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Hybrid Artificial Intelligence and Psychological Tests Based Autism Spectrum Disorders Identification Using 3D MRI Images

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Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects social communication and behavior with children, characterized by diverse symptoms and varying severity levels. This paper explores the application of artificial intelligence (AI) algorithms combined with efficient psychological tests for autism detection which is one of the most important and rapidly expanding ailments in the world that are now difficult to diagnose since there are no exact established diagnostic standards. In order to find biomarkers linked to various conditions, AI will analyse vast amounts of data, speeding up the diagnosis procedure and increasing the accuracy of the results. Beside common psychological scales, this study focuses on developing a three Dimensional (3D) deep learning models based approaches for ASD identification using structural Magnetic Reasoning Imaging (sMRI) and functional Magnetic Reasoning Imaging (fMRI) data, integrating models such as 3D Resnet, 3D DenseNet, and 3D VGG16 to extract spatial patterns associated with ASD. To evaluate the performance of our proposed system, we conducted several experiments based on multiple parameters that have been performed using the publicly challenged ABIDE dataset of unconstrained images. The obtained experimental results proved the effectiveness of the proposed system against other CNN architectures, as well as with recent state-of-the-art methods.

Keywords: Autism Spectrum Disorder (ASD), Psychological scales, sMRI, fMRI, 3D CNN, ABIDE, Accuracy.

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Introduction

The brain coordinates all the functions required with ease that enabling us to stay alive. From the rhythmic rhythm of breathing to the subtle ballet of blood circulation, digestion, and even the regulation of body heat, this incredible organ enables us to live with ease **(Elisabeth et al., 2003).** Apart from these physiological functions, the brain is also the center of our intellectual and emotional life. It is what allows us to perceive the world, to reason, to make decisions, and to remember. Every thought, every emotion, every move we make is the result of a complex and perfectly orchestrated brain activity.

And yet, despite this appearance of perfection, the brain is also vulnerable. A simple disruption of this intricate system can lead to severe disorders that affect our behavior, perception, and even our ability to communicate with others. Among the many disorders that can plague the brain, autism spectrum disorders are some of the more complex and confounding. Autism spectrum disorder (ASD) is a complex neurodevelopmental disorder characterized by persistent challenges in social interaction, communication, and restricted or repetitive behaviors. Individuals with ASD generally struggle with social signals, emotional regulation, and adapting to routines. The prevalence of ASD has been steadily increasing. The prevalence of ASD is estimated to be one in a hundred people worldwide **(Zeiden et al., 2022).**

Making early and accurate diagnoses is essential for timely intervention and improving the quality of life for affected individuals **(Zwaigenbaum et al ., 2015).** However, an accurate diagnosis may be difficult. Indeed, there is no medical test to diagnose the disorder, such as a blood test traditional Generally, traditional diagnostic methods rely on behavioral assessments and clinical evaluation, which are subjective, time-consuming, and prone to variability among practitioners. This approach depends on experienced professionals, and an incorrect diagnosis can impact families and education, increasing the risk of depression, eating disorders, and self-harm **(Hosozawa et al., 2021).**

The lack of objective biomarkers for ASD makes early detection challenging, leading to delayed interventions that can significantly impact cognitive and social development. As a result of that, there is a growing need for data-driven diagnostic methods that can complement existing clinical assessments and provide a more reliable understanding of ASD related brain alterations. Most recently, due to advances in technology, recent advances in neuroscience offer new opportunities for studying the brain processes involved with autism.

Structural Magnetic Resonance Imaging (sMRI) and resting-state functional MRI (rs-fMRI) that uses magnetic fields and radio waves to create detailed images of the internal structures of the body, particularly the brain are gaining popularity and significance in recent times **(Liu et al., 2017),** are the most widely used neuroimaging modalities that have been utilized for brain research in patients with (ASD), they're provides valuable insight into how people with ASD possess brains that differ from all other people's brains. Based on this data, researchers can tell whether there are usual brain activity patterns that can be attributed to autism, and ultimately could mean faster and more efficient diagnostic methods.

A large cohort of studies has considered automated computer-aided diagnosis of autism. One of these technologies is Deep Learning “DL”, which has aroused great attention recently, and its role in analyzing medical data has been proven to be effective and efficient in many tasks of computer-aided medical diagnosis, by enabling more accurate efficiency in many functions

of computer-aided medical diagnosis, including automated analysis of complex neuroimaging data and ASD detection based on.

In this research work, we present the development of an early diagnosis system for autism based on MRI data and psychological standards. The purpose of this work is to create a diagnostic support system that can detect autism much earlier than the appearance of its first clinical symptoms, which would allow intervention at a stage where treatments can be more effective. Sophisticated computational techniques are, however, required to process high-dimensional MRI data. This introduces the question of how deep learning can improve the accuracy, efficiency, and objectivity of ASD diagnosis based on MRI information.

Our paper is organized as follows, section 1 is a "Background" to this work, which describes autism spectrum disorder (symptoms, risks, etc.). In section 2, we state the challenges of early identification, diagnosis of ASD using artificial intelligence, and the latest findings of some previous studies using both machine learning (ML) and deep learning (DL). Section 3 gives a detailed description of the proposed 3D deep learning models (VGG16, ResNet and DenseNet). In section 4 an explanation to ABIDE (Autism Brain Imaging Data Exchange) dataset and its contents, with a description of its pre-processing. Then, we presents and discusses the most important performance metrics of the obtained results. Finally we have ended with a conclusion.

2 Literature Review

2.1 *Clinical Psychological Methods*

The severity of autism spectrum disorder in children can be assessed and diagnosed using psychological scales. These tools are used with further behavioural and developmental evaluations conducted by experts to determine a child's degree of autism.

2.1.1 The Childhood Autism Rating Scale (CARS)

CARS was created since 1988, it has validated psychometric data from several nations, is a simple tool to assess ASD.It is used to assess how severe autism is and how it affects the kid. It aids in distinguishing autistic youngsters from those with other developmental disorders. It is still regarded as one of the greatest and most popular clinical scales **(Stevanovic et al., 2021)**. In Indian population; the CARS showed strong psychometric properties for diagnosing suspected children of having autism, the study **(Russell et al., 2010)** achieved sensitivity of 81.4%, and specificity of 78.6%.

2.1.2 Autism Diagnostic Observation Schedule (*ADOS)*

ADOS is gold standard for official autism diagnosis evaluations **(Kamp-Becker et al., 2018)**. It is an interactive monitoring tool that evaluates social interaction abilities through a number of games and activities. Children from the age of two to adulthood can use it. In **(Bastiaansen et al., 2011)**. The ADOS was able to correctly classify 74.2% of the cases in our sample as having ASD or not (based on the clinical diagnosis assigned).

