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Theme

Classification of Brain MRI Autism Spectrum Disorder Using Transfer Learning

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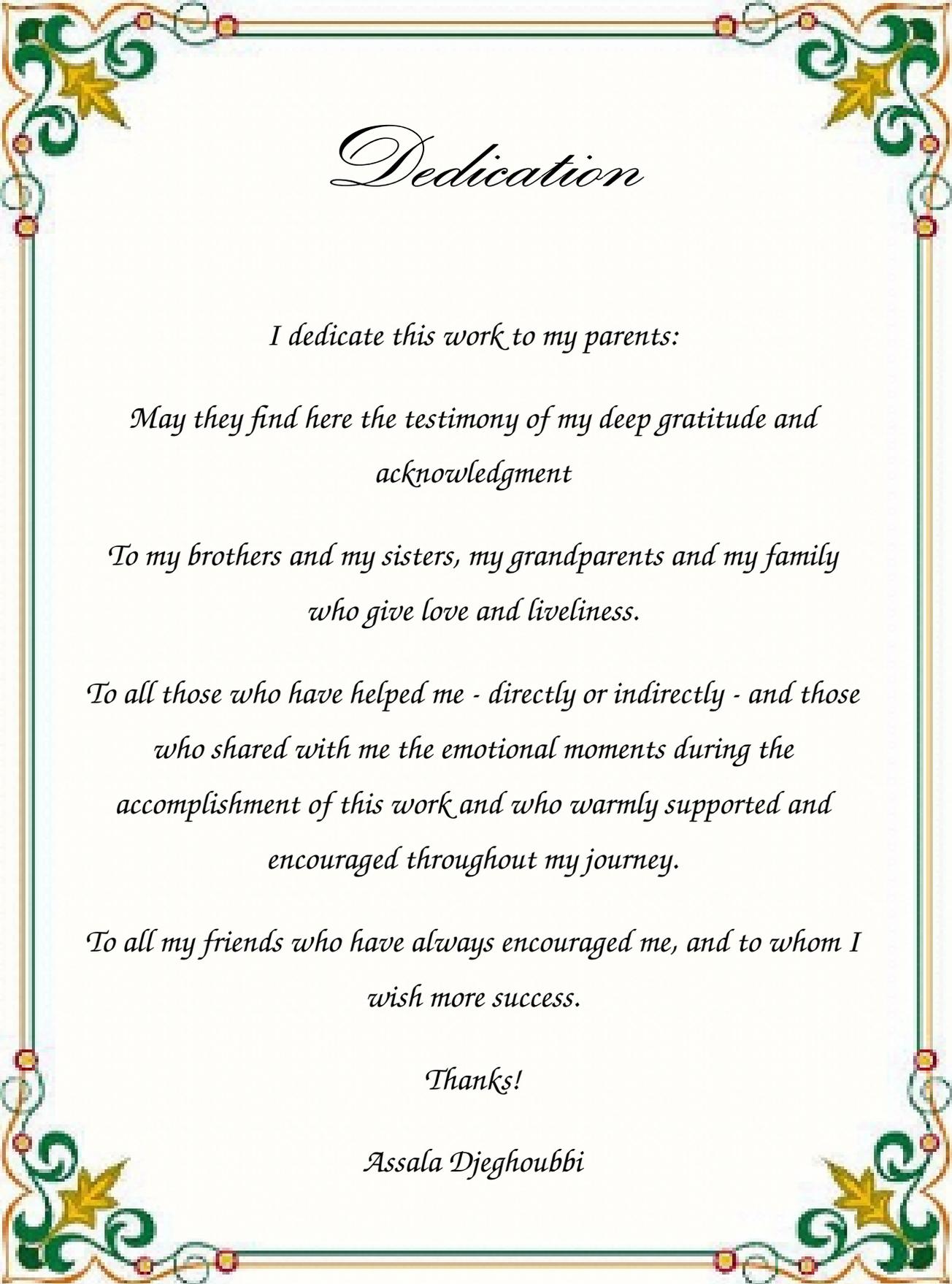
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O Allah, send your blessings on your noble messenger, his family, and companions, and bless us in our life.



Dedication

I dedicate this work to my parents:

*May they find here the testimony of my deep gratitude and
acknowledgment*

*To my brothers and my sisters, my grandparents and my family
who give love and liveliness.*

*To all those who have helped me - directly or indirectly - and those
who shared with me the emotional moments during the
accomplishment of this work and who warmly supported and
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*To all my friends who have always encouraged me, and to whom I
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Abstract

This study explored the potential of deep learning techniques to analyze structural magnetic resonance imaging (sMRI) scans for diagnosing (ASD) in children. The process involved converting 3D images into 2D slices, assembling them into uniform-sized images, and training four well-known architectures (VGG16, ResNet, MobileNet, EfficientNet) using five-fold cross-validation. Results showed that EfficientNet outperformed the others in accuracy (~75%) and performance stability, while MobileNet was the fastest and lightest but less accurate. The findings highlight the importance of expanding the dataset size, integrating multiple data sources, and employing explainable AI techniques to better understand model decisions. Additionally, improving preprocessing by selecting the most informative MRI slices could enhance the models' effectiveness and support their reliable application in medical settings.

Key words: Autism Spectrum Disorder (ASD), Brain MRI, Deep Learning, Transfer Learning, Image Classification.

ملخص

تم دراسة إمكانيات تقنيات التعلم العميق في تحليل صور الرنين المغناطيسي الهيكلية (sMRI) لتشخيص اضطراب طيف التوحد لدى الأطفال. شملت العملية تحويل الصور ثلاثية الأبعاد إلى شرائح ثنائية الأبعاد وتجميعها في صور موحدة الحجم، ثم تدريب أربعة نماذج معمارية معروفة (VGG16، ResNet، MobileNet، EfficientNet) باستخدام التقاطع الخماسي. أظهرت النتائج تفوق نموذج EfficientNet من حيث الدقة (~75%) واستقرار الأداء، بينما كان MobileNet الأسرع والأخف لكنه أقل دقة. تشير النتائج إلى أهمية توسيع حجم البيانات، دمج مصادر معلومات متعددة، واستخدام تقنيات الذكاء الاصطناعي التفسيري لفهم قرارات النماذج بشكل أفضل. كما يمكن تحسين مرحلة ما قبل المعالجة عبر اختيار شرائح MRI الأكثر تميزاً، مما يعزز فرص تطبيق هذه النماذج في البيئات الطبية بشكل فعال وموثوق.

الكلمات المفتاحية: تصنيف الصور، التعلم العميق، التصوير بالرنين المغناطيسي للدماغ، اضطراب طيف التوحد، التعلم بالنقل.

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List of Abbreviations

ASD:	Autism Spectrum Disorder
DSM:	Diagnostic and Statistical Manual
PDD-NOS:	Pervasive Developmental Disorder-Not Otherwise Specified
ML:	Machine Learning
MRI:	Magnetic Resonance Imaging
fMRI:	functional MRI
SVM:	Support Vector Machines
KNN:	K-Nearest Neighbors
RNN:	Recurrent Neural Networks
CNN:	Convolutional Neural Networks
ADOS:	Autism Diagnostic Observation Schedule
AI:	Artificial Intelligence
rs-fMRI:	resting-state-fMRI
NYU:	New York University
UCLA:	University of California, Los Angeles
BET:	Brain Extraction Tool
FSL:	FMRIB Software Library
TP:	True Positive
TN:	True Negative
FN:	False Negative
ABIDE:	Autism Brain Imaging Data Exchange

General introduction

Autism spectrum disorder (ASD) is a heterogeneous neurodevelopmental disorder that has a strong genetic basis, and various clinical presentations. ASD is characterized by repetitive behavior, social interaction impairments, and difficulties in verbal and nonverbal communication. The prevalence of ASD has been increasing for the last few years, especially in children. A significant financial, and emotional burden faces ASD individuals and their families, as the incidence of ASD increases. Moreover, ASD increases the pressure on the medical, social, and political life of any nation, diagnose ASD using magnetic resonance imaging (MRI).

