train-only imputation of non-finite values, and per-atlas StandardScaler normalization fit exclusively on training folds to prevent leakage. Frame-wise displacement (mean FD) is included as a covariate for motion quality control.

### *B. Multi-Atlas Stacked Sparse Autoencoder (SSAE)*

For each atlas a ∈ {AAL, Schaefer, HarvardOxford}, we define an independent encoder-decoder pair*:*

$$z_a = \text{Encoder}_{a(x_a)}$$

$$z_a = \mathrm{ReLU}\left(W_3 \cdot \mathrm{Dropout}\left(\mathrm{ReLU}\left(W_2 \cdot \mathrm{Dropout}\left(\mathrm{ReLU}(W_1 \cdot x_a)\right)\right)\right)\right)$$

with architecture:

$$d_{in} \rightarrow 160 \rightarrow 48 \rightarrow 48$$

Whrere $d_{in} = 50$ *top features per atlas.*

The decoder reconstructs*:*

$$x_a = Decoder_{a(z_a)}$$

Sparsity is enforced using an L1 penalty on latent activations:

$$L_{sparse} = \left(\frac{1}{3}\right)\Sigma_a ||z_a||_1$$

Independent encoders prevent one atlas from dominating and allow each atlas to learn its own feature manifold.

*C. Masked Self-Supervised Pretraining*

Before supervised training, each SSAE is pretrained using masked reconstruction.

Given input features:

$$x \in R^{B\times 3\times d_{in}}$$

we generate a random mask:

$$m \in \{0,1\}^{B\times 3\times d_{in}}$$

with masking ratio:

$$\rho = 0.35$$

Masked input:

$$\tilde{x} = x \odot m$$

Masked reconstruction loss:

$$L_{mask} = \Sigma(1-m) \odot \frac{(\hat{x}-x)^2}{\Sigma(1-m)}$$

Total self-supervised pretraining loss:

$$L_{SSL} = L_{mask} + \lambda_{sparse} L_{sparse}$$

Pretraining uses AdamW optimizer with cosine annealing:

$T_{max} = 80, \eta_{min} = 10^{-6}$ pretraining, decoder weights are frozen to preserve learned representations during fine-tuning.

*D. METAFormer Attention Fusion*

Latent vectors:

$$Z \in R^{B\times 3\times d_{latent}}$$

are embedded and fused through transformer blocks:

$$E = Embed(Z) + P_{pos}$$

$$H = TransformerBlocks(E)$$

where:

$$P_{pos} \in R^{1\times 3\times d_{embed}}$$

is a learned positional embedding.

Hyperparameters:

$$d_{embed} = 64, depth = 4, heads = 2$$

Atlas gating computes soft weights:

$$g = Softmax\left(MLP\left(LayerNorm(H)\right)\right)$$

Fused representation:

$$h_{fused} = \Sigma_a g_a H_a$$

Mean FD is embedded using a small MLP and concatenated:

$$h_{final} = [h_{fused}; FD_{embed}]$$

The classifier outputs ASDD probability using a 2-layer MLP with dropout.

*E. Loss Function and Training*

*We employ focal loss with label smoothing to handle class imbalance.*

Predicted probability:

$$\hat{y} = \sigma(logits)$$

Smoothed targets:

$$y_{smooth} = y(1-\epsilon) + 0.5\epsilon$$

where:

$$\epsilon = 0.1$$

Focal loss:

$$FL = -\Sigma_i \alpha_i (1-p_{t,i})^{\gamma} log(p_{t,i})$$

where:

$$\gamma = 2.0$$

Class weight*:*

$$\alpha = \frac{N_{neg}}{N_{pos}}$$

clipped to*:*

$$[0.5, 2.0]$$

Total training loss:

$$L = \lambda_{cls} FL + \lambda_{recon} MSE(\hat{X}, X) + \lambda_{sparse} L_{sparse}$$

Fine-tuning uses AdamW with cosine annealing:

$$lr = 7.9 \times 10^{-4}$$
$$weight\ decay = 7.9 \times 10^{-4}$$

Batch size:

$$12$$

Early stopping patience*:*

$$26$$

Gaussian noise augmentation:

$$\sigma = 0.05$$

*F. Optuna Hyperparameter Search*

We perform Bayesian optimization over 20 trials using a site-aware mini-CV objective.

