Autism detection based on MRI images using Deep Learning

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A thesis submitted to the Department of the "School of Data and Sciences"
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

Department of "School of Data and Sciences"
Brac University
January 2023

Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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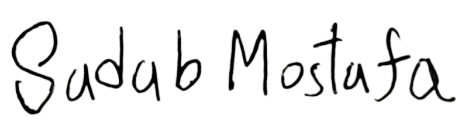

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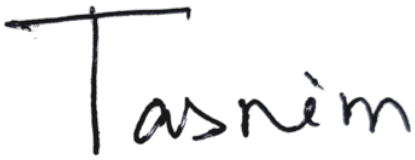

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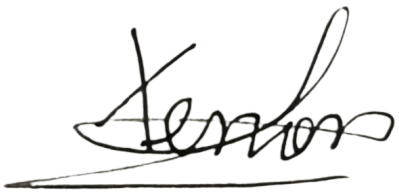

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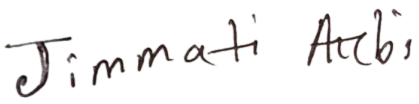

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Abstract

Autism spectrum disorder (ASD) is a neuro dysfunction or neurodevelopmental disorder. This causes a patient to have trouble with social interaction which causes social instability. It also causes speech problems or difficulty with any sort of verbal communication as well as nonverbal communication. The biggest issue with Autism is that it is difficult to diagnose it at an early level. The difficulty in diagnosing is due to the lack of a particular medical test for it. Researchers have yet to discover a biomarker or specific gene that can detect autism. Doctors still use outdated methods to identify autism nowadays. Doctors frequently keep track of a patient's behavior since childhood. To address this issue and diagnose autism, artificial intelligence will be used in our research to develop an ASD diagnosis method. Our research will employ neuroimages. Functional MRI and Structural MRI images will be used to train our neural network model.

ABIDE, a versatile dataset was used to initialize this research. This includes structural MRI and fMRI data from young and old ASD patients as well as healthy individuals. After examining the MRI pictures, a method was developed to pick out particular layers from those images. The dataset was then constructed using images from ABIDE for our models to train and test without performing any pre-processing. A variety of cutting-edge deep learning architectures were chosen to train using our created dataset. Novel architectures were used to attain an accuracy of 80% to practically 86%. Custom block was used later in the research to expand the dataset and achieve more accuracy.

Finally, based on our findings, a model will be found that can more accurately identify autism from MRI pictures.

Keywords: Deep Learning; Autism; Neuroimages; Biomarker; MRI; ABIDE; Generative Adversarial Network

Dedication

We dedicate this thesis work to our family members, who have always been our source of inspiration and support. Their love, encouragement, and belief in us have been the driving force behind our academic pursuits. We are eternally grateful for their unwavering love and support throughout our journey.
We also dedicate this work to our friends, who have stood by us through thick and thin. Their constant encouragement, support, and understanding have been invaluable to us. We are forever grateful for the laughter, the fun, and the memories we shared together, especially during the challenging moments of this thesis work. Thank you for being a part of our life.

Acknowledgement

First and foremost, We would like to express our deepest gratitude to Allah for granting us the strength, knowledge, and guidance to complete our thesis work. We would also like to extend our heartfelt thanks to our supervisor Dr. Muhammad Iqbal Hussain sir for his invaluable guidance, support, and patience throughout this entire process. We are also deeply grateful for the unwavering support and encouragement of our brother Sakib Mostafa, who has always been there for us, both emotionally and intellectually. Finally, We would like to express our love and appreciation to our family members for their unwavering love and support, without which this accomplishment would not have been possible. Thank you all from the bottom of our hearts.

Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

$ABIDE$ Autism Brain Imaging Data Exchange

ASD Autism spectrum disorder

ATM automated teller machine

CAD Magnetic

CNN Convolutional Neural Network

CT Computed tomography scan

DL Deep Learning

DNN Deep neural networks

DTI Diffusion tensor imaging

EPI Echo planar imaging

EPI Echo-planar imaging

$fMRI$ Functional Magnetic resonance imaging

$HIPAA$ Health Insurance Portability and Accountability Act

ML machine learning

MRI Magnetic resonance imaging

MSE Mean Squared Error

$NIFTI$ Neuroimaging Informatics Technology Initiative

NMR Nuclear Magnetic Resonance

PSA prostate-specific antigen

$ReLU$ The Rectified Linear Unit

RNN recurrent neural network

ROI Region of Interest

$SMOTE$ Synthetic Minority Oversampling Technique

$sMRI$ Structural Magnetic resonance imaging

SVM support vector machine

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Chapter 1

Introduction

1.1 Motivation

ASD (autism spectrum disorder) is a brain-based neurodevelopmental condition. This makes it difficult for a patient to interact with others, resulting in social instability. It also creates difficulty with speech, both verbal and nonverbal. Many ASD patients have certain well-known anomalies. Changed genes can sometimes be handed on to kids. These are examples of hereditary diseases. Repetitive behaviors such as hand flapping or rocking are also seen in certain cases. Only a small percentage of patients self-harm. However, as previously said, many more ASD factors have yet to be discovered. Many researchers think that Autism is caused by a mixture of recognized and unrecognized factors. This confluence of factors has an impact on people's natural development.

ASD affects various people in different ways. Children with autism frequently struggle to communicate with others, have language difficulties, and are unable to articulate their feelings. These issues result in a challenging life. If a child is not diagnosed in his childhood, most likely he/she will face a huge number of challenges growing up. According to [29], Autism affects around one out of every 100 children worldwide. Even though it is an average statistic, the number is surprisingly climbing. Even with extensive research into biomarkers for more reliable ASD detection, the conventional diagnosis approach relies on observation and interviews. Doctors generally monitor a child's developmental history and behavior to reach a diagnosis [37]. Developmental Screening is currently the most used method to detect autism [37]. In this procedure, the doctor compares one child to another of the same age using questionnaires and basic checklists based on research. The main disadvantage of these procedures is that they take a long time and are unreliable because the outcomes are based on the study of the patient's behavioral patterns which can differ from time to time based on their characteristics. Although early intervention does not cure autism. It can assist a child in developing the required abilities to function in society and life. As a result, diagnosing ASD in children is a critical task for their future success, as mentioned earlier detecting autism still has no reliable method. Researchers have yet to discover a biomarker or specific gene that can detect autism. Given a fraction of time, an assessment of the current state and situation of a cell or organism is known as a biomarker [7]. Simply put, Biomarkers are just medical signs that can be used to detect a disease. That is why researchers are still looking for a biomarker

to detect ASD. Many researchers tried to find biomarkers with genomics and gene testing, proteomics, metabolomics, transcriptomics, immune system, inflammation, and microRNA investigations [15]. Researchers also tried precisely measuring brain function and connectivity with Quantitative electroencephalography [1]. But still, there are no metabolic biomarkers that can diagnosis ASD properly. That is why researchers have now moved towards neuroimage-based detection methods to detect different brain diseases. Neuroimages can be acquired by magnetic resonance imaging, CT scan or Computerized Tomography, etc. Among all the methods, Researchers are more likely to use MRI due to its improved brain imaging capabilities. MRI is better than CT scan as it has a better contrast capability for soft tissues. It can easily spot the differences between muscle, fat, and different kinds of soft tissues. So, an MRI scan of a brain can provide more information about a brain and its cortex [34]. The anatomy, functional activity, and composition of the brain can all be determined using magnetic resonance imaging (MRI) [34]. T1 and T2 weighted images, sometimes known as T1 and T2 images, are two basic forms of MRI images that both carry information about the structural integrity of the brain. There is also another MRI known as Functional MRI (fMRI). This type of MRI image captures the functional activity of a brain for a certain time.

Our study's main goal is to overcome the difficulty in diagnosing autism using MRI images to detect autism using deep learning models. So that people will be able to just get an MRI scan of their children and use it to detect if they have autism or not.

1.2 Problem Statement

ASD is not a single condition. It demonstrates a common set of symptoms. A person with Autism might show a variety of symptoms and behaviors. The fact that these symptoms differ from person to person is even more interesting. Even if a doctor diagnoses two children with the same condition and age, the patients are likely to have various limitations and challenges. With social instabilities, verbal and nonverbal speaking issues, and challenges understanding social norms and practices, a person with ASD finds it challenging to live their lives. Currently, medical professionals and researchers mostly depend on questionnaires and behavioral observation. But still with proper and long observation and questions, sometimes it takes a long time to detect ASD. Which results in a child or individual without proper skill development. So, finding a proper method is a blooming problem for every researcher or doctor.

The problem with creating a Machine Learning based ASD detection model is that every individual is different. Not one single child or individual has anything in common. Their models often fail when there is a huge variety of data. This variation can be of sex, age, environmental factors, and many more. Some models work best for some specific sex, where it fails to detect when there is variation.

Many researchers attempted to detect ASD in normal individuals with resting state functional MRI data. They used different machine-learning-based approaches. A researcher from [12], got a 93.7% accuracy rate for female and 71.6% for male subjects. But they did not use all the subjects from their used dataset. They only

included a small number of subjects to conduct their research. The classification accuracy of machine learning-based Autism detection is higher when the number of individuals is less, according to a study in [11]. As the sample size grows larger, the classification accuracy decreases. As a result, this type of model will work only for a specific region of people. A model trained on a specific group will fail when it gets input from different sections.