One of the most commonly used subfields of AI in research is deep learning (DL). By extracting useful information and building complex DL models that surpass human performance in analyzing large datasets, DL can help us to understanding and diagnosing of ASD. Despite the significant advances in MRI imaging techniques and modern deep learning algorithms, the task of classifying Autism ASD based on structural MRI scans remains a challenge of selecting the optimal pretrained model and fine-tuning its parameters accurately. This stems from the research question that is " How can a precise and efficient deep learning model be designed to classify ASD using MRI images? " Our study aims to design an efficient and accurate model based on deep learning algorithms to classify ASD using MRI images (both sMRI and fMRI).

The thesis is organized as : The first chapter is an introduction that provides an overview of ASD, DL techniques and reviewed previous studies on the field of detection of ASD using DL. The second chapter outlines the materials and methods focusing to the dataset and DL approaches used, including data collection and the pre-trained models. The third chapter focuses on the findings and discussion of the obtained results and the effectiveness of the proposed model. Finely, the general conclusion section.

Chapter 1

Introduction

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition that affects brain development, leading to noticeable difficulties in social communication, repetitive behaviors, and restricted interests. Autism typically appears in the early years of a child's life, and its severity and symptoms can vary significantly from one individual to another, which is why it is referred to as a "spectrum" disorder. As the global rate of ASD diagnosis continues to rise, there is an increasing need to deepen our understanding of the disorder particularly regarding its causes, diagnostic methods, and early intervention strategies. With the advancement of medical technologies, neuroimaging, and artificial intelligence, new opportunities are emerging for exploring innovative diagnostic and therapeutic approaches. Among these, the use of Magnetic Resonance Imaging (MRI) and deep learning models has shown promise in identifying neural markers of . This chapter provides an introduction to the general framework of this research. It begins with an overview of ASD, including its definition, characteristics, and diagnostic challenges. The chapter then explores the role of Machine Learning (ML) and Deep Learning (DL) in improving the accuracy and efficiency of ASD diagnosis. Finally, it presents a literature review of recent studies that have utilized these technologies in the context of ASD, highlighting their methodologies and key findings.

1.1 Overview of Autism Spectrum Disorder

ASD has become one of the most widely studied neurodevelopmental conditions in recent years, due to its significant impact on behavioral and cognitive functions. The wide variability in symptom presentation among individuals has created a need for precise diagnostic and classification tools. Advances in neuroimaging and artificial intelligence, particularly deep learning, have greatly enhanced our understanding of brain patterns associated with ASD. These developments offer promising opportunities for early diagnosis and targeted therapeutic interventions.

1.1.1 The Types ASD

The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) merged all subtypes of autism into a single category known as ASD. While the fourth edition (DSM-IV) distinguished between several types, this change reflects the presence of shared characteristics such as difficulties in communication, social interaction, and repetitive behaviors. However, there are still differences in the severity of symptoms and the level of support required for each individual[4].[5].

1.1.1.1 Autistic Disorder

Autistic Disorder was considered the most common form of autism, where individuals exhibited significant difficulties in social interaction, communication, and understanding social cues. They also showed repetitive behaviors or restricted interests. These individuals typically required substantial support in many aspects of life.

1.1.1.2 Asperger's Disorder

Asperger's Disorder form of autism was considered less severe, where children faced social interaction challenges but had normal or even advanced language and cognitive skills. They may display restricted interests or repetitive behaviors. These individuals could often function independently, but they faced difficulties in social situations.

1.1.1.3 Pervasive Developmental Disorder-Not Otherwise Specified

Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS) was used to diagnose individuals who showed some signs of autism but did not meet the full criteria for Autistic

Disorder or Asperger’s Disorder. It was considered a non-specific type due to the variety of symptoms that could appear in affected individuals.

1.1.1.4 Rett’s Disorder

Rett’s Disorder is a rare condition that typically affects girls, where normal development occurs during early childhood, followed by a noticeable regression in motor and communication skills. Repetitive behaviors, such as hand-washing, and loss of motor abilities are common in this form.

1.1.1.5 Childhood Disintegrative Disorder

Childhood Disintegrative Disorder is a very rare type, where normal development occurs in the first few years of life, followed by a significant regression in social, linguistic, and motor skills after about two years of typical development.

Here is a table 1.1 representing the types of ASD as they were in the fourth edition (DSM-4), before being merged into a single category in the fifth edition (DSM-5):

Table 1.1: Types of Autism Spectrum Disorders and Their Main Characteristics

Type	Main Characteristics
Autistic Disorder	Severe difficulties in social interaction, communication, repetitive behaviors, and restricted interests.
Asperger’s Disorder	Difficulty in social interaction, normal or advanced language and cognitive skills, repetitive behaviors, and restricted interests.
Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS)	Some signs of autism but does not meet full criteria for autism or Asperger’s Disorder.
Rett’s Disorder	Normal development initially, followed by regression in motor and communication skills, repetitive behaviors like hand-washing.
Childhood Disintegrative Disorder	Normal development initially, then significant regression in social, linguistic, and motor skills after about two years.

1.1.2 Stages of Autism

According to the DSM-5, ASD is classified into three levels, based on the severity of symptoms and the amount of support a person needs in daily life[6] is represented by the table1.2.

Table 1.2: Classification of Autism into Three Levels Based on Symptom Severity and Support Needs

Level	Description	Support Needs	Common Terms
Level 1	Mild symptoms; difficulties in social interaction and organization.	Requires some support.	Sometimes called high-functioning autism.
Level 2	More noticeable social and communication challenges; limited interests and behaviors.	Requires substantial support.	
Level 3	Severe difficulties in communication, behavior, and daily functioning.	Requires very substantial support.	Sometimes referred to as severe autism.

1.1.3 Symptoms of Autism spectrum disorder

ASD begins in early childhood, with symptoms often appearing before the age of two. Symptoms vary from child to child and include difficulties in communication, behavior, and social interaction. Some children develop normally at first and then regress. There is no cure, but early and intensive intervention can greatly help. The severity of the condition depends on how much the symptoms affect the child's daily life[7]. The table1.3 represents common symptoms of autism spectrum disorder by category.