2.1.3 (Psycholinguistic Abilities Assessment Profile Scale (PEP-3)

PEP-3 scale is both diagnostic and evaluative. Along with determining a child's skills and weaknesses, it assesses the severity of autism **(Zhagüi-Tenesaca et al., 2024).** It is appropriate for kids between the ages of two and seven and a half. In **(Abderrahmane et al., 2024),** 116 children with autism spectrum disorder, aged from 2 to 12 years were used to validate the PEP-

3's applicability in the Arab (Algerian-Tunisian) context in February 2024. The PEP-3's principle validity was further enhanced by each subtest's good internal consistency; the results show that the scale exhibits an overall stability rate of 0.95 in the Algerian-Tunisian environment.

2.2 *Artificial Intelligence Methods*

Early autism identification is being revolutionised by artificial intelligence algorithms . Early and precise diagnosis is made possible by these technology, which examine children's voice and speech variations, facial expressions, behavioural patterns and MRI images.

2.2.1 Machine learning techniques

Machine learning is a branch of artificial intelligence which is based on involving statistical models that help computers to learn and decide without being explicitly coded. It includes training techniques on large data base to identify patterns and relationships and then using these patterns to predict about new data **(Jordan et al., 2015).** Traditional studies have examined some machine learning models for the diagnosis of ASD. It's typically a two-label problem with the dataset having two labels: ASD and typically Control (ASD/TC) individuals. **Table 1** gives results of some studies that utilized ML for classification of MRI images for ASD detection:

Table 01: ASD diagnosis using MRI and ML models: (SVM), (RF), and (LR).

Model	Data	Subjects	Max Accuracy	Reference
SVM Support Vector Machine	fMRI	403 ASD, 468 TC	67.28%	**(Yang et al., 2021).**
	fMRI	506 ASD, 548 TC	72.2%	**(Liu et al., 2020).**
	sMRI	151 ASD, 151 TC	AUC 0.77	**(Alvarez et al., 2020).**
	fMRI	403 ASD, 468 TC	60.89%	**(Brahim et al., 2020).**
	fMRI,	505 ASD, 530 TC	71.1%	**(Kunda et al., 2023).**
	fMRI, sMRI	49 ASD, 41 TC	78.89%	**(Ma et al., 2021).**
RF Random Forest	fMRI	432 ASD, 556 TC	60.63%	**(Ingalhalikar et al.,2021).**
	fMRI	306 ASD, 350 TC	73.75%	**(Reiter et al., 2021).**
LR Logistic Regression	fMRI,	505 ASD, 530 TC	71.1%	**(Kunda et al., 2023).**
	fMRI	403 ASD, 468 TC	60.89%	**(Brahim et al., 2020).**

2.2.2 Deep learning techniques

Deep learning is a form of machine learning that analyses extensive relationships and patterns in data using multi-layered neural networks. It has demonstrated success across a range of domains and is modelled immediately following the structure and operation of the human brain**. (Mathew et al., 2020).** Deep learning techniques, in particular convolutional neural networks

(CNNs), have shown strong promise in analyzing neuroimaging data such as Magnetic Resonance Imaging (MRI) and functional MRI (fMRI), as well as behavioral and genetic data, to detect patterns indicating ASD. These models can automatically learn complex features from high-dimensional data, enabling more objective and replicable diagnoses. **Table 02** some important related works that utilized 2D CNN for ASD classification.

Table 02: ASD Diagnosis Using CNN.

Model	Dataset	No. of cases	Max Accuracy	Reference
CNN	fMRI	539 ASD, 573 TC	84.05%	**(Sewani et al., 2020).**
	fMRI	539 ASD, 573 TC	80%	**(Kashef et al., 2022).**
	sMRI	592 ASD, 571 TC	66%	**(Sharif et al., 2022).**
	fMRI	79 ASD, 105 TC	94.70%	**(Ahammed et al., 2021).**
	fMRI	491 ASD, 528 TC	82.12%	**(Othmani et al., 2023).**

We emphasized difficulties of current diagnostic methods based on the nature of the disease and variations of symptoms. By discussing the brain development features of ASD, we have stated two brain imaging techniques, sMRI and fMRI. In particular, fMRI can be used to detect and analyze the abnormalities in brain connectivity in autism. Given that fMRI is non-invasive, it is particularly suited for use in children, yielding valuable information on the disrupted brain networks in ASD patients. As a conclusion, we have taken into account the various methods and models applied to diagnose autism with special focus on representing and utilizing data from MRI and implementing them in different classification models.

3 The Proposed Algorithms

This section provides extensive discussion of the proposed 3D Convolutional Neural Network (3D-CNN) architecture **(Chengping et al., 2020)** intended for Autism Spectrum Disorder (ASD) identification from neuroimaging data and phenotypic datasets . **Fig.1** shows a summary of the most important stages of the proposed system. The model uses 3D images of MRI and fMRI neuro-image collected from the ABIDE dataset. The neuro-images are pre-processed before training the model to ensure consistent data representation by normalization and resizing.

