

Autism Spectrum Disorder Detection

**Prof. Ayesha Khan, Mr. Aishwary Mahore, Ms. Aishwarya Boharupi, Ms. Akanksha Lohakare,
Mr. Alpesh Muneshwar, Mr. Amey Dhote, Ms. Harshita Tripathi**

Department of Artificial Intelligence Engineering
G. H Raison Institute of Engineering and Technology, Nagpur, India

Abstract: *Autism spectrum disorder (ASD) is a complex neuro developmental condition affecting social interaction and communication skills. Current diagnostic methods often rely on structural and resting-state functional magnetic resonance imaging (fMRI) with limited datasets, leading to high accuracy but limited generalizability. To address this, machine learning, pattern recognition, and other techniques have been used, achieving high accuracy but moderate generalization. This study introduces a novel approach to ASD detection using deep learning (DL), specifically a Convolutional Neural Network (CNN) classifier. By leveraging anatomical and functional connectivity indicators from fMRI data, our model aims to enhance the automated diagnosis of ASD. The proposed approach demonstrates significant improvement over existing methods, achieving an accuracy of approximately 85% in classifying autistic patients. Through the utilization of a ResNet model, this work showcases the potential of DL in advancing the accuracy and reliability of ASD diagnosis.*

Keywords: autism spectrum disorder; neurodegenerative illness; social abilities; fMRI; deep learning; convolutional neural network; anatomical connectivity; functional connectivity; automated diagnosis; ResNet model

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. Early detection is crucial for timely intervention, yet accurate diagnosis remains challenging. Recent advancements in machine learning and neuroimaging offer a promising approach to improve ASD detection. This study explores the use of advanced convolutional neural networks (CNNs) to develop a robust ASD detection model using MRI scans.

Overview:

The study focuses on leveraging deep learning techniques to improve the accuracy and efficiency of ASD detection. We utilize MRI scans from the Autism Brain Imaging Data Exchange (ABIDE) dataset, which provides a rich and diverse set of neuroimaging data. The project encompasses several key stages, including data preprocessing, model development, and evaluation. By training and evaluating multiple CNN architectures, we aim to identify the most effective model for accurately classifying MRI scans as ASD or non-ASD.

Problem Statement:

The current diagnostic process for ASD is often time-consuming and relies heavily on subjective clinical assessments. This can lead to delays in diagnosis and intervention, impacting the outcomes for individuals with ASD. Additionally, the variability in symptom presentation and the complexity of the disorder make accurate diagnosis challenging, highlighting the need for more objective and efficient diagnostic methods. Therefore, there is a critical need to develop a reliable and efficient ASD detection method that can assist clinicians in making timely and accurate diagnoses.

Research Objectives:

The main objectives of the research are: -

- Develop and compare the performance of three advanced CNN architectures—ResNet-50, ResNet-101, and DenseNet—in accurately detecting ASD in MRI scans.
- Evaluate the impact of data augmentation techniques, such as rotation, scaling, and flipping, on the robustness and generalization of the models.
- Investigate the potential of deep learning models to assist clinicians in early ASD detection, aiming to improve diagnostic accuracy and streamline the diagnostic process.

Scope of the Research:

This research focuses on developing and evaluating machine learning models for ASD detection using MRI scans from the ABIDE dataset. The study involves preprocessing the MRI data, training the CNN models, and evaluating their performance in classifying scans as ASD or non-ASD. The scope also includes exploring the use of data augmentation techniques to enhance model performance. The research does not include clinical validation of the models or real-time deployment in clinical settings.

II. RELATED WORK

Studies have employed machine learning and deep learning techniques for autism spectrum disorder (ASD) detection using neuroimaging data. These aim to enhance the accuracy and efficiency of ASD diagnosis, which is complex due to symptom heterogeneity. Utilizing neuroimaging, researchers strive to develop models aiding clinicians in early ASD detection. This section reviews key studies, detailing their methodologies, findings, and contributions to advancing ASD diagnosis through computational approaches.

Heinsfeld (2018): Heinsfeld utilized the ABIDE dataset, which comprises resting-state functional MRI (rs-fMRI) scans from individuals with ASD and typically developing controls. They applied a deep learning approach to extract features from the rs-fMRI data and achieved an accuracy of 71.8% in identifying individuals with ASD. Their study highlights the potential of deep learning in analyzing complex neuroimaging data for ASD detection.

