Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Deep Learning Models for Autism Spectrum Disorder Prediction Using MRI Images from ABIDE II Dataset

Nema Rose D. Rivera[1,2*], Thelma D. Palaoag[3]

[1]*Doctor in Information Technology Student, Department of Information Technology, College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines*
[2]*Faculty Member, Don Mariano Marcos Memorial State University, College of Computer Science, Agoo, La Union, Philippines*
[3]*Program Coordinator, Department of Information Technology, College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines*
Email: nrrivera@dmmmsu.edu.ph

This study evaluates the effectiveness of various deep learning models in predicting Autism Spectrum Disorder (ASD) using MRI images from the ABIDE II dataset. The primary objective is to determine the potential of these models for accurate ASD classification. Three deep learning architectures were utilized: SqueezeNet, GoogleNet, and ResNet50. Data augmentation was applied, and each model was trained on MRI images for 60 epochs at a learning rate of 1e-05. Additionally, 10-fold cross-validation was performed to evaluate model robustness. The results showed that SqueezeNet achieved a training accuracy of 75.78% and a validation accuracy of 66.60% without cross-validation. GoogleNet reached a training accuracy of 66.41% and a validation accuracy of 65.06%, while ResNet50 showed a training accuracy of 65.37% and a validation accuracy of 64.09%. Notably, using 10-fold cross-validation, ResNet50 achieved an improved validation accuracy of 65.98%. These findings indicate that deep learning models can effectively predict ASD using MRI images, with SqueezeNet demonstrating the highest accuracy without cross-validation, while ResNet50 showed superior generalization with cross-validation. These findings suggest the potential for further optimization and exploration of additional data attributes to improve prediction accuracy.
Keywords: autism detection, machine learning, ABIDE, MRI images

1. Introduction

Autism Spectrum Disorder is a life-long neurodevelopmental disorder characterized by atypical brain development, leading to impaired nuero-functions in speech, motor coordination, social activities and communication as compared to the individuals of Typical Development(TD) [1-4]. Despite significant advancements in understanding its neurobiological underpinnings, there remains a substantial gap in the early and accurate diagnosis of ASD. This gap persists due to the complex and heterogeneous nature of the disorder, which complicates the identification of reliable biomarkers and the development of effective diagnostic tools. Individuals with ASD frequently experience comorbidities such as intellectual disabilities, seizure disorders, and anxiety, further complicating their developmental paths. The challenges associated with the disorder extend beyond the individual, significantly impacting families, caregivers, and guardians. The emotional and practical burden of caring for someone with ASD can lead to increased stress and financial strain on families. According to various studies, the lifetime healthcare costs for individuals with ASD are estimated to be $3.6 million [5]. These costs encompass a range of expenses, including medical care, therapies, and support services, highlighting the extensive economic and social implications of ASD not just for individuals but for their entire support network.

According to the Centers for Disease Control and Prevention (CDC), the prevalence of ASD has increased, with roughly 1 in 36 children affected [6]. ASD has a genetic component, meaning that certain hereditary factors play a role in its development [7,8]. However, these genetic influences are not a sole determinant; they interact with various environmental factors, highlighting the complexity of how ASD develops in individuals.

Given this complexity, early detection and intervention become even more crucial. Research indicates that the brain's remarkable plasticity during early childhood allows for a more effective response to interventions when ASD is detected and treated early. Initiating treatment in these crucial early years can lead to significantly improved outcomes compared to interventions that start later in life. This underscores the importance of timely diagnosis and intervention in maximizing the potential for positive developmental changes.