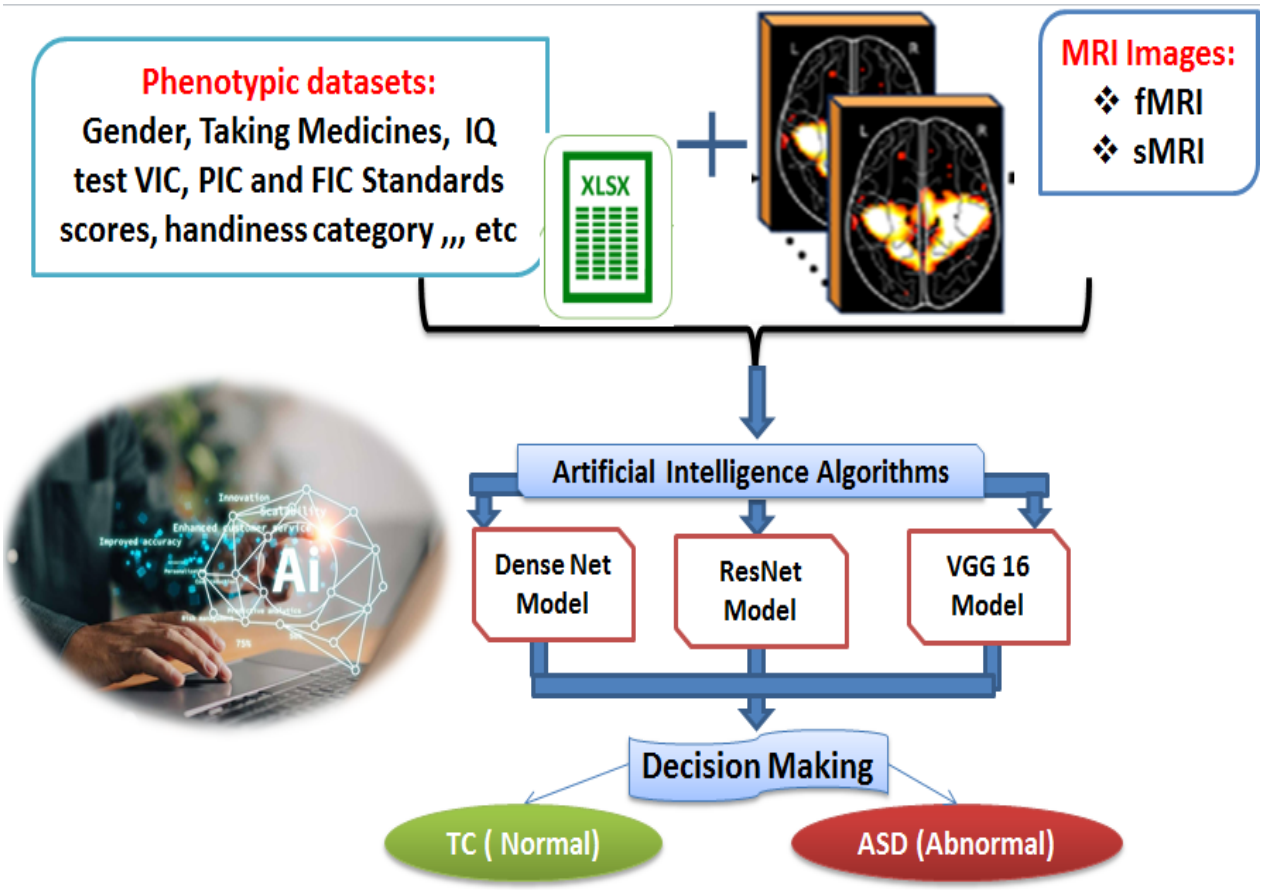


Fig. 1 Architecture of the proposed ASD detection algorithm.

A. Phenotypic Data Set

A phenotypic data set is a collection of psychologycal scales that describes an organism's observable traits (phenotypes) and characteristics, from complex clinical symptoms, biochemical levels, behaviors, and family histories to physical attributes like height and eye color. It is essential for connecting genetic makeup to real-world traits in research, medicine, In our cas the phenotypic data set consists of 73 different tests for each patient.

N	Desciption	Variable
1.	ABIDE identification number	Numerical
2.	Diagnostic group	Numerical
3.	DSM-IV-TR Diagnostic category	Numerical
4.	Age	Numerical
5.	Gender	Numerical
6.	Handedness category	String
7.	Handedness score	Numerical
8.	FIQ standard score	Numerical
9.	VIQ standard score	Numerical
10.	PIC standard score	Numerical
11.	IQ test administered for full scale IQ	String

12.	IQ test administered for verbal IQ	String
13.	IQ test administered for performance IQ	String
14.	Reciprocal social interaction subscore (A)	Numerical
15.	Abnormalities in communication subscore (B)	Numerical
16.	Restricted and repetitive behaviors subscore (C)	Numerical
17.	Abnormalities in development before36 months (D)	Numerical
18.	Was ADI scored by research reliable personnel?	Numerical
19.	Autism diagnostic module	Numerical
20.	Classic total ADOS score	Numerical
21.	Communication total score of the classic ADOS	Numerical
22.	Social total subscore of the classic ADOS	Numerical
23.	Sterotyped behaviors total score of the classic ADOS	Numerical
24.	Was ADOS scored by research reliable personnel?	Numerical
25.	Social affect total subscore for Ghotham algorithm of ADOS	Numerical
26.	Restricted/repetitive behavior score for Ghotham algo of ADOS	Numerical
27.	Social affect + repetitive behavior score for Ghotham algo	Numerical
28.	Individually calibrated severity score for Ghotham algorithm	Numerical
29.	Social responsiveness scale version	Numerical
30.	Total raw score for Social responsiveness scale	Numerical
31.	Social awareness subscore raw total	Numerical
32.	Social congnition subscore raw total	Numerical
33.	Social communication subscore raw total	Numerical
34.	Social motivation subscore raw total	Numerical
35.	Autistic mannerism subscore raw total	Numerical
36.	Social communication Questionnary total	Numerical
37.	Total raw score of the autism Quotient	Numerical
38.	Any other comorbidities?	String
39.	Currently taking medications?	Numerical
40.	Active ingredient of any current psychoactive medications	String
41.	OFF stimulant 24 hours prior the scan	Numerical
42.	Vineland adaptative behavior of repetitive language V scaled	Numerical
43.	Vineland adaptative behavior of expressive language V scaled	Numerical
44.	Vineland adaptative behavior of written language V scaled	Numerical
45.	Vineland adaptative behavior- communication standard score	Numerical
46.	Vineland adaptative behavior of personal daily living skills score	Numerical
47.	Vineland adaptative behavior of domestic daily living skills score	Numerical
48.	Vineland adaptative behavior of community daily living skills score	Numerical
49.	Vineland adaptative behavior of daily living skills standard score	Numerical
50.	Vineland adaptative behavior of interpersonal relationship score	Numerical
51.	Vineland adaptative behavior play and leisure time V scaled score	Numerical
52.	Vineland adaptative behavior of copyng skills V scaled score	Numerical

53.	Vineland adaptative behavior socialization standard score	Numerical
54.	Sum of V scores (Communication + daili living skills + socialization)	Numerical
55.	Vineland adaptative behavior of composite standard score	Numerical
56.	Vineland adaptative behavior scales informants	Numerical
57.	WISC-IV verbal comprehensive index	Numerical
58.	WISC-IV perceptual reasoning index	Numerical
59.	WISC-IV working memory index	Numerical
60.	WISC-IV processing speed index	Numerical
61.	WISC-IV slim scaled	Numerical
62.	WISC-IV vocabulary scaled	Numerical
63.	WISC-IV information scaled	Numerical
64.	WISC-IV block design scaled	Numerical
65.	WISC-IV picture concepts scaled	Numerical
66.	WISC-IV matrix reasoning scaled	Numerical
67.	WISC-IV digit span scaled	Numerical
68.	WISC-IV letters-number sequencing scaled	Numerical
69.	WISC-IV coding scaled	Numerical
70.	WISC-IV symbol research scaled	Numerical
71.	Eye status during rest scan	Numerical
72.	Age of anatomical scan in years	
73.	Body mass index	

B. 3D CNN Models

The 3 D CNN models consists of the following parts:

- Input layer: 3D MRI data (sMRI/fMRI).
- 3Dconvolutional layer: The convolutional layer is fundamental to any CNN. It applies filters to the input image to create feature maps, capturing local patterns with 64 filters of size 3x3x3 and a ReLU activation function.
- Max pooling layers serve to downsample the spatial dimensions of the input volume, thereby emphasizing salient features for more efficient computational processing. A max pooling layer with a pool size of (2x2x2) was used.
- Batch normalization normalizes the output from the activation function, aiding in faster and more stable training, (BN)applied after each convolutional and max pooling layer to enhance the stability and efficiencyciency of the model.