So, to solve this problem, we found a dataset created by a vast group of people of different ages and gender. The problem is to create a model that can be effective for all variations of data.

1.3 Research Objectives

Our main objective is to find a model that can recognize autism from MRI pictures effectively. For achieving this goal, we have used Deep learning and Machine learning process with image processing. We employed MRI for neuroimages due to its improved brain imaging capabilities. So, our main contributions to this research paper and this field is finding appropriate MRI slices with trial and error basics, implementing different deep learning models, and analyzing results. Then, finding the best architecture among our tested ones. Then we implemented a modified traditional architecture with custom layers. We also found a fusion solution to get better accuracy. To sum up, the main goal of our research will be:

- Pre-process two large MRI-based datasets named ABIDE I and ABIDE II of ASD and healthy patients.
- Selecting MRI slices according to trial and error basics.
- Implementing different Deep learning architectures.
- Evaluating the model for better understanding.
- Further recommendation for improving the model.
- Analyzing the impact of modern architectural concepts on MRI scans.
- Finding similarities and connections between ABIDE I and ABIDE II datasets.
- Trying to create a fusion-based approach between sMRI and fMRI images.
- Improving pre-existing traditional models with our healthy block.

1.4 Thesis Organization

- In **chapter 1,** We introduced our research. This chapter is all about introducing Autism and its effect in the present world. After giving an introduction we're trying to address a problem here, our research objective, and our aim and goal for this research.

- In **chapter 2,** We explored different research papers related to our study. This is a background study for our research. How others tried solving this problem and what solutions they came up with. Here we also gave information about our used architectures.

- In **chapter 3,** The dataset we used was briefly introduced.. We also mentioned the data types and how they were acquired. Besides the talk about datasets, We described the pre-processing we did on the existing data.

- In **chapter 4**, We have used different pre-existing deep-learning models to train on different types of datasets that we created from chapter 3. After researching many parameters and different combinations of data, we tested and got some results. We also implemented a new healthy block to reduce overfitting during training and get better accuracy.

- **Chapter 5** Consists of results of our used model, new approaches, and discussion about it.

- Lastly, in **chapter 6,** we concluded our work while mentioning some scopes about the things that can be done in the future.

Chapter 2

Background

2.1 Literature Review

Many researchers have tried to come up with a method that can detect autism efficiently and accurately. If we dive down, we can see that there are lots of methods and techniques used to solve this problem. MRI and fMRI-based machine learning models are becoming more popular in developing accurate ASD diagnosis approaches. In [9], They used a Denoising autoencoder as a deep learning model with features selected by using Pearson correlation Coefficient. According to [9] the purpose of their work was to detect autism in individuals by using a large dataset created with MRI images of brain activities. They proposed a deep learning model trained with the mentioned MRI images of brain scans. These brain scans are known as functional MRI images. From functional brain imaging data, they looked for patterns of functional connectivity that may be used to objectively diagnose ASD subjects. Their proposed method helped them to achieve an accuracy score of 70% detecting ASD against normal patients from the dataset which was quite higher than other works. There is an anticorrelation between the anterior and posterior sides of the brain in their classification pattern. According to [9] the results imply that deep learning approaches are capable of reliably classifying large multi-site datasets.

Some researchers achieved an accuracy of 77.7% in [14] by dividing the brain into different regions of interest. After dividing they created brain networks with fMRI images. Apart from these methods of detecting ASD, Let's read more about how people used different techniques to achieve greater accuracy.

The research paper [17] states that to make a better decision machine learning by using advanced patterns of smart techniques. Advanced features of machine learning like logistic regressions, decision trees, and other vector machines have already been applied to datasets that are familiar with autism to create predictive models. These machine-learning models are known to improve physicians' ability to make accurate diagnoses. It shows that Input, Output, Feature selection, and Noise Minimization are the most important steps to apply in machine learning techniques to complete tasks related to diagnosis and these ensure better results.

The research paper [2] demonstrates that models which have deep belief networks and a build to block the restricted Boltzmann machine can also be used in deep

learning methods to get a better result. To visualize high-dimensional data, they demonstrate a novel constraint-based approach. This approach leads to a result that shows deep learning methods are capable of learning physiologically important representations as well as detecting latent relations from neuroimaging data.

In the research, paper [5], Inter-site neuropsychiatric categorization is shown in the research publication [37] with an application to the ABIDE dataset, which is a large dataset of multi-site autism (N=871). Because they want to find the best predictive biomarkers, they are looking at pipelines. Functionally specified brain regions are used in these R-fMRI algorithms to create participant-specific connectomes. Three human specialists performed a quality visual review of the dataset before it was pre-processed, looking for high movement peaks, ghosting, and other scanner anomalies like inadequate brain coverage. Out of the original 1112 participants, 871 were able to participate. After reducing the number of voxels in the predicted connectomes, areas of interest (ROIs) rather than single voxels were used to identify connectome nodes. According to the study, this neuropsychiatric condition was indicated using supervised learning for individuals from the same acquisition sites or distinct, hidden ones. Using the whole ABIDE dataset, the pipeline could predict 67 percent of the results correctly.

The study [31] uses a functional magnetic resonance imaging (fMRI) dataset for ASD diagnosis and combines a deep learning methodology with the F-score feature selection method. ABIDE, a global fMRI dataset, is used to test the suggested technique (Autism Brain Imaging Data Exchange). Network topology research found that the route length and cluster coefficient decreased significantly in ASD, suggesting that a random network had replaced the small-world design. As a biomarker, the functional connectivity traits picked by our technique may provide light on the underlying pathophysiology of ASD. Their technique selects fMRI functional connectivity characteristics with an average score of 64.53 percent on combined datasets and 70.9 percent on the whole ABIDE dataset.

As already said, Autism is still difficult to detect due to complex mental symptoms and a lack of neurobiological evidence in person. According to [20] they examined the structural and functional basis of an ASD brain using fourteen various deep learning models. The most noteworthy models were the Convolutional neural network (CNN) and the Recurrent neural network. They utilized an open-source autism dataset with over a hundred MRI images and they also used a dataset with structural scans. Their work illustrated the usage of deep learning-based neural networks to detect and analyze mental conditions. According to [16], their research classified several areas of the brain to identify composite mental conditions including autism. They did it while condensing clinicians' logical thinking to deliver a cost-effective time-efficient diagnosis approach.

[16] states that They presented the Auto-ASD-Network model to distinguish persons with ASD from a normal ones with the help of fMRI scans. There proposed solution had 2 hidden layers including the multilayer perceptron technique. But with this kind of model, there is a risk of overfitting. So, they used a data augmentation technique known as SMOTE. It creates bogus values or information to reduce the

problem of overfitting. By reducing overfitting, they improved their classification accuracy. There is a popular search method known as ATM. They used it to update the hyperparameters of their proposed support vector machines classifier. The ATM feeds information from deep neural networks. Their model achieved above 70 percent classification accuracy for different fMRI-based datasets while having a maximum score of 80 percent. Because of their ATM-based updating, the score of the support vector machines classifier (SVM) was improved by 26 percent. multilayer perceptron performance was increased by 16 percent and the current detecting approach of Autism classification by 14 percent. According to [16], they planned to get better results from their deep learning models. For this goal, they will do more sorts of augmentations with different simulation methodologies. Which in total will give better results for detecting and classifying mental diseases including Autism.

Research paper [3] used a deep learning technique to fMRI large data. They employed DNN, a nonlinear hierarchical model, to create a subject-transfer decoder. The DNN-based subject-transfer decoder is the first of its kind. When tested on a large fMRI database, their DNN-based decoder outperformed competing baseline approaches like support vector machines in decoding accuracy (SVM). They used principal sensitivity analysis (PSA) to examine the decoder's learned information. The results showed that the discriminative characteristics shared by all of the participants in the dataset were easy to spot. The trained decoder's subject transferability may be partly attributed to its subject-independent properties, which were effectively depicted in its PSA.

In this research, [19], 14 alternative models, including recurrent neural networks along with convolutional neural networks, were utilized to explore the structural and strategic underpinnings of ASD. They showed how psychiatric diseases may be analyzed and diagnosed using deep neural networks. 3D convolutional neural networks designed to see mixtures of brain regions reflected the most often cited portions of the brain that the model used to identify the images. Additionally, they used recurrent neural networks to effectively address the brain region's sequence. This paper streamlines the logical thinking that physicians can utilize to assure a cost- and time-effective diagnosis process while identifying the distinctive brain regions that define a complicated psychiatric disease.

In this paper [10], a computer-aided diagnosis (CAD) method is proposed to identify autism using structural magnetic resonance (MR) brain pictures at various life stages. To increase improvement classification robustness, the method incorporates form properties generated from the cerebral cortex (Cx) and white matter of the brain (CWM). Cx alterations in autism are linked to CWM dysfunction. According to this research, the CAD system starts by segmenting Cx and CWM with a 3D combined model that combines amplitude, structure, and geographic data. The Spherical Harmonic (SPHARM) is then operated in the reconstructed Cx mesh to compute four metrics for each mesh point. Distance maps of its gyri are created for analysis, and three new form features for these gyri are acquired. Ultimately, the retrieved outline components are sent into a deep multi-level network for feature fusion and detection. It was tested on participants from the ABIDE database from 8 to 12.8 years as well as the NDAR/Pitt database from 16 to 51 years and found

to be 97% accurate.

