Al-Kindy College Medical Journal (KCMJ)

Research Article

Application of Artificial Intelligence in Diagnosing Autism Spectrum Disorder based on Structural Brain MRI using EfficientNet-B0 and Convolutional Block Attention Model

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Article history:
Received 16 September 2025
Accepted 12 January 2026
Available online 1 August 2026

DOI: 10.47723/we9kh834

Keywords: ABIDE II KKI_1; Attention Mechanism; Autism; CBAM; Deep Learning; Efficient Net-B0; MRI.

ABSTRACT

Background: Autism spectrum disorder is a progressive neurological disorder that affects 1 in 60 children; early detection is vital for disease control and to prevent further progression. The latest diagnostic criteria for autism spectrum disorder, based on assessing behavior, are often time-consuming, costly, and necessitate a specialist.

Aim: This study proposes a model that helps clinicians diagnose autism spectrum disorder based on MRI neuroimaging.

Subjects and Methods: This retrospective diagnostic modeling study proposes a deep learning framework that combines EfficientNet-B0 with a Convolutional Block Attention Model and advanced data augmentation strategies for diagnosing autism spectrum disorder. The model was trained on the mid-slice axial T1-weighted MRI scan that belongs to the ABIDE II KKI_1 dataset.

Results: The experimental results of the proposed model achieve an accuracy of 95.37%, with recall, precision, and F1-score all exceeding 93%, with better performance compared with traditional architectures such as SqueezeNet and ResNet50.

Conclusions: The study approach achieves a high level of accuracy, sensitivity, and specificity; thus, it may be viewed as a valuable computer-aided diagnostic tool in autism spectrum disorder detection.

Introduction

Autism Spectrum Disorder (ASD) is a complicated neurodevelopmental disorder that entails social interaction deficits, communication problems and unusual repetitive behaviors[1]. Behavioral assessment has been the main diagnostic method used conventionally, despite being vital; they tend to be subjective and less critical in identifying underlying neurological patterns of abnormality. Structural brain MRI (sMRI) is a powerful non-invasive tool that identifies structural brain changes related to ASD. MRI can improve diagnostic confidence, especially when there is complexity or ambiguity in clinical assessment of behavioral disturbance [2]. MRI changes in ASD may include enlargement of the subarachnoid space, periventricular hyperintensities, mild enlargement of cerebral ventricles, Mega cisterna magna, persistent cavum septum pellucidum, thin corpus callosum, and increase brain volume, most of these changes can be seen in mid axial section [3,4]. MRI is useful in planning individualistic interventions to be more geared towards stimulating or promoting the affected part of the brain [2]. Based on such considerations, there is an increasing demand in automated diagnostic tools, which utilizes data of neuroimaging. Recently neuroimaging classification using artificial intelligence and deep learning methods had been shown significant promise, especially those using convolutional neural networks (CNNs) which is a traditional method with high overfitting [5]. This study proposes a model that uses EfficientNet-B0, supplemented with a Convolutional Block Attention Model (CBAM), to focus on a more valuable location and channel tuples. Instead of simple data augmentation, a more sophisticated techniques were used through advanced augmentation strategies (Cut Mix, Mix Up, Aug Mix) to enhance the variety of training and make the model more robust in diagnosing new cases. This study aimed to gain a better classification levels , reduce overfitting and confirm validity of the model results thorough cross-validation. It highlights the possibilities of neuroimaging and artificial intelligence in providing more specific and objective diagnosis of ASD.

Subjects and Methods

It was a retrospective diagnostic modeling study. The experimental data used in this study was acquired at the Kennedy Krieger Institute (KKI) location of the Autism Brain Imaging Data Exchange II (ABIDE II) program. A total of 211 brain MRI for 140 males and 71 females, 56 of them having autism spectrum disorder (ASD) and 155 are controls. Ages range 8-13 years. All participants were scanned using high-resolution T1-weighted structural MRI (s MRI). The dataset is publicly available through the Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC) platform at: https://www.nitrc.org/frs/?group id=404 [6,7].

This study employed a proposed deep learning model for ASD classification using 3D mid-slice axial T1-weighted brain MRI scan, of the ABIDE II dataset to train and test the suggested model. Mid slice image shows most of the ASD relevant structural changes. The work flow illustrated in figure 1.

