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Autism Spectrum Disorders Identification from MRI Using Deep Learning

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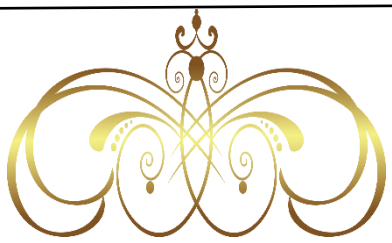

DEDICATIONS

In the name of Allah, the Most Compassionate, the Most Merciful, and peace be upon His Messenger. Thanks be to Almighty God first and foremost for the great blessings bestowed upon me. I dedicate this work to my dear parents: my father, Boubaker, and my mother, Samira, for their unwavering support and for providing me with all the conditions necessary for my studies. They are the main reason, after God, for my reaching this stage of education. I also want to thank my brothers and all my family for their continuous support.

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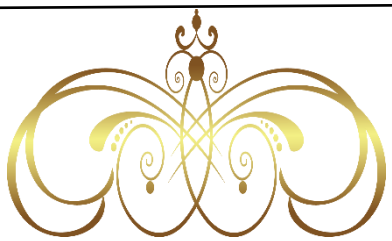
Abd Esammad



DEDICATIONS

In the name of Allah, the Most Compassionate, the Most Merciful, and peace be upon His Messenger. Thanks be to Almighty God first and foremost for the great blessings bestowed upon me , First of all, I dedicate this modest work to my dear parents. TO MY MOTHER, YERHAMHA, my father, LAKHDAR, may ALLAH protect him for his support of me and for providing me with all the conditions for studying. They are the main reason after God for my reaching this stage of study. I also want to thank my older sister, RATIBA, the second mother. My sister ALDGIA

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Abd Eddaim

Abstract

Autism Spectrum Disorder is a neurodevelopmental condition that affects social communication and behavior, characterized by diverse symptoms and varying severity levels. Accurate and early diagnosis remains crucial for effective intervention and support.

This study focuses on developing a deep learning model with a 3D convolutional neural network (CNN)based approach for ASD identification using sMRI and fMRI data, integrating models such as 3D Resnet, DenseNet, and VGG16 to extract spatial patterns associated with ASD.

To evaluate the performance of our proposed system, we conducted several experiments based on multiple parameters have been performed using the publicly challenged ABIDE dataset of unconstrained images. The obtained experimental results proved the effectiveness of the proposed system against deep CNN architectures, as well as with recent state-of-the-art methods.

Key Words: autism spectrum disorder, fMRI, functional, convolutional neural network, CNN, ABIDE.

Résumé

Le trouble du spectre autistique est une affection neurodéveloppementale qui affecte la communication sociale et le comportement, caractérisée par divers symptômes et des niveaux de gravité variables. Un diagnostic précis et précoce reste crucial pour une intervention et un soutien efficace.

Cette étude se concentre sur le développement d'un modèle d'apprentissage en profondeur avec une approche basée sur un réseau neuronal convolutif (CNN)3D pour l'identification des TSA à l'aide de données sMRI et IRMf, intégrant des modèles tels que Resnet 3D, DenseNet et VGG16 pour extraire les modèles spatiaux associés aux TSA.

Pour évaluer les performances de notre système proposé, nous avons mené plusieurs expériences basées sur de multiples paramètres qui ont été réalisées à l'aide de l'ensemble de données ABIDE publiquement contesté d'images sans contrainte. Les résultats expérimentaux obtenus ont prouvé l'efficacité du système proposé contre les architectures CNN profondes, ainsi qu'avec les méthodes récentes de pointe.

Mots clés : trouble du spectre autistique, IRMf, fonctionnel, réseau neuronal convolutif, CNN, ABIDE.

ملخص:

اضطراب طيف التوحد هو حالة عصبية نمائية تؤثر على التواصل الاجتماعي والسلوك، وتتميز بأعراض متنوعة ومستويات شدة متفاوتة. ويظل التشخيص الدقيق والمبكر أمرًا بالغ الأهمية للتدخل والدعم الفعالين.

تركز هذه الدراسة على تطوير نموذج تعليمي عميق قائم على نهج الشبكة العصبية التلافيفية ثلاثية الأبعاد (CNN) لتشخيص اضطراب طيف التوحد باستخدام بيانات التصوير بالرنين المغناطيسي الوظيفي (sMRI) والرنين المغناطيسي الوظيفي (fMRI)، ودمج نماذج مثل 3 D Resnet وDenseNet وVGG16لاستخراج النمط الجزئي المرتبط باضطراب طيف التوحد.

لتقييم أداء نظامنا المقترح، أُجريت العديد من التجارب بناءً على عدة معايير باستخدام مجموعة بيانات ABIDE العامة غير المقيدة. أثبتت النتائج التجريبية التي تم الحصول عليها فعالية النظام المقترح ضد هياكل CNN العميقة، بالإضافة إلى أحدث الأساليب المتطورة.

الكلمات المفتاحية: اضطراب طيف التوحد، التصوير بالرنين المغناطيسي الوظيفي، الشبكة العصبية التلافيفية الوظيفية،

ABIDE ،CNN

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List of Acronyms

ABIDE	Autism Brain Imaging Data Exchange
ADHD	Attention Deficit Hyperactivity Disorder
ADOS	Autism Diagnostic Observation Schedule
ADI-R	Autism Diagnostic Interview- Revised
AE	Autoencoder
ASD	Autism Spectrum Disorder
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANOVA	Analysis Of Variance
BOLD	Blood Oxygen Level Dependent
Caltech	California Institute of Technology
CARS-2	Childhood Autism Rating Scale- Second Edition
CCS	Connectome Computation System
CMU	Carnegie Mellon University
CNN	Convolutional Neural Network
CPAC	Configurable Pipeline for the Analysis of Connectomes
DL	Deep Learning
DISCO	Diagnostic Interview for Social and Communication Disorders
DTI	Diffusion Tensor Imaging
fMRI	Functional Magnetic Resonance Imaging
KKI	Kennedy Krieger Institute
Leuven	University of Leuven
LDA	Linear Discriminant Analysis
MaxMun	Ludwig Maximilians University Munich
MEG	Magnetoencephalography
ML	Machine Learning
MRI	Magnetic Resonance Imaging
NYU	NYU Langone Medical Center

OHSU	Oregon Health and Science University
Olin	Institute of Living at Hartford Hospital
PET	Positron Emission Tomography
PDD-NOS	Pervasive Developmental Disorder-Not Otherwise Specified
Pitt	University of Pittsburgh School of Medicine
RS-fMRI	Resting-State Functional Magnetic Resonance Imaging
ReLU	Rectified Linear Unit
SBL	Social Brain Lab
SDS	SanDiego State University,
SPECT	Single-photon emission computed tomograph
sMRI	structural Magnetic Resonance Imaging
Stanford	Stanford University
TC	Typical Controls
Trinity	Trinity Centre for Health Sciences
UM	University of Michigan
USM	University of Utah School of Medicine
UCLA	University of California, Los Angeles
Yale	Yale Child Study Center
3Di	Developmental, Dimensional and Diagnostic Interview
X-ray	X-radiation

General Introduction

The master conductor of life, 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. 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 is not a disease one "catches" or "cures". 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[1].

Making early and accurate diagnoses is essential for timely intervention and improving the quality of life for affected individuals.[2], 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 [3].

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[4] 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. 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.

Thesis Structure:

The dissertation is organized as follows:

- Chapter 1ST: is a "Background" to this work, describes autism spectrum disorder (symptoms, risks, etc.), The challenges of early identification, diagnosis of ASD, and description of the deep learning models used in this study, and the latest findings of previous studies.
- Chapter 2nd: gives a detailed description to the ABIDE (Autism Brain Imaging Data Exchange) dataset and its contents, with an explanation of its preprocessing. Then, we present an explanation of the models of DL that were proposed for this study(VGG16, ResNet,… etc).
- Chapter 3th: This final chapter presents and discusses the most important result.

Chapter 01

ASD and Deep Learning: A Foundational Overview

1.1 Introduction

Autistic Spectrum Disorder (ASD) is a complex neurodevelopmental condition that affects behavior, communication, and social interaction. The chapter gives a general introduction to ASD, including its definition, symptoms, etiology, and traditional diagnostic methods. It also emphasizes the importance of early diagnosis and describes how ASD is associated with brain structural and functional changes. Key terms used in brain imaging.

The chapter then shifts its gears towards machine learning and deep learning usage in ASD detection. The chapter covers fundamental deep learning ideas with emphasis on Convolutional Neural Networks (CNNs) and transfer learning using models including VGG16, ResNet, and DenseNet. Finally, A review of current literature pinpoints the success and accomplishment of AI-based techniques in the diagnosis of ASD.

1.2 Autism Spectrum Disorder

1.2.1 Definition of ASD

Autism Spectrum Disorder (ASD) is a collection of neurodevelopmental disorders that affect communication, social interaction, and behavior. The term "spectrum" describes the range of symptoms and severities that exist in individuals with autism. Some have high intellectual functioning, while others have severe problems with communication and daily living.

Alongside restricted, repetitive patterns of behavior, interests, or activities. These difficulties affect how individuals perceive and socialize with others, often leading to impairments in social relationships and daily functioning.

Autism spectrum disorder begins in early childhood and eventually causes problems functioning in society socially, in school, and at work, for example. Often, children show symptoms of autism within the first year. A small number of children appear to develop normally in the first year, and then go through a period of regression between 18 and 24 months of age when they develop autism symptoms[5].

Below is a figure that shows the data and statistics related to the incidence of autism spectrum disorder

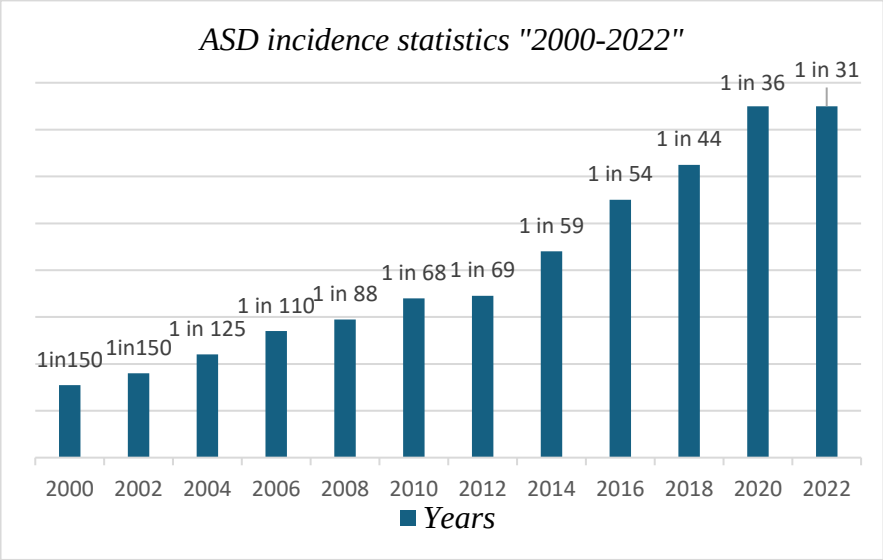

Figure 1-1: Autism spectrum disorder incidence statistics[6]

1.2.2 Symptoms and Causes

ASD is considered a spectrum because symptoms and severity vary widely among individuals. Some may be nonverbal, while others have fluent speech; some require substantial support, while others live independently. The diagnosis now includes previously separate conditions like Asperger's syndrome and PDD-NOS [7].

Core features of ASD include problems with communication, repetitive behaviors, and social interaction deficits. Individuals may struggle with non-verbal and verbal communication, including speech delays or difficulty understanding social cues. Repetitive behaviors and a keen interest in narrow topics are also common. Social challenges can involve difficulty understanding social rules, forming relationships, or responding appropriately in social situations.

Sensory processing differences are also common, with hypersensitivity or hyposensitivity to stimuli like sounds, lights, touch, or taste, often causing sensory overload and anxiety[8], [9]. These sensitivities are now part of ASD's diagnostic criteria.