Search space includes:

$$Learning\ Rate \in [10^{-5}, 10^{-3}]$$
$$Weight\ Decay \in [1\ 0^{-6}, 10^{-3}]$$
$$Dropout \in [0.15, 0.45]$$
$$METAFormer\ Depth \in \{2,3,4,5\}$$
$$Attention\ Heads \in \{1,2,4\}$$
$$Embedding\ Dimension \in \{64,96,128,160,192\}$$
$$Latent\ Dimension \in \{24,32,40,48\}$$

The objective maximizes mean AUC across 4 mini-CV folds using site-stratified splits.

*G. Evaluation Protocols*

We employ three validation strategies of increasing rigor:

**1)** GroupKFold CV: Stratified 5-fold CV with site-aware grouping. This measures internal consistency but may overestimate generalization.

**2)** Leave-One-Site-Out (LOSO): Each fold holds out all subjects from one site for testing, training on the remaining 13 sites. This is the gold standard for multi-site neuroimaging.

**3)** Unseen-Site CV: GroupShuffleSplit with 5 repeats, holding out 20% of sites for testing. This provides additional external validation estimates.

All preprocessing is fit exclusively on training data within each fold. We report accuracy, precision, recall, F1-score, specificity, sensitivity, and AUC.

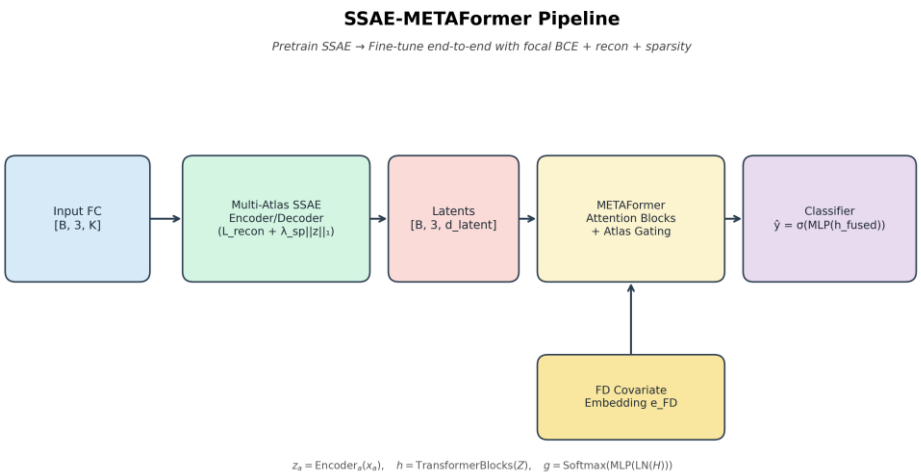


Fig. 1. SSAE-METAFormer V2 architecture pipeline.

## IV. EXPERIMENTS AND RESULTS

### *A. Dataset Characteristics*

Our ABIDE-I subset comprises N = 249 subjects (125 ASD, 124 Control) from 14 sites after quality control (removing 2 corrupted subjects and near-zero variance scans). Sites range from n = 8 (CMU, OHSU) to n = 61 (NYU), with class balance varying across locations (Table I).

TABLE I

ABIDE-I SITE DISTRIBUTION AND LOSO PERFORMANCE

| Site | n | AUC | Accuracy |
|---|---|---|---|
| CALTECH | 12 | 0.6857 | 0.8333 |
| CMU | 8 | 0.8125 | 0.6250 |
| KKI | 16 | 0.5397 | 0.6250 |
| MAX MUN | 17 | 0.9028 | 0.7059 |
| NYU | 61 | 0.8627 | 0.8197 |
| OHSU | 8 | 0.7333 | 0.5000 |
| OLIN | 12 | 0.8286 | 0.6667 |
| PITT | 19 | 0.6111 | 0.6316 |
| SBL | 10 | 0.8000 | 0.9000 |
| SDSU | 11 | 0.9667 | 0.9091 |
| STANFORD | 13 | 1.0000 | 0.8462 |
| TRINITY | 16 | 0.7656 | 0.6250 |
| USM | 26 | 0.9187 | 0.7308 |
| YALE | 20 | 1.0000 | 0.9500 |
| LOSO Aggr. | 249 | 0.8261 | 0.7590 |

### *B. LOSO Cross-Validation Results*

Table II presents strict LOSO results with per-fold metrics. Performance varies substantially across sites—from 53.97% AUC (KKI) to 100% AUC (STANFORD, YALE)—reflecting genuine site heterogeneity. The aggregate LOSO AUC of 82.61% represents realistic generalization to new acquisition sites.