In this context, the advancement of diagnostic tools is vital, and recent years have seen the increasing application of Machine Learning (ML) classifiers to neuroimaging data for diagnosing psychiatric disorders, including ASD. These methods promise to facilitate and expedite the diagnostic process, potentially revolutionizing early diagnosis [9,10,11,12] and treatment for ASD, offering new hope for affected individuals and their families. Magnetic resonance imaging (MRI) is a powerful tool for detecting various neuropsychiatric and neurodegenerative disorders, such as schizophrenia[13,14], dementia, depression[15], autism[16,17,18], ADHD[19], and Alzheimer's[20], by observing anatomical patterns using structural MRI data or linking changes in the brain's functional architecture to psychiatric health conditions using functional MRI data. Studies applying ML algorithms to ASD brain imaging data have achieved impressive results. For instance, one study classified individuals as autistic or typically developing (TD) based on their fMRI brain activation, achieving up to 97% accuracy within single sites of the ABIDE dataset. This study also identified a specific pattern of brain activation linked to a psychological factor, self-representation, which was prevalent in control patients but nearly absent in autistic participants [21]. In another study,

researchers obtained a 76.67% classification accuracy when differentiating ASD participants from IQ-matched typically developing participants in a sample of 178 individuals [22]. These findings underscore the potential of ML algorithms to accurately classify and understand the neural underpinnings of ASD, offering a significant step forward in the field of neuroimaging and neurodevelopmental disorder diagnosis.

Building on this progress, Santana et al. (2022) conducted a comprehensive review on the application of resting-state fMRI (rsfMRI) in autism research, noting a significant increase in the number of studies up until 2019 [23]. They emphasized the expanding body of research, which suggests continued growth in subsequent years, underscoring the importance of incorporating newer studies and various MRI modalities to understand autism more thoroughly and improve diagnostic and therapeutic approaches.

The Autism Brain Imaging Data Exchange (ABIDE) dataset stands as a cornerstone in neuroimaging research, offering an extensive collection of brain imaging data from individuals with Autism Spectrum Disorder (ASD) and typically developing (TD) controls. This dataset has been instrumental in deepening the understanding of the neural mechanisms underlying not only ASD but also other brain disorders [24, 25, 26]. By enabling large-scale analyses and cross-site comparisons, ABIDE has facilitated numerous studies. For instance, Nielsen et al. [27] utilized the ABIDE dataset to classify individuals with autism versus control subjects based on brain connectivity measurements. Analyzing 964 subjects, the study generated 7266 regions of interest (ROIs) from seed voxels, forming a connectivity matrix by calculating pairwise correlations between each ROI. This study exemplifies the dataset's capacity to support complex, large-scale analyses, significantly contributing to our comprehension of ASD.

The selection of machine learning model categories—classical linear, classical nonlinear, and deep learning—plays a crucial role in determining model performance in neuroimaging data analysis. Notably, deep learning models generally outperform classical linear models, which in turn tend to outperform classical nonlinear models. In a comprehensive study by Mellema (2022), a systematic evaluation of 12 different machine learning classifiers was performed to assess their effectiveness in ASD studies [28]. These models were selected for their varied statistical complexity and proven high performance in similar research contexts. The analysis included three classical linear ML models known for their simplicity, six classical nonlinear ML methods of moderate complexity, and three deep learning approaches of higher complexity. Classical models were implemented using Scikit-learn and XGBoost, whereas deep learning models utilized Keras, TensorFlow, and Caffe. Among the deep learning models, a classifier combining a dense neural network with a bidirectional long short-term memory (LSTM) network achieved high prediction performance, even with non-sequential fixed vector data. Furthermore, the BrainNetCNN classifier, a graph-convolutional network, was trained using solely the functional connectivity matrix, demonstrating its utility in this domain. This thorough evaluation highlights the superior capability of deep learning models in uncovering complex patterns in neuroimaging data, reinforcing their potential in advancing ASD research.

Moreover, the extracted 2D images from the MRI dataset hold significant potential for identifying autism. Studies have demonstrated the efficacy of 2D MRI scans in various

neuroimaging research, including the detection of neurodevelopmental disorders. For instance, the use of 2D convolutional neural networks (CNNs) has shown promise in classifying autism from MRI scans, leveraging the high-resolution structural details captured in 2D images [29]. Other research has utilized 2D MRI slices to train machine learning models for the early diagnosis of autism, highlighting the practical applications and potential impact of such approaches [30]. These studies underscore the importance of using 2D MRI data as a potent tool for advancing autism identification and research.