The goal of this study [21] is to determine and give a complete province overview of ML research for ASD diagnosis using structural magnetic resonance imaging (MRI), functional MRI, and hybrid imaging approaches. In the next years, ML technology is predicted to contribute to the early and rapid detection of ASD and to be accessible to specialists. According to this analysis, ASD has yet to be identified using ML and DL technologies, although progress is predicted. To enhance ML and DL models, more visual data, particles, and realistic feature extraction approaches are required.CNN feature extraction is conducted automatically in DL models, and layered AE, with a high feature level, has the potential for accurate ASD detection. More analysis is needed to use ML as well as DL methodologies, such as how to use neuroimaging data to tackle constraints and issues.

From the above discussion, it can be said that researchers used different sorts of models and methods to detect ASD using different datasets. Most of the researchers used denoising and different types of feature selection. With normal Feature selection and F-score-based feature selection, some researchers achieved an accuracy of 65% to almost 80%. Some also used Brain networks, Deep belief networks, and Auto-ASD-network Models to Detect ASD. Convolutional and recurrent neural networks and deep neural network (DNN) was also used. In total, Different researchers used different deep learning and machine learning approaches with feature selection and denoising to solve the problem of detecting ASD with MRI images. Currently, there are many new deep learning and machine learning models and algorithms are coming to light. Day by day technology is improving by a vast difference. These can be used to get greater accuracy while detecting ASD. Our goal is to go deeper in this field to get better results more accurately.

2.2 Used Model

Deep learning is a sort of machine learning that resembles the functioning of the human brain by using neural networks with three or more layers and learning from a significant quantity of data. Without the aid of pre-processing or human specialists, these neural networks can automatically extract features from unstructured input, such as text and photos. For instance, whereas in classical machine learning, the hierarchy of characteristics would be created by a human expert, deep learning algorithms may determine which attributes (such as ears) are most essential in differentiating between different animals in a series of photographs.

MRI images have very few structural differences between ASD patients and healthy one. Every day new architecture is coming into the picture. These are creating new ways to study different neural problems, and ASD is one of them. Deep Learning is mainly used for machine learning and feature extraction. Normal Machine Learning model fails to work with MRI images because of less number of features. As a result of fewer features and differences in brain structure normal traditional model often fails to determine the classification of autism. So, we have selected 3 architecture for now. Those are ResNet-50, VGG-16 and Inception-V4. These four falls under Deep Learning models. But these models will not perform well due to the close features of MRI images. After implementing the architectures, to get better results we moved toward new solutions. So, for our overall approach, we talked about using some deep learning models. Let's talk about the architectures of those models.

2.2.1 ResNet

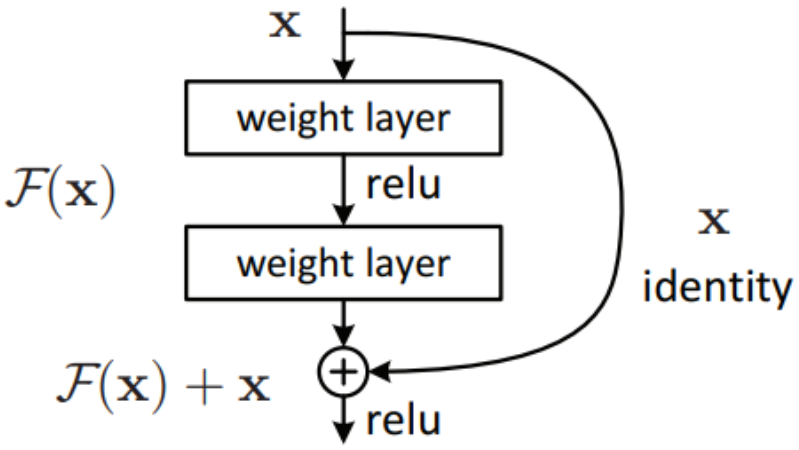

Figure 2.1: Building block of ResNet [6]

Reset or Residual network [6] was first introduced in a research paper by a group of researchers in 2015. Due to the problem of the gradient becoming 0 or very high, which is also known as the vanishing gradient, researchers come up with the architecture of Resnet by introducing the concept of 'Residual blocks. The deeper layer we can use, the more accurate results we get. So, to get deeper without the vanishing problem, Resnet uses a method known as 'skip connections. It mainly connects the activation layer with the further layer while skipping layers in between. By skipping layers, a residual block is formed. Many residual blocks together created the architecture of ResNet. Instead of learning the underlying mapping, these layers fit a residual mapping. In 2.1 F(x) is a residual function. Here, the x input is directly connected to the output of a convolution network. ResNet allows or creates a backup route for the gradient to flow. This way it avoids the problem of vanishing gradient. This skip layer with the help of the identity function also makes sure that higher or deeper level layers will perform as well as the lower or shallow level layers. ResNet uses two types of blocks.

- Identity Block: this is known as a building block. This is also known as

the residual block. 2.1 is an identity block of ResNet. It simply routes the activation function to a deeper layer of the network. This identity block will do the work of skip connection.

- Convolutional Block: convolutions are typically used to increase or decrease the dimensional along the filter dimension. It's the same as 2.1 with only a change at the direct path. x goes directly to a Convolutional layer and then it goes to the ReLu. It can be used when the input and output dimensions of the sample do not match.

2.2.1.1 ResNet 50

Reset 50 is just another version of ResNet. It uses 5 stages. These 5 stages have their convolution and identity block present. Stages 2 and 5 use 2 identity blocks while stage 3 uses 3 blocks and lastly stage 4 uses 5 blocks. This Residual block or Identity block helps to make the model deeper. This is how it generates a 50-layer deep model. It has 23 million trainable parameters. As our MRI images have small differences between them, ResNet 50 will be an optimal model for our research.

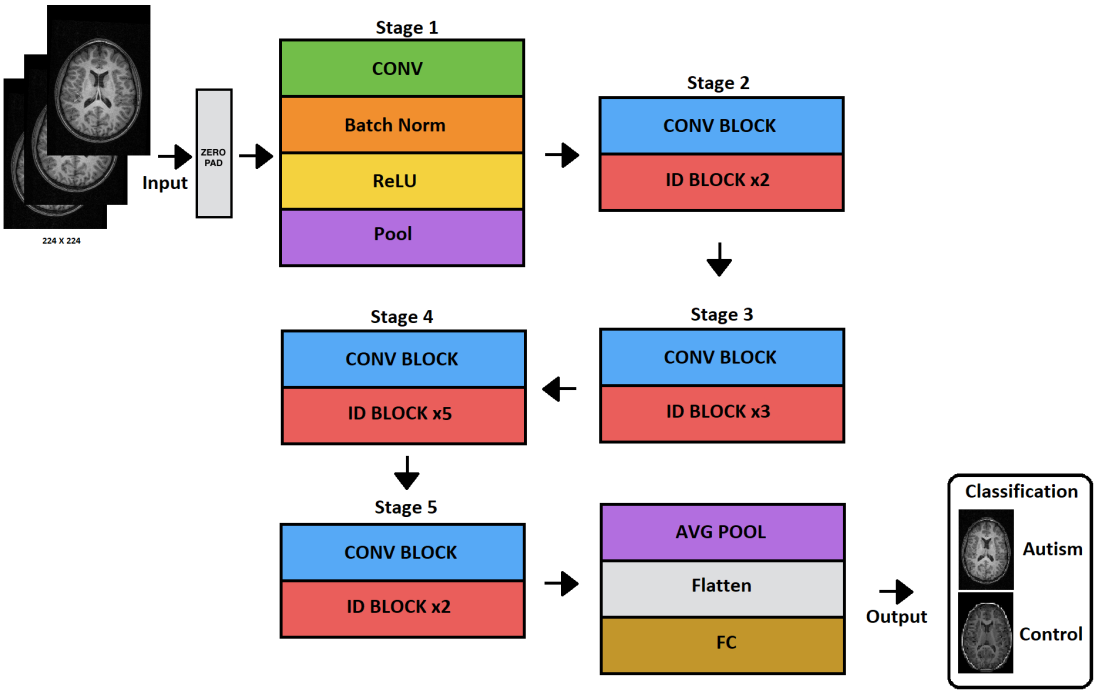

Figure 2.2: ResNet 50 Architecture

2.2.2 VGG-16

Vgg16 is one of the best computer vision architectures today. It is currently the most used architecture for image classification. VGG is a Convolutional Neural Network (CNN). VGG is a CNN model, which was created for mainly classification. The 16 in VGG16 means the 16 layers with weights. Here weights are nothing but learnable parameters. So, VGG has Convolutional layers, Dense layers, and Pooling layers. These 3 specific types of layers all together are 16 learnable layers. Usually, the Convolutional layer and pooling layers are spread among the whole model's network. Each Convolutional layer is of 3X3 size. Which makes VGG16 a uniform and balanced model.

