Deep Learning Approaches for Early Autism Detection Using sMRI Data: A Study of Brain-Behavior Relationships

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INTRODUCTION

- Autism Spectrum Disorder (ASD) affects 1 in 31 children and presents with diverse cognitive, sensory, and behavioral challenges [1]. Currently, ASD diagnosis primarily relies on subjective behavioral assessments, which can introduce significant variability and diagnostic uncertainty
- Objective neuroimaging techniques such as sMRI and fMRI have the potential to reveal subtle, heterogeneous brain patterns associated with ASD, providing crucial complementary diagnostic insights
- Leveraging deep learning, which excels at extracting complex features from high-dimensional data, presents a promising avenue for enhancing ASD classification accuracy and consistency

OBJECTIVES

This study aims to: (1) Develop and evaluate baseline deep learning classifiers using individual MRI modalities (sMRI and fMRI) (2) Integrate sMRI and fMRI data using attention-based fusion, and assess if multimodal fusion enhances ASD classification over unimodal approaches

LITERATURE REVIEW

- Clinical assessments like ADOS and ADI-R remain gold standards but introduce diagnostic subjectivity [4]
- To reduce computational load and minimize noise in MRI data, studies frequently limit analyses to central brain slices (approximately 40–175 slices) or adopt hybrid approaches like 2.5D input, where a small stack of adjacent slices provides limited 3D context using lightweight 2D convolutional kernels [3]
- Traditional ML methods using handcrafted feature achieve moderate accuracy (~60–70%) [5]. In contrast, advanced DL approaches including 3D CNNs, GNNs, RNNs, and transformer models have improved performance modestly, typically hovering around ~70–75% accuracy [2,6]

DATA & PREPROCESSING

- We used the publicly available Autism Brain Imaging Data Exchange (ABIDE I + II) dataset, a large, multi-site MRI collection spanning 18 international sites and 1,025 subjects (488 ASD, 537 Controls)
- Each subject includes: (1) T1-weighted sMRI scan (97 x 115 x 97) (2) Resting-state fMRI data processed into: (a) 100×100 functional connectivity matrix (b) 200×100 BOLD time series (Schaefer-100 atlas)
- **PREPROCESSING:**

Figure 1: Brain extraction process for a T1-weighted MRI scan; original slice (left), binary brain mask (middle), and brain-only output (right)

EXPERIMENTAL DESIGN

1. **EXPERIMENT 1 - sMRI ONLY**

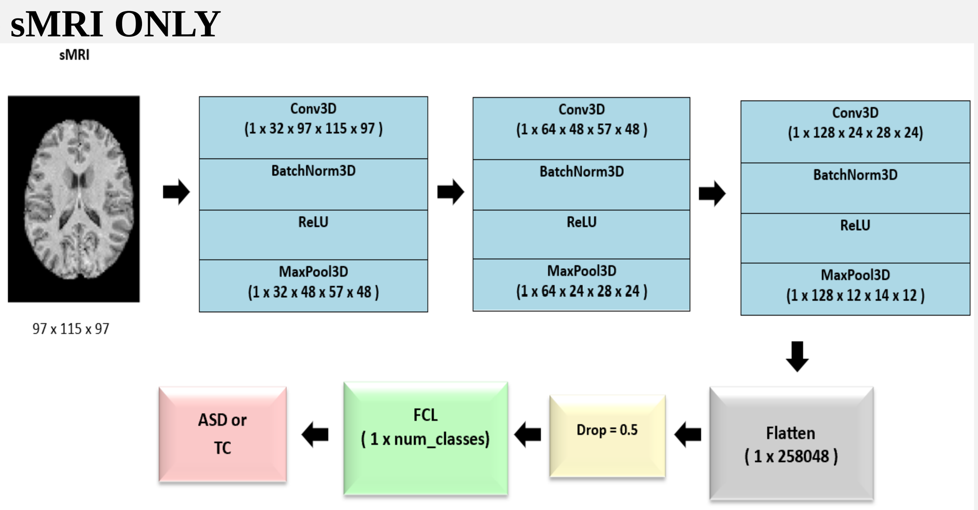


Figure 2: A 3D CNN was trained on T1-weighted structural MRI volumes to extract volumetric features. The architecture includes three convolutional blocks with batch normalization, ReLU, max pooling, and a final fully connected layer.