Other signs include deficits in social-emotional reciprocity (e.g., difficulty with back-and-forth conversations, sharing interests or emotions), problems with nonverbal communication (like eye contact, facial expressions, and gestures), and difficulties in forming age-appropriate relationships. Individuals may also show restricted and repetitive behaviors, including stereotyped movements, insistence on sameness, highly focused interests, and unusual sensory responses [7].

The following diagram shows a summary of the symptoms and causes of ASD.

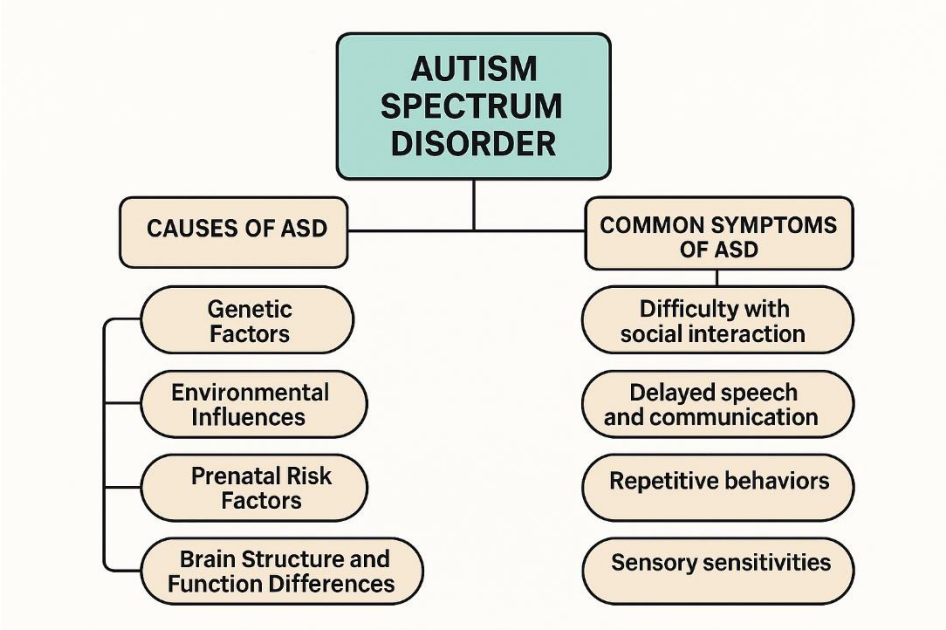

Figure 1-2: Some Symptoms and Causes of ASD

1.2.3 Diagnoses of ASD

Diagnosing autism is one of the hardest things because it is so hard to identify. Nowadays, autism is mostly diagnosed based on behavioral tests and observations by relatives or people close to the person. Most of these tests are designed to catch autism early because it usually manifests itself in the first few years of life.

1.2.3.1 Diagnoses Methods

The diagnosis of ASD often relies on semi-structured assessment tools, which follow a core set of questions but allow for adjustments based on responses. Here are some examples of semi-structured tests: (ADI-R), (ADOS-2), and the (DISCO)[10].

- ADI-R gathers information from parents or caregivers, suitable for individuals 18 months and older, and aligns with DSM-5 and ICD-11. It focuses on social interaction [11].

- ADOS-2 involves standardized activities and planned social situations to observe communication and behavior relevant to ASD. It includes five modules tailored to age, language ability, and developmental level, and is used with both children and adults [12].

- DISCO is a comprehensive, semi-structured interview that tracks an individual's development and behavior patterns over time. It aims to capture a full picture of the

individual rather than just assigning a label, and measures both autistic symptom intensity and comorbidities. It is suitable for parents of children of any age [10].

- The Childhood Autism Rating Scale–Second Edition (CARS-2) helps differentiate between ASD and other cognitive disorders, particularly distinguishing mild-to-moderate vs. severe autism, and is widely used in clinical and research settings[13]

However, these tools rely heavily on human observation, which can introduce bias due to differences in perception, mood, or examiner expertise. Behavior-based assessments may miss symptom subtleties since behavior varies with context, mood, and rapport. This makes such assessments potentially incomplete or inaccurate, and their effectiveness is dependent on the examiner's training.

Therefore, researchers are exploring new diagnostic techniques that aim to be earlier and more precise.

1.2.3.2 Importance of Early Diagnoses of ASD

Early diagnosis of autism spectrum disorder (ASD) is crucial because it enables children to access specialized interventions during the most formative years of brain development, leading to significantly improved long-term outcomes. When ASD is identified early, ideally before age 2 or 3, children can benefit from targeted therapies that enhance communication, social skills, and adaptive behaviors, often resulting in greater independence and better academic and social integration as they grow[14], [15], [16].

Research consistently shows that children diagnosed and treated early are more likely to achieve significant gains in cognitive abilities, daily living skills, and social interactions, and may require less intensive support later in life [17]. Studies also indicate that approximately 20–30% of children with ASD experience a regression in skills typically between 15 and 30 months of age, highlighting the importance of early detection and intervention to support recovery and ongoing development[18], [19]

Additional research suggests that early intervention improves cognitive, language, and social outcomes and may also help normalize brain function in young children with autism. Detecting and addressing autism early offers the best opportunity for positive developmental progress and reduces the long-term impact of the disorder.

1.2.4 Brain Changes and ASD

Autism Spectrum Disorder presents with a wide range of symptoms and severities, making diagnosis and understanding its causes challenging. One crucial process in typical brain development is neural pruning, which eliminates excess neurons and synaptic connections during early childhood and adolescence, enhancing the efficiency of neural networks[20].

In children with ASD, this pruning process appears to be disrupted or delayed, leading to an excess of synapses and neurons. This overabundance may contribute to the sensory sensitivities and information processing differences seen in autism[21].

A study by Courchesne et al. (2011) found that autistic children, especially males, had 67% more neurons in the prefrontal cortex than neurotypical peers, suggesting that such abnormalities originate during prenatal development[22]. Further, a 2017 neuroimaging study of infants at high risk for autism showed cortical surface area overgrowth between 6–12 months, followed by brain volume increases between 12–24 months, correlating with the severity of later social deficits[23].

Other research has reported early brain overgrowth during infancy in autistic children, followed by slowed or halted growth later in childhood, particularly in the frontal and temporal lobes[22].

1.3 Brain Imaging Techniques for ASD Identification

Brain imaging techniques have become increasingly important in the detection and understanding of autism spectrum disorder (ASD), because they are not limited by age, making it possible for earlier detection. We have available to us a variety of anatomical and functional neuroimaging methods, including X-ray, MRI, MEG, fMRI, PET, and SPECT. Anatomical imaging is specialized for the visualization and analysis of the brain's anatomical properties, such as size, volume, and the detection of abnormalities, while functional imaging is used to identify brain areas and processes associated with cognitive or behavioral tasks [24].

In young children, developmental rates can vary extensively, and therefore, anatomical imaging might not be trustworthy in identifying autism[25]. Instead, examining brain function, and more particularly network communication, might yield more valid information about the difference between autistic and control subjects.

Here, The Non-invasive methods such as structural and functional magnetic resonance imaging (MRI and fMRI) come in particularly handy. It is widely used since it is readily available and harmless to children. This non-invasive technique measures neural connections by tracking changes in the Blood Oxygen Level Dependent (BOLD) signal across different brain areas [23].

Are allows researchers and clinicians to objectively measure brain anatomy and activity, revealing differences in brain structure, connectivity, and function associated with ASD[26], [27]. The information that is acquired is four-dimensional images that reveal structural and functional attributes of the brain.

1.3.1 Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) is a non-invasive and radiation-free medical imaging technique that uses strong magnetic fields and radiofrequency (RF) pulses to generate detailed images of internal body structures, particularly the brain. An MRI scanner contains a large superconducting magnet that creates a powerful magnetic field, which aligns the hydrogen protons naturally present in body tissues [28].

When a radiofrequency pulse is applied at a specific resonance frequency, the aligned protons absorb energy and shift out of alignment. Once the pulse is turned off, these protons return to their original state, emitting weak radio signals in the process. These signals are detected by receiver coils and processed by a computer to create high-resolution, cross-sectional images of the body [29].

Over the years, MRI technology has advanced significantly, from basic imaging systems to highly specialized tools capable of providing exceptional spatial resolution and contrast sensitivity. Modern MRI enables clinicians and researchers to distinguish between different tissue types with great accuracy, making it invaluable for diagnosing various neurological, musculoskeletal, and cardiovascular conditions [28].

MRI is especially critical in brain imaging, allowing detailed analysis of brain morphology, structural connectivity, and developmental changes without exposing patients, especially children and vulnerable populations, to ionizing radiation. Advanced techniques such as functional MRI (fMRI) and diffusion tensor imaging (DTI) now allow researchers to investigate brain activity, white matter integrity, and neural pathways, which are essential in studying disorders like ASD, Alzheimer’s disease, and epilepsy [30].

Figure 1-3: Magnetic Resonance Imaging (MRI) scanner[31]

1.3.2 Structural Magnetic Resonance Imaging

Structural Magnetic Resonance Imaging (sMRI) is a non-invasive neuroimaging technique that provides detailed information about the anatomy of the brain, including the size, shape, volume, and integrity of gray and white matter. It uses high-resolution T1-weighted images to generate contrast based on tissue composition—specifically, the higher density of neuronal cell bodies in gray matter and the presence of myelinated axons in white matter [32].

sMRI is widely used in both clinical and research settings to assess brain morphology and detect abnormalities such as tumors, atrophy, traumatic brain injuries, and neurodevelopmental disorders. It is especially valuable for quantifying volumes or cortical thickness in regions like the hippocampus, amygdala, or subcortical nuclei, which are often implicated in conditions such as Alzheimer's disease, Autism Spectrum Disorder (ASD), and schizophrenia [33].

Additionally, sMRI plays a critical role in longitudinal studies by enabling researchers to track brain development, maturation, or degeneration across time. Its ability to precisely map structural changes without the use of ionizing radiation makes it ideal for repeated imaging, particularly in pediatric and geriatric populations.

Special MRI scanners allow us to obtain high-quality three-dimensional images that enable us to observe the brain from three aspects (Axial, Coronal, and Sagittal) as we see in the figure.

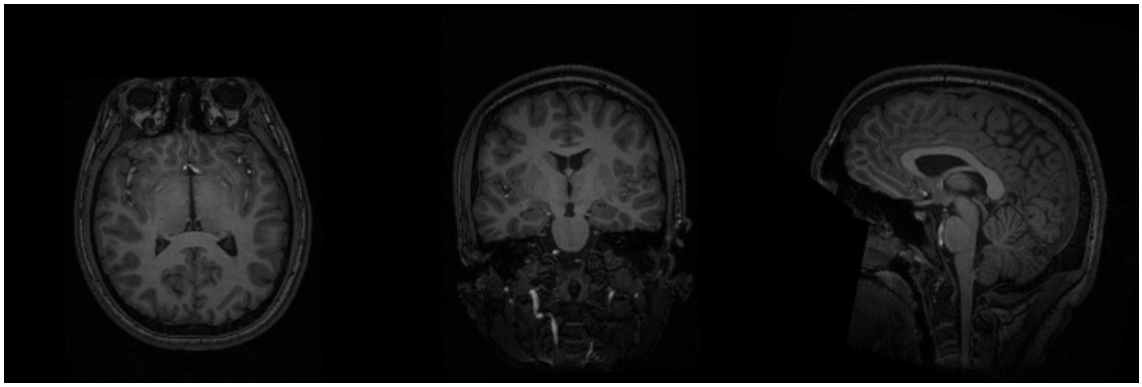

Figure 1-4: Structural MRI of ASD Subject(In the form of slices): Axial, Coronal, and Sagittal

1.3.3 Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging (fMRI) is an automatic neuroimaging technique that quantifies and maps brain activity by measuring hemodynamic changes (blood flow, oxygenation rates) in cerebral tissue, following the blood-oxygen-level-dependent (BOLD) contrast principle[34].

When a specific brain region becomes active, it consumes more oxygen, leading to increased blood flow and a rise in oxygenated hemoglobin, which alters the magnetic properties of the tissue and can be detected by the MRI scanner[35]. fMRI has excellent spatial and temporal resolution, which allows researchers and doctors clinicians to localize brain function, and understand how different brain regions work together and study the effects of various diseases or conditions, study neural networks, and probe the response to a variety of cognitive, sensory, or motor tasks in real time[36].