This research aims to leverage deep learning techniques to predict Autism Spectrum Disorder (ASD) using neuroimaging data from the ABIDE II dataset. By identifying potential biomarkers through advanced analysis of brain imaging data, this study seeks to enhance diagnostic accuracy and enable earlier intervention strategies. The implications of this research are profound, as establishing reliable biomarkers could significantly improve the understanding of ASD's neurobiological underpinnings and inform personalized treatment approaches. Ultimately, this work has the potential to transform autism diagnostics and intervention, offering hope for better outcomes for individuals with ASD and their families.

2. Materials and Methods

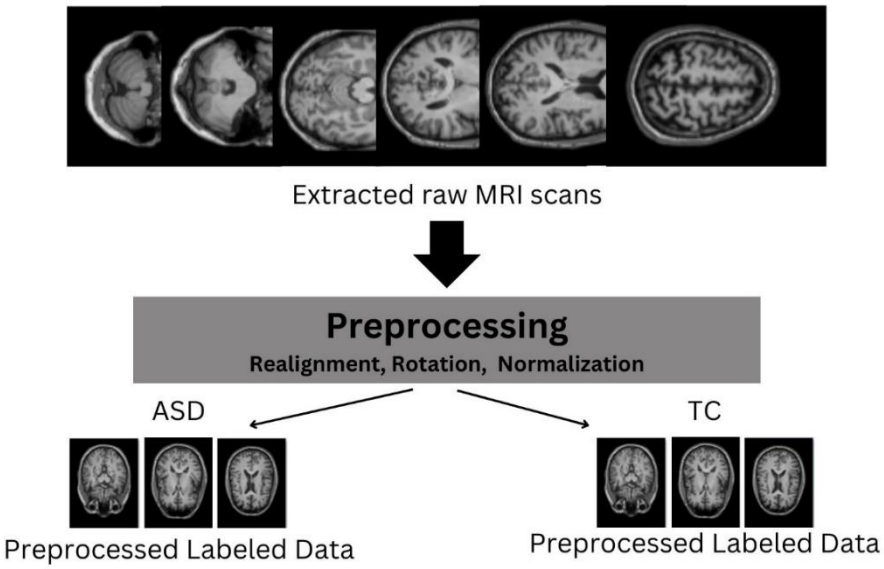
A. Dataset Acquisition

The ABIDE II dataset [31] served as the cornerstone for this research, comprising MRI data from 1,054 subjects, including longitudinal data from previous subjects. The dataset is divided into two distinct classes: the ASD group, with 497 subjects, and the TC group, with 555 individuals. Both baseline and longitudinal data were used, ensuring a comprehensive analysis of the ASD population over time. In addition to MRI scans, the dataset includes valuable phenotypic and demographic information such as diagnosis, age, handedness, and IQ, which were utilized for reference and labeling purposes. These datasets were sourced directly from the ABIDE II website, a large-scale initiative that aggregates and shares brain imaging data from individuals with ASD and typically developing controls across multiple international sites. The ABIDE II project benefits from contributions from renowned institutions, including the Barrow Neurological Institute (BN), Erasmus University Medical Center (EMC), ETH Zurich (ETH), and Indiana University (IU), among others. These institutions provided a diverse array of data, including both structural and functional MRI scans, along with detailed phenotypic profiles.

For this study, we specifically leveraged the resting-state MRI dataset, which is crucial for understanding the neurobiological underpinnings of ASD. This comprehensive approach not only enriches the dataset but also enhances the robustness of our findings by incorporating longitudinal data of the same subjects, allowing for a greater number of MRI scans datasets.

B. Rs-fMRI preprocessing

To prepare the resting-state functional MRI (rs-fMRI) data for machine learning classification, several preprocessing steps were implemented to enhance the quality of the image data. The figure describes the overall process of preprocessing the images.