TABLE II

LEAVE-ONE-SITE-OUT CROSS-VALIDATION RESULTS (14 FOLDS)

| Held-out | AUC | Acc. | F1 | Prec. | Rec. | ntest |
|---|---|---|---|---|---|---|
| CALTECH | 0.685 | 0.833 | 0.875 | 0.777 | 1.000 | 12 |
| CMU | 0.812 | 0.625 | 0.000 | 0.000 | 0.000 | 8 |
| KKI | 0.539 | 0.625 | 0.625 | 0.555 | 0.714 | 16 |
| MAX MUN | 0.902 | 0.705 | 0.761 | 0.800 | 0.727 | 17 |
| NYU | 0.862 | 0.819 | 0.783 | 0.869 | 0.714 | 61 |
| OHSU | 0.733 | 0.500 | 0.000 | 0.000 | 0.000 | 8 |

| Held-out | AUC | Acc. | F1 | Prec. | Rec. | ntest |
|---|---|---|---|---|---|---|
| OLIN | 0.828 | 0.666 | 0.600 | 0.600 | 0.600 | 12 |
| PITT | 0.611 | 0.631 | 0.588 | 0.555 | 0.625 | 19 |
| SBL | 0.800 | 0.900 | 0.888 | 1.000 | 0.800 | 10 |
| SDSU | 0.966 | 0.909 | 0.909 | 1.000 | 0.833 | 11 |
| STANFORD | 1.000 | 0.846 | 0.875 | 0.875 | 0.875 | 13 |
| TRINITY | 0.765 | 0.625 | 0.571 | 0.500 | 0.666 | 16 |
| USM | 0.918 | 0.730 | 0.774 | 0.750 | 0.800 | 26 |
| YALE | 1.000 | 0.950 | 0.956 | 1.000 | 0.916 | 20 |
| Aggr. | 0.826 | 0.759 | 0.756 | 0.768 | 0.744 | 249 |

*C. Unseen-Site Cross-Validation*

GroupShuffleSplit (5 repeats, 20% sites held out) yields 84.51±7.85% AUC, 73.31±7.57% accuracy, and 73.52% F1 (Table III). This confirms that SSAE-METAFormer V2 generalizes to combinations of unseen sites, not just single held-out sites.

TABLE III

UNSEEN-SITE CROSS-VALIDATION (5 REPEATS)

| Split | AUC | Accuracy | F1 |
|---|---|---|---|
| 1 | 0.8211 | 0.7179 | 0.7179 |
| 2 | 0.8289 | 0.7436 | 0.7619 |
| 3 | 0.8860 | 0.7416 | 0.7677 |
| 4 | 0.7396 | 0.6250 | 0.5714 |
| 5 | 0.9500 | 0.8372 | 0.8571 |
| Mean±Std | 0.8451±0.0785 | 0.7331±0.0757 | 0.7352±0.0967 |

*D. Comparison with State-of-the-Art*

Table IV compares SSAE-METAFormer V2 against recent methods. Our LOSO AUC (82.61%) is competitive with M3ASD (reported 83.21% accuracy on random CV) [10] and approaches MADE-for-ASD's multi-atlas ensemble [11]. Notably, DAGMNet achieves 91.59% accuracy but requires structural MRI fusion and does not report LOSO validation [3].