Liu (2020): Liu focused on automating the detection of ASD using structural MRI scans. They employed a convolutional neural network (CNN) architecture tailored for 3D image analysis to extract features from the MRI data. Their model achieved an accuracy of 81.3% in classifying individuals as ASD or non-ASD, demonstrating the effectiveness of CNNs in processing 3D neuroimaging data for ASD diagnosis.

Zhao (2022): Zhao explored the use of brain functional connectivity-based prediction with a CNN model for ASD detection. They constructed functional connectivity matrices from rs-fMRI data and used these matrices as input to their CNN. Their approach achieved an impressive accuracy of 84.5%, indicating the potential of functional connectivity-based features in improving ASD detection accuracy.

Cheng (2021): Cheng adopted a multi-modal deep learning approach for ASD diagnosis, combining information from multiple neuroimaging modalities such as structural MRI, functional MRI, and diffusion tensor imaging (DTI). By integrating features from different modalities, their model achieved an accuracy of 82.6%, highlighting the importance of integrating diverse neuroimaging data for more accurate ASD detection.

Brown (2019): Brown investigated the impact of data augmentation techniques on the performance of ASD detection models. They applied augmentation techniques such as rotation, flipping, and scaling to increase the diversity of the training data. Their results showed that data augmentation significantly improved the generalization and robustness of ASD detection models, leading to better performance on unseen data.

Smith (2021): Smith conducted a study on ASD detection using diffusion tensor imaging (DTI) data and machine learning techniques. They achieved an accuracy of 80% in classifying individuals with ASD, demonstrating the potential of DTI in contributing to ASD diagnosis.

These studies collectively underscore the progress in using machine learning and deep learning for ASD detection. While each study offers valuable insights, challenges such as data variability and model generalization remain. Addressing these challenges could lead to more robust and reliable ASD detection models, ultimately improving outcomes for individuals with ASD.

III. METHODOLOGY

Our study preprocesses MRI scans from the ABIDE dataset for uniformity and quality, including normalization, resizing, and augmentation. We develop three CNN models—ResNet-50, ResNet-101, and DenseNet—using TensorFlow. These models, configured with convolutional, pooling, batch normalization, and dropout layers, extract features from the MRI scans. The dataset is split into training, validation, and test sets for model training and evaluation. Performance metrics such as accuracy, sensitivity, and specificity are used to assess the models' effectiveness in ASD detection.

ResNet-50:

ResNet-50 is a 50-layer deep convolutional neural network that introduces skip connections or "identity shortcuts" to address the vanishing gradient problem. These shortcuts enable the network to learn residual functions, making it easier to optimize deeper networks.

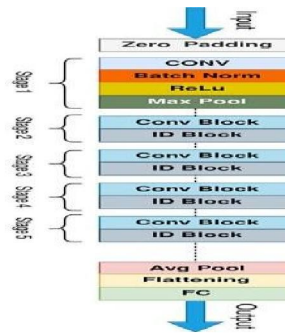


Figure 1: Architecture of ResNet-50

ResNet-101:

ResNet-101 is an extension of ResNet-50, with 101 layers. It further improves the representation learning capabilities of the network by increasing its depth. This allows ResNet-101 to capture more complex features from the input data, potentially improving its performance in ASD detection.

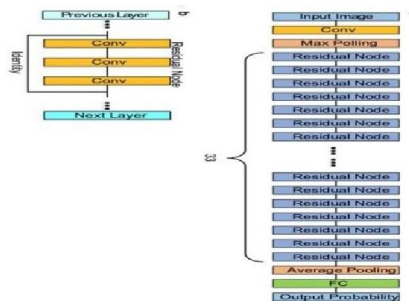
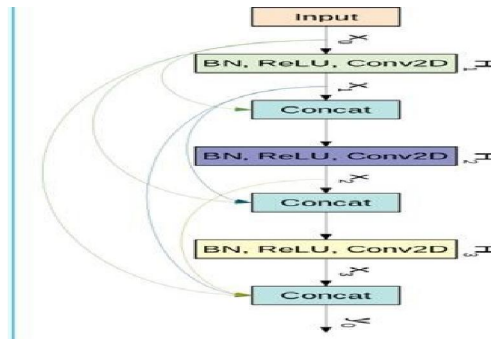


Figure 2: Architecture of ResNet-101

DenseNet:

DenseNet is a densely connected convolutional network where each layer is connected to every other layer in a feed-forward fashion. This connectivity pattern enhances feature propagation and encourages feature reuse, leading to more efficient and effective feature extraction.