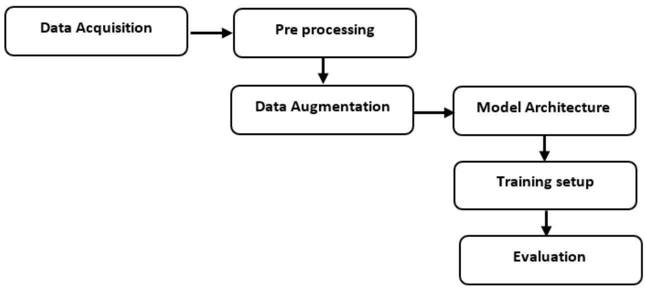

Figure 1: Overview of the proposed deep learning architecture and preprocessing pipeline for ASD classification from structural MRI data.

All neuroimaging scans were provided in the NIfTI format and underwent a standardized preprocessing pipeline prior to conversion into 2D inputs for the convolutional neural network. First, each MRI volume was inspected and preprocessed to improve anatomical consistency across subjects. To generate the 2D representations used in this study, a mid-slice was extracted from the axial orientation of each 3D volume. The mid-slice was defined as the voxel layer located exactly at the center index of the z-axis (i.e., slice index = Num slices / 2). This slice was selected because it consistently captures regions relevant to autism-related structural changes. Figure (2) shows the samples of mid slice axial section of brain MRI. Each extracted slice was exported to PNG format, resized to 224 × 224 pixels, and its pixel intensities were normalized to the range [0, 1] to ensure compatibility with the input expectations of the pretrained backbone and to promote stable optimization during training. To enhance model robustness and prevent overfitting, advanced augmentation strategies were employed during training:

- Mix Up (α = 0.4): linearly blends two training images and their labels, improving robustness and decision boundaries.
- Cut Mix (α = 1.0, probability = 0.5): replaces a random patch of one image with a patch from another, forcing the model to learn more spatially diverse features.
- Aug Mix (severity = 3, width = 2, depth = -1): applies multiple chained augmentations and blends the originals to enhance resilience to image perturbations.

These techniques are part of a broader class of mix-based augmentation methods that synthesize new training examples by combining input samples and labels or chaining diverse transformations, which has been shown to significantly enhance performance across various deep learning tasks [8]

This pipeline ensures that all inputs are anatomically aligned, artifact-reduced, uniformly scaled, and augmented to maximize the performance and reproducibility of the proposed deep learning model.

The proposed model is based on EfficientNet-B0, a computationally efficient convolutional neural network known for its compound scaling approach, which uniformly scales depth, width and resolution. The base model was initialized with pretrained ImageNet weights, facilitating transfer learning from natural image recognition to extracting features of medical imaging tasks [9], then the Convolutional Block Attention Module (CBAM) was inserted in the network. CBAM is an attention mechanism that sequentially applies channel-wise and spatial attention to enhance discriminative feature representation by emphasizing informative brain regions while suppressing irrelevant features [10] as shown in figure (3).

Following the attention mechanism the architecture includes a dense fully connected layer, activated with Re LU, followed by a dropout layer to prevent overfitting and a Soft max layer that outputs class probabilities of the two categories: ASD and Control.

The EfficientNet-B0 is a convolutional neural network architecture that fully fine-tuned. The Convolutional Block Attention Model (CBAM) is a lightweight, plug-and-play attention model. CBAM Improves EfficientNet-B0 for Medical Imaging, Channel attention improves discriminative feature selection, crucial for subtle ASD-related structural changes in MRI images. Spatial Attention enhances localization of structural abnormality or brain regions asymmetry. [9,10]