Its applications range from rudimentary research in cognitive neuroscience to clinical utility such as pre-surgical planning, diagnostics for neurological and psychiatric disorders, and disease progression or treatment monitoring[37].

By offering a dynamic window into brain function, fMRI has significantly advanced our understanding of the human brain and its disorders.

1.3.3.1 Functional Magnetic Resonance Imaging in Resting-state

Resting state fMRI is a form of fMRI that can be utilized to investigate brain activity when a subject is not performing any specific task. Instead of assessing how the brain responds to external stimuli or tasks, resting state fMRI investigates the activity of the brain while at rest, usually with eyes closed or gazing at a point in space.

RS-fMRI is a non-invasive neuroimaging technique that analyzes spontaneous, low-frequency fluctuations in the Blood Oxygen Level Dependent (BOLD) signal to map the brain's intrinsic functional connectivity. Unlike task-based fMRI, Rs-fMRI does not require active participation, making it ideal for studying infants, sedated patients, or individuals with cognitive impairments[38].

Resting state fMRI has the benefit of being non-invasive and not involving the subject doing anything in particular, so it can be applied to a general population, even those who would struggle with task-based fMRI. It provides baseline information on the brain's default patterns of activity, which is useful for looking at normal brain function and most disorders.

Resting-state fMRI is widely used to study brain disorders such as ADHD, schizophrenia, bipolar disorder, and autism by identifying changes in functional connectivity associated with these conditions[39], [40].

Additionally, rs-fMRI is used to investigate how brain connectivity evolves throughout development and aging, providing insights into both typical and atypical brain maturation. These applications make rs-fMRI a valuable tool for understanding the neural basis of various brain disorders and developmental processes[41].

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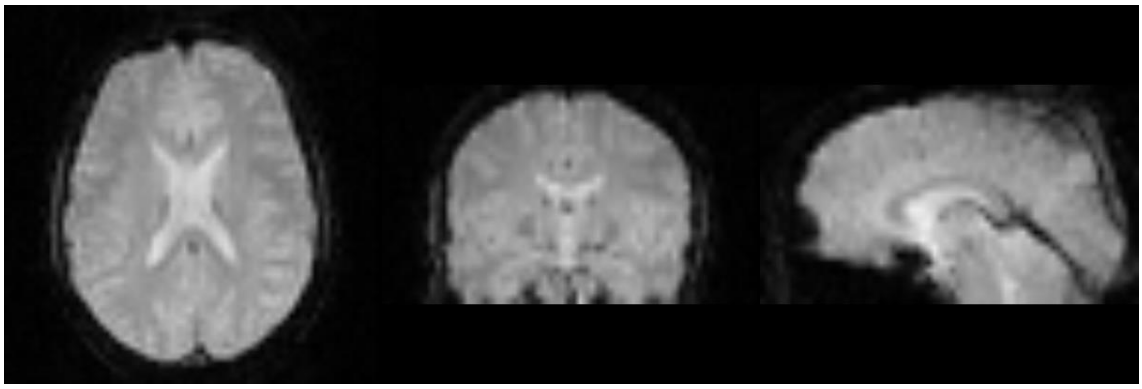


Figure 1-5: Functional MRI of an ASD subject

1.4 Machine and Deep Learning Approach for ASD Identification

Over the last couple of years, physicians and researchers have tried to adopt various new and rapid means, Mechanisms, and methods of the process of disease detection of every kind, but With the arrival of artificial intelligence, the latter has revolutionized the medical Field due to its use of rapid detection and disease diagnosis.

Such technologies are preferred to be implemented in medical detection systems because they move at a rapid pace and are efficient. As a result, there has been interest among health practitioners and researchers to explore how AI algorithms would be applied to detect disease, thus, clinical evaluation of AI algorithms must be performed well before they are implemented in practice.

The integration of AI, especially Machine Learning (ML) and Deep Learning (DL) Algorithms, into ASD diagnosis represents a significant advancement, offering improved accuracy, efficiency, and accessibility. While challenges remain regarding data quality, ethical considerations, and clinical adoption, ongoing research continues to enhance the robustness and utility of these AI-driven diagnostic techniques[42].

1.4.1 Machine Learning Algorithms

Machine learning (ML) is a field within artifi (AI) that involves creating algorithms and statistical models that allow computers to learn from information and improve performance on a specific task without explicitly being programmed. The core aim is for computers to recognize patterns, predict something, or make decisions based on the data they've been exposed to.

Machine learning can be divided into these main types :

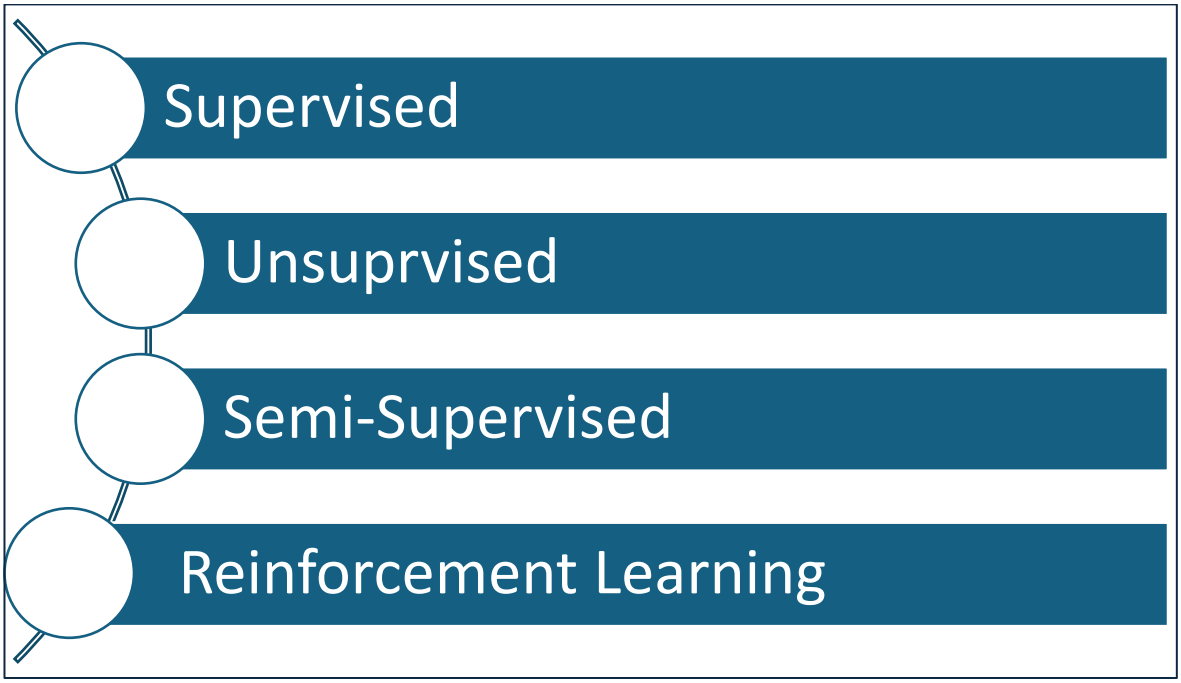


Figure 1-6: Types of machine learning

1.4.2 Deep Learning Algorithms

Deep learning (DL) is a branch of machine learning. It's a simulation process where electronic devices, such as computers, focus on training Artificial Neural Networks to simulate the function and structure of the human brain. This advanced form of machine learning has increased in popularity due to its success in handling complex patterns and large data sets, involves computer models consisting of multiple layers of abstraction, and has been enhanced with various technologies, especially in applications like computer vision, natural language processing, and speech recognition[43].

Artificial Neural Networks (ANN), on which DL is based, are inspired by the neurons in the human brain. Artificial neural networks consist of multiple layers of nodes, or artificial neurons, that are connected and work together to analyze data and identify patterns. The network builds a deeper and more abstract representation of the input as the data passes through each layer.

Some essential concepts in DL include:

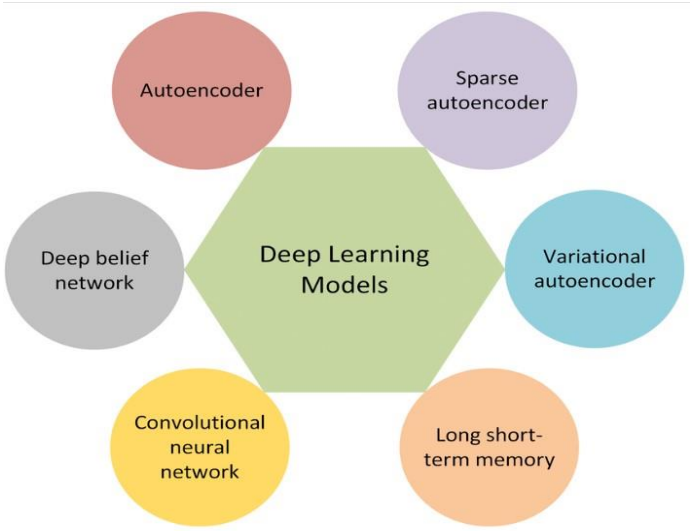


Figure 1-7: Deep Learning types

1.4.3 Difference Between Deep learning And Machine learning

Machine learning and deep learning form the backbone of artificial intelligence as they are utilized on a wide scale in data science with strong and advanced applications.

Machine learning is a broader category that involves algorithms learning from data to make predictions or decisions, often requiring human intervention for feature engineering. In contrast, deep learning is a specialized subset of machine learning that employs a set of algorithms, similar to neural networks, to simulate human intelligence.

Machine learning (ML) and deep learning (DL) primarily vary in that ML can handle structured data by performing the task of feature extraction and classification, whereas DL can handle structured and unstructured data, such as images and sound.

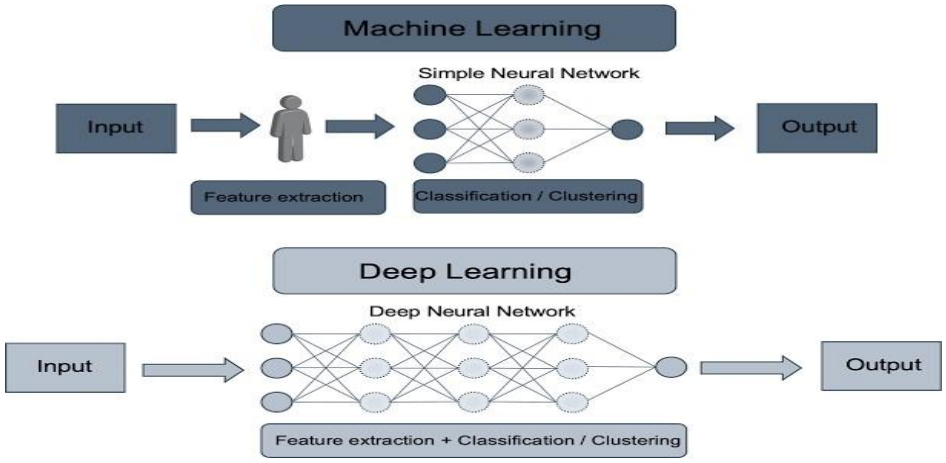


Figure 1-8: Schematic of the difference between Deep learning and Machine learning.

1.4.4 Convolutional neural networks

A Convolutional Neural Network (CNN) is a type of deep learning model used extensively in video analysis, computer vision, and image recognition. CNNs process images as inputs, extracting learnable weights and features automatically through spatial hierarchies using backpropagation. The architecture includes layers such as convolutional, pooling, and fully connected layers.

CNNs consist of three main types of layers:

- Convolution and aggregation layers for feature extraction
- A fully connected layer for transforming features into final outputs, commonly in classification tasks

Their strength lies in their ability to categorize, learn, and recognize patterns and shapes, making them effective in both simple and complex tasks.