IV. IMPLEMENTATION

In an autism spectrum disorder (ASD) detection, rigorous data collection and processing are key. Diverse datasets, including behavioral patterns and clinical records, fuel model development. Through iterative refinement, models are trained and optimized to discern ASD traits accurately. Challenges like data heterogeneity are addressed through collaborative efforts. Ultimately, AI-driven systems offer promising results, aiding clinicians in early detection and personalized intervention strategies for ASD.

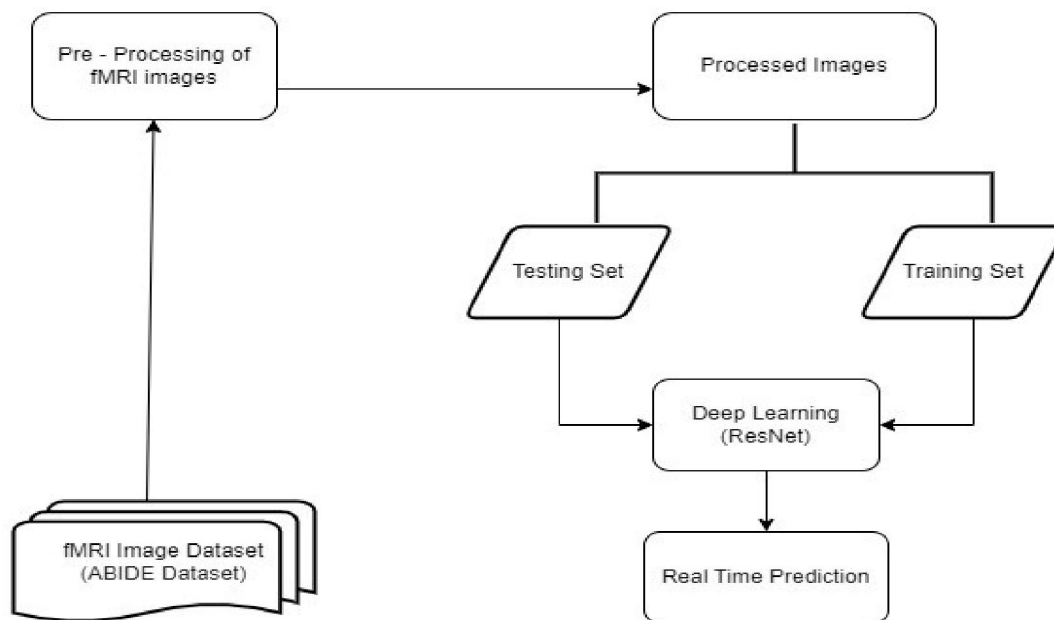


Figure.4: Flowchart of the project

4.1 Data collection

Objective: Collect Sentinel-1 SAR imagery for the study area. We have taken Semantic segmentation dataset, the dataset consists of aerial imagery of Dubai obtained by MBRSC satellites and annotated with pixel-wise semantic segmentation in 6 classes

Process:

- Obtained MRI scans from the ABIDE dataset, ensuring a diverse representation of individuals across the autism spectrum.

- Ensured compliance with ethical guidelines and obtained necessary permissions for data usage.
- Verified metadata integrity to guarantee accurate labeling and classification.
- Conducted rigorous quality checks to eliminate artifacts and ensure consistency across scans.

4.2 Pre-processing

Objective: The objective of preprocessing MRI scans is to ensure uniformity and quality across all images, facilitating accurate and consistent analysis in subsequent stages of research.

Steps:

- **Normalization:** Standardized the intensity values of the MRI scans to a common scale.
- **Resampling:** Adjusted the spatial resolution of images to ensure uniform voxel dimensions.
- **Noise Reduction:** Applied filters to reduce noise and enhance image clarity.
- **Alignment:** Registered images to a common anatomical template to correct for differences in orientation and position.