The layers were repeated for an additional three convolutional layers, each with progressively more filters: 8, 16, 32, 64, and 128.

- After the convolutions, a global average pooling layer was applied to obtain a global representation of the extracted features.

- Next, a dense layer with 4096 units and ReLU activation was employed to flatten the extracted feature weights. To prevent overfitting, a dropout regularization rate of 0.5 was applied to the dense layer.
- Finally, the output classification layer was composed of a single unit and a sigmoid activation function for binary classification, distinguishing between ASD and TC subjects.

3.1 3D-VGG16 Like model

VGG16 is a deep CNN with three fully connected layers, five convolutional blocks, and 138 million parameters that was created by the Visual Geometry Group at the University of Oxford **(Al-Khater et al., 2024)** known for its ease of use and potent performance in tasks like image classification and facial recognition, it achieved the 2014 ImageNet competition with an accuracy of 91.90%. For ASD detection from 3D MRI with an input image shape of (176, 256, 256, 1). It employs a series of 3D Convolutional blocks with 8 to 128 filters of size (3x3x3) each are followed by BN batch normalization, ReLU activation. Next, a 3D max pooling with a pool size of (2x2x2) was used to extract spatial features effectively and to downsample the feature maps. After the flatten layer, the model proceeds to a fully connected architecture for classification. Includes two dense layers of 4096 units each with ReLU activation, BN, for facilitating stable and effective learning. Dropout with a 0.5 rate is applied after each of the dense layers to prevent overfitting by randomly disabling half of the neurons while training. The output layer consists of 2 units with a sigmoid activation function providing a probability score for every class in the binary classification problem with one encoded label {ASD/TC}.

3.2 3D-ResNet Like model

Residual Neural Networks, or ResNets, use residual (skip) connections to solve the vanishing gradient issue in deep networks. **(Wanni, et al., 2023) .** 3D ResNet convolutional neural network is proposed for the identification of ASD from 3D MRI images. This begins with a 3D convolutional layer with a large kernel (7×7×7) followed by batch normalization, ReLU activation, then a 3D max pooling with a pool size of (3x3x3) for down sampling. The core of the model is four residual blocks with increasing filter sizes (32, 64, 128, and 256). each residual block includes two 3D convolutional layers(3x3x3) with batch normalization and ReLU activation (only after the first CNN), and a skip connection that adds the input to the output of these layers which allows input to bypass the block, avoiding vanishing gradients and enabling feature reuse connected finally with ReLU activation.

When the dimensions of the input and output are different, a (1×1×1) convolution is applied to the shortcut to balance the dimensions. After the residual blocks, there comes a global average pooling layer with a pool size of (3x3x3) to down-scale the 3D feature maps to a vector, which is then passed to a dense layer with 512 units and dropout for regularization. Finally, the model outputs class probabilities through a sigmoid activation function.

3.3 3D-DenseNet Like model

Dense Network links each layer to all preceding layers by concatenating feature maps, enhancing information flow, gradient propagation, and parameter efficiency **(Uemura et al.,**

2020) 3D Dense Net model is designed for 3D MRI images for ASD identification. It starts with an initial 3D convolution layer with 32 filter of size (3x3x3) to extract basic features, followed by consecutive dense blocks and transition layers. There are various layers in a dense block where feature maps are concatenated rather than added, promoting feature reuse and improved gradient flow. Inside every dense block, 4 units of Batch Normalization and ReLU activation are performed in succession, followed by a (3x3x3) Conv 3D layer. Each layer's output is concatenated with the earlier layers inside the same block. Between blocks, immediately followed by a transition layer, in sequence, the transition layers consist of Batch Normalization followed by a conv 3D of size (1×1×1), and 3D Average Pooling (typically with pool size= (2x2x2) and stride= (2x2x2)). The transition layer in Dense Net plays a key role in compressing feature maps and reducing spatial dimensions between dense blocks. Before sending it to the next block. After the final block with transition layer a global average pooling compresses the spatial information, followed by a fully connected(dense) layer with 128 neurons and a dropout with 0.5 rate is applied for regularization. The model ends with a sigmoid-activated output layer for binary classification.

4 The Experimental Results

In this section, we have elucidated the methods used in this research work for the identification of ASD, the research design, data collection, preprocessing methods, deep learning model architecture, training, and evaluation procedures. The data collection and preprocessing procedures are detailed, including the source of the datasets used and the steps taken to ensure data quality and diversity, even the material used.

Following the methodologies outlined in the previous section, this section discusses the evaluation of the model's performance using a variety of quantitative measures and qualitative assessments. Results, analysis, and implications of the ASD prediction model will be discussed.

4.1 Data *Collection and Preprocessing*

Data availability can go a long way to assist research move forward. Therefore, in a bid to facilitate discoveries along with comparisons in Autism research, the Autism Brain Imaging Data Exchange (ABIDE) project has compiled functional and structural brain imaging data from various laboratories worldwide into a repository known as ABIDE.

4.1.1Dataset Collection

In this work, we have used the ABIDE (Autism Brain Imaging Data Exchange) datasets, which serve as an essential resource for enhancing our understanding of autism spectrum disorder (ASD). By providing a comprehensive collection of neuroimaging data from both individuals with ASD and typically developing controls, these datasets enable researchers to explore the complexities of brain connectivity and the abnormalities associated with autism. This invaluable resource plays a crucial role in advancing innovation and discovery in the fields of neuroimaging and autism research. ABIDE encompasses two major collections: ABIDE I and ABIDE II. Each collection was created by aggregating datasets that were independently gathered from over 24 international brain imaging laboratories, making them accessible to researchers worldwide. The ABIDE dataset is publicly available at **(ABIDE., 2025)**.

The ABIDE-I initiative began in August 2012 and involved 17 international sites. It includes resting-state functional MRI (RS-fMRI), anatomical, and phenotypic data, all of which are shared across various platforms. The database consists of 1,112 datasets, with 539 from individuals with Autism Spectrum Disorder (ASD) and 573 from typical controls, ages ranging from 7 to 64. Since its inception, ABIDE I has been utilized in numerous research projects worldwide, demonstrating that brain imaging can reveal properties of the brain related to autism. The shared data has proven to be very valuable for autism research.

ABIDE-II was established to advance discovery science related to the brain connection in individuals with Autism Spectrum Disorder (ASD). To date, ABIDE II has aggregated over 1,000 additional datasets that feature enhanced phenotypic characterization, particularly regarding core ASD measures and associated symptoms. Additionally, two collections include longitudinal data from 38 individuals collected at two time points, separated by a 1 to 4-year interval. Currently, ABIDE II comprises 19 sites, including ten charter institutions and seven new members, contributing a total of 1,114 datasets from 521 individuals with ASD and 593 controls, with an age range of 5 to 64 years. These data were openly released to the scientific community in June 2016.