Initially, the raw images from the ABIDE II dataset were realigned using the Statistical Parametric Mapping (SPM) 12 toolbox in MATLAB 2024a, which corrected for any head movements that may have occurred during data acquisition. The realignment process involves estimating the movement parameters across time points to correct for subject motion during scanning, which is crucial for accurate temporal alignment of the images. The realignment is accomplished using the spm_realign function, that generated a set of transformation parameters based on the calculated motion. The parameters were then applied to the original images, creating a new set of realigned neuroimaging informatics technology initiative (NIfTI) files. Following the realignment, fMRI scans were extracted from the time series for each subject, yielding three brain scan images per participant.

Given the heterogeneity of data sources across multiple sites and the variability in the imaging technology employed, many of the raw scans exhibited distortions such as stretching and twisting, along with differing dimensions. To standardize the dataset, all images underwent rotation, resizing, and normalization procedures, resulting in a uniform image resolution of 277x277 pixels. These preprocessing steps are crucial for ensuring consistency in the quality of the neuroimaging data, thereby facilitating more accurate machine learning classification and analysis of brain function in studies related to Autism Spectrum Disorder (ASD) .

Finally, the data images were labeled according to the two categories: Autism Spectrum Disorder (ASD) and typically developing (TD) individuals. The dataset included a total of 1,620 images for ASD and 1,836 for TD, culminating in 3,456 images sourced from 1,152 subjects.

C. Machine Learning

Deep learning models were applied and rigorously evaluated on a categorized dataset to assess their performance in classifying neuroimaging scans. Specifically, the architectures utilized

included SqueezeNet, GoogleNet, and ResNet, each selected for their unique strengths in image classification tasks.

SqueezeNet was employed to classify neuroimaging data for autism prediction. SqueezeNet is a lightweight deep learning architecture, designed to reduce model size while maintaining high accuracy. It achieves this through the use of fire modules, which consist of squeeze layers and expand layers. The squeeze layers utilize 1x1 convolutional filters to reduce the number of input channels, while the expand layers apply a mix of 1x1 and 3x3 filters to capture spatial features. These filters can learn patterns within a small neighborhood of pixels, which is essential for understanding the spatial arrangement of brain structures in the MRI data. This dual approach allows SqueezeNet to maintain spatial resolution while extracting diverse features at various scales. This architecture minimized the number of parameters compared to traditional CNNs, making it efficient for resource-constrained environments. During training, SqueezeNet's efficiency in parameter management and its ability to learn complex feature representations from MRI scans were leveraged to enhance the classification accuracy of ASD and TD subjects. This study demonstrates SqueezeNet's capability to effectively analyze neuroimaging data, providing a promising approach for identifying potential biomarkers for autism with reduced computational demands.

In this study, GoogleNet, another deep learning architecture, was employed to efficiently classify complex neuroimages for autism prediction. GoogleNet employs inception modules, which process multiple convolutional filters of different sizes in parallel, enabling the model to capture both fine-grained details and broader patterns from MRI scans. This design allows for diverse feature extraction, enhancing the model's ability to learn intricate representations of the data. Unlike traditional CNNs, GoogleNet uses global average pooling instead of fully connected layers, reducing model size and mitigating overfitting. With its 22-layer depth facilitated by inception modules, the network effectively propagates gradients during training, improving accuracy. Additionally, GoogleNet's efficient parameter management makes it suitable for limited computational resources, such as mobile or embedded systems in clinical settings, allowing for real-time neuroimaging analysis. This study leveraged GoogleNet's capabilities to enhance classification performance, contributing to the identification of potential biomarkers for autism.