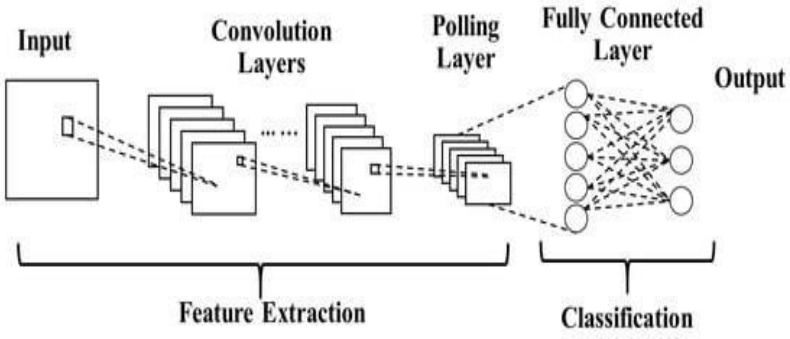


Figure 1-9: Architecture of Convolutional Neural Network

1.4.4.1 Convolutional Layers

The convolutional layer is the backbone of CNNs. It applies learnable filters (kernels) to input data, extracting local features and generating feature maps. It performs mathematical computations to combine information, identifying specific features within the input.

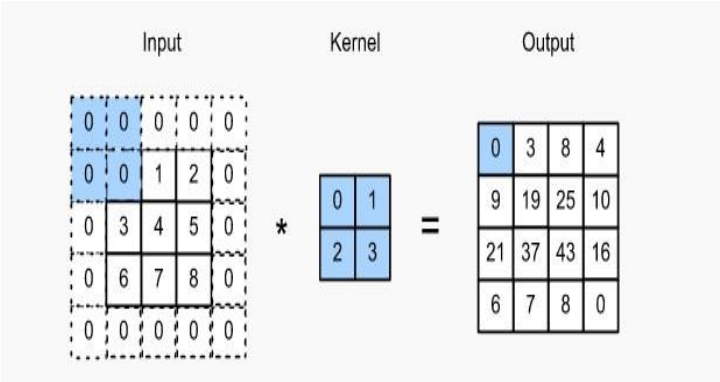


Figure 1-10: Representation of a Convolutional Layer

1.4.4.2 ReLU Activation Layer

CNNs use nonlinear activation functions like ReLU (Rectified Linear Unit) to introduce nonlinearity. After extracting feature maps, the network passes them through ReLU layers to improve learning of complex patterns.

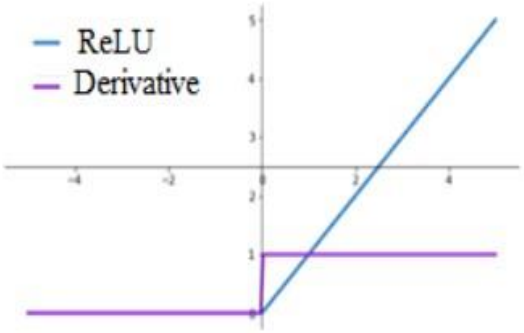


Figure 1-11: Relu Activation function

1.4.4.3 Pooling layer

Pooling layers reduce the spatial dimensions (height and width) of feature maps while retaining essential information. Max pooling is commonly used, selecting the largest value in a region. Pooling helps with dimensionality reduction, overfitting prevention, and translation invariance.

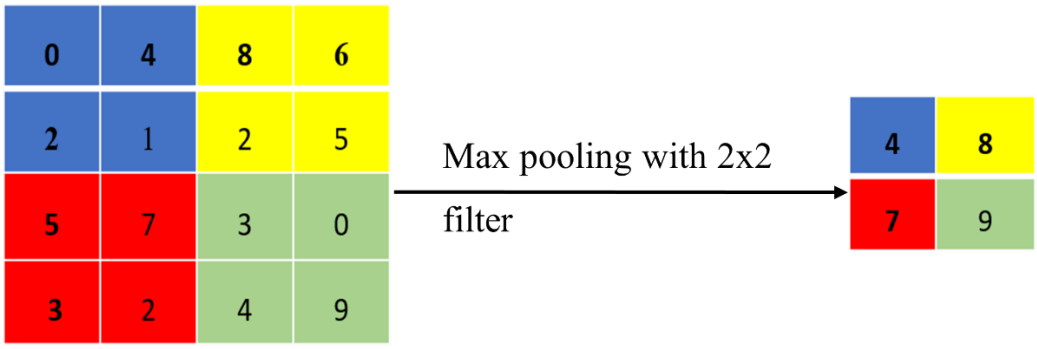


Figure 1-12: Example of pooling layer (Max Pooling)

1.4.4.4 Fully connected layer

The fully connected (dense) layer is added after the convolutional and pooling layers. It flattens the features into one-dimensional vectors and learns higher-level, nonlinear features by connecting each neuron to all neurons in the previous layer. This layer handles the final classification or regression task by combining the abstracted features.

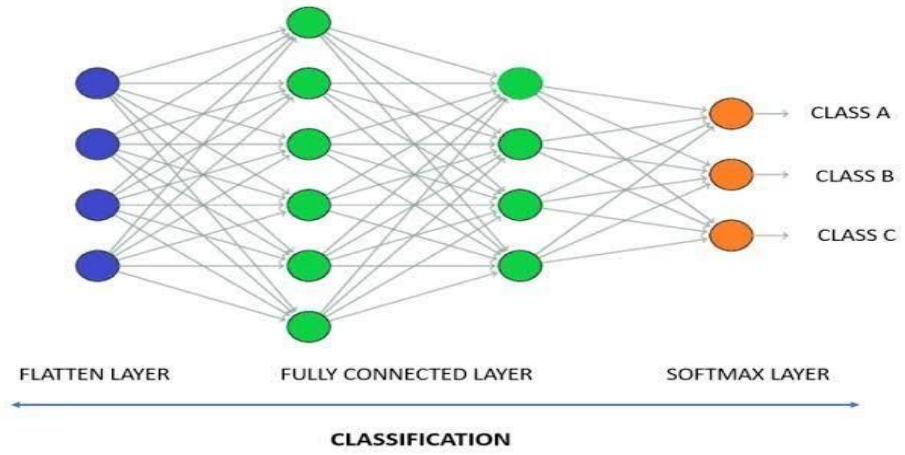


Figure 1-13: Schematic of Fully connected network

1.4.4.5 Output Layer

The output layer delivers the final prediction, based on the problem type—binary or multi-class classification, regression, or even image generation. It typically uses activation functions like SoftMax (for multi-class classification) or sigmoid (for binary classification) to produce the final output, such as an image's class label.

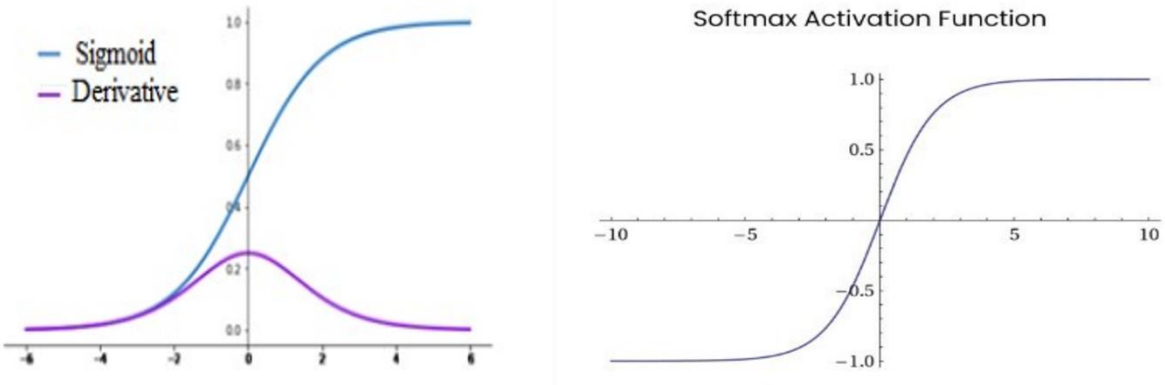


Figure 1-14: Sigmoid & SoftMax Activation function

1.4.5 Transfer Learning

Transfer learning improves performance on a new task by transferring knowledge from a related, pre-trained model. It's commonly applied in image detection and discrimination, where pre-trained CNNs with imported weights are used instead of training from scratch. This approach helps overcome data scarcity and enhances target task performance.

The process uses methods like classification, inference algorithms, Bayesian networks, and Markov networks, with ongoing research focused on improving efficiency, reducing training time, and boosting accuracy. Transfer learning allows models trained on one task to be adapted and reused in another, making it essential for modern machine learning.

Some pre-trained CNN Models that were used in this study:

1.4.5.1 VGG16 Model

VGG16, developed by the Visual Geometry Group at the University of Oxford, is a deep CNN with 138 million parameters, five convolutional blocks, and three fully connected layers. Known for its simplicity and strong performance in tasks like face recognition and image classification, it achieved 91.90% accuracy in the 2014 ImageNet competition. It uses uniform 3×3 convolutional filters, making it ideal for fine-tuning in transfer learning.

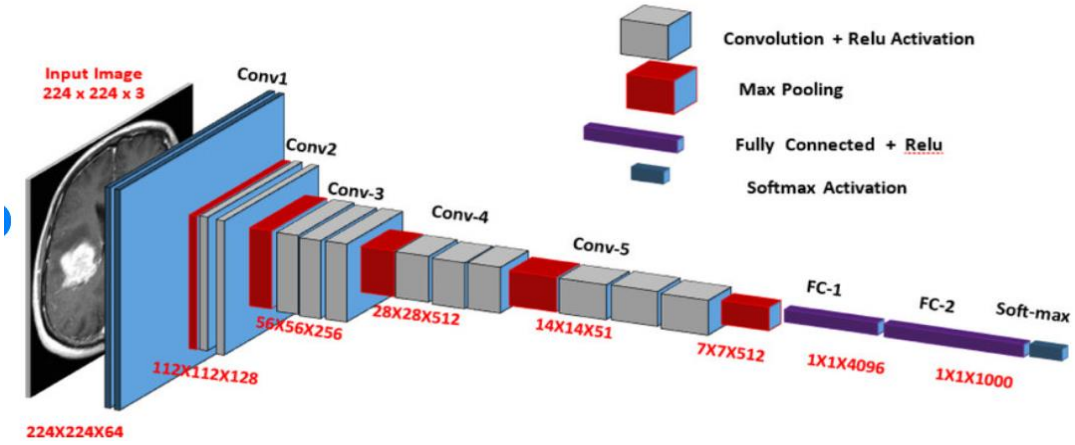


Figure 1-15: Architecture of VGG16

1.4.5.2 ResNet Model

ResNet (Residual Neural Network) addresses the vanishing gradient problem in deep networks using residual (skip) connections. ResNet-50, with 25 million parameters and 48 convolutional layers, achieved 92.29% accuracy in the 2015 ImageNet competition. Other versions, like ResNet-101 and ResNet-152, vary in depth. ResNet's scalability and pattern recognition abilities make it foundational in computer vision, although it may face filter redundancy and require high-quality datasets.

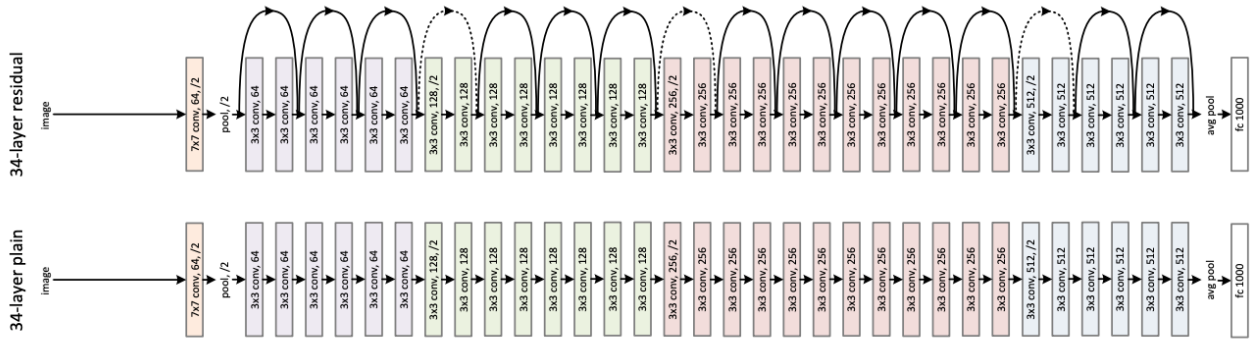


Figure 1-16: Architecture of ResNet

1.4.5.3 DenseNet Model

Dense network (Densely Connected Convolutional Network) connects each layer to all previous layers by concatenating feature maps, improving information flow, gradient propagation, and parameter efficiency. It uses dense blocks, transition layers, and a growth rate hyperparameter. Despite using fewer parameters (about one-fifth of ResNet), it maintains high accuracy and efficient training, especially useful in resource-constrained environments.