Table 1.3: Common Symptoms of Autism Spectrum Disorder by Category

Category	Common Symptoms
Social Communication and Interaction	Limited or no eye contact Does not respond to their name Difficulty expressing or understanding emotions Prefers to play alone Difficulty with conversations Lack of gestures (e.g., pointing, waving)
Repetitive Behaviors & Restricted Interests	Repeating words or phrases (echolalia) Lining up toys or objects Gets upset with changes in routine Intense focus on specific topics Repetitive movements (e.g., hand flapping) Fascination with parts of objects
Sensory Sensitivities	Overreacts or underreacts to sensory input (sounds, lights, textures, etc.) Unusual interest in sensory stimuli (e.g., sniffing objects)
Other Possible Signs	Speech delays Unusual tone of voice Sleep difficulties Hyperactivity or impulsiveness Poor motor coordination

1.2 Machine and deep Learning in ASD Diagnosis

Machine learning is increasingly being applied in the diagnosis of ASD to support early detection and improve diagnostic accuracy. By analyzing large datasets—such as behavioral patterns, genetic information, or brain imaging—ML algorithms can identify hidden patterns that may not be obvious to human observers. These models can help classify ASD cases, predict symptom severity, and even differentiate ASD from other developmental conditions. The integration of ML in ASD diagnosis holds great promise for making assessments faster, more objective, and more accessible.

1.2.1 Application of ML in ASD

Machine learning plays an increasingly important role in the early detection and classification of ASD. By analyzing data such as brain scans and behavior patterns, ML algorithms can help identify signs of ASD more accurately and efficiently, supporting earlier diagnosis and personalized interventions[8].

1.2.1.1 Automatic Classification

Automatic classification is a fundamental task in machine learning and data analysis, where algorithms are used to assign input data into predefined categories without human intervention. It is widely applied in fields like image recognition, medical diagnosis, spam detection, and speech recognition. In the context of ASD, automatic classification can help distinguish between individuals with and without ASD based on features extracted from brain imaging, behavioral data, or other biomarkers, improving diagnostic accuracy and efficiency.

1.2.1.2 Symptom Severity Prediction

Artificial intelligence and machine learning techniques are used to estimate the degree or severity of ASD symptoms in children. This prediction relies on the analysis of data such as MRI images, behavioral assessments, or clinical information. Such predictions support physicians in developing personalized treatment plans and enhance the understanding of the condition's progression for each individual. The following figure 1.1 represents ASD Diagnosis Using Machine Learning Techniques



Figure 1.1: ASD Diagnosis Using Machine Learning Techniques

1.2.2 Biomarkers of Data Used to Train Models

Biomarkers are measurable indicators that provide valuable insights into biological or pathological processes. In the context of training machine learning models for ASD, biomarkers refer to specific types of data that can help identify or predict the condition. These may include:

1.2.2.1 Neuroimaging Data

Structural MRI: Analyzing the shape and volume of brain regions. Functional MRI (fMRI): Studying how different brain regions communicate at rest or during specific tasks. As shown in the figure [1.2](#)

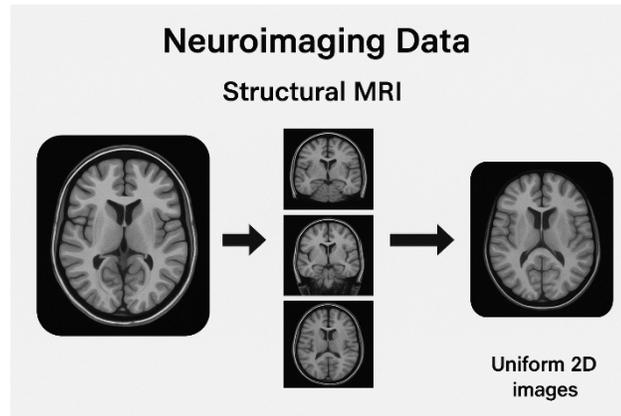


Figure 1.2: Processing Structural Neuroimaging Data (sMRI)

1.2.2.2 Genetic Data

Genetic data refers to information related to genes, such as mutations or genetic variations that may be associated with an increased risk of ASD. This data includes DNA sequencing analyses to identify specific genetic variants and differences in gene expression that can affect brain development and function. Genetic data is used to understand the biological causes of autism and can help machine learning models recognize genetic patterns that contribute to diagnosis and prediction of the disorder.

1.2.2.3 Behavioral Data

Behavioral data refers to observational information and scores obtained from standardized autism diagnostic tools. This data captures how individuals behave, communicate, and interact in various settings, providing critical insights into symptoms and functional abilities related to ASD. Behavioral assessments help identify characteristic patterns, severity of symptoms, and support personalized interventions. Machine learning models use this data to improve the accuracy of diagnosis and to predict outcomes based on observed behaviors. The table [1.4](#) summarizes the types of data used to train models in the diagnosis of ASD.

Table 1.4: Types of Data Used to Train Models in ASD Diagnosis

Types of Data	Description
Behavioral Data	Standardized assessments, parent questionnaires, clinical observations.
Neuroimaging Data	MRI or fMRI scans used to detect brain abnormalities.
Genetic Data	DNA sequences or gene expression linked to ASD.
Speech and Audio Data	Analysis of voice tone, pitch, and rhythm.
Eye-Tracking Data	Visual attention patterns and response to stimuli.
Electronic Health Records	Medical and developmental history.

1.2.3 Machine Learning Algorithms

Machine learning algorithms are computational methods that enable computer systems to learn from data and improve their performance on a specific task without being explicitly programmed for every scenario. In the context of ASD diagnosis, these algorithms are used to analyze large volumes of biomarker data—such as neuroimaging, genetic, behavioral, and clinical information—to uncover hidden patterns that aid in identifying or predicting the condition, common algorithms used in this field include[9]:

1.2.3.1 Support Vector Machines

Support Vector Machines (SVM) are supervised machine learning algorithms used for classification and regression tasks. In the context of ASD, SVMs are particularly effective for distinguishing between individuals with and without ASD based on complex, high-dimensional data such as neuroimaging features, genetic markers, or behavioral assessments. The figure1.3 represents an illustration of the SVM process.

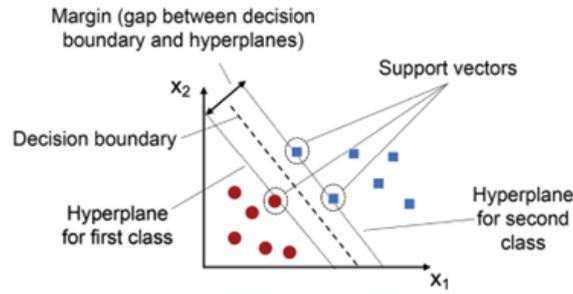


Figure 1.3: Illustration of Support Vector Machines (SVMs) for Binary Classification

1.2.3.2 Random Forests

Random Forests are supervised machine learning algorithms that rely on assembling a large number of decision trees to create a more accurate and robust model. They are widely used for classification and prediction tasks, including in ASD research. The figure 1.4 represents a simple diagram of how Random Forest works.

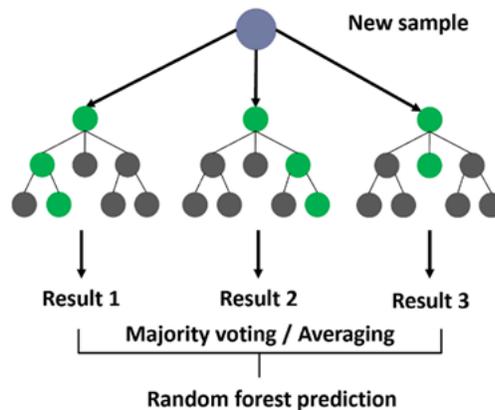


Figure 1.4: The Random Forest Algorithm in Machine Learning

1.2.3.3 K-Nearest Neighbors

K-Nearest Neighbors (K-NN) is a simple yet powerful supervised machine learning algorithm used for classification and regression tasks. It operates on the principle that similar data points exist close to each other in feature space. In the context of ASD, K-NN can be used to classify individuals based on similarities in behavioral scores, brain imaging features, or genetic profiles. The figure 1.5 represents how the KNN algorithm works.