ResNet-50 is deep convolutional neural network and was selected for this study due to its robust architecture for handling complex image classification tasks. ResNet-50 introduces residual learning through skip connections, which helps mitigate the vanishing gradient problem and allows the network to learn more effectively from deeper layers. To leverage learned features from the dataset, which include edge detectors, texture descriptors, and more complex patterns found MRI data images. These features served as a strong foundation, allowing the model to recognize and differentiate between various image from its label. The final layers of ResNet-50 were fine-tuned or replaced to adapt to the new dataset, which consists of labeled MRI scans categorized as either Autism Spectrum Disorder (ASD) or Typically Developing (TD). The adaptation process involves retraining these layers on the MRI data, where the model learns to identify the subtle and specific features relevant to distinguishing between classes. This fine-tuning helps the model adjust its parameters to better fit the characteristics of the neuroimaging data, leveraging the pre-trained features as a starting point while adapting to the new, domain-specific task. The training process consisted of

multiple iterations where the model learns to minimize the loss function, which quantifies the difference between the predicted labels and the actual labels (ASD or TD). During each iteration, the Adam optimizer was employed to adjust the model's parameters. The Adam optimizer handles sparse gradients and adapt the learning rate of each parameter to ensure a faster and more stable convergence.

D. Augmentation

To optimize the dataset for training, data augmentation techniques were applied to increase the diversity and robustness of the MRI scans without collecting additional data. This approach helps in mitigating overfitting and improving the generalization capability of the deep learning models.

For SqueezeNet, data augmentation included random rotations, translations, and horizontal reflections. These transformations ensured that the model learned to recognize features from different angles and orientations, making it more robust to variations in head position and other spatial characteristics of the MRI scans. GoogleNet utilized similar augmentation techniques, such as random cropping, scaling, and intensity adjustments. These augmentations allowed the inception modules within GoogleNet to capture a wide range of spatial and intensity variations, improving its ability to detect fine-grained and broad patterns in the MRI data. ResNet-50 employed a comprehensive set of augmentations, including brightness, contrast, and saturation adjustments, along with geometric transformations like rotations and translations. This extensive augmentation strategy helped ResNet-50 to become more resilient to different variations in the MRI scans, enhancing its feature extraction capabilities.

Overall, the application of data augmentation across SqueezeNet, GoogleNet, and ResNet-50 was integral in optimizing the dataset. It expanded the training dataset, effectively reducing the risk of overfitting by preventing the models from memorizing the training data. This improvement in generalization allowed the models to perform better on the validation and test datasets, leading to higher accuracy and robustness in classifying MRI scans for autism prediction. This technique significantly contributed to the reliability and accuracy of autism prediction in this study.

3. Results and Discussion

Table 1 shows the results from the deep learning models trained on the MRI dataset demonstrate varying performance across architectures under different training conditions. The training accuracy and validation accuracy were measured with and without cross-validation, using 60 epochs at a learning rate of 1e-05.

Table 1 Average Performance Metrics of Deep Learning Models with and without Cross-Validation

Model	Without cross validation		With 10-fold cross validation	
	Training Accuracy	Validation Accuracy	Training Accuracy	Validation Accuracy
SqueezeNet	75.78	66.60	73.40	63.40
GoogleNet	66.409	65.06	64.45	62.74
ResNet50	65.37	64.09	67.31	65.98

In the absence of cross-validation, SqueezeNet achieved the highest training accuracy of 75.78% and a validation accuracy of 66.60%. This indicates that SqueezeNet was particularly effective in learning from the training data, potentially due to its compact architecture that allows for efficient parameter utilization. GoogleNet followed with a training accuracy of 66.41% and validation accuracy of 65.06%, showing a reasonably robust performance but lacking the generalization seen in SqueezeNet. ResNet50, while slightly behind, recorded a training accuracy of 65.37% and a validation accuracy of 64.09%, suggesting it also managed to learn useful representations but may have struggled with overfitting given its relatively deep architecture.