2. **EXPERIMENT 2 - fMRI ONLY**

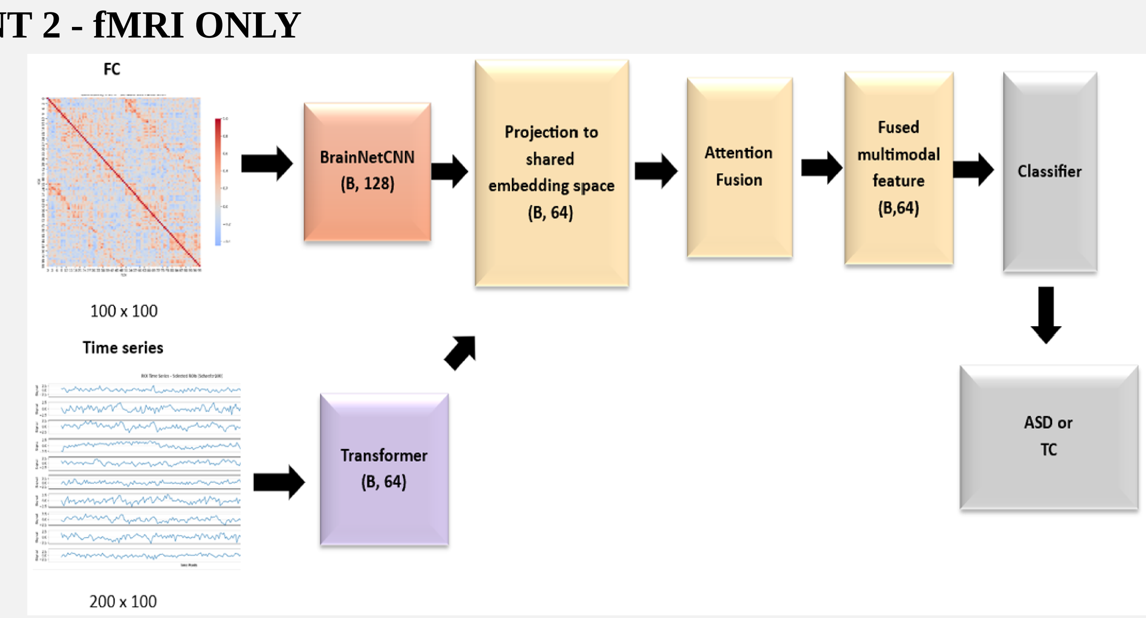


Figure 3: Functional connectivity matrices and BOLD time series were processed using BrainNetCNN and a Transformer encoder respectively. The feature vectors are projected to a common embedding space. Attention-based fusion was applied to integrate static and temporal features.