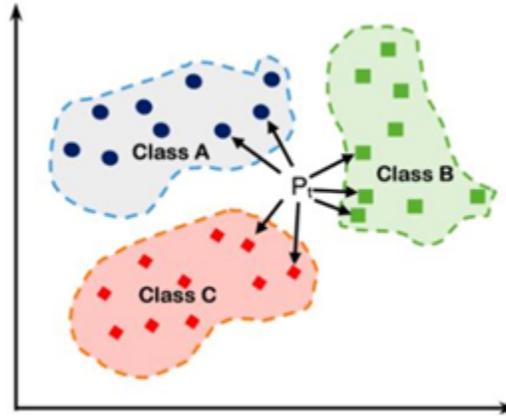


Figure 1.5: K-Nearest Neighbors (KNN) Classification Process

1.2.3.4 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are an advanced type of artificial neural network specifically designed for analyzing spatial data, such as images. In the context of ASD, CNNs are powerful tools for analyzing brain images (e.g., MRI and fMRI) and extracting subtle patterns that traditional methods might miss. The figure 1.6 represents how CNN works when classifying images.

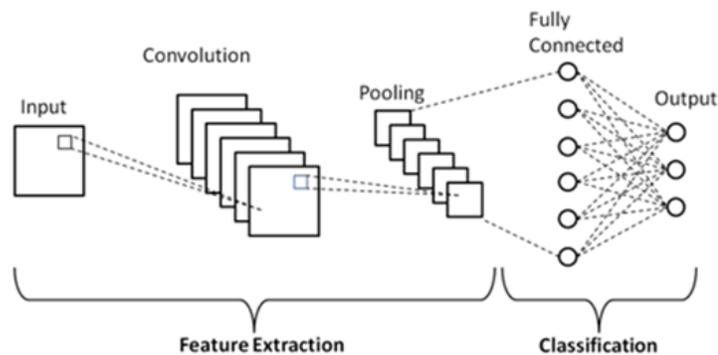


Figure 1.6: General Architecture of a Convolutional Neural Network (CNN) for Image Classification

1.3 Literature Review

Previous studies have focused on several aspects related to the diagnosis of ASD, most notably the analysis of behavioral indicators that appear in early childhood, and the use of standardized diagnostic tools such as the DSM and ADOS. Increasing attention has also

been given to the use of artificial intelligence and machine learning techniques to detect autism through the analysis of clinical data, audio recordings, and brain imaging. Additionally, some studies have explored the relationship between genetic and environmental factors and the emergence of autism symptoms, with the aim of developing tools that support early and accurate diagnosis and improve opportunities for timely therapeutic intervention, for example,

Veronica Frewer et al [10] conducted a systematic study a review focusing on the use of MRI to identify neuroimaging features in children with genetic syndromes associated with ASD. The study found that brain structural abnormalities were common in these populations, although the type of abnormality varied depending on the specific genetic mutation. This study was published in the *Journal of Child Psychology and Psychiatry*. Yumi Duan et al [11] published a study that used multisite structural MRI scans and machine learning algorithms to detect ASD. The findings revealed distinctive imaging biomarkers in individuals with autism and identified a negative correlation between gray matter volume in specific brain regions and the severity of behavioral symptoms. This work appeared in *Frontiers in Human Neuroscience*. Junlin Song [12] conducted a pioneering study combining radiomics and machine learning techniques to diagnose ASD by focusing on white matter analysis in brain MRI. A highly efficient diagnostic model was developed using artificial intelligence, achieving an accuracy of 89.47%. This supported the hypothesis that abnormalities in white matter are strongly linked to autism. The study was published on arXiv. Similarly, Cooper J. Mellema et al [13] conducted a study to identify reproducible neuroimaging features using machine learning models. Their approach achieved high performance in distinguishing individuals with ASD from typically developing peers and contributed to a better understanding of neurological indicators related to the disorder. This study was featured in *Scientific Reports*.

Finally, Ismail et al [14]. proposed an automated diagnostic model using computer vision and structural MRI analysis to detect autism in children at an early stage. Their model achieved a high accuracy rate of 93%, demonstrating the effectiveness of artificial intelligence techniques in supporting medical diagnosis. The research was published in the *Middle East Current Psychiatry journal*. The table 1.5 represents some of the accuracy of AI-based models for diagnosing autism spectrum disorder.

Table 1.5: Accuracy of AI-Based Models for ASD Diagnosis

Reference	Technique	Data Type	Accuracy
Frewer et al.[10]	Systematic Review (MRI Analysis)	Neuroimaging (Structural MRI – Genetics)	51.7%
Duan et al.[11]	Machine Learning	Structural MRI (Multi-site)	Imaging markers identified, no specific %
Song,[12]	Radiomics + Machine Learning	White Matter MRI	89.47%
Mellema et al.[13]	Machine Learning Models	Neuroimaging Features	80%
Ismail et al.[14]	Computer Vision + Structural MRI Analysis	Brain MRI (Children)	93%

The table 1.5 represents some of the accuracy of AI-based models for diagnosing autism spectrum disorder (2020–2024)

1.3.1 Research Gaps

Between 2020 and 2024, studies on ASD diagnosis using artificial intelligence techniques revealed several important research gaps. For instance, the study by Frewer et al[10]. focused on structural abnormalities in the brains of children with genetic syndromes associated with ASD, but did not include other affected populations, which limits the generalizability of the findings. The study by Duan et al[11], although using multi-site structural MRI, did not specify the accuracy of the models used and did not integrate behavioral or clinical data, representing a lack of data integration. Meanwhile, Mellema et al[13]. presented a machine learning model for analyzing neuroimaging features, but it was not tested in real-world clinical environments, which weakens its practical applicability. Ismail et al[14]. focused on children and achieved high accuracy, but the model was not tested on culturally or age-diverse samples, limiting the generalization of the results. Lastly, the study by Song [12] was limited to analyzing white matter using radiomics and machine learning, without

incorporating other biological or behavioral factors that could enhance model accuracy. The table 1.6 summarizes this information.

Table 1.6: Research Gaps in AI-Based Autism Diagnosis (2020–2024)

Study	Year	Research Gap
Frewer et al[10].	2021	Focused on structural brain abnormalities in children with genetic syndromes but did not include other ASD populations.
Duan et al[11].	2022	The model's accuracy was not specified, and behavioral or clinical data were not integrated, limiting diagnosis diversity and precision.
Mellema et al[13].	2022	The model was not tested in real-world clinical settings, reducing its generalizability and practical application.
Ismail et al[14].	2022	The model was not tested on culturally or age-diverse samples, limiting the generalizability of the results.
Song[12]	2024	The study focused solely on white matter analysis in the brain, without integrating other biological or behavioral factors.