Introducing a 10-fold cross-validation revealed a decline in performance across all models. SqueezeNet's training accuracy dropped to 73.40%, with a validation accuracy of 63.40%. This indicates that the model's ability to generalize to unseen data decreased, which is a common challenge when more rigorous validation techniques are applied. GoogleNet's training accuracy also saw a reduction to 64.45%, with a validation accuracy of 62.74%, further highlighting the difficulties of maintaining high generalization in deeper networks. Interestingly, ResNet50 exhibited an improvement in validation accuracy to 65.98%, despite a slight drop in training accuracy to 67.31%. This suggests that ResNet50's architecture, particularly its residual connections, may confer better generalization capabilities even with more stringent validation methods.

4. Conclusions

This study evaluated deep learning models—specifically SqueezeNet, GoogleNet, and ResNet50—on MRI scans for autism classification, providing valuable insights into their performance capabilities. SqueezeNet emerged as the top performer, achieving an impressive training accuracy of 75.78% and a strong validation accuracy of 66.60% without cross-validation. These results underscore SqueezeNet's effectiveness in feature extraction from neuroimaging data, highlighting its potential for practical applications in autism diagnosis. However, the introduction of 10-fold cross-validation revealed a performance decline across all models, emphasizing the challenges related to generalization when tested on unseen data. This decline in performance is consistent with challenges observed in the broader field of medical image classification, where model accuracy often decreases when evaluated on real-world, unseen datasets due to factors like dataset variability and noise.

ResNet50, despite its lower initial performance, demonstrated a significant improvement in validation accuracy, reaching 65.98% with cross-validation. This enhancement indicates that deeper architectures like ResNet50 are better equipped to learn complex representations that can adapt to varying data conditions, thus showcasing their robustness in handling diverse input scenarios. In comparison to other baseline results in the medical field, where deep learning models often achieve validation accuracies ranging from 60% to 85% for tasks like disease classification and early diagnosis from medical imaging, ResNet50's performance is competitive, particularly in the context of a challenging neurodevelopmental disorder like autism. GoogleNet delivered moderate results, further highlighting the importance of careful model selection based on dataset characteristics and specific goals.

The findings of this study highlight the critical importance of selecting appropriate model architectures and incorporating data augmentation strategies to optimize performance in neuroimaging applications. SqueezeNet's strong results without cross-validation reflect its efficiency in capturing relevant features for autism classification. Meanwhile, ResNet50's improved validation accuracy with cross-validation demonstrates its capacity for generalization in more rigorous evaluation settings, which aligns with current literature in neuroimaging, where models are often fine-tuned to balance between accuracy and generalization.

These results are consistent with similar studies in the field of medical image classification. For instance, studies in medical imaging have demonstrated that deep learning models such as CNNs and ResNet variants can outperform traditional machine learning classifiers, with accuracy rates generally ranging from 70% to 90% for tasks like detecting tumors in CT scans or classifying Alzheimer's disease from brain MRI scans. Such outcomes suggest that while deep learning models, particularly those like ResNet50, may not always achieve the highest training accuracy, their ability to generalize and handle complex, unseen data makes them a promising choice for autism diagnosis.

5. Implications

The implications of this study extend across several domains of model architecture selection, dataset robustness, and the search for ASD biomarkers. The findings underscore the importance of choosing the right model for specific neuroimaging tasks. While SqueezeNet demonstrated strong performance in terms of training accuracy, the improvements observed in ResNet50 with 10-fold cross-validation highlight the significance of deeper architectures in learning complex representations and their capacity for generalization. This suggests that future research in deep learning should focus on balancing model complexity with computational efficiency, while also emphasizing the importance of data augmentation and robust cross-validation techniques to optimize model performance and reliability.

Moreover, the study highlights the critical need for robust and comprehensive data in neuroimaging studies like ABIDE II dataset. The findings suggest MRI scan may potentially work well in predicting autism but may also perform better if the study included additional data attributes, such as temporal information. Integrating longitudinal MRI data to capture changes over time may provide deeper insights into the progression of autism and enhance the predictive power of the models. Furthermore, ensuring high-quality, well-annotated data is essential for training reliable and accurate deep learning models, advocating for ongoing efforts to expand and refine datasets like ABIDE II to support more sophisticated and accurate neuroimaging analyses.