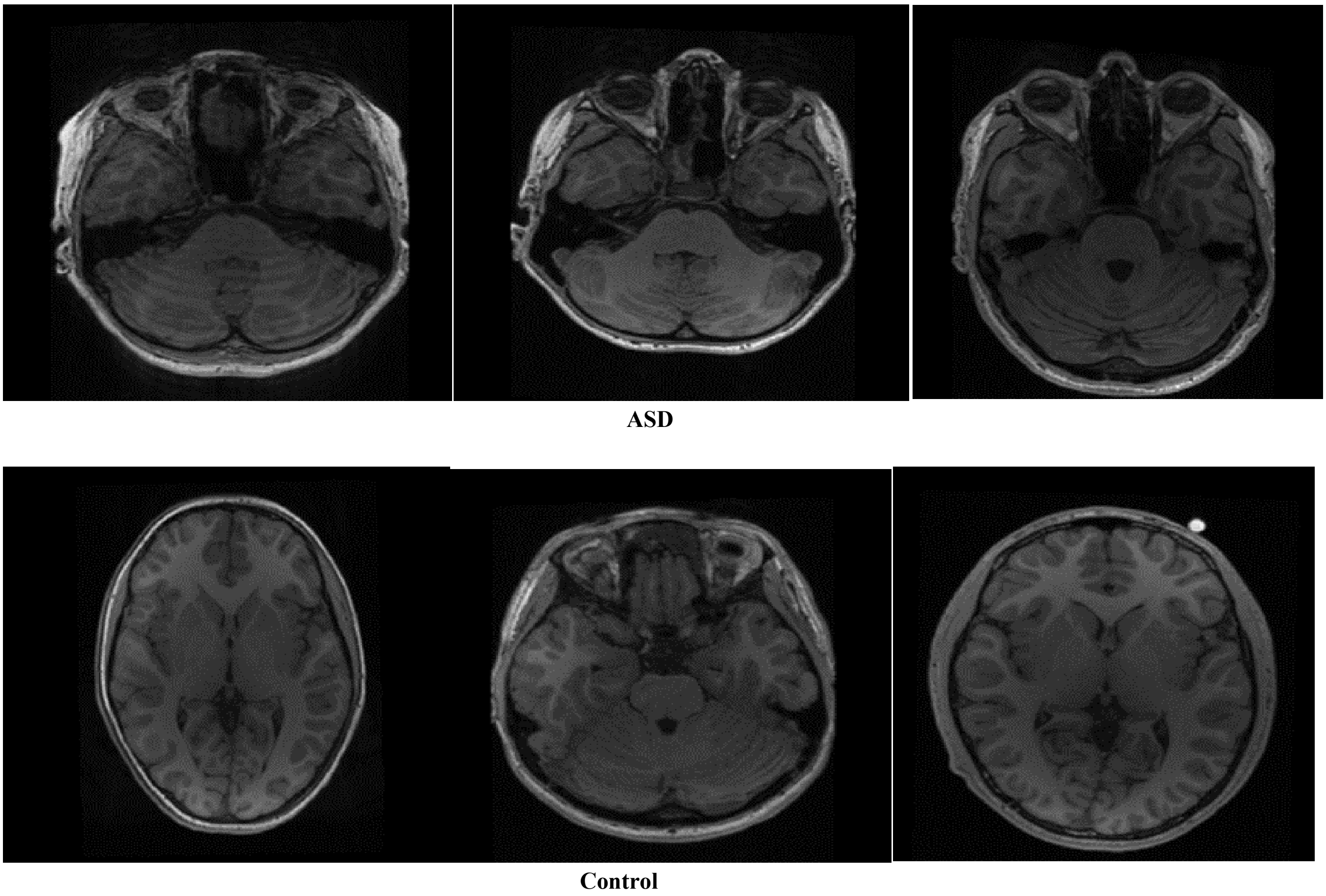

Figure (2): Samples of mid-slice images after preprocessing from the (ABIDE II KKI_1) dataset.