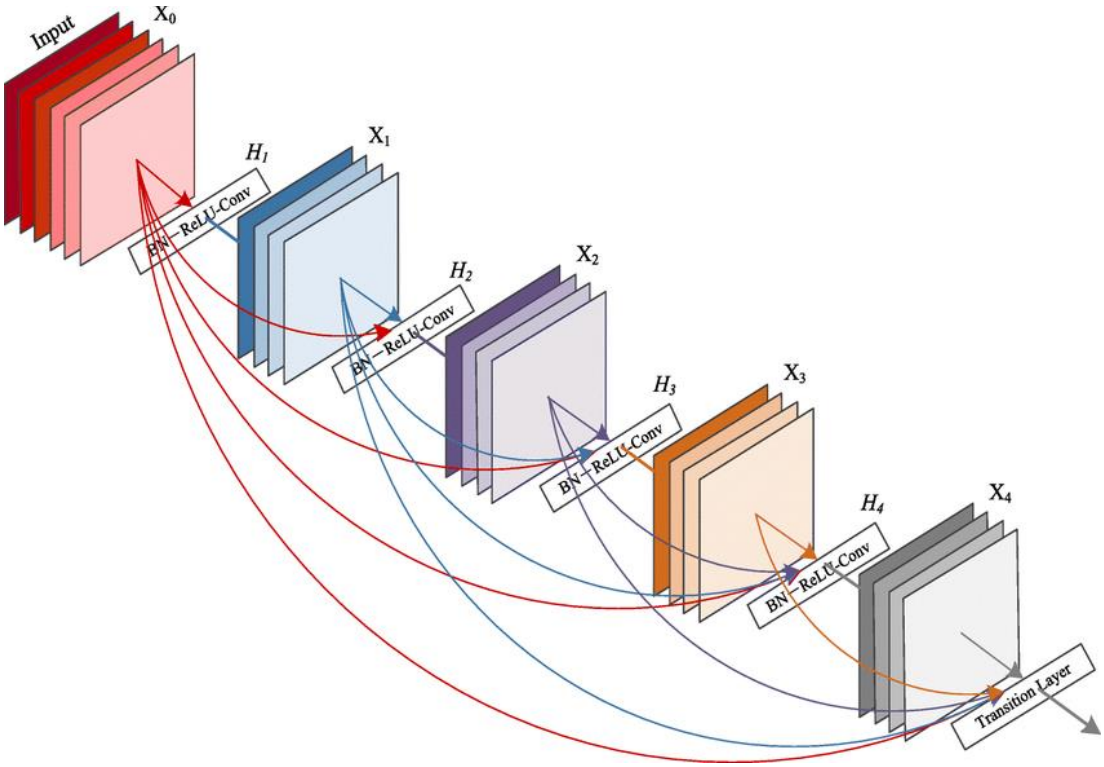


Figure 1-17: Architecture of DenseNet model[44]

1.4.6 Literature review

1.4.6.1 Summary of state-of-the-art using Machine learning for diagnosis of ASD

Traditional studies have examined some machine learning (ML) 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 some of the studies that utilized ML for classification.

Table 1-1: ASD diagnosis using MRI and ML models: Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR).[55]

Model	Data	Nb.subj	Prepro	MaxAcc	Source
SVM	fMRI	403 ASD, 468 TC	CPAC	67.28%	[45]
	fMRI	506 ASD, 548 TC	CPAC	72.2%	[46]
	sMRI	151 ASD, 151 TC	FSL	AUC 0.77	[47]
	fMRI	403 ASD, 468 TC	CPAC	60.89%	[48]
	fMRI, Phenotypique	505 ASD, 530 TC	-	71.1%	[49]
	fMRI, sMRI	49 ASD, 41 TC	-	78.89%	[50]
RF	fMRI	432 ASD, 556 TC	DPARSF	60.63%	[51]
	fMRI	306 ASD, 350 TC	FSL	73.75%	[52]
LR	fMRI, Phenotypique	505 ASD, 530 TC	-	71.1%	[53]
	fMRI	403 ASD, 468 TC	CPAC	60.89%	[54]

1.4.6.2 Summary of state-of-the-art using Deep learning for diagnosis of ASD

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.

The following table gives some of the papers that utilized CNN for classification.

Table 1-2: ASD Diagnosis Using CNN[55]

Model	Dataset	No. of cases	Preprocessing	Max Accuracy	Ref.
CNN	fMRI	539 ASD, 573 TC	CPAC	84.05%	[55]
	fMRI	539 ASD, 573 TC	CPAC	80%	[56]
	sMRI	592 ASD, 571 TC	–	66%	[57]
	fMRI	79 ASD, 105 TC	CCS	94.70%	[58]
	fMRI	491 ASD, 528 TC	DPARSF	82.12%	[59]

1.5 Conclusion

In this chapter, a solid foundation was created in studying Autism Spectrum Disorder through finding definitions, risk factors, and the importance of early diagnosis. 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 talked about how brain imaging techniques, and fMRI in particular, 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.

In the Conclusion of chapter, 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.

In an attempt to provide a comprehensive overview, we also prepared tables of performance of these models, highlighting their effectiveness in the state of the art. This comparison has insightful information on the merits and demerits of each methodology, making the selection of the most appropriate techniques for specific diagnostic tasks easy.

Chapter 02

Materials and Methods

2.1 Introduction

In this chapter, we will elucidate 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.

Chapter 2 provides a comprehensive overview of the methodology and deep learning approach adopted to predict ASD. This chapter serves as a crucial foundation for the subsequent chapters, where the results, analysis, and implications of the ASD prediction model will be discussed.

2.2 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.

2.2.1 Dataset Collection:

2.2.1.1 Autism Brain Imaging Data Exchange Database

In this work, we 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 [60].

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 connectome 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.

2.2.1.2 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. The following table 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 2-1: Demographic characteristics of the participants by site in the ABIDE dataset[55]

Site	ASD	Control	Age Range	Total
Caltech	19	19	17.0-56.2	38
CMU	14	13	19-40	27
KKI	22	33	8.0-12.8	55
MaxMun	24	33	7-58	57
NYU	79	105	6.5-39.1	184
Olin	20	16	10-24	36
OHSU	13	15	8.0-15.2	28
SDSU	14	22	8.7-17.2	36
SBL	15	15	20-64	30
Stanford	20	20	7.5-12.9	40
Trinity	24	25	12.0-25.9	49
UCLA 1	49	33	8.4-17.9	82
UCLA 2	13	14	9.8-16.5	27
Leuven 1	14	15	18-32	29
Leuven 2	15	20	12.1-16.9	35
UM 1	55	55	8.2-19.2	110
UM 2	13	22	12.8-28.8	35
Pitt	30	27	9.3-35.2	57
USM	58	43	8.8-50.2	101
Yale	28	28	7.0-17.8	56
17 sites	539	573	7 to 64	1112

The data used in this study is detailed between:

Table 2-2: Summary of the number of subjects

Site / **Data**	**sMRI**	**fMRI**
ABIDE-I	1102	1112
ABIDE-II	1114	1113
ABIDE-I+ABIDE-II	2216	2225

2.2.2 Preprocessing

Preprocessing in the medical field is essential, particularly with diverse imaging data. Various brain imaging machines produce images that exhibit different characteristics [61], 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.

2.2.2.1 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.

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 extracranial matter, from MRI scans. This process is essential for preprocessing in both functional and structural neuroimaging analysis.

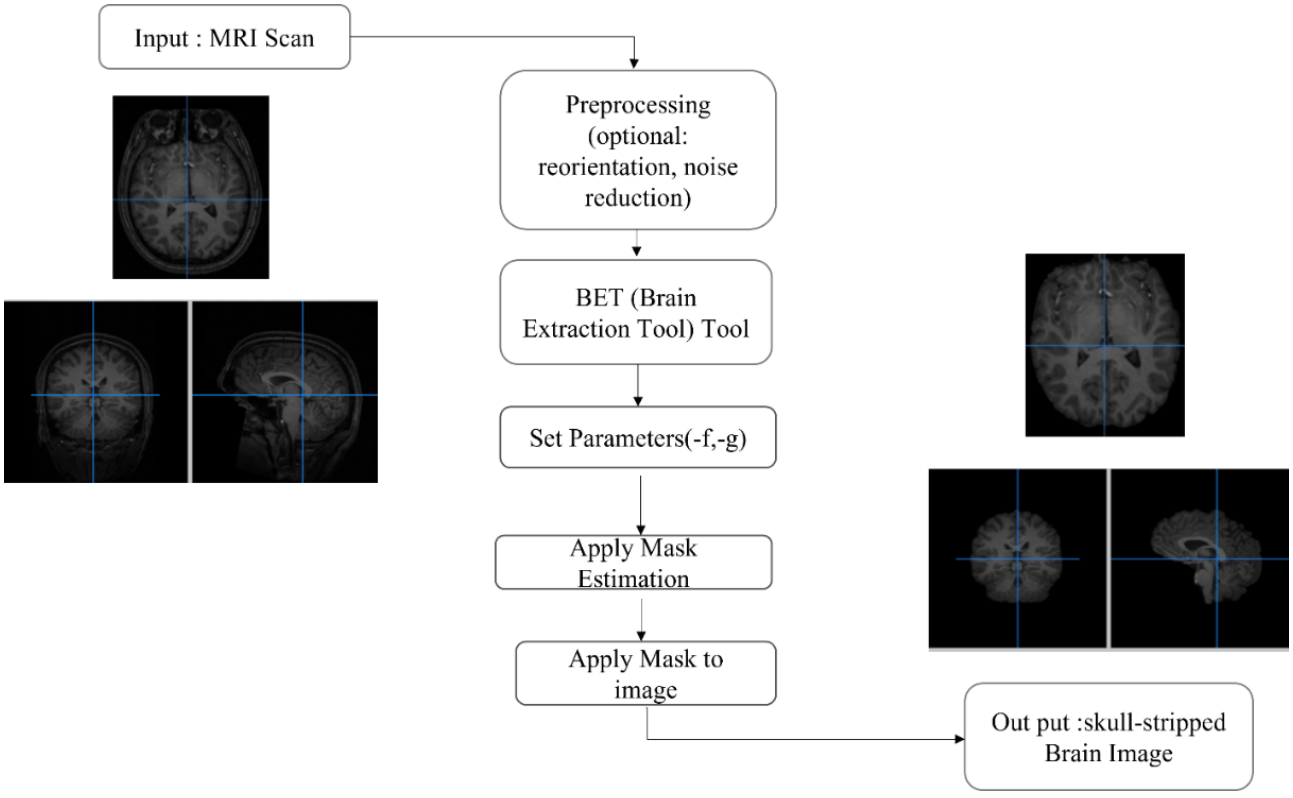


Figure 2-1: Dataset Preprocessing

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 thesis, 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.

2.3 Proposed system

This study proposed a 3D-CNN model architecture that is simple yet effective in handling 3D neuroimaging data. The model uses raw 3D images of mri and fMRI neuroimage collected from the ABIDE dataset. The neuroimages are preprocessed before training the model to ensure consistent data representation by normalization and resizing. This involved normalization and resizing processes in order to enhance comparability and normalize spatial units.