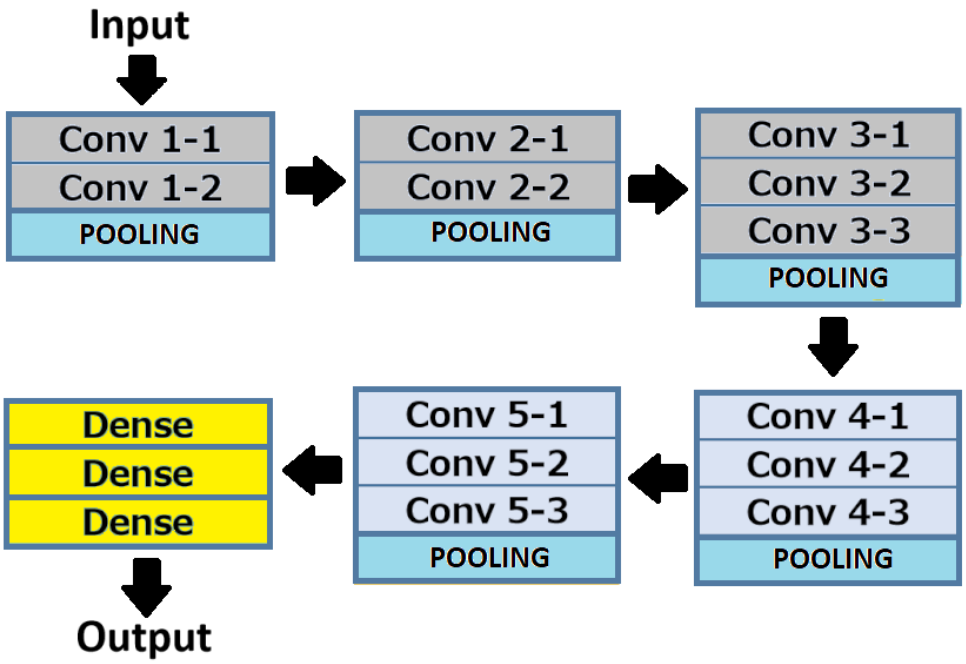

Figure 2.3: VGG-16 Architecture

2.2.3 Inception

The Inception network [36] also referred to as the Inception Module is a deep learning architecture that is made of repeating components. Inception Modules are used in Convolutional Neural Networks that increase computational power and allow deeper Networks by reducing dimensionality. The module also solves the problem of expensive computation and overfitting.

Conventional filters can only learn linear functions which is a problem for nonlinear functions so the researchers get rid of it by connecting layers of convolutional types. These convolutional layers are multi-layer perceptrons. Usually, these perceptions need to be more complex but they are the same as 1*1 convolutions so they can be easily fitted in the CNN framework [36]. Inception networks also increase the abstraction power of the convolutional layers by spatially averaging the feature maps at the final layer and feeding these vectors to the softmax classifier directly. This task also reduces the parameter that decreases the risk of over-fitting and computational load. Researchers prove that it improves the robustness of spatial translation and referred to it as global average pooling.

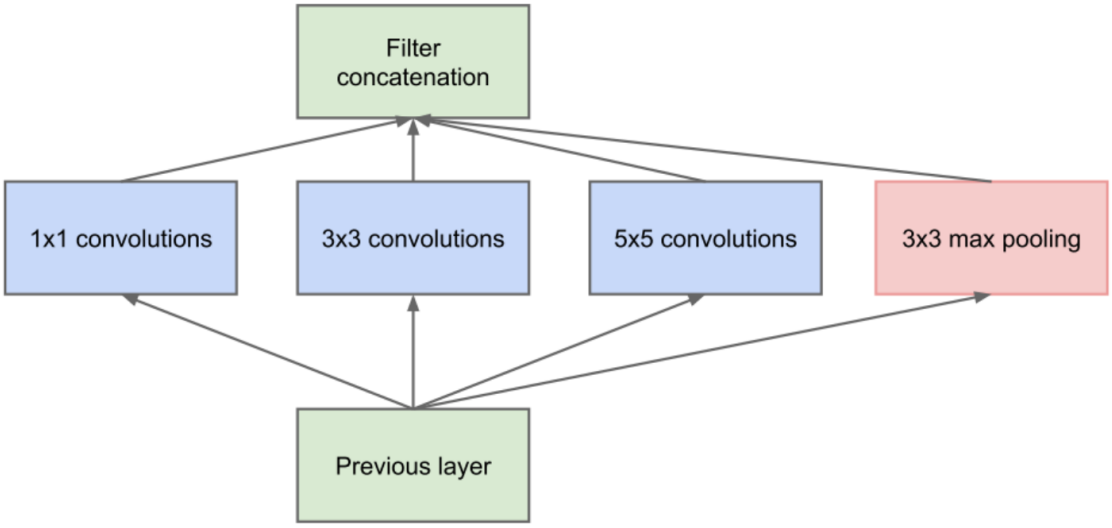

Figure 2.4: Inception Network process

Gradually researchers update the Inception network so there are 4 versions of the Inception module. To improve convergence researchers introduced additional losses tied to the classification error of intermediate layers and this will only be used in the training phase and output will be erased during inference.[4] Then researchers invented Inception v2 and showed how a in convolution a kernel larger than 3*3 can be used efficiently by making it a series of smaller convolutions. For example, they suggest instead of using 7*7 filters we should pair 1*7 and 7*1 convolutional layers.[8] By applying these tricks we also get Inception v3. Then comes Inception v4 which is a streamlined version of v3 with a uniform architecture and better performance. Researchers also speed up training by developing residual connection variants of Inception v1 and v2 both.

Chapter 3

Dataset and Data Processing

3.1 Introduction

In a deep learning-based classification, the model's success heavily relies on the data being used. The MRI acquisition technique varies for different institutions, and noise exists in the acquired images. So, it is extremely important to ensure that an ASD diagnosis system can perform accurately on a versatile dataset. Neuroimages in this case MRI can be captured with various scanners and different parameters. So, to create a versatile approach to detect ASD, the approach must be able to work on all variations of parameters. To get different datasets in one place an organization named "international Neuroimaging Data Sharing Initiative" In short INDI created a data exchange platform Called ABIDE to keep track and store all different datasets of ASD MRI and healthy patients in one place. ABIDE has two datasets known as ABIDE I and ABIDE II. 24 different neuroimaging laboratories around the world contributed to creating these two datasets.

3.1.1 Autism Brain Imaging Data Exchange I

ABIDE I is the first of its kind for a versatile dataset of MRI neuroimages. The ABIDE I dataset is created by collecting data from 17 neuroimaging laboratories, which collected the data independently. Moreover, collecting medical data is very difficult. Most hospitals and medical institutes do not keep data for a long time. As a result, it is a very difficult task to build a dataset big enough to train a model and if someone succeeds to build an MRI model of an ASD patient, it wouldn't be versatile enough to generalize the model. In this dataset, there are functional MRI images (rs-fMRI), structural MRI images (T1-weighted), and phenotypic information of patients. There is information on 1112 subjects in the dataset, where 539 subjects have ASD and 572 subjects are healthy. Also, the subjects in ABIDE 1 age between 6.5 years to 64 years, with a median of 14.7 years. As already mentioned, the data of ABIDE 1 is collected independently. As a result, it contains a variety of MRI images of the different scanners and their different parameters. So, a system that works on such a versatile dataset, should be able to tackle the generalized challenges in ASD.

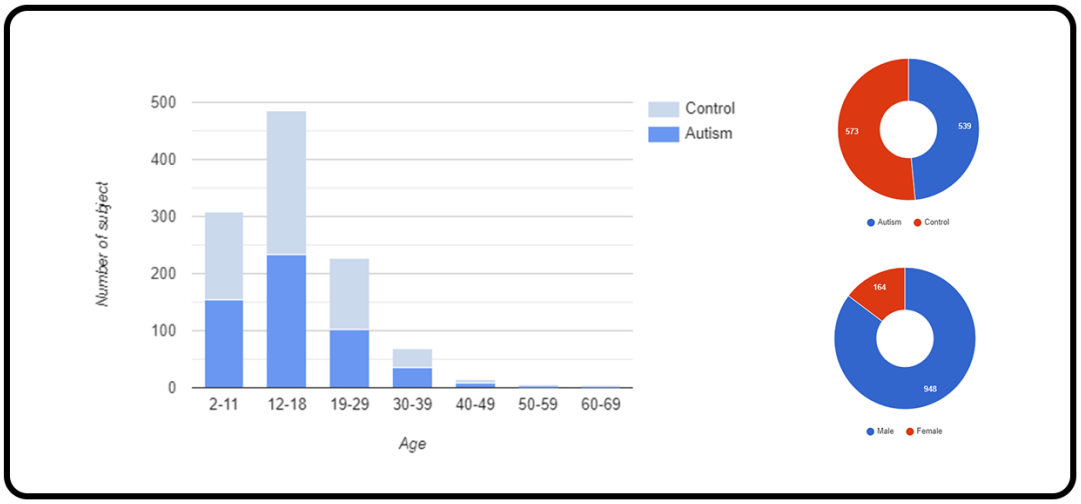

Figure 3.1: Abide I information

3.1.2 Autism Brain Imaging Data Exchange II

The ABIDE I study showed that it is possible to gather MRI data from multiple sites and use it to research ASD. However, the complexity of the brain's connections and the wide range of characteristics within ASD mean that larger and more thoroughly characterized study groups are necessary for further progress in understanding ASD. Initial analysis of ABIDE I data also supports this need. That's why ABIDE II was established. It has collected data from more than 1000 individuals with ASD and controls, with greater attention paid to specific characteristics of ASD and related symptoms. Some of the data has been collected over some time, with 38 individuals being studied at two points. The study involves 19 sites and has a total of 1114 datasets from 521 individuals with ASD and 593 controls. The age range for participants is 5 to 64 years old. All of the data has been made available to researchers and follows HIPAA guidelines, with no personal identifying information included.