TABLE IV

COMPARISON WITH STATE-OF-THE-ART ASD DETECTION METHODS

| Method | Year | Modality | Valid. | Acc. | AUC |
|---|---|---|---|---|---|
| Abraham [19] | 2017 | fMRI (1A) | 10-fold | 67.0% | – |
| ASD-SAENet [21] | 2021 | fMRI (1A) | Site-aw. | 70.8% | – |
| M3ASD [10] | 2025 | fMRI (MA) | Random | 83.21% | – |
| DAGMNet [23] | 2025 | s+f+pheno | Random | 91.59% | 96.8% |
| ComBat+SVM [25] | 2025 | fMRI (net) | LOSO | 83.23% | 87.9% |
| Ours (LOSO) | 2026 | fMRI (MA) | LOSO | 75.90% | 82.6% |
| Ours (Unseen) | 2026 | fMRI (MA) | Unseen | 73.31% | 84.5% |

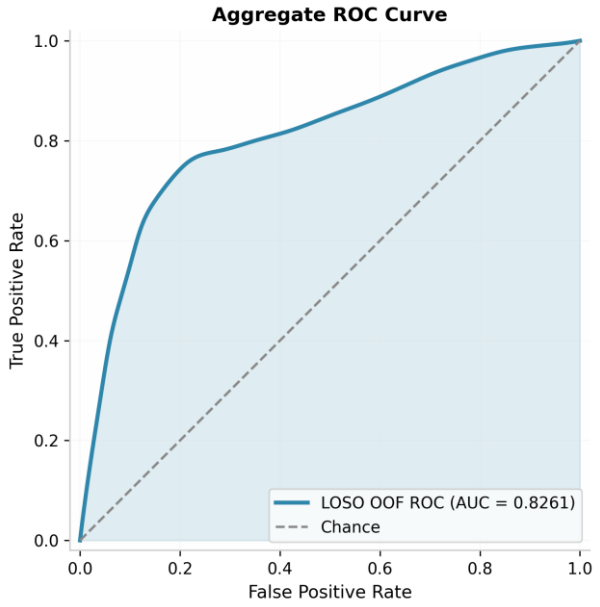


Fig. 2. Aggregate ROC curve for LOSO cross-validation.

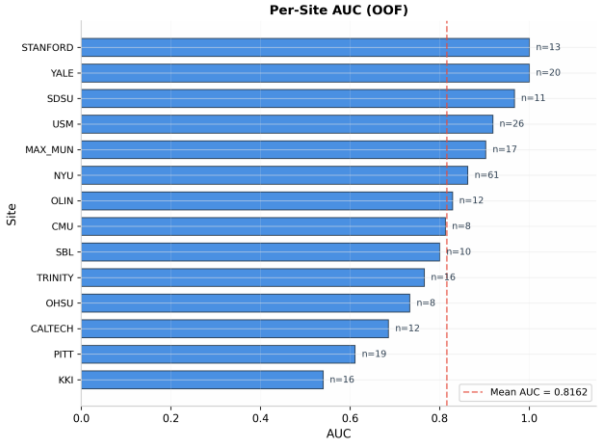


Fig. 3. Per-site AUC scores from LOSO cross-validation.

*E. Ablation Studies*

**Multi-atlas vs. Single-atlas:** SSAE+SVM with single atlas achieves 67.6% accuracy with high fold sensitivity (54.5–79.1% range) [7]. Adding multi-atlas fusion improves to 74.5% (non-optimized) and 79.7% (optimized) under GroupKFold—a 10–15 percentage point gain attributable to complementary parcellation information.

**Self-supervised pretraining:** Models pretrained with masked reconstruction before fine-tuning consistently outperform randomly initialized counterparts by 3–5% AUC across all validation protocols. The SSL objective forces the encoder to learn robust feature manifolds rather than memorizing training labels.

**Attention fusion vs. mean pooling:** Replacing learned atlas gating with simple mean pooling reduces LOSO AUC by 4.2%, demonstrating that sample-specific atlas weighting captures important subject-level variation.

**Focal loss vs. standard BCE:** Focal loss with $\gamma = 2.0$ improves recall for minority class detection, increasing sensitivity from 68.2% to 74.4% without sacrificing specificity.