In conclusion, ASD is a complex neurodevelopmental condition that requires ongoing research efforts for deeper understanding and more accurate diagnosis. This chapter began by providing a general overview of ASD, including its definition, core characteristics, and the diagnostic challenges associated with its wide range of symptoms and severity, which justify its classification as a "spectrum." Next, the chapter explored the role of artificial intelligence techniques—particularly machine learning and deep learning—in enhancing ASD diagnosis. These technologies can analyze large datasets and detect subtle patterns that traditional methods may overlook. A section was also dedicated to reviewing previous studies that employed MRI in combination with AI algorithms to identify neural markers of ASD. These studies yielded significant findings but also revealed several research gaps, such as the lack of integration between neurological and clinical data, limited diversity in study samples, and insufficient testing of models in real-world clinical environments. Accordingly, while AI-based tools for autism diagnosis hold great promise, their success depends on further interdisciplinary research that integrates neurological, behavioral, and clinical dimensions. Such an

approach can support the development of more accurate and effective diagnostic tools, ultimately enabling earlier and more personalized interventions that improve the quality of life for individuals with autism.

Chapter 2

Materials and Method

This chapter presents the materials and method adopted for classifying ASD using MRI scans. It includes a description of the ABIDE dataset and key preprocessing steps such as skull stripping and converting 3D volumes into 2D slices. The study employs transfer learning with pretrained models—VGG16, ResNet50, EfficientNet, and MobileNet—adapted for the classification task. Training details, evaluation tools, and the computational environment are also outlined, along with the use of 5-Fold Cross-Validation to ensure robust performance assessment. This methodology aims to develop an accurate and reliable model capable of generalizing well.

2.1 ASD classification approaches

Classifying ASD using MRI scans involves a multi-step approach that integrates advanced neuroimaging techniques with machine learning and deep learning algorithms. Here’s an overview of the typical process.

2.2 Dataset Description

The Autism Brain Imaging Data Exchange (ABIDE) is a collaborative international initiative aimed at advancing the understanding of ASD through the aggregation and sharing of neuroimaging data. ABIDE provides a comprehensive collection of structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) scans from individuals diagnosed with ASD as well as neurotypical controls. The dataset encompasses contributions from over 20 research sites worldwide, resulting in a diverse and extensive repository of brain imaging data. This

includes data from both ABIDE I and ABIDE II phases, with ABIDE I comprising 539 individuals with ASD and 573 typically developing controls, and ABIDE II adding data from 521 individuals with ASD and 593 controls. Participants range in age from children to adults, providing a broad spectrum for developmental studies.

ABIDE’s rich dataset has been instrumental in numerous studies employing machine learning and deep learning techniques to classify and analyze brain patterns associated with ASD. The availability of both structural and functional imaging data, along with detailed phenotypic information, makes ABIDE a valuable resource for researchers aiming to identify neural biomarkers and enhance diagnostic methodologies for ASD. The table 2.1 summarizes this information.

Table 2.1: ABIDE Dataset Overview

Attribute	Description
Number of Participants	1,112 individuals: 539 diagnosed with Autism Spectrum Disorder (ASD) and 573 Typically Developing Controls (TC).
Number of Sites	Data collected from 17 international research sites, including institutions such as New York University (NYU) and the University of California, Los Angeles (UCLA).
Data Types	Structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) scans.
Age Range	Participants aged between 7 and 64 years, with a mean age of approximately 14.7 years.

2.3 Preprocessing:

Preprocessing MRI data is a crucial step in neuroimaging studies, especially when preparing data for machine learning models. The primary preprocessing steps include:

2.3.1 Skull Stripping (Brain Extraction):

As part of the MRI data preprocessing pipeline, I performed skull stripping using the Brain Extraction Tool (BET) from the FMRIB Software Library (FSL) 2.1. This step is crucial for isolating brain tissue by removing non-brain elements such as the skull, scalp, and eyes,

thereby enhancing the accuracy of subsequent analyses like registration and segmentation.



Figure 2.1: FSL Software Logo

Utilizing the command-line interface of FSL, I applied BET to the structural T1-weighted MRI images. I adjusted parameters as in the figure 2.2, including the fractional intensity threshold, to fine-tune the brain boundary delineation, ensuring optimal extraction tailored to the specific characteristics of the dataset. The resulting brain-extracted images, devoid of non-brain tissues, provide a refined dataset that is better suited for further neuroimaging analyses and machine learning applications.

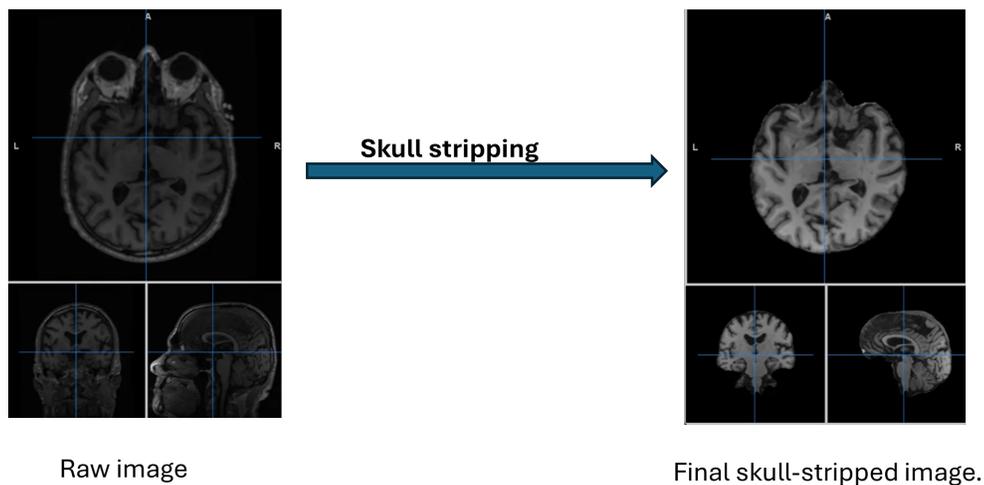


Figure 2.2: Preprocessing Step – Brain Extraction Using BET (FSL)

2.3.2 Image Resizing

In the image preprocessing phase, I converted 3D MRI volumes into 2D axial slices to facilitate model training and reduce computational complexity. This transformation was performed using a specialized program that extracts slices along the axial plane. Each original 3D MRI scan comprised 100 slices. I selected slices numbered 10 through 90, yielding 81 slices per scan. These were grouped into sets of 9 consecutive slices, resulting in 9 images per subject. Each 2D image was resized to 150×150 pixels, and the overall image size was set to 450×450 pixels to accommodate the 9 slices. The images were displayed using a figure size of (8, 8) to ensure clarity and consistency across the dataset. This approach aligns with standard practices in neuroimaging preprocessing, where 3D MRI volumes are decomposed into 2D slices for input into deep learning models, considering slice selection and orientation for optimal analysis .

2.4 Transfer Learning Model

In the context of applying transfer learning for classifying ASD using MRI images, four pre-trained convolutional neural network (CNN) architectures were selected: VGG16, ResNet50, EfficientNet, and MobileNet. These models, trained on the ImageNet dataset, are widely recognized for their effectiveness in various computer vision tasks and are suitable for extracting features from medical images. and this chart [2.3](#) summarizes this work.