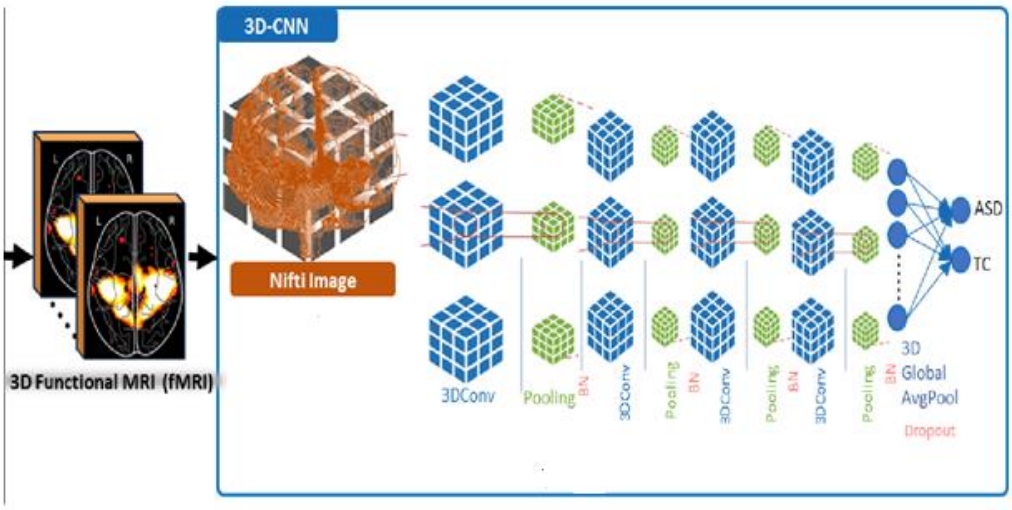


Figure 2-2: Exemple of Architecture of 3D-CNN Models

2.3.1 3D-VGG16 Like model

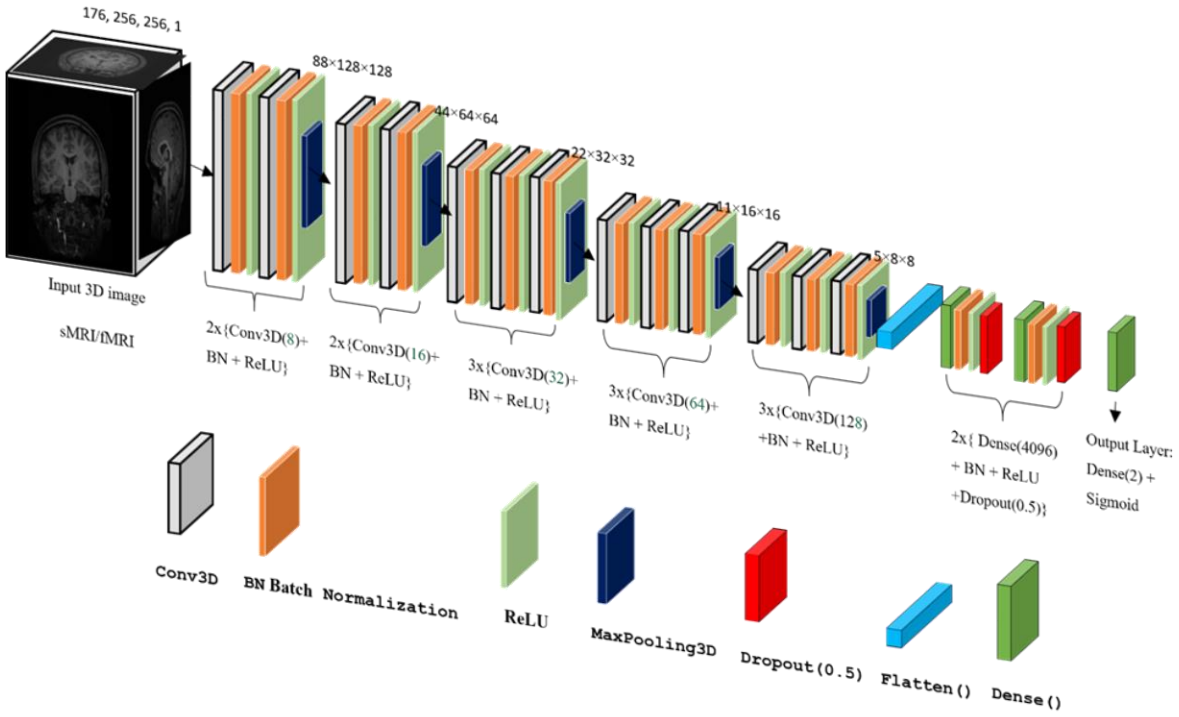


Figure 2-3: Custom 3D VGG16 Model

This is a 3D CNN model from the VGG 16 architecture for ASD detection from 3D MRI with an input 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.

Finally, 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}.

2.3.2 3D-ResNet-like model

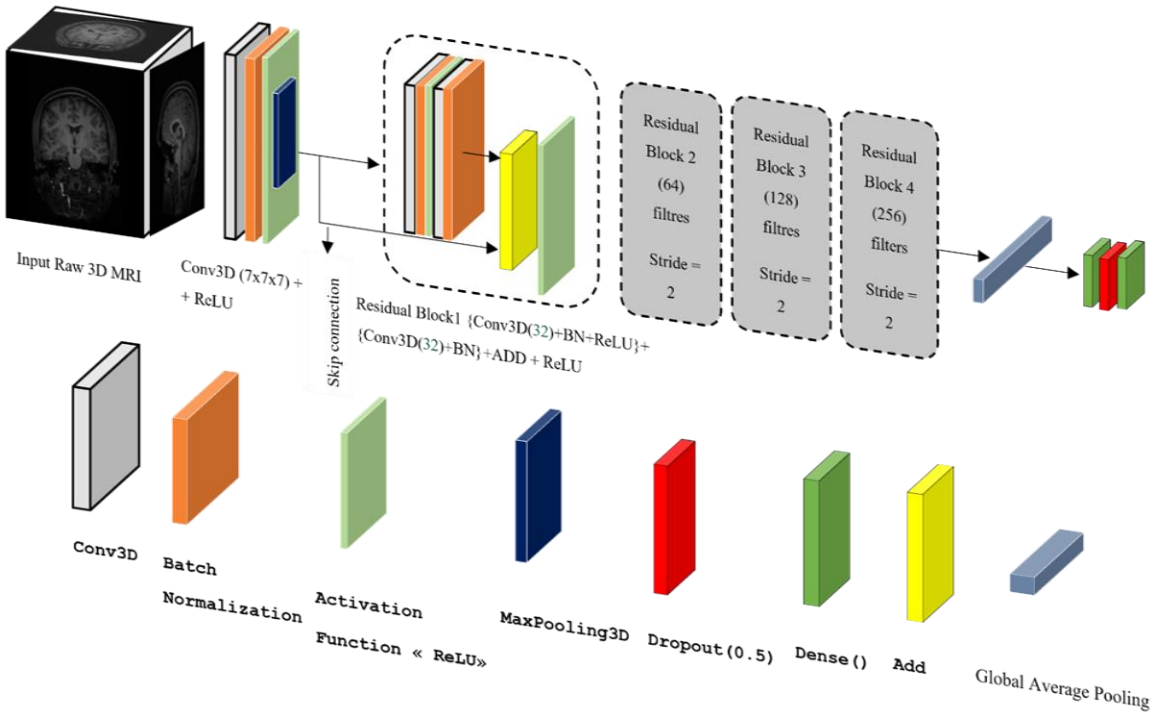


Figure 2-4: Custom 3D ResNet Model

This is a 3D ResNet convolutional neural network 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.

2.3.3 3D-DenseNet Like model

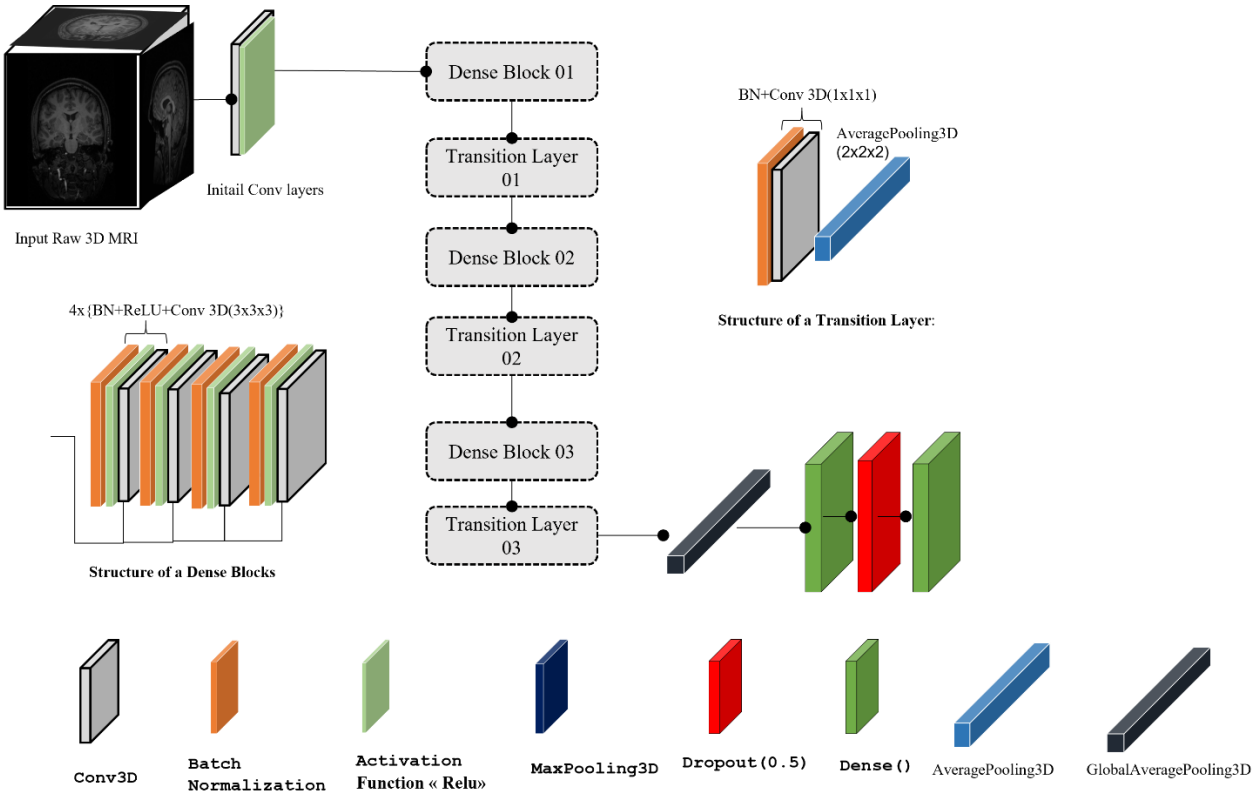


Figure 2-5: Custom 3D DenseNet model

This 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.

2.4 Conclusion

This chapter gave a clear definition of the material and methods involved in developing an effective deep learning model for autism spectrum disorder (ASD) detection. Starting from research design, going through data collection and preprocessing, all aspects have been articulated well to ensure that the input data maintains its integrity, reliability, as well as variability. The application of high-quality datasets, as well as extensive preprocessing steps, has laid a solid basis for effective training of the model.

Moreover, deep learning architecture and training procedures have been thoroughly described with reasons for model selection along with optimization techniques used to attain performance. Methods of validation and metrics used for assessment have also been elaborated with the aim to keep it transparent as well as replicable.

By offering a clear and concise methodological framework, this chapter provides an impetus to the analysis and discussion of the performance of the model in the remaining chapters. Materials and methods discussed here not only guide technical implementation but also contribute towards the scientific merit of the overall research process.

Chapter 03

Results and Discussion

3.1 Introduction

This chapter documents the results and extensive discussion of the proposed 3D Convolutional Neural Network (3D-CNN) architecture intended for Autism Spectrum Disorder (ASD) identification from neuroimaging data. Following the methodologies outlined in the previous chapter, this section discusses the evaluation of the model's performance using a variety of quantitative measures and qualitative assessments.

In addition, comparative studies with existing approaches are introduced to put the performance of the proposed system into perspective. Discussion of possible causes why the model is weak or robust, including the impacts of data preprocessing, training mechanisms, and design choices, is introduced as well.