.4.I2 Dataset description

The ABIDE dataset is a valuable resource for research on ASD. It pools information from various institutions worldwide, with each institution contributing a specific number of ASD participants and typical control participants. The participants span a wide age range, allowing variability and common characteristics of ASD across groups to be studied. The information is collected from very credible websites such as Caltech, Carnegie Mellon University, and New York University, among others. **Table 03** provides the breakdown of the number of participants per site by distribution, number of ASD participants, control subjects, age range, and overall number of participants per site.

Table 03: Demographic characteristics of the participants by site in the ABIDE dataset.

Collection Site	ASD	Control	Age Range	Total
California Institute of Technology **'Caltech'**	19	19	17.0-56.2	38
Carnegie Mellon University **'CMU'**	14	13	19-40	27
Kennedy Krieger Institute **'KKI'**	22	33	8.0-12.8	55
Ludwig Maximilian University of Munich **'MaxMun'**	24	33	7-58	57
NewYork University **'NYU'**	79	105	6.5-39.1	184
Olin Center Institute of Livingat Hartford Hospital **'Olin'**	20	16	10-24	36
Oregon Healthand Science University **'OHSU'**	13	15	8.0-15.2	28
SanDiego State University **'SDSU'**	14	22	8.7-17.2	36
Social Brain Lab **'SBL'**	15	15	20-64	30
Stanford University **'Stanford'**	20	20	7.5-12.9	40
Trinity College Institute of Neuroscience **'Trinity'**	24	25	12.0-25.9	49

University of California LosAngeles 1 **'UCLA 1'**	49	33	8.4-17.9	82
University of California LosAngeles **2 'UCLA 2'**	13	14	9.8-16.5	27
University of Leuven **1 'Leuven 1'**	14	15	18-32	29
University of Leuven **2 'Leuven 2'**	15	20	12.1-16.9	35
University of Michigan **1 'UM 1'**	55	55	8.2-19.2	110
University of Michigan **2 'UM 2'**	13	22	12.8-28.8	35
University of Pittsburgh School of Medicine **'Pitt'**	30	27	9.3-35.2	57
University of UtahSchool of Medicine **'USM'**	58	43	8.8-50.2	101
Yale School of Medicine **'Yale'**	28	28	7.0-17.8	56
17 sites	539	573	7 to 64	1112

Table 04 summarizes quantification description of the combined data set:

Table 04: Summary of the number of subjects.

Site / Data	Smri	Rs-fMRI	ASD/TC
ABIDE-I	1102	1112	539/573
ABIDE-II	1114	1113	521/593
ABIDE-I+ABIDE-II	2216	2225	1060/1166

.4.13 Preprocessing Techniques

Preprocessing in the medical field is essential, particularly with diverse imaging data. Various brain imaging machines produce images that exhibit different characteristics **(Sensory issues., 2025)**, Preprocessing helps to minimize differences in data by standardizing formats and correcting any abnormalities. There are various techniques for preprocessing functional images, including timing correction and standardizing formats from different acquisitions. This process is crucial for reducing noise in the data, as even a small amount of noise can lead to inaccurate results.

A. FMRIB Software Library

FSL (FMRIB Software Library) is a comprehensive library of analysis tools for FMRI, MRI and diffusion brain imaging data. developed by the University of Oxford, includes various specialized tools such as BET for brain extraction, FSL provides command-line and graphical interfaces and is compatible with Linux, macOS, and Windows (via WSL). Due to its robust features and integration with other neuroimaging pipelines, FSL is a preferred tool in many studies involving autism spectrum disorder (ASD) and functional connectivity analysis **[(Autism Sensory Processing , 2025)**.

This methodology began with the application of FSL's Brain Extraction Tool (BET is utilized for skull stripping on structural MRI images. Its primary function is to remove non-brain tissues, such as the skull, scalp, and other extra cranial matter, from MRI scans. This process is essential for preprocessing in both functional and structural neuroimaging analysis as shown in **Fig.5**.

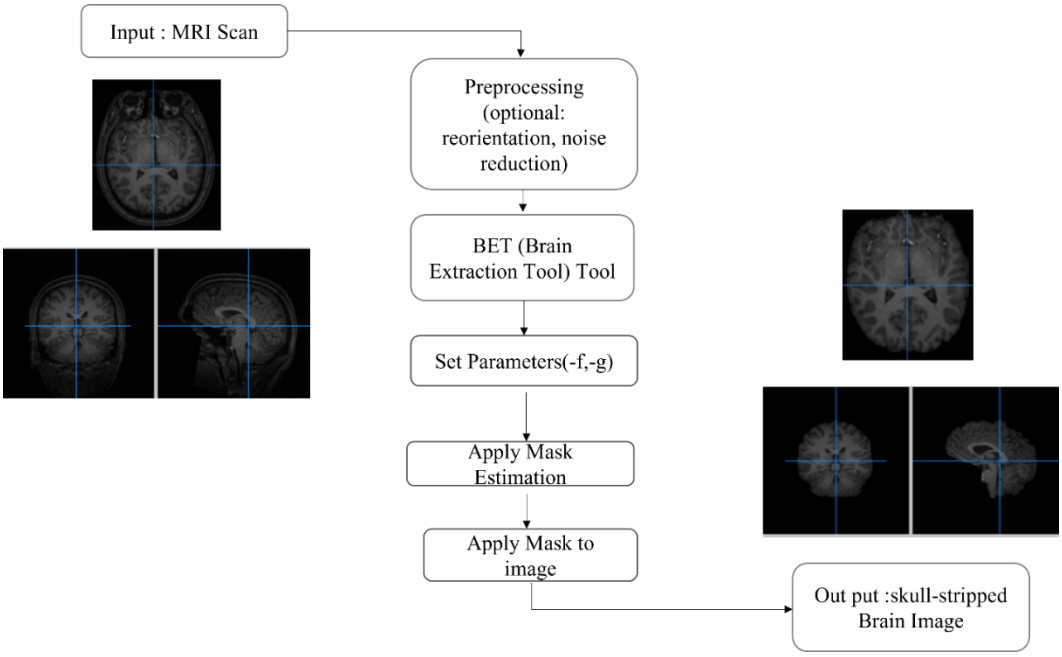


Fig.5 : Dataset Preprocessing (Skull- stripping)

The ABIDE dataset consists of MRI scans from different international sites, and each site might use different models of scanners, acquisition protocols, and image resolutions. Therefore, the dataset differs considerably in the spatial dimensions of the samples, i.e., width, height, and depth of the 3D brain volumes. For consistency and compatibility with deep learning models, particularly convolutional neural networks (CNNs), a standard input shape must be chosen.

For the paper, we selected the volume dimension 176×256×256 as a constant dimension for all sMRI volumes. This was informed by a trade-off between keeping anatomical information that is prominent to ASD diagnosis, minimizing data loss through resizing, and adhering to memory and computation constraints while training 3D CNN models such as the modified VGG16.