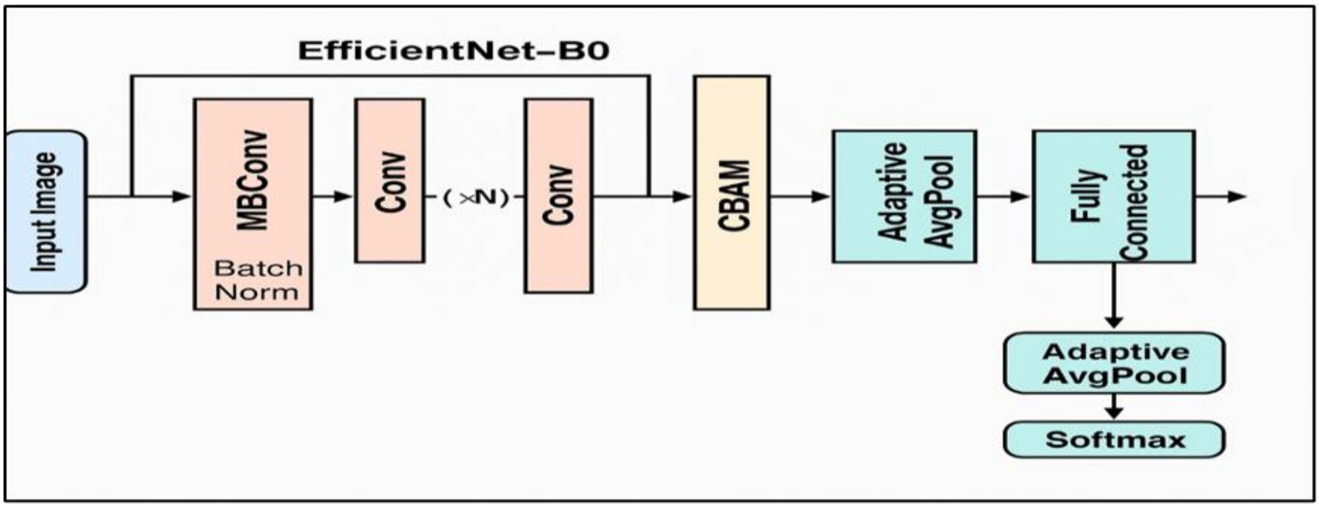

Figure 3: The proposed model.

Results

To evaluate the classification performance, a comprehensive set of metrics was computed on the validation set, which includes accuracy, precision, recall, sensitivity, F1-score, and specificity [11,12].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1 Score} = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \tag{4}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

The final results were analyzed using the python, Py Torch. To rigorously evaluate the effectiveness of the proposed EfficientNet-B0 with CBAM architecture, its performance was systematically compared with two widely adopted convolutional neural network (CNN) models: ResNet50 [13] and Squeeze Net [14]. ResNet50 employs residual learning, enabling the training of very deep networks that achieve a robust performance across diverse image classification tasks. It has been extensively applied in medical imaging, including brain MRI analysis. Squeeze Net, in contrast, is a lightweight architecture optimized for computational efficiency, maintaining competitive accuracy with significantly fewer parameters, making it suitable for real-time or resource-limited clinical environments. The models were trained for five different durations: 10, 20, 30, 40, and 50 epochs. In order to divide the data that was conducted in this study into training and validation sets, a Stratified Shuffle Split tool of the scikit-learn library was used. This is a tool that enables the division of the data with the balance of classes between the various sets, 70 % of the data can be used to train the data and 30 % to validate the data. The random state helps to reproduce identical splitting in the future experiment to eliminate the bias due to the uneven distribution of the classes (Autism vs. Control). This strategy can contribute to the enhancement of the accuracy of the model and stability throughout the training and evaluation process.