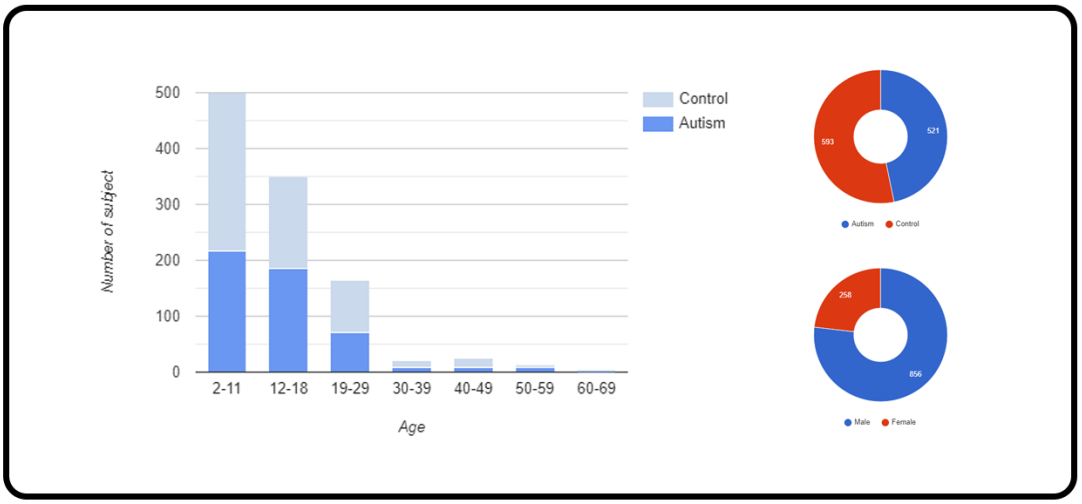

Figure 3.2: Abide II information

3.2 MRI Images

Medical technology known as magnetic resonance imaging (MRI) uses radio waves to create pictures of the tissues inside the body. MRI may be used to analyze organs, tissues, and skeletal systems without causing any harm. The patient is not exposed to radiation during an MRI, in contrast to tests that use X-rays. It produces thorough images of the interior of the body that help with many illnesses' diagnoses. MRI machines produce images of inside body tissues using strong electromagnetic fields, magnetic fluctuations, and radio waves. MRI does not employ radiation or X-rays, in contrast to CT and PET scans. MRI technology can detect brain tumors, brain injuries, skeletal abnormalities, neurodegenerative illnesses, stroke, dementia, infections, and headache causes. A computer, radio wave transmission and reception equipment, and a magnet make up an MRI machine. Having an MRI is a painless procedure. During the process, the patient is moved on a flatbed into the MRI scanner while lying on the bed. The patient's position inside the scanner will vary depending on the body part being examined, with the patient being placed either head-first or feet-first. The MRI scanner is run by a radiologist who has received training in doing imaging investigations. The total scan might take anywhere from 15 to 90 minutes, based on the size of the area being examined and how many photos are necessary. MRI images can be of different types. sMRI,fMRI, DTI, EPI, etc.

3.2.1 Structural MRI

The major difference between rs-fMRI and structural MRI is that rs-fMRI captures the functional activity of the brain at different time points and structural MRI captures the structural integrity of different regions of the brain. A neuroimaging technique known as structural MRI uses magnetic resonance imaging (MRI) to obtain precise images of the structure of the brain. To provide precise images of the anatomy of the brain, structural MRI uses a powerful magnetic field to align the body's hydrogen atoms before injecting a radio frequency pulse to disrupt the alignment. A tiny amount of energy is released as the atoms realign themselves, and the MRI equipment picks this energy up and processes it to produce an image of the brain. Structural MRI can be used to identify abnormalities in the brain, such as tumors, aneurysms, or other abnormalities in brain structure. It is also used to evaluate brain injury or damage, such as after a stroke or head injury.
For structural images, different researchers have used different methods and morphology to detect autism. But very few people have worked with Structural MRI images as it is for neural networks.

3.2.1.1 Structural MRI Preprocessing

T1-weighted MRI captures the brain image in slices and together can generate a three-dimensional view. In ABIDE 1 there are 256 slices of images for every patient and the resolution of each slice is 176 $\times$ 256. Figure 3 shows 256 slices of one individual. The acquisition of T1-weighted pictures is done using brief TE and TR intervals. TE is the amount of time that has passed between the echo signal and the RF signal that was sent to the brain slice, and TR is the interval between successive pulses. The bright part of different segments of the brain is usually determined by the relaxation time of various tissues of our brains.

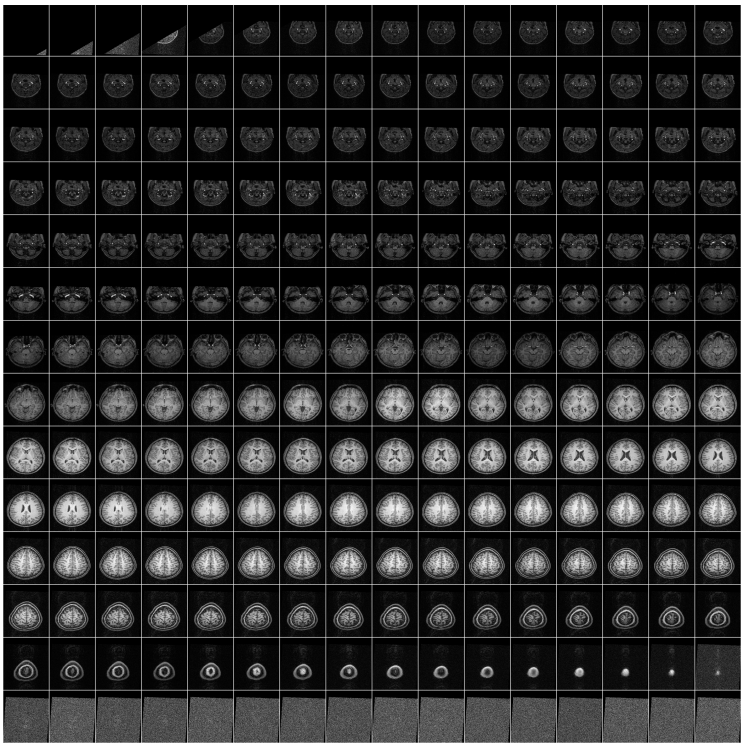

Figure 3.3: 256 slices of one individual Structural MRI

We can use the 256 images of every individual to train a model. But as seen from Figure 3.3, some first and last images contain very little to no information. Using them in a deep learning model for classification may not help the process. Also, very few images contain information about the whole brain. Moreover, if we see closely, consecutive have almost minor differences. Differences can be seen if we take images from very far apart. So, we believe that rather than using all the MRI images of a patient it will be more beneficial to use images from a specific part of the brain. A researcher also used this theory and used slices between 160 to 180 numbers [26]. Images of ABIDE 1 have 3 versions present. These versions are image planes. There are Axial, Sagittal, and Coronal imaging planes shown in figure 6. So, each individual has a total of 256*3 slices because of the three different planes available. For simplicity, we extracted the axial plane for our research.

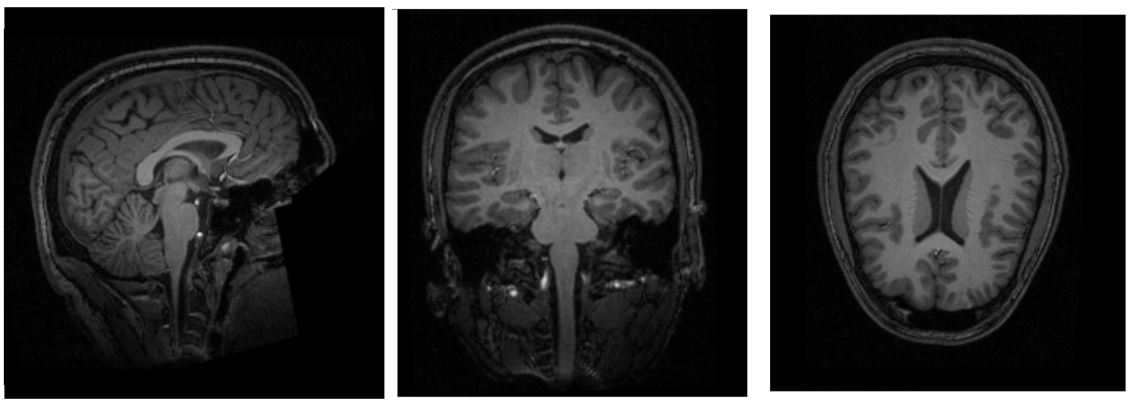

Figure 3.4: Axial, Sagittal, Coronal Plane of one individual subject

The images of ABIDE 1 are in NIFTI format. So, in the first step, we extract T1-weighted MRI images as PNG/JPG. We used MATLAB to extract the images. In the next step, we selected slices that will remain constant for all the patients. Once we find a particular set of slices, we extracted the images of the mentioned slices for all the samples in the dataset. We selected the set of slices in a trial-and-error manner, where we worked with different sets to find the set that works the best. Next, we created a training, testing, and validation set from the available images to train the deep-learning models. We developed a system that can diagnose ASD most accurately using these data. After examining the raw data of T-1 MRI, it looked like