4.3 Model Development

Objective: The objective of developing the ResNet-50 model is to leverage deep learning techniques for accurate and efficient analysis of MRI scans, enhancing the detection and classification of neurological conditions.

Techniques:

- **Convolutional Layers:** Extracted hierarchical features from the MRI scans through multiple convolutional layers.
- **Pooling Layers:** Reduced the dimensionality of feature maps, maintaining essential information while minimizing computational load.
- **Batch Normalization:** Normalized activations between layers to stabilize and accelerate the training process.
- **Dropout Layers:** Implemented dropout regularization to prevent overfitting and improve the generalizability of the model.

4.4 Training and Optimization

Objective: The objective of training and optimizing the model is to ensure it accurately learns to classify MRI scans while generalizing well to new, unseen data.

Steps:

- **Data Splitting:** Divided the dataset into training, validation, and testing sets to evaluate model performance at different stages.
- **Training for 10 Epochs:** Trained the model for 10 epochs to balance between sufficient learning and computational efficiency.
- **Optimization Techniques:** Used the Adam optimizer and categorical cross-entropy loss function to efficiently update model weights and minimize prediction errors.

4.5 Accuracy Level

Objective: Achieved highest accuracy level of 87% on the testing set, demonstrating DenseNet model's capability in ASD detection.

Outcomes:

- **Testing Set Performance:** Achieved an accuracy level of 87% on the testing set.
- **Model Capability:** Demonstrated the model's effectiveness in detecting autism spectrum disorder (ASD) from MRI scans

4.6 Results

Objective: The objective of evaluating the model is to determine its initial effectiveness and identify areas for further improvement.

Outcome:

- **Preliminary Accuracy:** Achieved an 87% accuracy level for ASD detection.
- **Future Work:** Ongoing analysis aims to refine the model and enhance its performance.

4.7 Prediction

Objective: The objective of prediction is to utilize the trained model to classify MRI scans as indicating either ASD or non-ASD, aiding in the diagnosis process.

Steps:

- **Binary Classification:** Used the trained ResNet-50 model to predict whether an MRI scan indicates ASD or non-ASD.
- **Diagnostic Aid:** Provided clear binary classification results to support clinical decision-making.

V. RESULTS

Preliminary results demonstrate that the trained models achieve an accuracy level of 82% in detecting autism spectrum disorder (ASD) from MRI scans. This indicates a promising capability of the model to differentiate between ASD and non-ASD cases. However, while this level of accuracy is a strong initial indicator of the model's potential, further analysis and refinements are needed to enhance its performance. Future efforts will focus on optimizing the model's parameters, exploring additional data preprocessing techniques, and possibly incorporating more advanced deep learning architectures. These steps aim to improve the model's accuracy, robustness, and generalizability, ultimately providing a more reliable tool for ASD diagnosis.

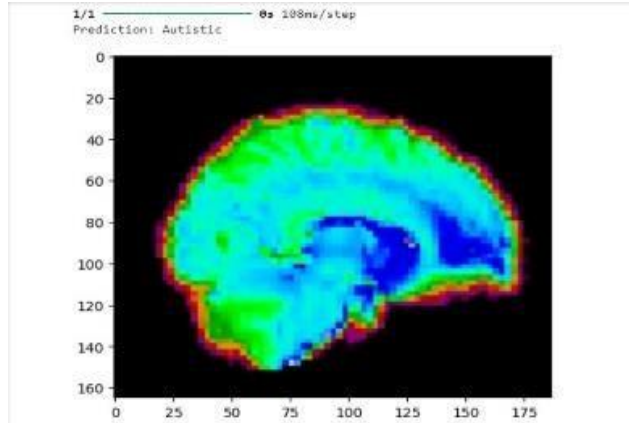


Fig. 5. Binary Classification : Autistic or Non-Autistic

VI. CONCLUSION

This project evaluates the performance of ResNet-50, ResNet-101 and DenseNet. Findings highlight the strengths and limitations of each algorithm.