On the other hand, for functional MRI (fMRI), where we are sampling brain activity across time, we used a lower resolution of 64×64×40 per volume. This is a standard preprocessed resolution for 4D fMRI data (except the temporal dimension) and is typical in neuroimaging research to balance spatial resolution with computational tractability. Abiding by these resolutions across the dataset enables model input uniformity, improved convergence during training, and improved reproducibility of our findings.

B. *Data Augmentation*

It is a technique to improve generalization and model robustness by introducing realistic variability in MRI scans. It helps models learn better, especially in limited data like ASD diagnosis. In 3D MRI data augmentation methods like random flipping, rotation, scaling, and

noise expose the model is exposed to diverse training examples, enhancing its ability to recognize meaningful patterns in unseen data. This is particularly important in ASD classification, where data collection is costly and sample sizes are often small. In our ASD classification project, 3D augmentation plays a critical role in increasing data variability and reducing overfitting. However, working with 3D data presents unique challenges compared to 2D images. 3D volumes are large and require more memory and processing power, applying transformation in 3 axes is technically more complex. The type of data augmentation techniques used are the following:

- Random flipping
- Random rotation
- Gaussian noise
- Zoom and scaling

C. Cross validation

Cross Validation is a technique used to evaluate performance and generalization of a model, especially when the dataset is limited as the case of ASD diagnosis, the data is divided into k equal folds, the model trained on k folders and validated on remaining folder, the process repeated k times each time using different fold as the validation set, The final performance is calculated as the average of all K runs, in our study the cross validation was critical due to the small sample and the need to evaluation the model performance, we use 5 folders in this study,4 folders for training and one for validation, and the process was repeated 5 times with each fold used once as the validation set.

D. Early stopping

Early stopping is a way to regularize a model while it is being trained to keep it from overfitting. It keeps an eye on how well the model does on the validation set throughout training and stops the training process when performance stops getting better**.** We employed early stopping in our ASD classification project to stop training the model once it had reached its best performance. We used early stopping with a patience of 10 to 15 epochs. This means training stopped if the validation loss did not improve for 10 to 15 consecutive epochs.

4.2.Parameter Setting

A. Batch size

Is the number of training samples that were passed to the model at once before the model updates its internal parameters (Weights). In our case, Memory usage is high due to dimensionality and the size of 3D fMRI data. When using a GPU, memory usage can quickly become a limitation. Therefore, a batch size of 4 or 8 is usually safe. The batch size should be reduced further to fit the available GPU resources.

B. Epochs

It is the number of iterations that defines how long the model trains; the models are trained at an epoch: 50–100.

C. Learning rate

Determines the step size at each iteration while moving toward. It controls how much the model updates its weights in response to the error during training. MRI data is complex and high-dimensional; the model needs to carefully learn patterns between ASD and TC. We use 1e-4 (0.0001).

D. *Validation-split*

It is a method that separates the dataset into parts for training, another for validation, and a test. We use two splits, 0.1 and 0.2.

E. *Regularization*

It is a set of strategies used to help deep learning models avoid overfitting, We have used the Adam optimizer.

4.3.Training and Results

This section presents the training and results of our autism classification models. We have trained four models (VGG16, ResNet and DenseNet) using datasets from ABIDE. We have also evaluated the models on an independent test dataset using metrics such as accuracy, precision, recall, and F1 score. We have compared the performance of the different models and datasets to identify the most effective combinations. The results provided insights into the performance of each model and the impact of dataset variations. Altogether, these tasks took approximately ten weeks and almost 3 months of full-time work. The dataset was split using a two-phase strategy. Initially, a stratified 80/20 train-test split was performed to separate the training and testing portions. Subsequently, 5-fold stratified cross-validation was applied to the training set to optimize model performance and validate generalizability. **Table 5** outlines the detailed partitioning strategy and the corresponding utilization at each stage.

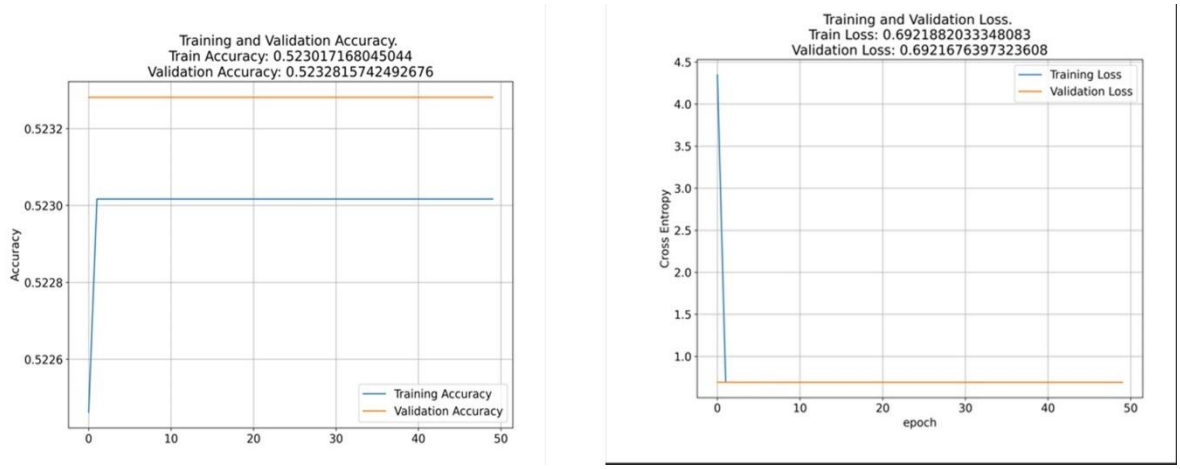
Table 5 Data Splitting and Evaluation Strategy

Stage	Dataset Portion	Purpose	Used In
Initial Dataset	100% of the data	Complete dataset	Baseline input for all subsequent preprocessing
Train-Test Split	80% → Train_files	Used for model training and cross-validation	
	20% → Test_files	Held-out set reserved for final model evaluation	Used exclusively for final testing and performance metrics
Cross-Validation	80% Training data	Stratified K-Fold (5-fold) applied to training data	Each fold: 4 parts for training, 1 part for validation
Final Evaluation	20% Test set	Assessment on unseen data after training and validation	Metrics: confusion matrix, accuracy, F1-score

4.3.1. 3D VGG16 Model

After training the model with these settings and based on the results obtained, we can conclude that the VGG 16 network is not suitable for fMRI–based ASD classification, performing in terms of low accuracy of 52% in the Epoch of 50, batch size 8, and validation

split 0.1 or 0.2. The results indicate that the VGG 16 model fails to learn effectively features from fMRI and struggles to capture patterns necessary for accurate ASD classification.