Finally, this study exposes a gap in the search for reliable biomarkers for Autism Spectrum Disorder (ASD). While deep learning models showed promise in classifying autism from MRI scans, the variability in performance across models underscores the fact that no single model architecture is universally optimal. This variability highlights the need for continued exploration of diverse model architectures, data augmentation techniques, and multimodal approaches that combine neuroimaging with genetic and behavioral data. Future research

should aim to identify robust biomarkers for ASD, ultimately leading to earlier, more accurate diagnoses and personalized treatment approaches for individuals with autism.

Acknowledgements

The authors thank University of the Cordilleras, the Commission on Higher Education and the Don Mariano Marcos Memorial State University for their support towards the fulfillment of this scholarly endeavor.

References

1. Mahan, S., & Matson, J. L. (2011). Children and adolescents with autism spectrum disorders compared to typically developing controls on the Behavioral Assessment System for Children, (BASC-2). Research in Autism Spectrum Disorders, 5(1), 119-125
2. Raju, V. L., Aishwarya, B., Kumar, V. P., Kumar, K. A., Reddy, P. N., & Rao, M. J. (2022). Deep learning approach to predict autism spectrum disorder (ASD). Int. J. Food Nutr. Sci, 11, 3619-3631.
3. Santana, C. P., de Carvalho, E. A., Rodrigues, I. D., Bastos, G. S., de Souza, A. D., & de Brito, L. L. (2022). rs-fMRI and machine learning for ASD diagnosis: a systematic review and meta-analysis. Scientific reports, 12(1), 6030.
4. Kong, Y., Gao, J., Xu, Y., Pan, Y., Wang, J., & Liu, J. (2019). Classification of autism spectrum disorder by combining brain connectivity and deep neural network classifier. Neurocomputing, 324, 63-68.
5. Cakir, J., Frye, R. E., & Walker, S. J. (2020). The lifetime social cost of autism: 1990□2029. Research in Autism Spectrum Disorders, 72, 101502.
6. Maenner, M. J. (2021). Prevalence and characteristics of autism spectrum disorder among children aged 8 years□autism and developmental disabilities monitoring network, 11 sites, United States, 2018. MMWR. Surveillance Summaries, 70.
7. Wang, C., Geng, H., Liu, W., & Zhang, G. (2017). Prenatal, perinatal, and postnatal factors associated with autism: a meta-analysis. Medicine, 96(18), e6696.
8. Hertz-Picciotto, Irva, Lisa A. Croen, Robin Hansen, Carrie R. Jones, Judy Van de Water, and Isaac N. Pessah. "The CHARGE study: an epidemiologic investigation of genetic and environmental factors contributing to autism." Environmental health perspectives 114, no. 7 (2006): 1119-1125.
9. Kassraian-Fard, P., Matthis, C., Balsters, J. H., Maathuis, M. H., & Wenderoth, N. (2016). Promises, pitfalls, and basic guidelines for applying machine learning classifiers to psychiatric imaging data, with autism as an example. Frontiers in psychiatry, 7, 177.
10. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & S□nchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.
11. Varshney, N., More, A., Singh, K. U., Dewangan, D. K., Pathak, K. K., & Parida, P. K. (2023, December). Machine Learning-Based Analysis of fMRI Data for Autism Spectrum Disorder Diagnosis. In 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI) (Vol. 1, pp. 1-6). IEEE.
12. Rivera, N. R. D. (2024). Machine Learning-Based Exploration of Structural MRI for Autism Spectrum Disorder Detection. Nanotechnology Perceptions, 569-577.
13. Jafri, M. J., Pearlson, G. D., Stevens, M., & Calhoun, V. D. (2008). A method for functional network connectivity among spatially independent resting-state components in schizophrenia. Neuroimage, 39(4), 1666-1681.
14. Calhoun, V. D., Sui, J., Kiehl, K., Turner, J., Allen, E., & Pearlson, G. (2012). Exploring the psychosis functional connectome: aberrant intrinsic networks in schizophrenia and bipolar disorder. Frontiers in psychiatry, 2, 75.