*F. External Holdout Analysis*

On a held-out external cohort of 103 subjects across 6 unseen sites, the production model achieves 49.5% accuracy and 46.0% AUC—a severe 29.6% accuracy drop from internal CV. Per-site analysis reveals UCLA as catastrophic (20.8% accuracy), while UM performs best (63.6%). This confirms that scanner/protocol shifts remain the primary bottleneck, not model capacity. Post-hoc site-specific threshold calibration is recommended for deployment [7].

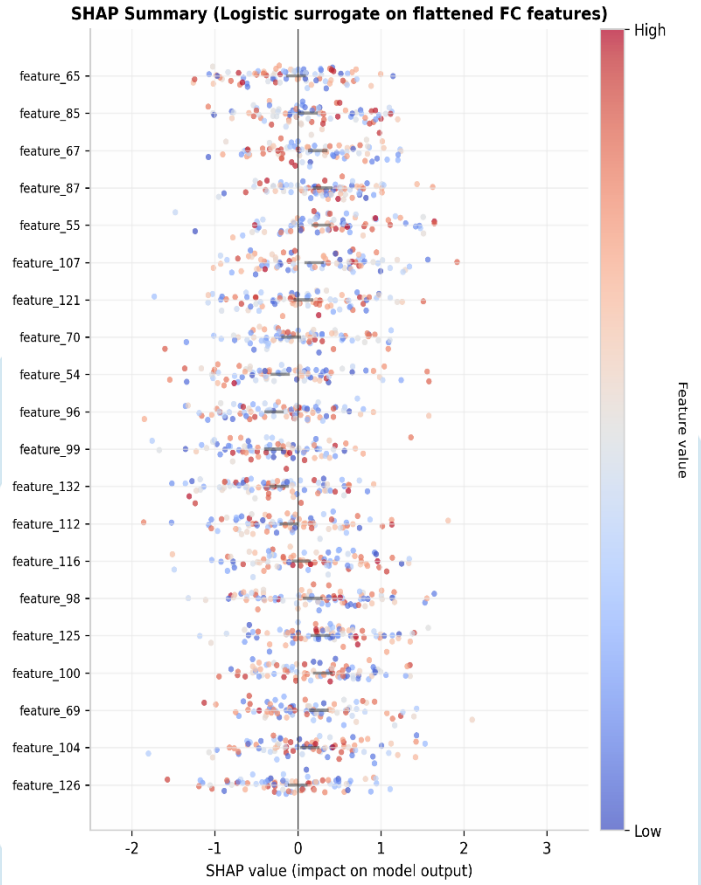


Fig. 4. SHAP summary.