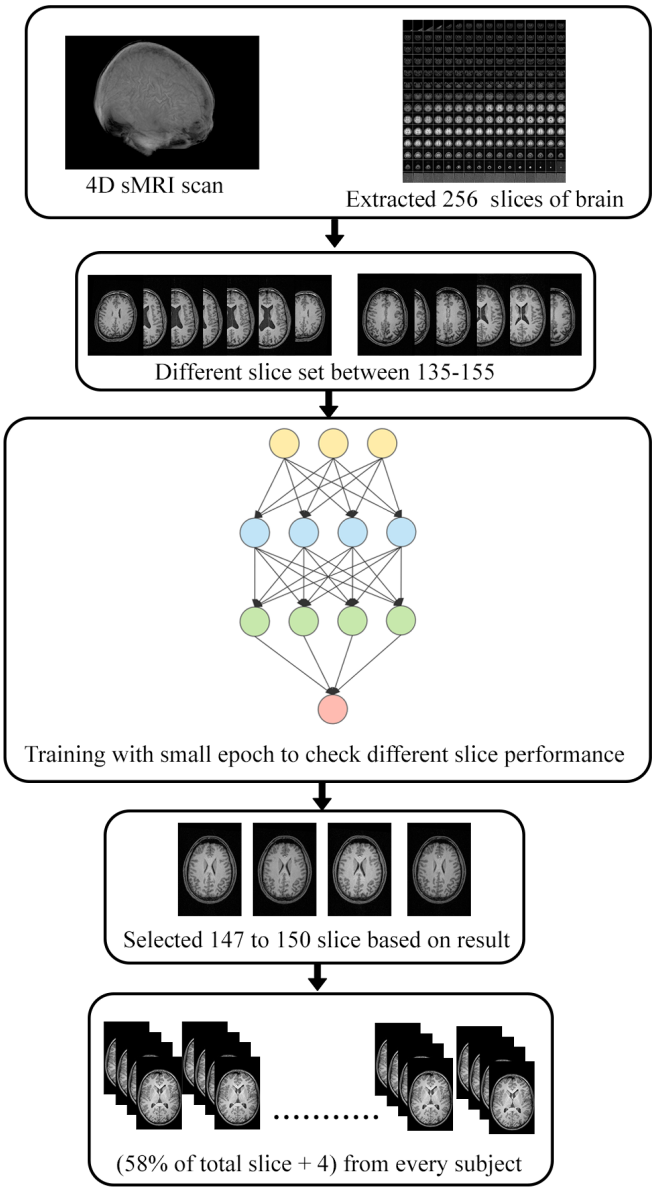

Figure 3.5: sMRI data extraction

slices 127 to 195 have more structural images. Then by analyzing more we found that 135 to 155 has more noticeable brain structure present. Then using a simple CNN algorithm, we experimented with different slices between 135 to 155 to find

more optimal results. We have selected slices 147,148,149 and 150 shown in figure 3.6. But, In abide, there are some MRI images where 256 slices are not present. In a real-life scenario, sometimes different parameters of the scanning machine can produce different slice numbers. In that case, finding similar slices just by specific numbers will be challenging. That is why we came up with a percentage-based solution. As already mentioned, 147 to 150 number slices contain more structural information. So we found out the fractional percentage of the slice. 147 to 150 slices are 58% of 256 slices. So we extracted every 58% number slice from each sample of ABIDE dataset. This is how we extracted data for our research from ABIDE I and ABIDE II datasets.

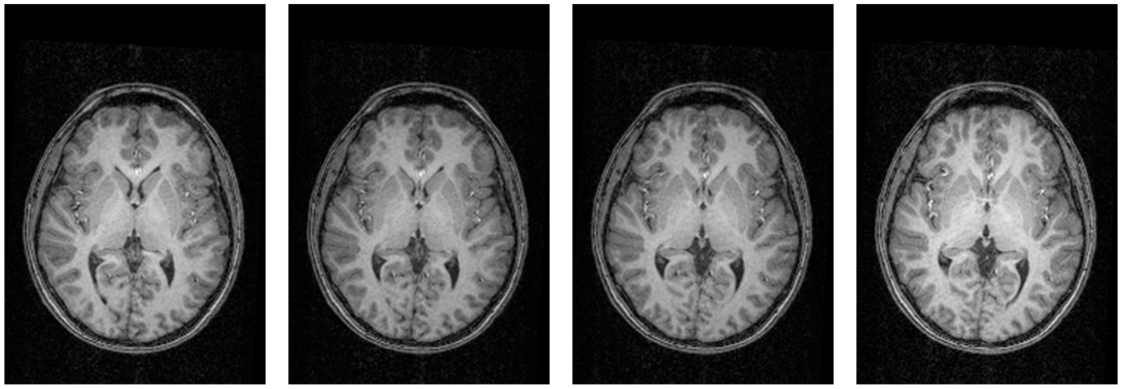

Figure 3.6: Selected Slices from Structural MRI

3.2.2 Functional MRI

Functional magnetic resonance imaging (fMRI) is a method of studying the brain by detecting variations in blood flow to identify active regions of the brain. It works by measuring the oxygenation of the blood, which is an indicator of brain activity. When a specific region of the brain is in use, it demands an increased amount of oxygen, resulting in an increase in blood flow to that area.

A strong magnetic field is used by the functional magnetic resonance imaging (fMRI) device to align the hydrogen atoms within the body. The fMRI machine creates an image of the brain by detecting the small amount of energy emitted as the alignment of atoms is disrupted and then returns to its original alignment after a reading frequency pulse is applied.

One of the benefits of fMRI is that it is non-invasive, meaning that it does not require any kind of surgery or injection of contrast agents. It is also relatively safe, as the magnetic field used is similar to that of a standard MRI machine. fMRI has several applications, including the study of brain function, the detection of brain abnormalities, and the evaluation of brain injury or damage. It is also used in the research of neurological diseases like Alzheimer's and Parkinson's disease as well as mental health issues like schizophrenia and depression. The limited temporal resolution of fMRI makes it difficult to detect rapid changes in brain activity, which is one of its limitations. Additionally, because of its poor spatial resolution, it is unable

to identify activity in the brain's tiniest regions. Despite these limitations, fMRI remains a valuable tool in the field of neuroscience and has contributed greatly to our understanding of the brain and how it works. Functional MRI captures these activities of the brain for different time stamps using NMR signal [9] or change in blood flow. In figure 3.7, MRI is captured for different time stamps for an individual subject from ABIDE dataset. Different researchers used time series information of the fMRI images [9]Many researchers also used K-Means. FCM and Genetic Threshold techniques segmentation for detecting autism using fMRI image [22].

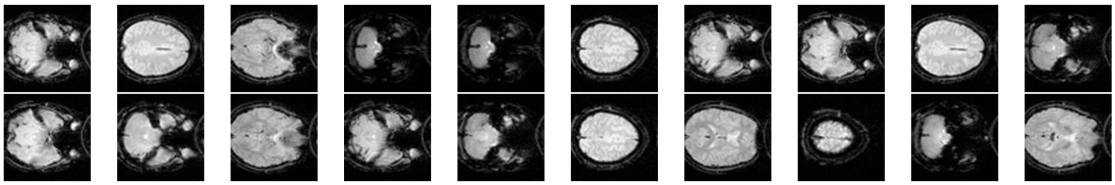

Figure 3.7: fMRI of one individual for different time

3.2.2.1 Functional MRI Preprocessing

As mentioned earlier, fMRI data has a low temporal resolution with low spatial resolution. That's why using these images often results in bad accuracy. There are some methods of extracting different images from fMRI data. Stat plotting, EPI plotting, Glass brain plotting, etc are available. We used the EPI plotting technique for our research.

EPI generates a complete image using only one data point, or "shot," whereas traditional MRI constructs an image using multiple individual signal samples [35]. Amazing speed advantages are possible. To produce an image whose contrast is primarily determined by the intrinsic tissue magnetization parameter, T2, as an example, T2-weighted imaging typically requires the time between excitation pulses (TR) to be two to three times longer than the intrinsic tissue magnetization parameter T1. Since biological samples typically have a T1 of around a second, the TR must be at least three seconds (cerebrospinal fluid, or CSF, can have significantly longer T1s of several seconds). Our traditional T2 weighted scan takes around 384 seconds to complete, which is more than 6.5 minutes. A more or less typical method is used to build an MR image from 128 repeated samples. The EPI approach can gather image data for a similar resolution image in 40 to 150 milliseconds (depending on the hardware and required contrast). This is a speedup of more than 10,000 times.

fMRI data are 4 dimensional. So, 4D data can not be used to plot as an EPI image. So, we used a python function for generating mean images from a 4d fMRI image. We first calculated the mean of 4D images by individually averaging over time [33]. This function gives an output of PNG data. While extracting the images from 4d fMRI data, we used a parameter of nilearn to ensure the MNI coordinates of the point where the cut will be performed. Then using another parameter, we choose the axial view or Z axis of the brain scan. This returned a PNG image with 10 brain states merged. Then using another python script, we cropped the images into 10 slices of the brain image. Now some slice has fewer brain details available. So, using another python script, we gave a threshold for details and reduced brain

scans with fewer details. This way we created our dataset for EPI images of the brain.