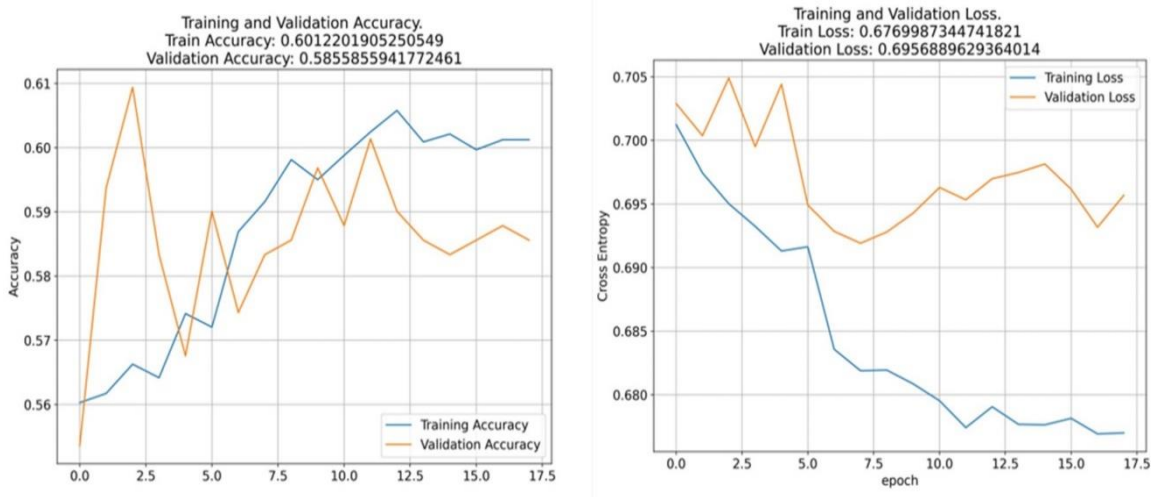
(a) *(b)*

Fig.2 : VGG 16 curve. (a) Training and Validation Accuracy. (b) Training and Validation Loss

Figure 2 (a) demonstrates the changes in accuracy. Both training and validation accuracy are nearly identical, suggesting that there is no overfitting. However, the model's accuracy is close to 50%, which indicates the model is not learning any discriminative features. The evolution of the "loss function" over 50 epochs is depicted in figure 2 (b). The flat curves across all epochs indicate that the model stopped learning early.

4.3.2. 3D DenseNet Model

After training the model with the current settings 50 epoch, batch size maximum 8, and validation split 0.1 or 0.2,5, and based on the results obtained, taking into account the difference in accuracy of the network results in the studied database, this model achieved accuracy between 60 % and 70% in training data but the model has overfitting when it arrives to 70%, this result confirms to us that the model DenseNet learnt from data but very slowly.



(a) *(b)*

Fig.3 : DenseNet curve. (a) Training and Validation Accuracy. (b) Training and Validation Loss

Figure 3 (a) illustrates the training and validation accuracy. It shows that the accuracy gradually increases and stops at 18 epochs due to early stopping based on the patience parameter. The validation accuracy fluctuates in training and does not show a consistent upward trend, which suggests that the model is learning but with difficulty, possibly due to limited data variability.

In addition to the training and validation loss curves as shown in figure 3 (b), the training loss shows a steady and continuous decrease over the 18 epochs, indicating that the model is successfully minimizing the error on the training data. The validation loss decreases only during the initial epochs and then begins to fluctuate and gradually increase. The growing gap between these two loss curves is in favor of concluding that the model is struggling to generalize well, and more regularization or more data are required to be able to improve validation performance.

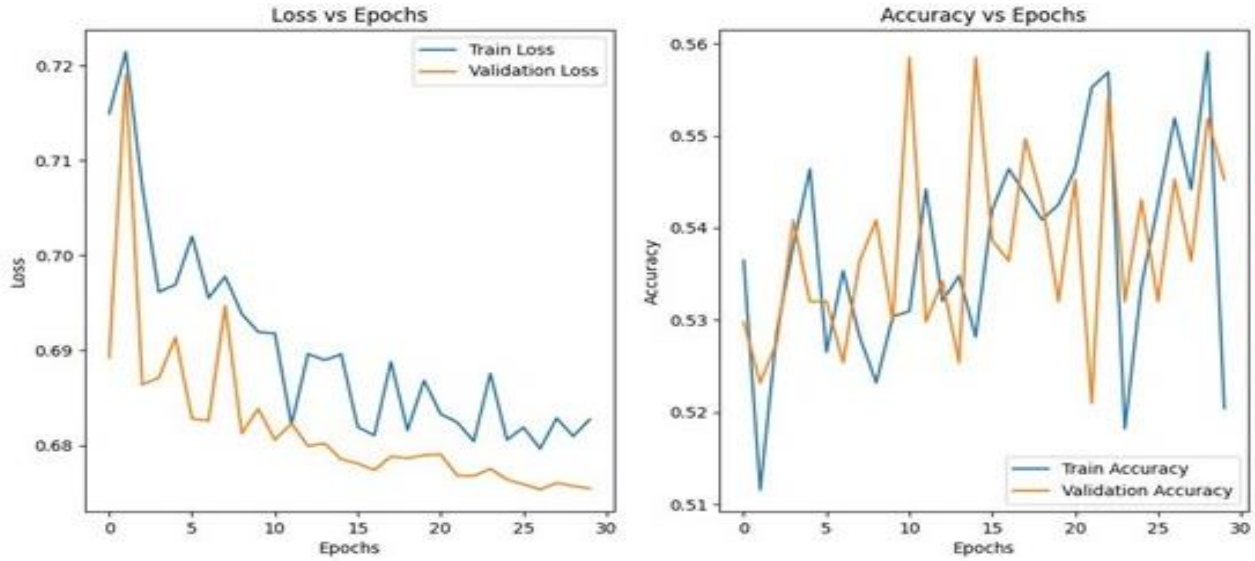
Based on the obtained confusion matrix of Dense Net model, it identified 168 true positives and 91 true negatives but also misclassified 125 false positives and 68 false negatives. The performance metrics are summarized in Table 06:

Table 06: Summary of DensNet Model Performance.

Precision	Recall	F1-Score	Test Accuracy	Training Accuracy
0.573	0.712	0.634	0.573	0.60

4.3.3. 3D ResNet Model

After training the model with the current settings, 50 epochs, batch size maximum 8, validation split 0.1 or 0.2, and based on the results obtained.



(a) *(b)*

Fig.4 : ResNet curves (a) Training and Validation Loss (b) Training and Validation Accuracy.