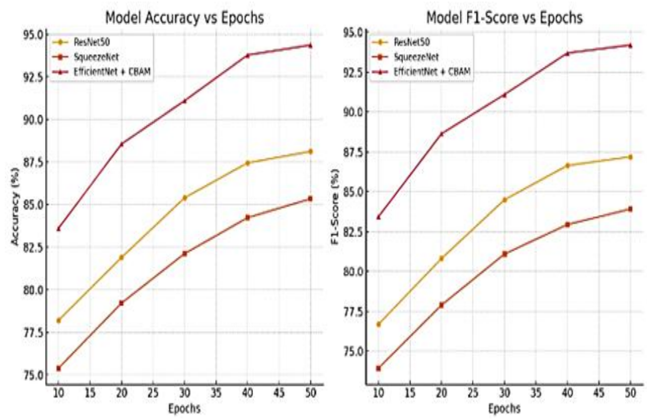

Figure 4: Accuracy and F1-Score progression

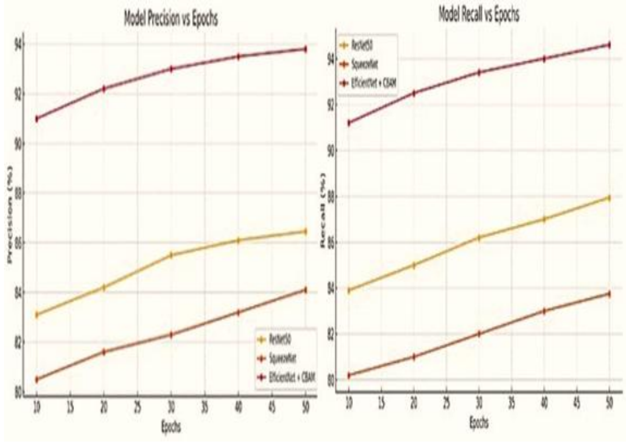

Figure 5: Precision and Recall progression

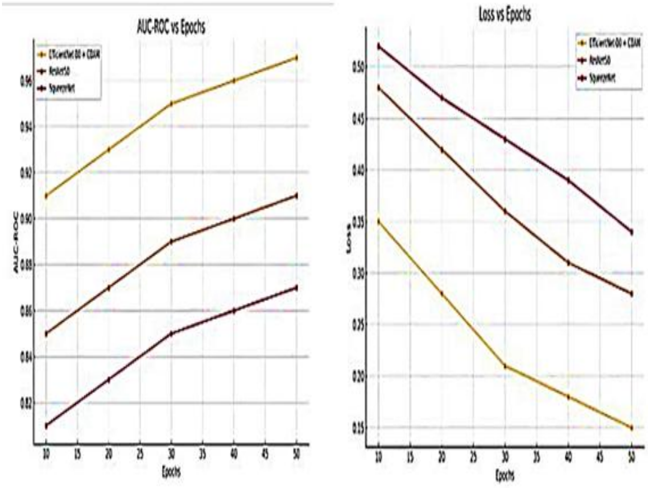

Figure 6: AUC-ROC and Loss progression

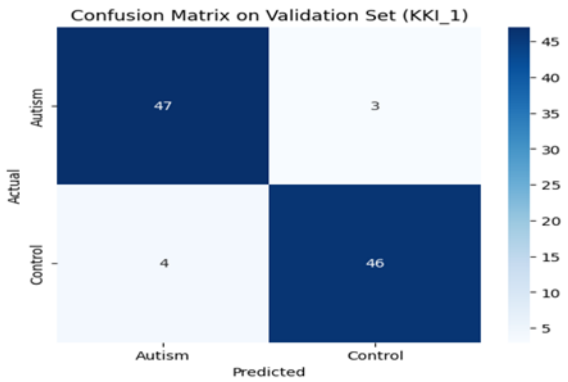

Figure 7: Confusion matrix of EfficientNet-B0 with CBAM for ASD vs. Control classification

Performance was evaluated at each epoch on validation set, using standard metrics; accuracy, precision, recall sensitivity, F1-Score and specificity as presented in Table (1). All models were implemented and analyzed using the python, Py Torch. The following settings were used during training, Cross Entropy Loss, Adam optimizer with a learning rate set at 0.0001, chosen for its adaptive learning capability, Epochs 50 complete passes through the training dataset were used to ensure convergence. Batch Size is 16, Hardware with an NVIDIA CUDA-enabled GPU.

Table one presents the validation results of the model across 50 epochs, showing its performance on the validation set, which was not directly used during training. Figures 4, 5, and 6 illustrate the dynamic behavior of model performance metrics across epochs. The performance is strong in terms of precision, recall, and F1-score.

In Figure 7, The Confusion matrix created by the code above illustrates the model's performance on the KKI-1 validation set. The rows indicate the real classes (Autism and Control), whereas the columns denote the forecasted classes. Each cell indicates the number of samples in that category. The validation accuracy of the model is (95.37%).