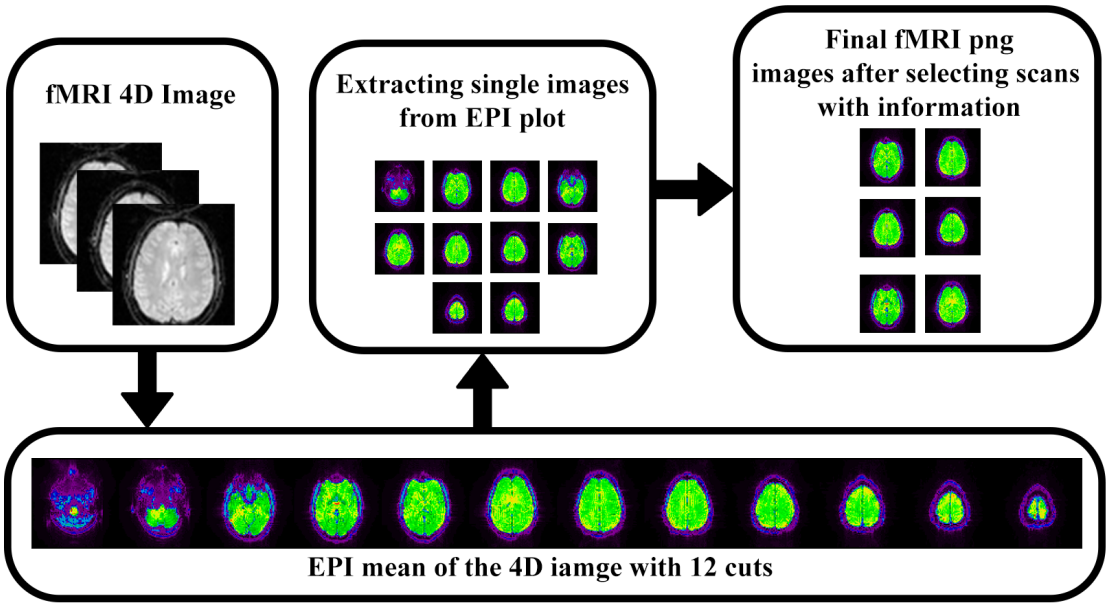

Figure 3.8: Preprocessing Steps for fMRI

Chapter 4

Experimentation

Firstly, we choose some famous and most-used architectures for our research. After doing background studies, we came to know that most of the research with MRI-based classification tends to give a lower accuracy number. But recently there have been many state of the art deep learning models created every day. With this model, new approaches can be found to existing solutions. So, we implemented some of the most used architectures to diagnose autism. Then we compared the results with existing approaches. Currently, there are very few MRI-based classifications with modern architectures available. So our first approach was to use different deep learning-based models. We have chosen ResNet50, VGG, and Inception. We used these models for classification and achieved a greater accuracy level for detecting Autism with MRI images.

In figure 4.1, we have mentioned our overall work process for deep learning-based models. Firstly, we collected our dataset. Then among all the MRI images, we selected some specific slices of the 256 slices of MRI images. These specific slices consist of both Autism and healthy subjects MRI. Then we split the images into training, testing, and validation set. The ratio for each of them is in the following order 60%, 20%, and 20%. Then using the training and validation set we fed the data to our selected algorithms. Then we evaluated the model using the completely untouched testing set. Next, according to the result, we kept tweaking the algorithms. After a certain tweaking, we re-selected different slices and do the whole process again and again until we get better results. We selected the set of slices in a trial-and-error manner, where we worked with different sets to find the set that works the best. Then, when we got satisfied with our results we finalized that model and generated a confusion matrix and accuracy test to determine the accuracy of our model. This whole process was done for all of our selected models.

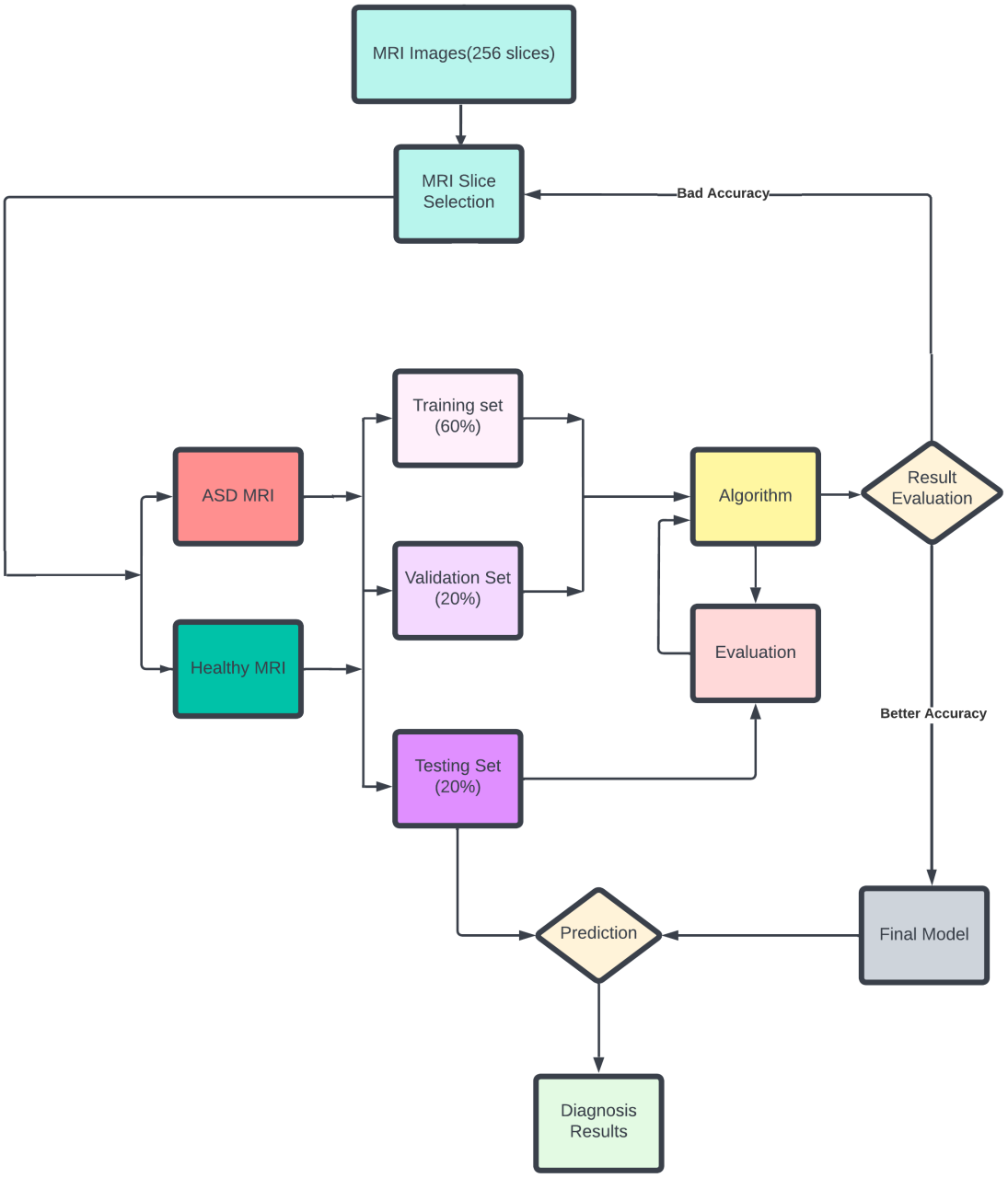

Figure 4.1: Block Representation of our proposed method

But we expected these out-of-the-shelf models to fail as these pre-trained model fails to classify medical images. So we implemented Transfer learning.

4.1 Modified deep learning models with transfer learning

The deep learning model fails with a small dataset. As MRI images are hard to get, it's very difficult to gather research data. Moreover, this data often varies from machine to machine. There are many variations present in MRI datasets. That's why the deep learning model often fails to generate good results when training from scratch. That's why using a pre-trained model is the right and better way to go. This is known as transfer learning. This can save time and resources compared to training a model from scratch and can also improve the performance of the model. But usually, this pre-trained model is trained with thousands of categories or classes. But here in the autism detection problem, there are only two classes of autism and control subjects. That's why we don't need thousands of neurons to train our model, we only need 2 neurons for our binary classification. To achieve that, we replaced the top layers of our models. We excluded top layers when importing our models. Then we freeze other layers to save time as those were already trained with pre-trained weights. Then we added 4 Dense layers and an average pooling layer. This added layer will be trained with our new dataset and then we will follow 4.1 steps to train and get results. The average pooling layer was used to reduce the dimensions of the feature maps. The pooling layer simplifies the feature map generated by a convolution layer by summarizing the features in a specific area, which in turn reduces the number of parameters that need to be learned and the computational effort required by the network. The dense layer's name came from the purpose it serves. It is a layer that is densely connected with its previous layers. The neuron of this layer is densely connected to every single neuron of its previous layers.

4.2 Combined Approach with two different datasets of ABIDE

We trained 3 models with both ABIDE I and ABIDE II datasets. In both cases, we used sMRI and fMRI data. So, in total, we used 3 models for 2 different datasets with 2 different image types. This was done to see the performance of different models with ABIDE Dataset. Also to see which model performs better. Our full process for this can be found here 4.2. We trained all these models with two different datasets with 2 different image formats to understand the connection between them. After training with sMRI and fMRI images, we compared those results for both ABIDE I and ABIDE II. Then we compared the results of three models between ABIDE I and ABIDE II to find a connection.