Figure 4 (b) illustrates the training and validation accuracy. It shows that both training and validation loss decrease gradually over 30 epochs. The validation loss is consistently lower than the training loss, which is unusual. This could suggest that regularization (dropout, weight

decay) is affecting training loss more, possibly some form of noise or difficulty in the training set compared to validation. Figure 4 (a) as shown in the figure, for both training and validation sets, show that accuracy varies significantly, ranging between about 51% and 56%. This instability may indicate the model is learning, but with high variance. The ResNet model shows stable loss reduction, but the accuracy fluctuates, indicating poor generalization. Because fMRI data is noisy and high-dimensional, ResNet may be too focused on local features without capturing broader functional patterns. Based on the obtained confusion matrix, the ResNet model demonstrates moderate performance on the test set. It correctly classified 145 positive cases (True Positives) and 100 negative cases (True Negatives), while misclassifying 91 positive cases (False Negatives) and 116 negative cases (False Positives). The performance metrics are illustrated in Table 07:

Table 07: Summary of ResNet Model Performance

Precision	**Recall**	**F1-Score**	**Test Accuracy**	**Training Accuracy**
0.556	0.614	0.583	0.567	0.56

4.3.4. The Best Result

The DenseNet model outperformed other architectures in this study, yet its overall performance remains modest. DenseNet's dense connectivity improves gradient flow and facilitates effective feature reuse, which is particularly beneficial when working with high-dimensional and limited fMRI data. Its parameter efficiency also helps mitigate overfitting, making it well-suited for neuroimaging-based classification tasks.

Despite these architectural advantages, the model's ability to distinguish individuals with Autism Spectrum Disorder (ASD) from typically developing controls (TC) remains limited. In our experiments, the DenseNet model achieved a training accuracy of 60.1%, a validation accuracy of 58.6%, and an AUC-ROC of 0.61.

The classification metrics for the ASD class were:

- Precision: 57.3% - Recall (Sensitivity): 71.2% - F1-score: 63.4%

These results suggest that while the model is reasonably good at identifying true ASD cases (high recall), it also misclassifies many TC cases as ASD (lower precision), limiting its clinical applicability. The F1-score of 63.4% indicates a trade-off between sensitivity and precision.

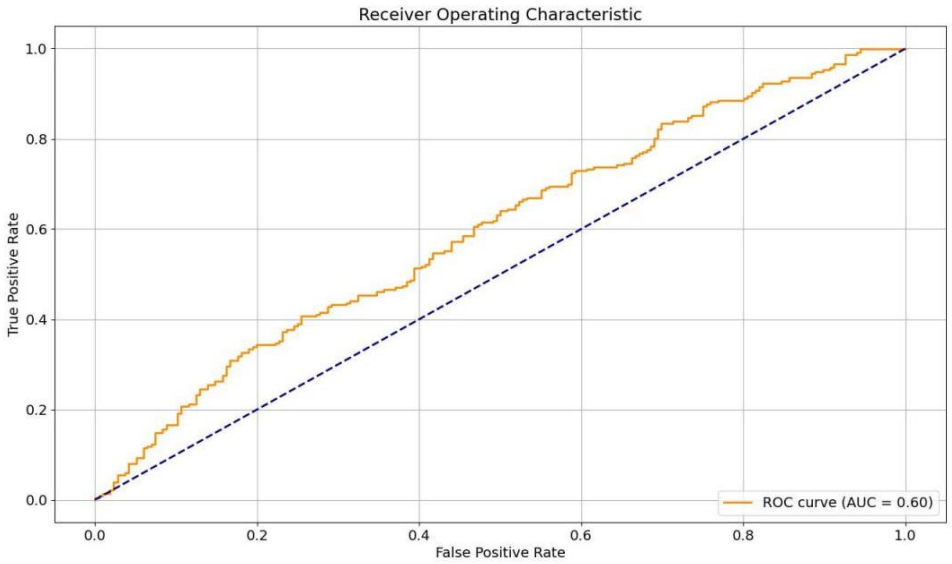


Fig.5 : AUC of DenseNet model

4.3.5. Discussion

In this study, we utilized MRI data from the ABIDE dataset to train and evaluate three deep convolutional neural networks: ResNet, DenseNet, and VGG16, for the binary classification of Autism Spectrum Disorder (ASD) versus typically developing controls (TC). ResNet and VGG16 performed worse than DenseNet, which had the highest accuracy among these models.

Our findings align with other research indicating restricted classification accuracy of deep learning models on ABIDE data. For instance**, [36]** reported test accuracies of 53.8% and 55.4% using ResNet50 and DenseNet121, respectively. Compared to these, our DenseNet model performed moderately better, although still far from clinical utility.

The modest accuracy (60%) achieved by our best-performing model likely stems from several well-known challenges associated with the ABIDE dataset. These include inter-site variability (scanner differences, acquisition protocols), small sample sizes relative to the complexity of deep models, and the subtlety of neuroanatomical differences in ASD. The brain alterations associated with ASD are often subtle, vary widely across individuals, and may not manifest consistently across different brain regions or populations.

Additionally, MRI alone may not capture enough discriminative information to enable robust classification. Potentially missing functional or connectivity-based markers that might improve classification. Future work should explore multi-modal approaches combining sMRI with rs-fMRI, apply domain adaptation techniques such as ComBat to reduce inter-site variability, in addition to more advanced deep learning architectures like Vision Transformers and Graph Neural Networks (GNNs). Feature selection and dimensionality reduction techniques, such as mutual information analysis, PCA, or autoencoders, may help reduce noise and improve model generalization, especially when dealing with high-dimensional neuroimaging data and limited sample sizes. Leveraging explainable AI tools (e.g., Grad-CAM) could help identify neuroanatomical features most relevant for ASD classification. Together, these strategies hold promise for advancing more accurate, robust, and clinically meaningful neuroimaging-based tools for early and reliable ASD diagnosis.

4.3.6. Comparison with State-of-the-Art Approaches

Compared to other approaches, our method achieved similar or slightly lower performance, likely due to the challenges of modeling complex and subtle patterns in raw fMRI data, as demonstrated in Table 8.

Table 08: Comparing our 3D CNN model to similar architectures

Model	Dataset	Test Accuracy
3D CNN (Othmani et al., 2023)	ABIDE I	58–59%
3D CNN (Chengping et al., 2020)	ABIDE I +II	~60%
ResNet50 (Garcia et al., 2024)	ABIDE I + II	53.8%
DenseNet121 (Ahammed et al., 2021)	ABIDE I + II	55.4%
Our approach	ABIDE I + II	**~57%**

5 Conclusion

This paper has presented a detailed analysis of the training, testing, and implementation of the proposed deep learning models for ASD detection from 3D MRI images and psychological scales. The paper described the tools and settings required to create a robust and scalable system. The most significant techniques, such as data augmentation, cross-validation, and early stopping, were employed to optimize training and improve generalization. The parameters were tuned to get stable convergence and minimize overfitting. Three 3D CNN models, namely VGG16, DenseNet, and ResNet, were trained and validated, and the best model was selected on the basis of accuracy and validation performance. Finally, comparison with state-of-the-art techniques confirmed the competitiveness and potential of the proposed system. Overall, this paper is a basic building block to comprehend the effectiveness of different 3D CNN architectures for ASD detection and opens up possibilities for future improvement and real-world implementation.

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