3. **EXPERIMENT 3 – MULTIMODAL FUSION**

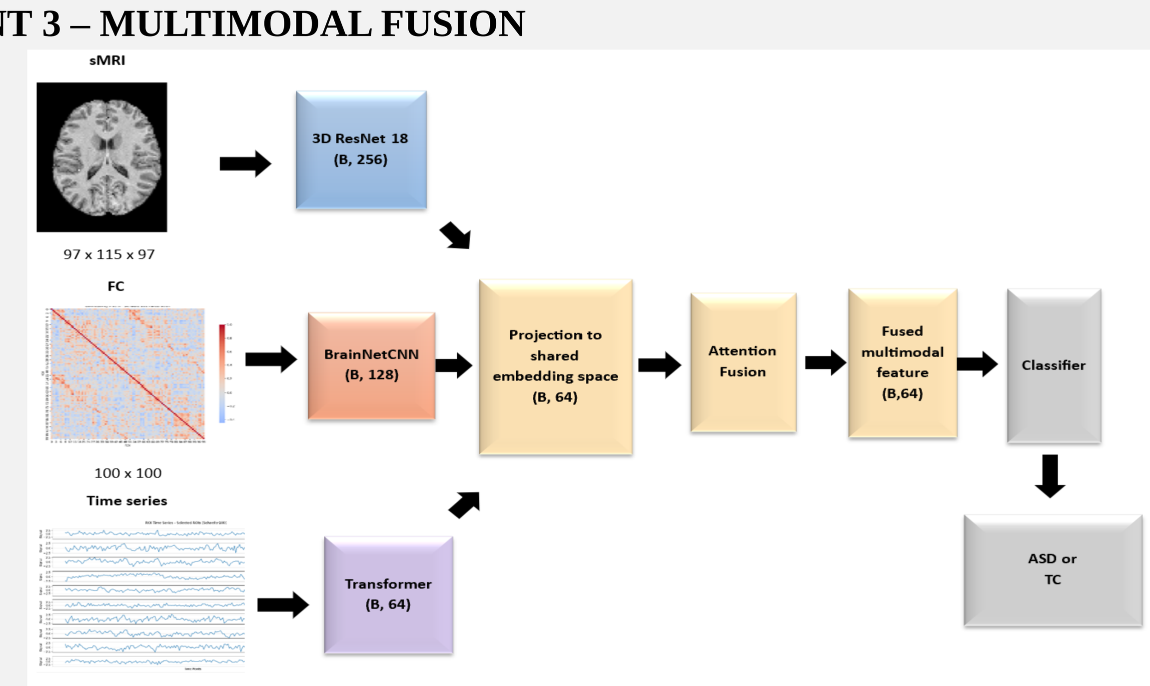
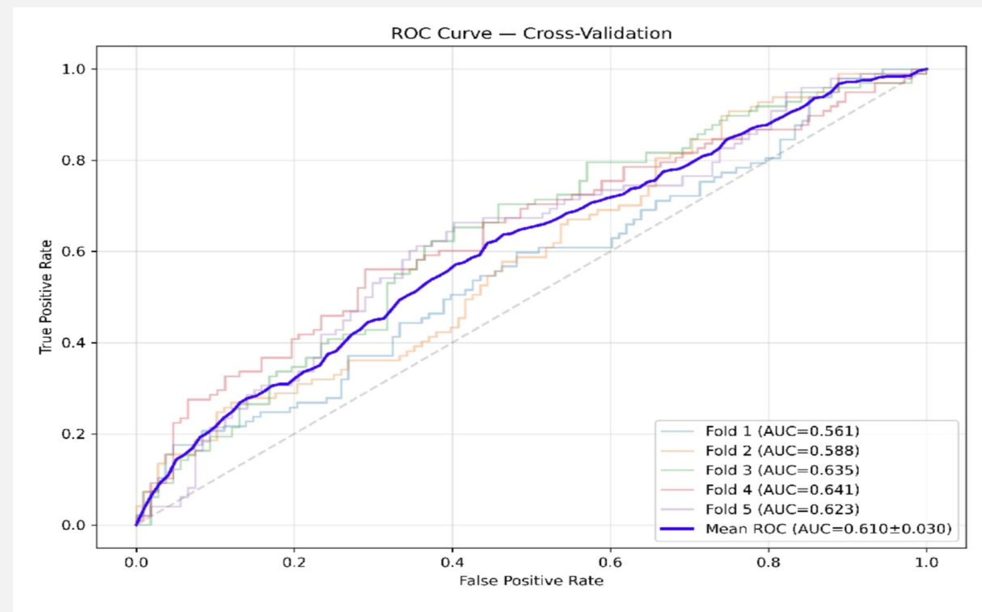


Figure 4: Feature vectors from sMRI (ResNet-18), fMRI connectivity (BrainNetCNN), and time series (Transformer) are first projected to a common space and are then fused using an attention mechanism. The combined representation was used for final ASD classification.