15. Craddock, R. C., Holtzheimer III, P. E., Hu, X. P., & Mayberg, H. S. (2009). Disease state prediction from resting state functional connectivity. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 62(6), 1619-1628.
16. Rakhimberdina, Z., Liu, X., & Murata, T. (2020). Population graph-based multi-model ensemble method for diagnosing autism spectrum disorder. Sensors, 20(21), 6001.Das
17. Plitt, M., Barnes, K. A., & Martin, A. (2015). Functional connectivity classification of autism identifies highly predictive brain features but falls short of biomarker standards. NeuroImage: Clinical, 7, 359-366.Das
18. Anderson, J. S., Nielsen, J. A., Froehlich, A. L., DuBray, M. B., Druzgal, T. J., Cariello, A. N., ... & Lainhart, J. E. (2011). Functional connectivity magnetic resonance imaging classification of autism. Brain, 134(12), 3742-3754.
19. Zhang, T., Li, C., Li, P., Peng, Y., Kang, X., Jiang, C., ... & Xu, P. (2020). Separated channel attention convolutional neural network (SC-CNN-attention) to identify ADHD in multi-site rs-fMRI dataset. Entropy, 22(8), 893.Das
20. Chen, G., Ward, B. D., Xie, C., Li, W., Wu, Z., Jones, J. L., ... & Li, S. J. (2011). Classification of Alzheimer disease, mild cognitive impairment, and normal cognitive status with large-scale network analysis based on resting-state functional MR imaging. Radiology, 259(1), 213-221.Das
21. Just, M. A., Cherkassky, V. L., Buchweitz, A., Keller, T. A., & Mitchell, T. M. (2014). Identifying autism from neural representations of social interactions: neurocognitive markers of autism. PloS one, 9(12), e113879.Fsdf
22. Plitt, M., Barnes, K. A., Wallace, G. L., Kenworthy, L., & Martin, A. (2015). Resting-state functional connectivity predicts longitudinal change in autistic traits and adaptive functioning in autism. Proceedings of the National Academy of Sciences, 112(48), E6699-E6706.
23. Santana, C. P., de Carvalho, E. A., Rodrigues, I. D., Bastos, G. S., de Souza, A. D., & de Brito, L. L. (2022). rs-fMRI and machine learning for ASD diagnosis: a systematic review and meta-analysis. Scientific reports, 12(1), 6030.
24. Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., & Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical, 17, 16-23.
25. Pires, L. M. D. O. (2023). Assessing brain functional connectivity in Parkinson□s disease using explainable Artificial Intelligence methods (Doctoral dissertation).
26. Li, W., Wang, S., & Liu, G. (2022, April). Transformer-based model for fMRI data: ABIDE results. In 2022 7th International Conference on Computer and Communication Systems (ICCCS) (pp. 162-167). IEEE.
27. Nielsen, J. A., Zielinski, B. A., Fletcher, P. T., Alexander, A. L., Lange, N., & Bigler, E. D. (2013). Multisite functional connectivity MRI classification of autism: ABIDE results. Front. Hum. Neurosci. 7 (SEP), 599.
28. Mellema, C. J., Nguyen, K. P., Treacher, A., & Montillo, A. (2022). Reproducible neuroimaging features for diagnosis of autism spectrum disorder with machine learning. Scientific reports, 12(1), 3057.
29. Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., & Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage: Clinical, 17, 16-23.
30. Li, G., Liu, T., Wang, L., Qin, J., & Jiang, R. (2021). A 2D slice-based deep learning model for identifying autism spectrum disorder. Journal of Neuroscience Methods, 347, 108955. https://doi.org/10.1016/j.jneumeth.2021.108955
31. Di Martino, A., & Milham, M. P. (2016). Autism Brain Imaging Data Exchange II (ABIDE II) [Data set]. Child Mind Institute. https://data-sharing.org/abide/abide-iiDas