Table 1. Performance comparison of ResNet50, Squeeze Net, and EfficientNet-B0 with CBAM across 50 epochs

Epoch	Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Specificity
10	ResNet50	78.21%	76.30%	77.10%	76.70%	79.00
	SqueezeNet	75.40%	74.10%	73.80%	73.95%	76.10
	EfficientNet + CBAM	83.62%	82.70%	84.20%	83.44%	85.00
20	ResNet50	81.90%	80.45%	81.20%	80.82%	82.50
	SqueezeNet	79.22%	78.00%	77.80%	77.90%	79.90
	EfficientNet + CBAM	88.56%	88.10%	89.20%	88.64%	89.90
30	ResNet50	85.40%	84.10%	84.90%	84.50%	86.00
	SqueezeNet	82.12%	81.30%	80.90%	81.10%	83.00
	EfficientNet + CBAM	91.10%	90.80%	91.40%	91.10%	92.10
40	ResNet50	87.45%	86.30%	87.00%	86.65%	88.10
	SqueezeNet	84.23%	83.00%	82.90%	82.95%	84.90
	EfficientNet + CBAM	93.78%	93.30%	94.10%	93.70%	94.50
50	ResNet50	88.12%	86.45%	87.94%	87.19%	88.90
	SqueezeNet	85.34%	84.10%	83.75%	83.92%	85.90
	EfficientNet + CBAM	95.37%	93.80%	94.60%	94.20%	94.70

Discussion

ASD affects 1 in 60 children according to the World Health Organization. Early diagnosis in the first few years of a child's life significantly improves intellectual, social, and behavioral disabilities and overall health. Diagnosis based on behavioral assessment may necessitate an expert pediatrician or psychologist, which may not be accessible at the time in a large number of medical institutions. With advanced technology, machine learning models act as effective diagnostic tool [15,16].

This study integrates EfficientNet-B0 with CBAM to improve the model's capacity to focus on critical regions in the input features, thus boosting the representational power. Furthermore, the incorporation of multiple advanced and non-traditional data augmentation techniques, including Cut Mix, Mix Up, and Aug Mix, provides a substantial improvement in model robustness. The relative analysis of various architectures indicates that the proposed EfficientNet-B0 with CBAM mechanism outperforms all other architectures namely ResNet50 and Squeeze Net, this model rested at the highest performance and robustness in all evaluation epochs across validation set, with incremental improvements with increasing epochs, this indicate superior model stability, faster convergence, and enhanced capability in distinguishing ASD from control cases on ABID KKI_1, with an accuracy of 95.37 %, F1-score of 94.2%, sensitivity of 94.6% and 94.7% specificity, the model showed great discrimination power and superior classification performance. These visualizations emphasize the robustness of the proposed architecture, the contribution of CBAM attention in capturing discriminative features relevant to ASD, and its suitability for automated ASD diagnosis.

ResNet50, on the other hand, experienced a slow improvement in the first 10 epochs 78.2% and 88.1% at the end of 50 epochs, yielding moderate recall and specificity value (87.9% and 88.9%, respectively). On the same note, Squeeze Net, even being lightweight design, it showed lower performance with an accuracy of 85.3%, and failed to leverage sensitivity and precision, which lacks feature representation to a complicated neuroimaging data. Efficient Net + CBAM model however, used the scaling of compounds and refinement of attention to extract from MRI data a richer spatial and channel-wise representations. The model performance was higher but proximal to U-Net + CNN + RBF model suggested by Lim et al. [17] (2024), when the accuracy was 94.79, but he didn't achieve fewer trainable parameters and faster convergence, because EfficientNet-B0 used in the current study is a lightweight model. It also performs better compared to the Autoencoder + CNN model used by Sewani and Kashef [15] (2020), which achieved an accuracy of up to 84.05%, their suggested model has more hierarchical features which are optimized through attention systems. The results of this study were more accurate than 3D-Res2Net with attention by Zhang et al. [18], with an accuracy of 75%. Sharma and Tanwar [16] (2024) used an CNN model based on rs-fMRI data of ABIDE I and obtained an accuracy of 93.41 percent, which means a high level of within-site generalization and a low level of cross-site validation. Moreover, in a study by Chen et al. [19] (2021), the information presented is the attention-based Node-Edge Graph Convolutional Network (ANEGCN) with multisite MRI data, the accuracy was 72.7%, the authors emphasized that a different imaging sites and acquisition protocols causing a high degree of heterogeneity that adversely influences the generalization of models. Yuneas and Felouat [20] (2024) concentrated on the selection of features with the help of ML/DL classifiers with high sensitivity and specificity. Their findings provide a complement to our results as they show balanced performance in terms of sensitivity (92.4%) and specificity (93.7%), tested on multiple sites, which makes the findings more clinical to interpret. Finally, ASDC-Net (CNN-based) with 76.72% accuracy was suggested by Chandra et al. [21] (2023) on 1035 subjects. Although it performed better than some previous models, it had a weakness of high cost of computation and a moderate diagnostic performance. Comparatively, the proposed EfficientNet-B0 with CBAM has a lightweight but highly performing architecture that can deliver efficient inference and strong discriminative learning, which is more viable for large-scale clinical use. The proposed current model was also superb in terms of sensitivity and specificity because the confusion matrix implying the consistency of both ASD and control subjects. This consistency highlights the model's potential as a clinical decision support tool that would aid in the early detection of ASD based on the structural abnormality seen on MRI.