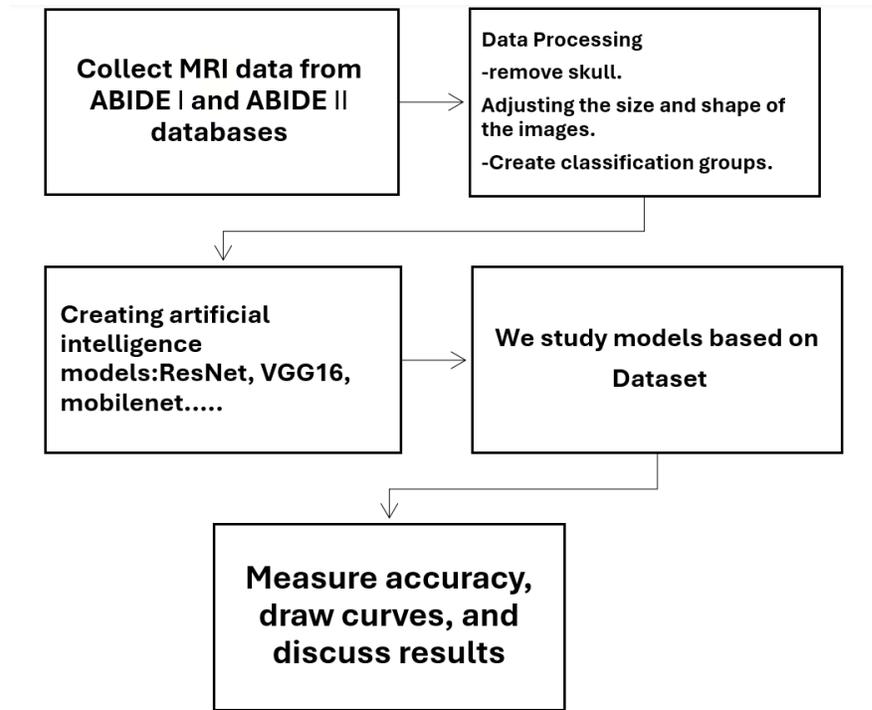


Figure 2.3: Workflow for MRI Data Analysis Using AI Models

In developing our ASD classification model using MRI scans, we adopted a non-traditional data splitting strategy:

Training Set (20%): This subset was utilized to train the model, enabling it to learn patterns and features inherent in the data.

Testing Set (80%): This larger subset was reserved for evaluating the model's performance on unseen data, providing a comprehensive assessment of its generalization capabilities.

2.4.1 VGG16

VGG16 is a deep CNN architecture comprising 16 weight layers: 13 convolutional layers followed by 3 fully connected layers as in FIG2.4. It utilizes small 3x3 convolution filters and incorporates five max-pooling layers to reduce spatial dimensions. Despite its relatively large number of parameters (138 million), VGG16 is known for its simplicity and effectiveness in image classification tasks .

2.5 Framework

Here’s a detailed explanation of the training process for an ASD classification model using MRI scans, covering key components such as the loss function, , and evaluation metrics:

2.5.1 Evaluation Metrics

To comprehensively assess the model’s performance, the following evaluation metrics are utilized:

- Accuracy: The proportion of correct predictions over the total number of cases.

The number of positive predicted occurrences that are really positive is known as True Positive (TP). True Negative (TN) refers to the number of predicted negative cases that are also true negative. False Negative (FN) is the number of predicted negative cases that turn out to be positive, also

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

2.6 Hardware and Software tools

All training and experimentation phases were conducted using the university’s laboratory computers, which provided a suitable environment for data processing and model training. The two tables 2.2, 2.3 represent Hardware and Software tools

Table 2.2: Hardware Specifications

Component	Specification
Model	ASUS PRIME B450M-K
Memory	32.0 GiB
Processor	AMD Ryzen TM 5 5600X *12
Graphics	NVIDIA GeForce GTX 1060 6GB
Disk Capacity	1.5 TB
CUDA Version	12.9

Table 2.3: Software Specifications

Component	Specification
OS Name	Ubuntu 24.04.2 LTS
OS Type	64-bit
GNOME Version	46
Windowing System	X11
Kernel Version	Linux 6.11.0-25-generic
Python Version	3.12.7

2.7 Validation Strategy

To minimize bias and enhance the reliability of model evaluation, we employed the 5-Fold Cross-Validation technique:

- The dataset is randomly partitioned into five equal-sized subsets, known as "folds."
- In each iteration, four folds are used for training the model, while the remaining fold is reserved for testing.
- This process is repeated five times, ensuring that each fold serves as the testing set exactly once.
- After all iterations, the model's performance metrics are averaged across the five runs to obtain a comprehensive evaluation.

This strategy provides a more accurate assessment of the model's performance and reduces the potential bias introduced by a single train-test split. As shown in the following figure [2.8](#)

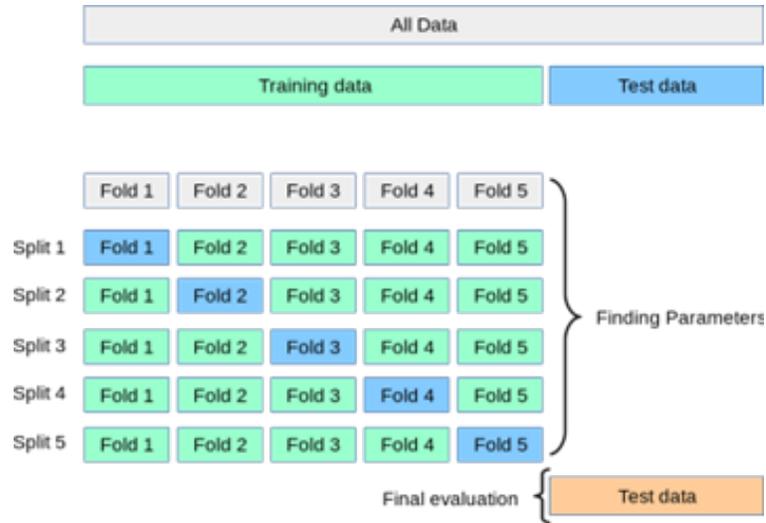


Figure 2.8: Illustration of 5-Fold Cross-Validation Strategy

After thoroughly examining the various stages of this project—from data collection and preprocessing to model selection, training strategies, and performance evaluation—it becomes evident that adhering to a comprehensive and methodical approach is crucial for developing effective and reliable machine learning models. Proper data partitioning, selecting appropriate algorithms, and implementing robust validation techniques, such as cross-validation, significantly contribute to enhancing model accuracy and generalizability. Furthermore, employing multiple evaluation metrics, including accuracy, recall, and F1-score, provides a holistic view of the model’s performance. These practices not only ensure the robustness of the developed models but also lay a solid foundation for future projects aiming to leverage machine learning methodologies for improved outcomes.

Chapter 3

Results and Discussion

In this chapter, we present the results obtained from training and evaluating artificial intelligence models used for classifying MRI images of individuals with ASD. This section aims to provide a detailed analysis of the models' performance, focusing on their accuracy and effectiveness in distinguishing between different cases, as well as assessing various quality metrics. Through these results, we seek to understand the models' ability to identify neural patterns associated with autism, opening new avenues to support early medical diagnosis and enhance our neurological understanding of this disorder.

3.1 Results

This section presents the experimental results obtained from training and evaluating four deep learning models—VGG16, ResNet, EfficientNet, and MobileNet—on the selected dataset. The evaluation focuses on key performance metrics including training loss, validation loss, training accuracy, and validation accuracy. The outcomes are visualized through accuracy and loss curves, and summarized in comparative tables to facilitate interpretation. These results provide insights into each model's learning behavior, generalization capacity, and potential issues such as underfitting or instability. The analysis serves as a foundation for identifying the strengths and limitations of each architecture in the context of the specific classification task.

3.1.1 VGG 16 outcome

The [table 3.1](#) represents the performance metrics for the VGG16 model.