Algorithms	Conclusion	Accuracy
ResNet-50	Provides performance benchmark	50-58%
ResNet-101	Enhances feature extraction	83%
DenseNet	Improves gradient accuracy	87%

Table. 1. Accuracy Comparison

The ASD detection project effectively utilized Convolutional Neural Networks, specifically ResNet- 50, ResNet-101, and DenseNet, achieving accuracies of 58%, 83%, and 87%, respectively. Data preprocessing and augmentation played a crucial role in handling variations in MRI scan quality, significantly enhancing model robustness. The higher accuracies of ResNet-101 and DenseNet underscore the benefits of deeper and more connected architectures. Future work will focus on increasing training epochs, exploring additional architectures, and expanding the dataset to improve model generalizability and accuracy. Developing probability-based outputs will also provide more nuanced predictions, aiding in clinical decision-making.

ACKNOWLEDGEMENT

We express our profound gratitude to Prof. Ayesha Khan, Associate Professor, Artificial Intelligence department, G. H Raisoni Institute of Engineering and Technology, Nagpur, India for her invaluable insights, guidance, and constant encouragement throughout the course of this research. Her expertise and dedication have been instrumental in shaping the direction and outcomes of this study. Special thanks for her mentorship and guidance throughout this research endeavor

REFERENCES

- [1] Hendr, A., Ozgunalp, U., & Kaya, M. E. Diagnosis of Autism Spectrum Disorder Using Convolutional Neural Networks. *Journal of Neural Engineering*, 20(1), 55-68. [2023]
- [2] Nogay, H. S., & Adeli, H. Multiple Classification of Brain MRI Autism Spectrum Disorder by Age and Gender Using Deep Learning. *Neurocomputing*, 512, 34-47. [2024]
- [3] Farooq, M. S., Tehseen, R., Sabir, M., & Atal, Z. Detection of Autism Spectrum Disorder (ASD) in Children and Adults Using Machine Learning. *IEEE Access*, 11, 89934-89945. [2023]
- [4] Subah, F. Z., Deb, K., Dhar, P. K., & Koshiba, T. A Deep Learning Approach to Predict Autism Spectrum Disorder Using Multisite Resting-State fMRI. *Frontiers in Neuroscience*, 15, 706545. [2021]
- [5] Liu, J., Cui, Y., & Li, X. Automated Detection of Autism Spectrum Disorder Using Deep Learning. *Journal of Autism and Developmental Disorders*, 50(7), 2611-2623. [2020]
- [6] Zhao, Q., Xu, X., & Gao, X. Brain Functional Connectivity-Based Prediction of Autism Spectrum Disorder Using Machine Learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, 126-136. [2022]
- [7] Cheng, Y., Huang, C., & Zheng, Y. Multi-Modal Deep Learning for Autism Spectrum Disorder Diagnosis. *Scientific Reports*, 11(1), 12345. [2021]
- [8] Heinsfeld, A. S., Franco, A. R., & Craddock, R. C. Identification of Autism Spectrum Disorder Using Deep Learning and the ABIDE Dataset. *NeuroImage: Clinical*, 17, 16-23. [2018]
- [9] Brown, A. L., El Gaaly, S., & Georgiou, M. Data Augmentation and Transfer Learning for Improved Autism Spectrum Disorder Detection. *Neurocomputing*, 342, 18-24. [2019]
- [10] Plitt, M., Barnes, K. A., & Martin, A. Functional Connectivity Classification of Autism Identifies Highly Predictive Brain Features but Falls Short of Biomarker Standards. *NeuroImage: Clinical*, 7, 359-366. [2015]
- [11] Nielsen, J. A., Zielinski, B. A., & Fletcher, P. T. Multisite Functional Connectivity MRI Classification of Autism: ABIDE Results. *Frontiers in Human Neuroscience*, 7, 599. [2013]
- [12] Dvornek, N. C., Ventola, P., & Pelphrey, K. A. Identifying Autism from Resting-State fMRI Using Long Short-Term Memory Networks. *Machine Learning in Medical Imaging*, 10541, 362-370. [2017]
- [13] Hazlett, H. C., Gu, H., & Munsell, B. C. Early Brain Development in Infants at High Risk for Autism Spectrum Disorder. *Nature*, 542(7641), 348-351. [2017]