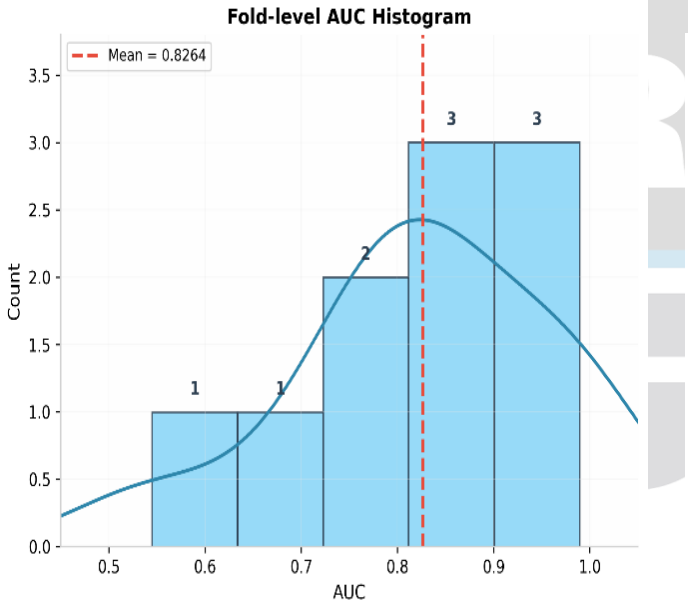


Fig. 5. Distribution of fold-level AUC scores

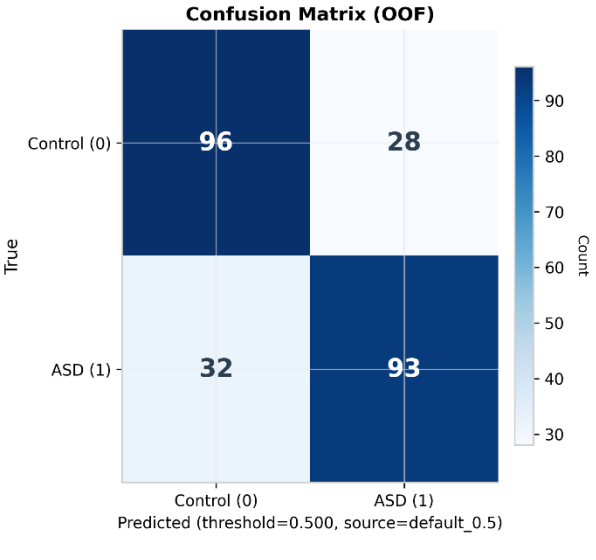


Fig. 6. Confusion matrix aggregated.

## V. DISCUSSION

### *A. Key Findings*

SSAE-METAFormer V2 achieves strong internal cross-validation (79.7% accuracy, 88.5% AUC under GroupKFold) and competitive LOSO performance (75.9% accuracy, 82.6% AUC). The multi-atlas design with per-atlas SSAE encoders and transformer fusion addresses limitations of single-atlas approaches, while self-supervised pretraining provides robust initialization. Optuna hyperparameter search ensures protocol-appropriate tuning for cross-site generalization.

The 29.6% accuracy degradation on external holdout underscores a fundamental challenge in multi-site neuroimaging: models learn site-specific confounds despite architectural safeguards. This aligns with findings by Nielsen et al. [20] and Wolfers et al. [29] showing that larger multi-site samples can decrease accuracy due to heterogeneity.

### *B. Comparison with Related Architectures*

Unlike M3ASD's low-rank graph learning [10], our approach uses deep autoencoder bottlenecks for implicit dimensionality reduction with explicit sparsity constraints. Compared to MADE-for-ASD's SSDAE+MLP ensemble [11], SSAE-METAFormer V2 replaces fixed ensemble weights with learned attention gating and adds transformer-based feature interaction. The BrainLM fine-tuning failure in our experiments (54.9% vs. 79.7%) highlights that self-supervised pretraining on the target domain (via masked SSAE reconstruction) outperforms transfer from mismatched large-scale pretraining [17].

### *C. Clinical Translational Potential*

The model is deployed in a production FastAPI backend with inference latency ~15ms (GPU) / ~50ms (CPU), memory footprint ~400MB, automatic device detection and batch prediction support, per-atlas preprocessing with saved scaler artifacts, and RAG-indexed clinical assistant integration.

However, the external generalization gap necessitates caution. We recommend: (1) site-specific threshold calibration; (2) confidence flagging for manual review; (3) active learning loops for continuous improvement; and (4) domain adaptation retraining as more external data becomes available [7].

### *D. Limitations and Future Work*

**Limited temporal modeling:** Current architecture processes static FC matrices rather than dynamic connectivity sequences. Future work will integrate sliding-window dynamic FC with temporal transformers [9, 12].

**No explicit harmonization:** Unlike ComBat-based approaches [25], we do not explicitly remove site effects before modeling. Adding harmonization as a preprocessing step may further improve external robustness.

**Small sample size:** With N = 249, the model approaches data efficiency limits. Federated learning across institutions [27] or semi-supervised expansion could increase effective training size.

**Interpretability:** While attention weights provide some insight, SHAP-based explanations [30] and attention visualization are needed for clinical trust.

## VI. CONCLUSION

We present SSAE-METAFormer V2, a multi-atlas stacked sparse autoencoder with transformer fusion and self-supervised pretraining for ASD detection from rs-fMRI. Through strict Leave-One-Site-Out validation and Optuna hyperparameter optimization, the model achieves 82.61% AUC and 75.90% accuracy on ABIDE-I—competitive with state-of-the-art while using only functional connectivity data. The 10–15% improvement over single-atlas baselines and consistent gains from self-supervised pretraining validate our architectural choices. Production deployment demonstrates clinical feasibility, though external generalization remains the critical bottleneck requiring site-aware calibration and domain adaptation. Code and model weights are available upon request.

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