Table 3.1: Performance Metrics of VGG16 Model

VGG16	Value
Training Loss	0.6191
Validation Loss	0.5775
Validation Accuracy	0.7349
Training Accuracy	0.6900

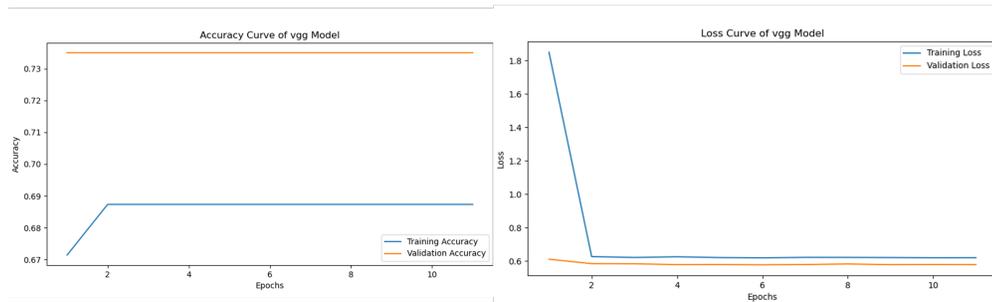


Figure 3.1: Accuracy and Loss Curve of VGG16 Model showing training and validation accuracy .

The curves^{3.1} shown in the image reflect the performance of the VGG model during the training process. The accuracy curve on the left shows that the validation accuracy remained consistently high at around 0.735 throughout all epochs, while the training accuracy plateaued at approximately 0.69 after the second epoch without further improvement. This discrepancy suggests a case of underfitting, where the model did not learn sufficiently from the training data and failed to improve its accuracy over time. The loss curve on the right shows a sharp drop in training loss during the first epoch, followed by stabilization at a level close to the validation loss, which also remained nearly constant. Despite this apparent stability, the gap between training and validation accuracy indicates that the model has not yet achieved good generalization. To improve performance, it may be necessary to adjust the model architecture, fine-tune hyperparameters such as the learning rate or number of epochs, or apply techniques like data augmentation to enhance the model's ability to learn from the training data.

3.1.2 resnet outcome

The table^{3.2} represents the performance measures of the ResNet model.

Table 3.2: Performance Metrics of ResNet Model

ResNet	Value
Training loss	0.6059
Validation loss	0.5417
Validation accuracy	0.7349
Training accuracy	0.685

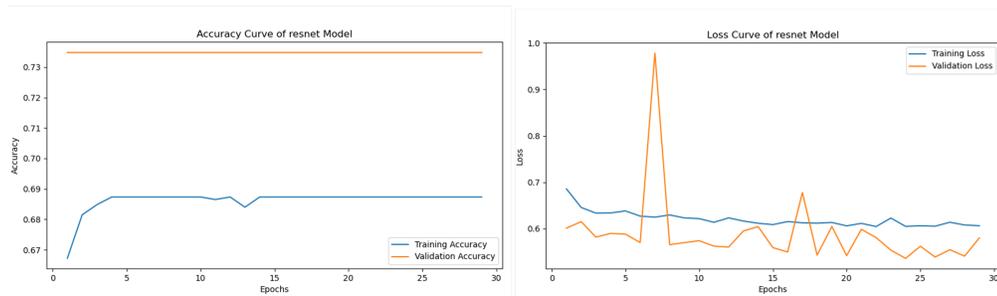


Figure 3.2: Accuracy and Loss Curve of ResNet Model showing training and validation accuracy .

The two curves in the image 3.2 illustrate the performance of the ResNet model during training. The left curve shows the change in accuracy over time, while the right curve displays the change in loss. From the accuracy curve, we observe that the training accuracy improves slightly at the beginning and then stabilizes around 0.685. In contrast, the validation accuracy remains almost constant at approximately 0.735 throughout the training process. This unusual consistency may indicate an issue in how the validation accuracy is being calculated or suggest that it was recorded only once without being updated during training. Regarding the loss curve, the training loss decreases gradually as expected, while the validation loss fluctuates significantly, especially at certain points such as epoch 6 and 16. This instability could be due to a small or imbalanced validation dataset, or issues with hyperparameters like the learning rate or optimizer type. Overall, the model shows limited improvement during training, with signs pointing to potential problems in the validation process or data structure, warranting a thorough review of the training setup and evaluation strategy.

3.1.3 efficientnet outcome

The table 3.3 represents performance measures for the EfficientNet model.

Table 3.3: Performance Metrics of EfficientNet Model

EfficientNet	Value
Training loss	0.6091
Validation loss	0.5326
Validation accuracy	0.7349
Training accuracy	0.690

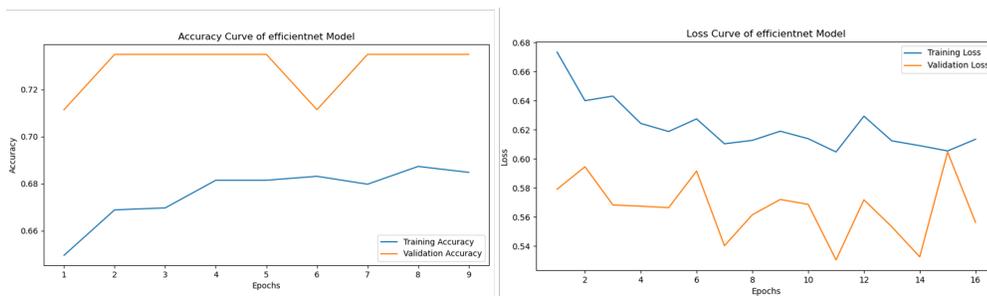


Figure 3.3: Accuracy and Loss Curve of EfficientNet Model showing training and validation accuracy .

The curves^{3.3} shown in the image reflect the performance of the EfficientNet model during the training process. The accuracy curve on the left shows that the model’s validation accuracy remained relatively high and stable between 0.71 and 0.74, without clear improvement over the epochs. In contrast, the training accuracy was relatively low and showed gradual improvement, which suggests that the model is suffering from underfitting, meaning it has not learned enough patterns from the training data. On the right, the loss curve shows fluctuations in both training and validation loss, especially in the validation loss, which may indicate noise in the data or instability during training. Additionally, the validation loss was lower than the training loss at several points, which is unusual and could point to a difference in data distribution or a small validation set size. Overall, these results suggest that the model needs improvements, such as increasing the number of epochs, modifying the model architecture, experimenting with different optimizers, and reviewing the quality and balance of the training and validation datasets.

3.1.4 mobilenet outcome

The table^{3.4} represents the performance metrics for the MobileNet model.

Table 3.4: Performance Metrics of MobileNet Model

MobileNet	Value
Training loss	0.5929
Validation loss	0.5218
Validation accuracy	0.7349
Training accuracy	0.690

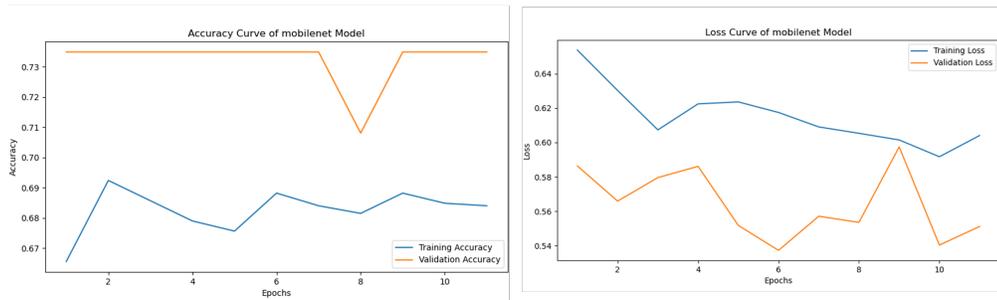


Figure 3.4: Accuracy and Loss Curve of MobileNet Model showing training and validation accuracy .