3.2 Work Environment

For the implementation and testing of the proposed (3D-CNN) model for the detection of ASD, a flexible and reliable working environment was required. Therefore, in this study, the choice of work environment played a significant role in managing computational complexity, ensuring reproducibility, and easing model development and experimentation.

This Table (3.1) explains the structure of the work environment for our thesis.

In this section, we present the hardware environment used for the application, The characteristics are Computer of the Scientific Research Center that offers powerful computational resources, including Graphics Processing Units (GPUs).

DL models are constructed using specific programming languages and packages, so that choosing a software environment is very important (see Table -3.1-).

Additionally important libraries “PyTorch, TensorFlow, and Keras, …etc. (More detail in Table 3.1)” and tools commonly used for building and training 3D CNN models, especially for tasks like medical image classification.

Once a model is written and running, it must be optimized for the best results. Traditionally, manual optimization involves tweaking the model’s settings (i.e., hyperparameters) to increase classification accuracy and reduce loss (error). However, manual methods are time-consuming and require significant experience. Alternatively, hyperparameter optimization can be automated using optimization packages (see Table 3.1).

Table 3-1: An introductory list of assistive tools.

Category	Tools	Properties
Hardware	Computer Scientific Research Center	**Processor**: Intel ® Xeon (R) Silver 4108 CPU @ 1.80GHZ x 16 **Installed RAM**: 93 GiB. **GPU**: GeForce RTX 2080 Ti Rev.A **Hard Drive**: 2.5 TB SSD. **System Type:** 64-bit operating system. **OS**: Linux Ubuntu 20.04.6 LTS
Software	Visual Studio Code	Visual Studio Code 1.100.1 version was installed on the laptop, which included Python 3.13.2
		Python 3.13.2 includes NumPy, open-cv, pandas, tensorflow, seaborn, sklearn, and Matplotlib were installed through VS code to handle data manipulation, analysis, and visualization tasks.
	Google Colaboratory (Google Colab)	Offers free access to powerful computational resources, including Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs). GPU Support Cloud Storage Integration Pre-installed Libraries Collaboration
Deep learning libraries	PyTorch TensorFlow, Keras	Frameworks to build and train 3D CNN models. Both support 3D convolution layers.
	Numpy Pandas	Scientific Computing & Data Handling
	Os, Matplotlib, Open CV , seaborn, nibabel, sklearn and	Handle data manipulation, analysis, and visualization tasks.
Optimization tools	Adam	A widely used optimizer that adapts the learning rate for each parameter
	Learning Rate Schedulers	Automatically adjust the learning rate during training to improve convergence.
	Regularization Tools, Callbacks, Data Augmentation	Prevent overfitting, monitor, and control training behavior dynamically.

3.3 The proposed Algorithm

To improve the generalizability and robustness of the ASD classification model, several essential techniques were employed during the training process, Such as the preprocessing, Data Augmentation, and normalization.

In this section, we present the various techniques that were used in this study. The diagram below shows a summary of the most important of these techniques.

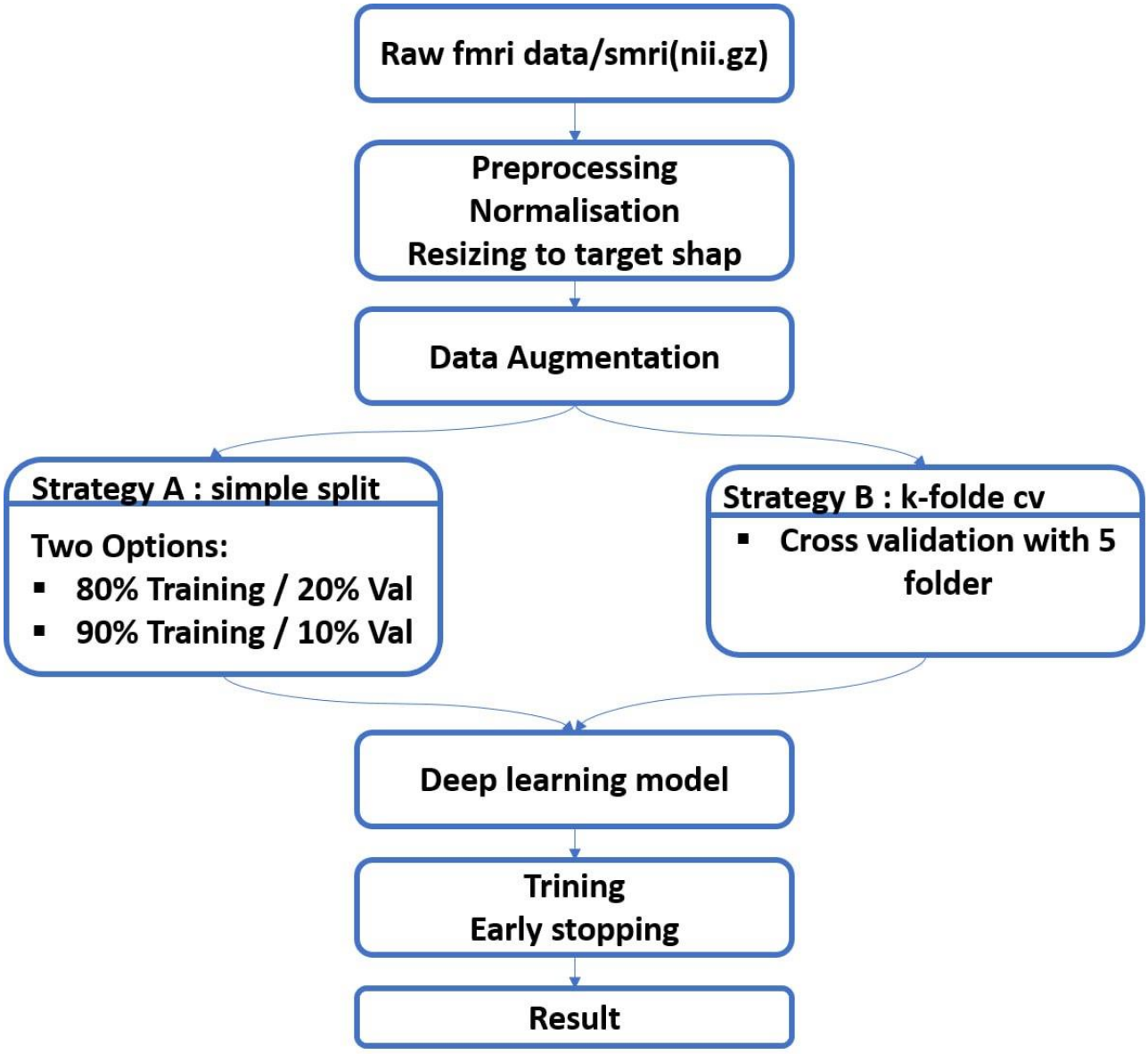


Figure 3-1: Flowchart of Proposed Algorithm

3.3.1 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:

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

3.3.2 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 pf 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 studey the cross validation was critical due to the small sample and the need to evaluation the model performance, we use 5 foldes in this study,4 foldes for trining and one for validation, and the process was repeated 5 times with each fold used once as the validation set

3.3.3 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.

3.4 Parameter Setting

- **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.

- **Epochs**

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

- **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).

- **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.

- **Regularization**

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

3.5 Training and Results

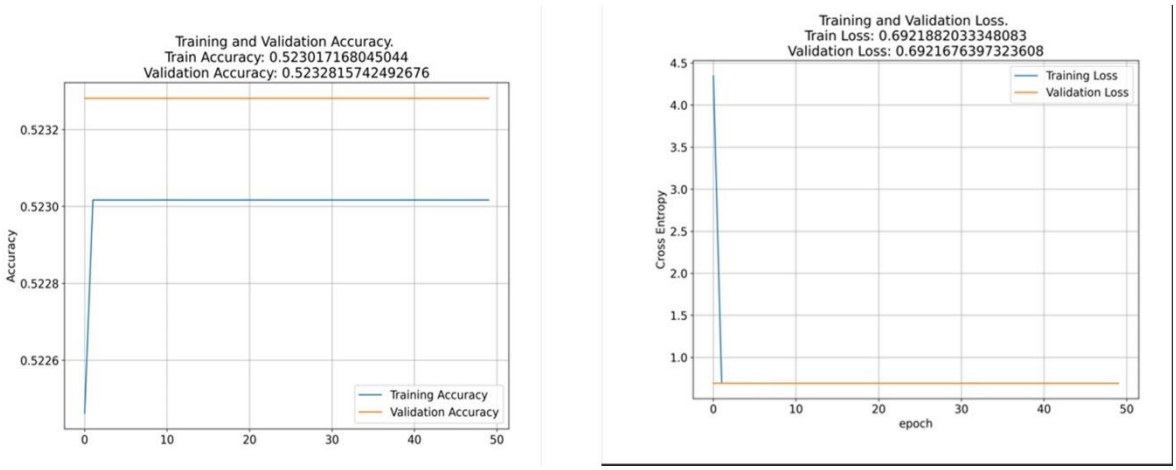
This section presents the training and results of our autism classification models. We have trained Three models (VGG16, ResNet,and DenseNet) using datasets from ABIDE. We also evaluate the models on an independent test dataset using metrics such as accuracy, precision, recall, and F1 score. We compare the performance of the different models and datasets to identify the most effective combinations. Through this section, we display the accuracy of our models in predicting groups from fingerprints. The results provide insights into the performance of each model and the impact of dataset variations.

For manually tuning the hyperparameters to maximize model accuracy. After the model was tuned, we ran and validated our model and extracted the classification metrics.

Altogether, these tasks took approximately ten weeks and almost 3 months of full-time work.

3.5.1 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)*

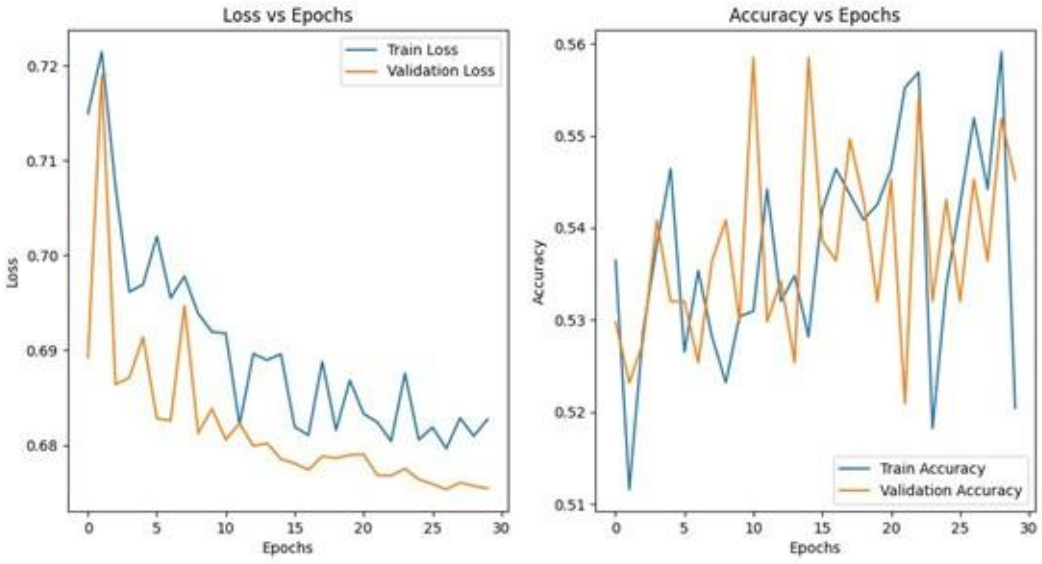
Figure 3-2: VGG 16 curve. (a) Training and Validation Accuracy. (b) Training and Validation Loss

The plan (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 graph (B). The flat curves across all epochs indicate that the model stopped learning early.