Limitations of the study include the small sample size, lack of data balance between the ASD and control group numbers, and the use of 2D middle-slice images rather than full-volume scans, which may affect model generalization.

Conclusion

The approach achieves high performance. It highlights its potential for clinical decision support systems in ASD diagnosis from brain MRI. It is a valuable and rapid tool for computer-aided ASD diagnosis and screening of Children with a high-risk family history, hence early detection for timely control and interventions.

Acknowledgments

The Authors sincerely acknowledge those who made the datasets available online at https://www.nitrc.org/frs/?group_id=404

Funding

No funding resources

Conflict of Interest

The authors declare that they have no conflicts of interest.

Data availability

Data are available upon reasonable request.

Author Contributions

The integrity of entire study guarantied by RR1, RR2; study concepts, data acquisition and data analysis, all authors; manuscript writing, editing RR1, RR2; revision for important intellectual content, approval of final version of the manuscript, all authors; agrees to ensure any questions related to the work are appropriately resolved, RR1, RR2; literature research, clinical studies, experimental studies, statistical analysis, all authors.

All authors meet the ICMJE criteria for authorship and agree to be accountable for all aspects of the work.

Ethical information

This research did not involve human participants, human personal data. Therefore, ethical review and approval were not required for this study in accordance with institutional guidelines and national regulations; the dataset images included in this study were freely accessible online at https://www.nitrc.org/frs/?group_id=404.

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References

[1] Al-Khalidi RR, Al-Khalidy RR, Kurdi SZ. Hybrid 3D CNN and Swin Transformer for Autism Classification Through Structural and Functional Brain MRI. Al-Rafidain Journal of Medical Sciences (ISSN 2789-3219). 2025 Nov 23;9(2):266-71. https://doi.org/10.54133/ajms.v9i2.2559

[2] Ecker C. The neuroanatomy of autism spectrum disorder: An overview of structural neuroimaging findings and their translatability to the clinical setting. Autism. 2017;21(1):18-28. https://doi.org/10.1177/1362361315627136