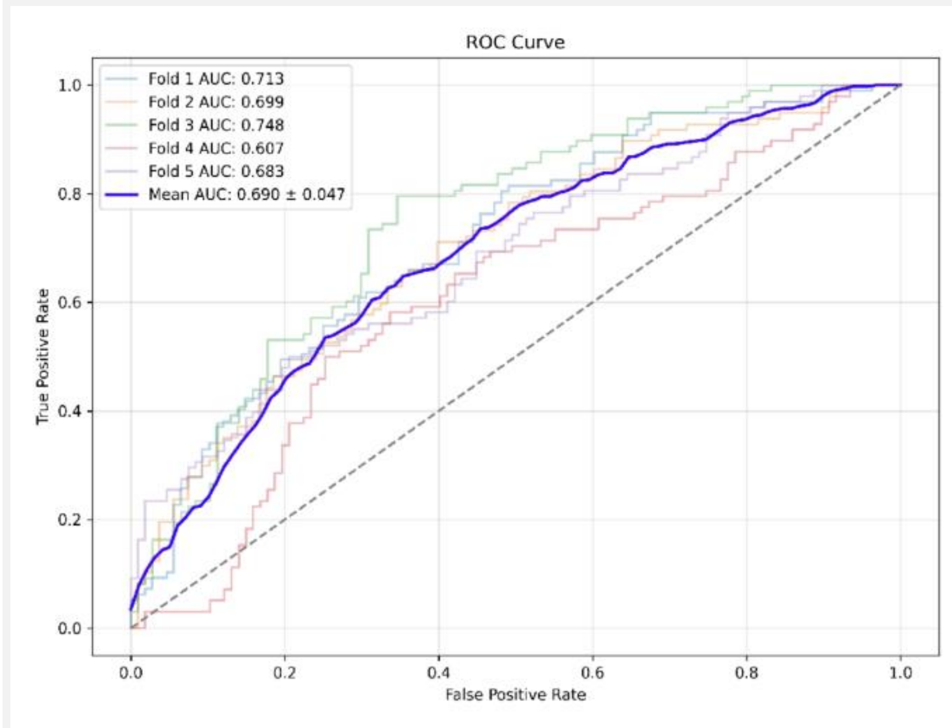
RESULTS

Model	Accuracy	Precision	Recall	F1 Score	AUC
sMRI-Only Model	60.00% ± 3.38%	0.6111 ± 0.050	0.6068 ± 0.250	0.5940 ± 0.150	0.610 ± 0.030
fMRI-Only Model	63.61% ± 3.18%	0.6196 ± 0.0331	0.6148 ± 0.0276	0.6168 ± 0.0270	0.6904 ± 0.0462
Multimodal Fusion	**66.83% ± 2.53%**	**0.6617 ± 0.0449**	**0.6370 ± 0.0827**	**0.6444 ± 0.0380**	**0.7120 ± 0.0273**

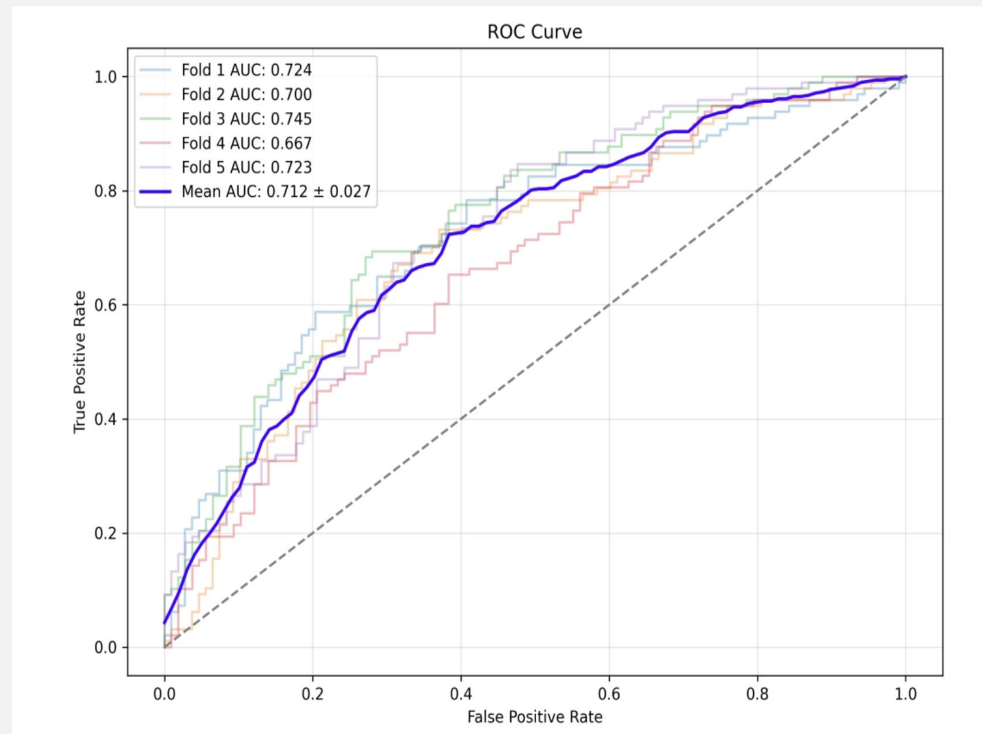
Table 1: Classification performance (mean ± std) across cross-validation folds for sMRI-only, fMRI-only, and multimodal models



(a)



(b)



(c)

Figure 5: ROC curves for (a) sMRI-only, (b) fMRI-only, and (c) multimodal fusion models. The multimodal model achieved the highest and most stable AUC (~0.71)

DISCUSSION

- Multimodal fusion outperforms unimodal models, achieving the highest accuracy (66.83%), F1 score (0.6444), and AUC (0.7120). This highlights structural and functional MRI data provide complementary information for ASD classification
- sMRI-only model achieved the lowest discriminative power (AUC ≈ 0.61), indicating that anatomical brain differences in ASD versus controls are quite subtle
- Attention-based fusion model likely learned to rely on whichever modality was more informative for a given subject, thereby compensating for one modality's weaknesses with the other's strengths