3.5.2 3D ResNet Model

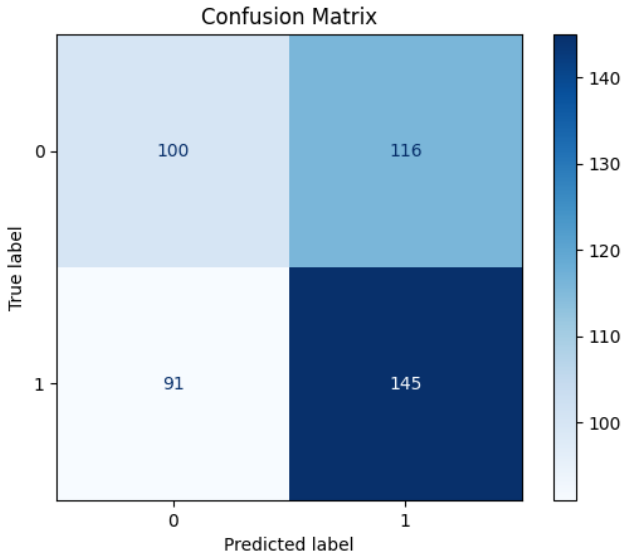
After training the model with the current settings, 50 epochs, batch size maximum 8, validation split 0.1 or 0.2, and based on the results obtained.



(a) *(b)*

Figure 3-3: ResNet curves (a) Training and Validation Loss (b) Training and Validation Accuracy

The graph (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. The curves (a) as shown in the figure, for both training and validation sets, 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 confusion matrix presented above, 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). This results in an overall accuracy of 56.7%, with a precision of 55.6%, a recall (sensitivity) of 61.4%, and an F1-score of 58.3%. These metrics indicate that while the model shows some ability to distinguish between the two classes, it struggles with generalization, particularly in minimizing false positives and false negatives.

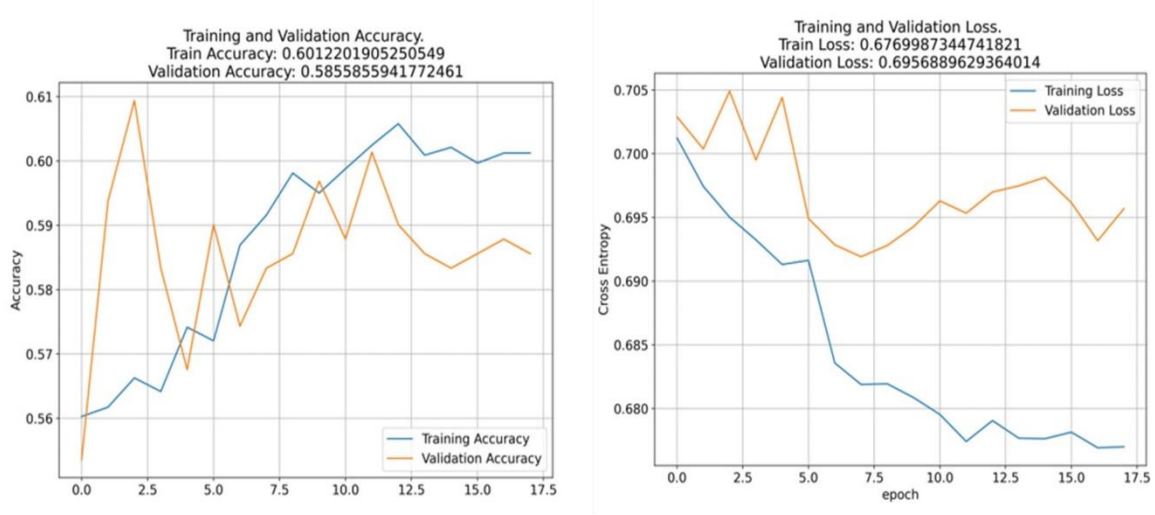
These results were computed based on the confusion matrix shown in Figure X, derived from the final test evaluation of the ReseNet model

Table 3-2: Summary of ResNet Model Performance

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

3.5.3 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 5 folde cross validation, and based on the results obtained, taking into account the difference in accuracy of the network results in the studied database, this model achieve in accuracy between 60 % and 70% in trining data but the model has overfitting when he arrive in 70%.

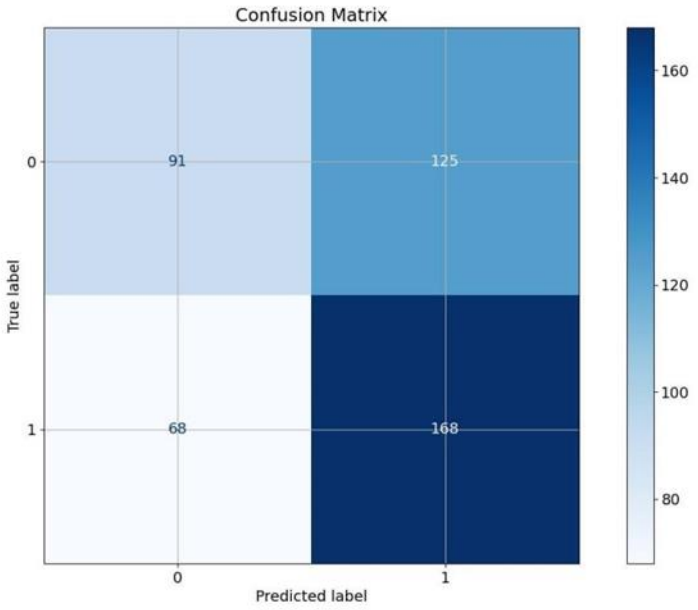


(a) *(b)*

Figure 3-5: DenseNet curve. (a) Training and Validation Accuracy. (b) Training and Validation Loss

Graph (a), as shown in the Figure, 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 (b) as shown in the figure, 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 confusion matrix presented above, the model correctly identified 168 true positives and 91 true negatives but also misclassified 125 false positives and 68 false negatives. This results in an overall accuracy of approximately 57.3%. The precision was calculated as 57.3%, indicating that just over half of the instances predicted as positive were correct. The recall was 71.2%, showing that the model was relatively better at identifying actual positive cases. The F1-score, which balances precision and recall, was 63.4%, reflecting the model's moderate ability to generalize

These results were computed based on the confusion matrix shown in Figure X, derived from the final test evaluation of the DenseNet model

Table 3-3: Summary of DensNet Model Performance

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

3.5.4 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.

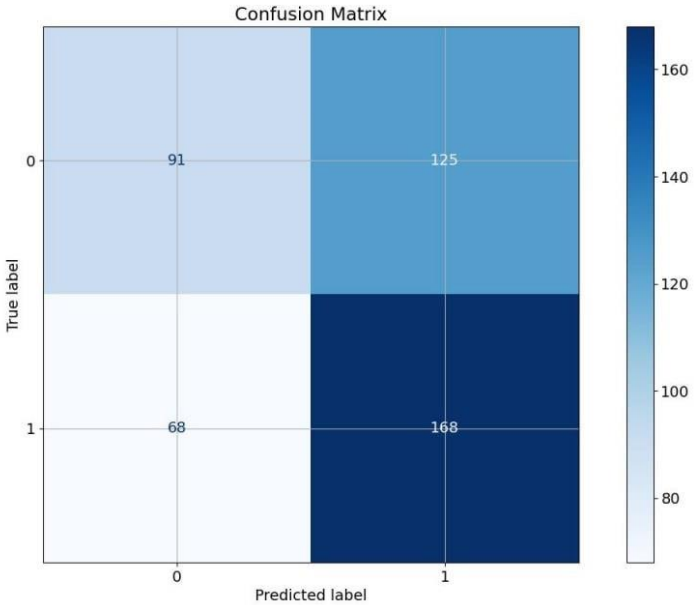


Figure 3-7: The Confusion Matrix of DenseNet Model

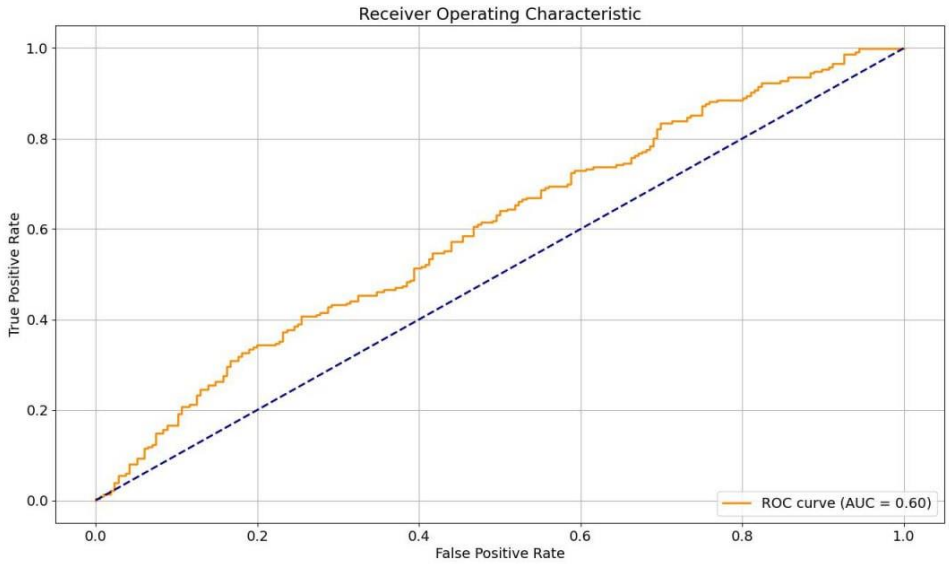


Figure 3-8: AUC Curve

3.6 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 test accuracy of about 60% among these models.

Our findings align with other research indicating restricted classification accuracy of deep learning models on ABIDE data. For instance, [62] 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.

3.7 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 3.2.

Table 3-4: Comparing our 3D CNN model to similar architectures

Approach	Accuracy	Réf
ResNet50	53.8%	[62]
DenseNet121	55.4%	[62]
3D CNN (custom architecture)	58–59%	[63]
3D CNN	~60%	[64]
Our approach	**~57%**	

3.8 Conclusion

This chapter has presented a detailed analysis of the training, testing, and implementation of the proposed deep learning models for ASD detection from 3D MRI images. From a starting point of an introduction to the work environment, particularly the use of Google Colab to minimize computational expenses, the chapter 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, the discussion provided an insight into the behavior and constraint of every model, and the comparison with state-of-the-art techniques confirmed the competitiveness and potential of the system proposed. Overall, this chapter 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.

General Conclusion

Technology is so developed today that machines can perform complex jobs using artificial intelligence. Deep learning is most suited to handle massive amounts of information from different sources and extract useful information that can be used. In AI, the area of computer vision is mentioned as the basis of enabling machines to interpret sense from digital pictures, video, and other images and utilize that gained intelligence in decision-making or suggestions.

This thesis explored the use of deep learning techniques, 3D Convolutional Neural Networks (3D-CNNs), to detect and diagnose ASD from brain MRI images. The work discussed in the three chapters forms a cohesive research work that contributes to the field of medical imaging and neurodevelopmental disorder diagnosis.

In Chapter 1 introduced Autism Spectrum Disorder (ASD), covering its definitions, symptoms, causes, and the importance of early diagnosis. It also discussed brain changes associated with ASD, the use of MRI in studies, and key deep learning models like VGG16, ResNet, and DenseNet, supported by a literature review.

Chapter 2 detailed the study's methodology, including data collection from the ABIDE database, preprocessing using FSL, and the design of three 3D CNN models based on VGG16, ResNet, and DenseNet for ASD classification.

Chapter 3 covered the implementation environment, training process, and evaluation techniques like data augmentation, cross-validation, and early stopping enhanced performance. One model achieved the best accuracy, showing strong results compared to existing methods.

Finally, this thesis provides an overall review of brain imaging techniques, analysis techniques, and machine learning and deep learning algorithms used in the analysis and detection of ASD based on 3D MRI scans.

These advances bring with them opportunities for better and more accurate techniques for early intervention and diagnosis, promising brighter prospects for more effective treatment and intervention models for individuals with ASD.

The results are encouraging and demonstrate the potential of 3D CNNs in helping diagnose ASD early and effectively. As a future direction, we plan to fuse multimodal data like behavior analysis, eye tracking, and clinical analysis, which can significantly enhance autism detection by capturing a broader range of behavioral and neurological markers. Such a multimodal fusion has the potential to increase diagnostic accuracy and enable more personalized interventions for individuals on the autism spectrum.

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