[3] Afify MF, Hasan RM, Abdel-Hakeem MN, Ali MW. Brain MRI in Children with Autism Spectrum Disorder. Minia Journal of Medical Research. 2025 Jan 1;36(1):214-9. https://doi.org/10.21608/mjmr.2024.273523.1682
[4] Chen R, Jiao Y, Herskovits EH. Structural MRI in autism spectrum disorder. Pediatric research. 2011 May;69(8):63-8. https://doi.org/10.1203/PDR.0b013e318212c2b3
[5] Sherkatghanad Z, Akhondzadeh M, Salari S, Zomorodi-Moghadam M, Abdar M, Acharya UR, Khosrowabadi R, Salari V. Automated detection of autism spectrum disorder using a convolutional neural network. Frontiers in neuroscience. 2020 Jan 14;13:1325. https://doi.org/10.3389/fnins.2019.01325
[6] Di Martino A, Milham MP, Chen B, Nath T, O'Connor D, Floris D, et al. Autism Brain Imaging Data Exchange II (ABIDE II – KKI site). NITRC; 2017. https://www.nitrc.org/frs/?group_id=404
[7] Di Martino A, Milham MP, Chen B, Nath T, O'Connor D, Floris D, et al. Autism Brain Imaging Data Exchange II (ABIDE II). NITRC/FCP-INDI; 2017. https://fcon_1000.projects.nitrc.org/indi/abide/abide_II.html
[8] Lewy D, Mańdziuk J. An overview of mixing augmentation methods and augmentation strategies. arXiv preprint arXiv:2107.09887. 2021 Jul 21. https://doi.org/10.48550/arXiv.2107.09887
[9] Tan M, Le Q. Efficientnet: Rethinking model scaling for convolutional neural networks. InInternational conference on machine learning 2019 May 24 (pp. 6105-6114). PMLR. https://doi.org/10.48550/arXiv.1905.11946
[10] Woo S, Park J, Lee JY, Kweon IS. Cbam: Convolutional block attention module. In Proceedings of the European conference on computer vision (ECCV) 2018 (pp. 3-19). https://doi.org/10.48550/arXiv.1807.06521
[11] Alkhalidy R, AlShemmary E. Accurate Bladder Cancer Classification and Prognosis with a Hybrid Vision Transformer. International Journal of Intelligent Engineering & Systems. 2025 Jan 1;18(1). https://doi.org/10.22266/ijies2025.0229.43
[12] Razaq R, AlShemmary EN, Lu Z. A survey on bladder cancer detection and classification using deep learning algorithms. InAIP Conference Proceedings 2024 Oct 11 (Vol. 3232, No. 1, p. 020026). AIP Publishing LLC. https://doi.org/10.1063/5.0236313
[13] Mukti IZ, Biswas D. Transfer learning-based plant diseases detection using ResNet50. In: 2019 4th International Conference on Electrical Information and Communication Technology (EICT). IEEE; 2019. p. 1-6. https://doi.org/10.1109/EICT48899.2019.9068780
[14] Iandola FN, Han S, Moskewicz MW, Ashraf K, Dally WJ, Keutzer K. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. arXiv preprint arXiv:1602.07360. 2016 Feb 24. https://doi.org/10.48550/arXiv.1602.07360
[15] Sewani H, Kashef R. An autoencoder-based deep learning classifier for efficient diagnosis of autism. Children. 2020 Oct 14;7(10):182. https://doi.org/10.3390/children7100182
[16] Sharma S, Tanwar S. Model for autism disorder detection using deep learning. Int J Artif Intell. 2024;13(1):391-8. https://doi.org/10.11591/ijai.v13.i1.pp391-398
[17] Chern LH, Al-Hababi AYS. A novel hybrid U-Net-RBF and CNN-RBF algorithm for autism spectrum disorder classification. J Cogn Sci Hum Dev. 2024. https://doi.org/10.33736/jcshd.6778.2024
[18] Zhang H, Wang Z. Multi-scale convolutional network for fMRI-based diagnosis of autism spectrum disorder. In: 2022 7th International Conference on Signal and Image Processing (ICSIP). IEEE; 2022. p. 377-81. https://doi.org/10.1109/ICSIP55141.2022.9887213
[19] Chen Y, Yan J, Jiang M, Zhao Z, Zhao W, Zhang R, Kendrick KM, Jiang X. Attention-based node-edge graph convolutional networks for identification of autism spectrum disorder using multi-modal mri data. InChinese Conference on Pattern Recognition and Computer Vision (PRCV) 2021 Oct 22 (pp. 374-385). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-88010-1_31
[20] Younas A, Felouat H. Autism Spectrum Disorder Classification Using The Most Correlated Features. In2024 8th International Conference on Image and Signal Processing and their Applications (ISPA) 2024 Apr 21 (pp. 1-6). IEEE. https://doi.org/10.1109/ISPA59904.2024.10536846
[21] Chandra A, Verma S, Raghuvanshi AS, Sharma M. ASDC-Net: Optimized convolutional neural network-based automatic autism spectrum disorder classification using rs-fMRI data. IETE J Res. 2023:1-10. https://doi.org/10.1080/03772063.2023.2196979