DATASET VARIABILITY & CHALLENGES

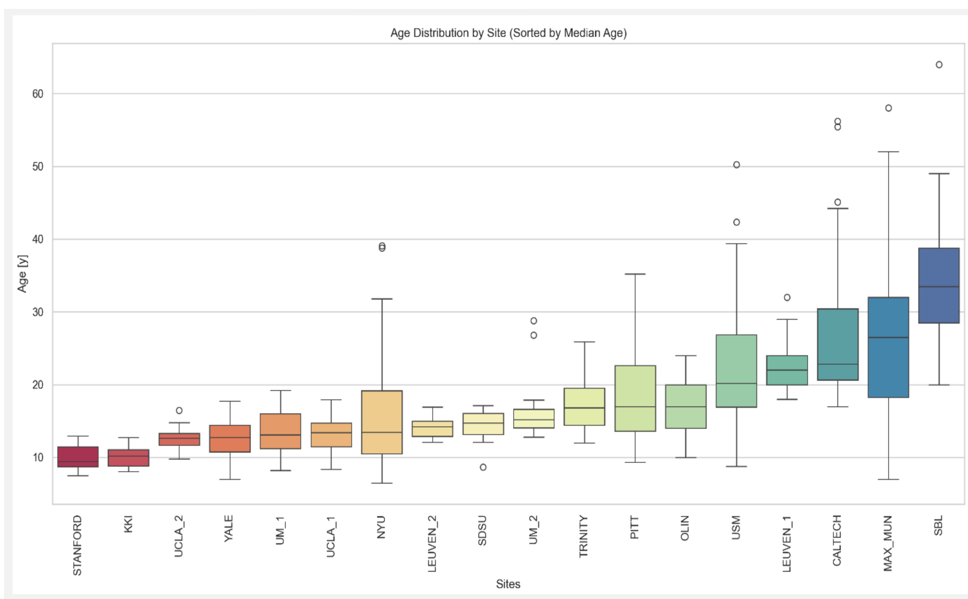


Figure 6: Age distribution across ABIDE sites shows wide variability. Age-related brain changes can confound ASD-related features, making it difficult for the model to isolate true diagnostic signals and reduce model generalizability.

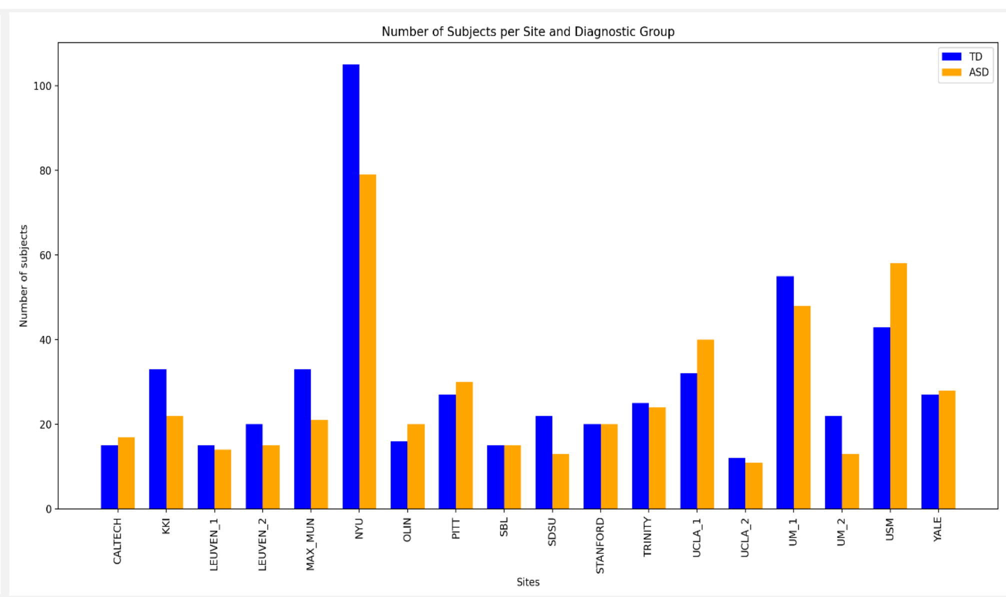


Figure 7: Number of ASD and TD subjects varies significantly across sites. This imbalance may cause the model to learn site-specific signatures rather than ASD-related patterns.

CONCLUSION & FUTURE WORK

This study highlights the potential of multimodal deep learning to improve ASD classification, though performance is limited by inter-site variability and subtle biomarkers. While structural and functional MRI each carry noise and variability, fusing both modalities modestly improves signal quality and model consistency. Our results affirm that multimodal integration is a promising direction. Future work involves harmonizing the data and using advanced strategies such as foundation models and contrastive pretraining to learn robust, domain-invariant features.

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