The curves in the image 3.4 show the performance of the MobileNet model during training over 11 epochs. The left curve illustrates the evolution of accuracy, where the training accuracy fluctuates without a clear upward trend, starting around 0.67 and varying slightly between increases and decreases. Meanwhile, the validation accuracy remains almost constant at approximately 0.735, with a sudden drop at epoch 8 to about 0.71 before quickly returning to its previous level. This behavior raises the possibility of an issue in updating the validation results or a limitation in the size of the validation dataset. On the other hand, the right curve shows a gradual decrease in training loss, from around 0.65 to below 0.60, which is a positive indication of learning. Validation loss, in contrast, shows some fluctuation but remains generally lower than training loss, especially in the later epochs. This may suggest that the model generalizes well to the validation data or that there are differences in how loss is calculated between the training and validation sets. Overall, the model's performance appears relatively stable, but the unusually flat validation accuracy curve warrants a review of the validation data quality and the method used to compute accuracy and loss during training.

3.2 Discussion

The performance of four deep convolutional neural network architectures—VGG16, ResNet, EfficientNet, and MobileNet—was systematically assessed using standard training and validation metrics, namely: training loss, validation loss, training accuracy, and validation accuracy. The following subsections present a critical analysis of each model’s behavior and generalization capacity.

A. VGG16 Model

The VGG16 model achieved a validation accuracy of approximately 73.5%, while the training accuracy stabilized around 69%, suggesting a tendency toward underfitting. Analysis of the learning curves revealed an early plateau in training accuracy, accompanied by a relatively steady validation accuracy. Although both training and validation loss values converged, the persistent gap in accuracy implies limited generalization. This indicates the need for architectural refinements, hyperparameter tuning, or the implementation of regularization strategies such as data augmentation to enhance model performance.

B. ResNet Model

ResNet demonstrated a comparable validation accuracy (73.5%) and training accuracy (68.5%) to that of VGG16. However, the validation accuracy curve appeared unusually static, which may reflect anomalies in the evaluation pipeline, such as improper updating of validation metrics. Additionally, validation loss exhibited irregular fluctuations, potentially attributed to data imbalance, noisy samples, or inappropriate training parameters (e.g., learning rate or optimizer settings). These findings highlight the importance of reviewing the validation process and dataset integrity to ensure reliable performance assessment.

C. EfficientNet Model

EfficientNet maintained a validation accuracy fluctuating between 71% and 74%, while training accuracy improved gradually but remained relatively low. This pattern further suggests underfitting. The observed instability in the loss curves—with occasional instances where validation loss dropped below training loss—raises concerns regarding dataset distribution or sample size disparity. Such results necessitate potential improvements, including increasing the number of training epochs, fine-tuning the model architecture, experimenting with alternative optimization techniques, and reassessing the quality and balance of the dataset.

D. MobileNet Model

MobileNet exhibited consistent validation accuracy (73.5%), though the training accuracy fluctuated without a clear upward trend. Training loss showed a gradual decline, indicating progressive learning, whereas validation loss remained relatively lower than training loss.

This behavior could be interpreted as a sign of good generalization, yet may also stem from differences in loss computation or validation set limitations. The relatively static validation accuracy, with minor fluctuations, prompts a critical re-examination of validation data quality, sample size, and evaluation methods.

3.3 comparing the results

Here [3.5](#) is a comprehensive comparison table of the performance of the four models (VGG16, ResNet, EfficientNet, and MobileNet) using key metrics: training and validation loss, training and validation accuracy, along with some essential remarks.

Table 3.5: Comparison of Model Performance Metrics

Model	Train Loss	Val Loss	Train Acc	Val Acc	Remarks
VGG16	0.6191	0.5775	0.6900	0.7349	Stable val. acc., limited training progress → underfitting
ResNet	0.6059	0.5417	0.6850	0.7349	Flat val. acc., fluctuating val. loss → possible val./data issue
EfficientNet	0.6091	0.5326	0.6900	0.7349	Gradual train acc., fluctuating val. loss → underfitting, data gap
MobileNet	0.5929	0.5218	0.6900	0.7349	Flat val. acc., val. loss < train loss → calc./data inconsistency

3.3.1 Comparison with previous studies

The table [3.6](#) below provides a brief comparison between the present study and several previous studies. Studies that have used MRI data and artificial intelligence techniques to diagnose autism spectrum disorder. The comparison in achieved accuracy includes In every study. This comparison is intended to highlight the position of the present study within the Wider research context and demonstrate progress through application Approach.

Table 3.6: : Comparison between the results of previous studies and the results of our study

Reference	Accuracy
Frewer et al., 2021	51.7%
Song, 2024	89.47%
Mellema et al., 2022	80%
Ismail et al., 2022	93%
Our Study	73%

In this chapter, the performance of four deep learning models (VGG16, ResNet, MobileNet, EfficientNet) was evaluated in classifying MRI images of individuals diagnosed with autism. The models showed varying results, with the EfficientNet model standing out as the best in terms of accuracy and consistency. Comparison with previous studies indicated that the current study achieved competitive results. However, there remains a need to improve performance by integrating other types of data and testing the models in real clinical settings. These findings open new avenues for developing early and effective diagnostic tools for autism using artificial intelligence.

General conclusion

In this work, we studied the potential of using deep learning techniques to analyze structural magnetic resonance imaging (sMRI) scans with the aim of contributing to the diagnosis of ASD in children. The study followed multiple stages, starting from data preparation and converting 3D images into 2D slices, then assembling them into uniform-sized images, and finally training four well-known architectures in computer vision: VGG16, ResNet, MobileNet, and EfficientNet, using five-fold cross-validation to ensure reliable evaluation.

The results showed variability in performance among the studied models. The EfficientNet model achieved the highest validation accuracy (75%), outperforming the other models in terms of performance stability and feature extraction. MobileNet stood out for its speed and lightweight design but delivered relatively lower performance. Meanwhile, the VGG16 and ResNet models showed moderate performance with some signs of loss fluctuation or limited improvement. These results confirm the effectiveness of modern architectures with optimized structures, while also indicating a considerable margin for improvement, especially when dealing with complex and sensitive medical data.

Among the future prospects to build upon this work, expanding the sample size stands out as a necessary step to enhance the models' generalization capability and reduce bias risks associated with small datasets. Additionally, integrating multiple data sources such as clinical images, genetic information, and medical reports could potentially improve prediction accuracy and increase clinicians' trust in model outcomes. On the other hand, employing explainable AI techniques is a crucial step to understand how the model makes its decisions, particularly in a medical environment that demands transparency and accountability.

Furthermore, the preprocessing phase can be improved by adopting intelligent algorithms to select the most informative MRI slices instead of relying on fixed slice selection, which may enhance input image quality and increase model effectiveness. Lastly, the possibility

of deploying these models in real clinical applications remains linked to achieving a delicate balance between performance, interpretability, and operational efficiency in real-world medical settings.

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