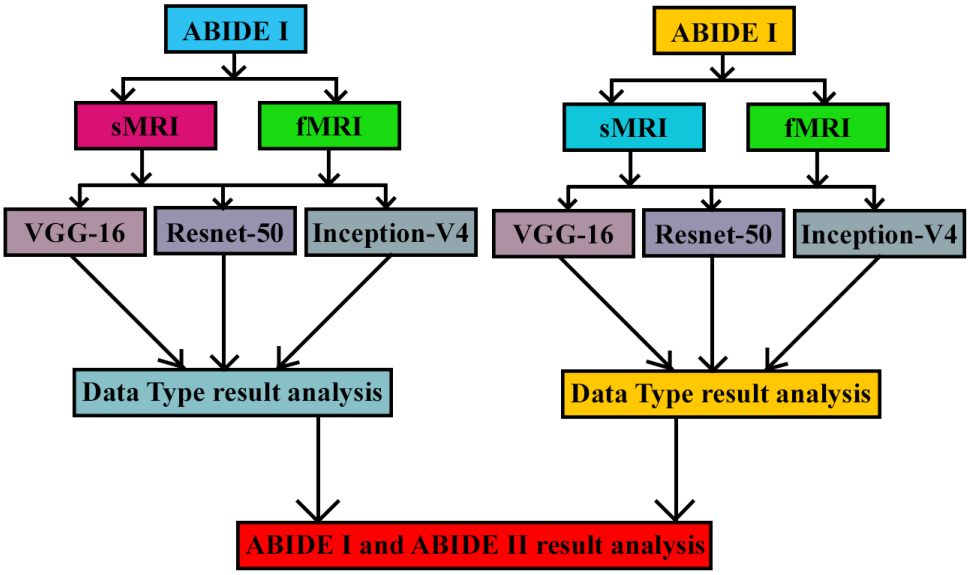

Figure 4.2: Our approach to understanding both datasets better

4.3 Our Healthy Block to get better performance

We have developed a sequential block. Our sequential block consists of a Dropout layer, an activation layer, a dense layer, and lastly a batch normalization layer. Our block healthy block has 4 dense layers with different neurons. This block helps to increase the accuracy of the classification of autism and healthy patient without overfitting and by eliminating dying ReLU or gradient death. As it helps to eliminate gradient death and stops the model from overfitting, we named it a healthy block. We used certain numbers of "healthy blocks" on top of traditional deep learning models. First, on the top of existing models, we used a dropout layer and then flatten it followed by a batch normalization call. Then we used our "healthy block". After 4 blocks, we normalized the outputs and used another dense layer with softmax activation to give binary output. We used these specific layers inside our "healthy block" because of the purpose they serve.

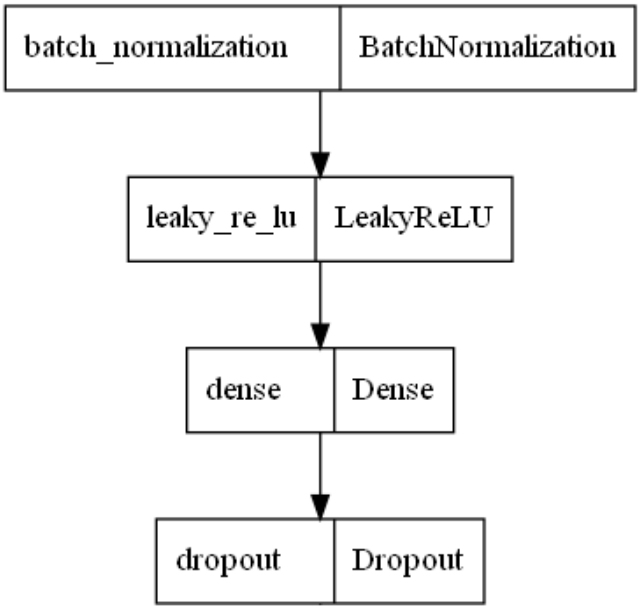

Figure 4.3: Healthy Block

- **Batch Normalization:** The activations of a neural network can be normalized using the batch normalization approach. Batch normalization is used to lessen internal covariate shift, which is the shift in the distribution of network activations brought on by training-related changes in network parameters. The training process may become more stable and converge more quickly as a result. In actuality, batch normalization is carried out by first scaling and shifting the normalized activations using learnable parameters after normalizing them using the mean and standard deviation of the activations in a batch of input data. This is usually used before or after the activation layers [18]. As already mentioned, this helps to standardize the inputs for activation layers or outputs after passing through activation layers. It solves a major problem called internal covariant shift. This covariant shift slows down the process of converging a model. A covariant shift happens when the input distribution changes and the layers of the model try to learn from it. Batch normalization helps to light out the inputs to each layer. That's why the shifting problem gets minimized.

- **Activation Layer:** An activation layer consists of activation functions that are used to compare the given input values to a threshold value. When the input value is more than the threshold value, the neuron gets activated. If the input value is below the threshold value, it is disabled, which prevents its output from being delivered to the next layer. For our activation layer, we used Leaky ReLU. It came from the ReLU activation function. When using the conventional ReLU function, a neuron will be set to 0 and will not generate any output if it gets a negative input value. This may result in some neurons being "dead" and not improving the performance of the network as a whole. This problem is known as gradient death. So to avoid 0, Leaky ReLU leaks a small percentage of the positive number to make the output positive. It tries to keep the mean activation close to 0.

- **Dense Layer:** it is the most used neural network layer. The name came because of the dense connection between layers because of this layer. All neurons of one level are connected to every other neuron of the next level. This layer is also called a fully connected layer. To convert the input data into a higher-level representation, the neurons in a dense layer apply weights that they acquire during training. The parameter inside the dense layer means the number of neurons it will have [30].

- **Drop out Layer:** Dropout layer is used to select some random neurons in the model and ignore them while training. It temporarily removes the neuron's ability to contribute to the training process. When some neurons are dropped out of the model, other neurons will have to step in and handle the representation needed to produce predictions for the missing neurons. Thus, the network learns to represent multiple independent internal predictions. It removes overfitting from a model. Overfitting happens when the data can not contain all the information to classify. This causes overfitting. Drop out layer reduces the chances of overfitting.

- **Flatten layer:** As the name suggests, it flattens the multi-dimensional tensor inputs into 1D input.

As mentioned in chapter 3, Collecting the MRI dataset is a handful of jobs. There are very less datasets and images present. Moreover, these datasets consist variety of images. No single brain looks the same, so training on a small database causes overfitting problems. That's why we used drop-out layers. Then these images with less information cause faulty assumptions. This can be called bias. To solve these negative biases we used activation layers. Lastly, real-world testing data can be different. This variation in data distribution can occur in covariate shifts. As MRI can be very different from one another, A model may face covariate shifts and it will make wrong predictions based on that, That's why we used multiple layers of batch normalization to handle the covariant shit problem. By keeping notes about these difficulties a model may face, we came up with the healthy net. This healthy net block improved our model's accuracy. We used 4 healthy blocks to get better performance. We added 4 layers after some testing to get the best results. The whole architecture can be seen on 4.4.

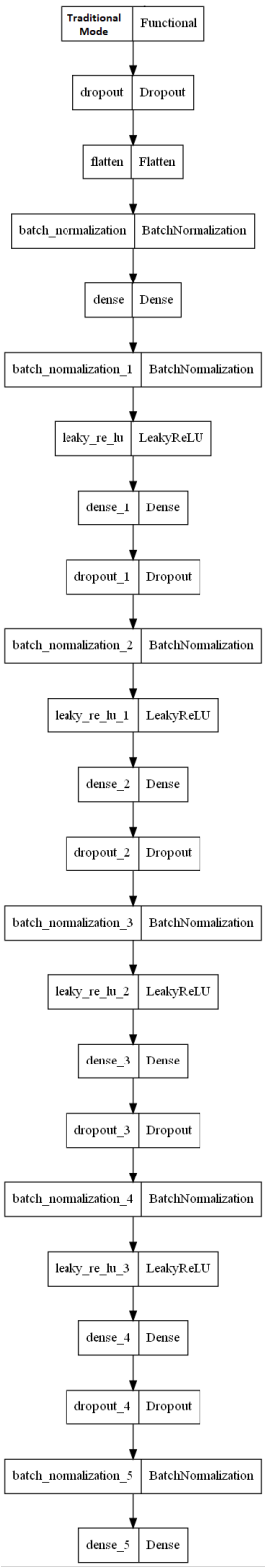

Figure 4.4: Healthy net architecture

4.4 Label fusion of sMRI and fMRI data:

We thought of creating a fusion-type algorithm to combine sMRI and fMRI data to get better results. To do that, we proposed using two trained models and getting the testing result from them. So, to label the fusion of both models, we first took some subjects' fMRI and sMRI data. Then, we preprocessed both of the data with the steps that we mentioned earlier. After that, we used the fMRI data to train our custom model. The same process was used with sMRI data as well. After following this process, we got the results of the subject's both fMRI and sMRI data. We repeated this process several times resulting in an array of results of the subject in both models. Then we used our custom algorithm to fusion those data and predict the optimized decision. By using this, we were hoping to get better accuracy since the algorithm iterates through all the results and predicts the best possible decision.

for the algorithm 4.5, we got 4 similar size arrays with n amount of elements. Here, n represents the number of iterations of the training and 4 arrays contain all the probability from sMRI and fMRI model training. Then, the algorithm adds all the probability of the subject being autistic and normal in a separate dictionary that is assigned to the subject. Then, it compares the total probability of that subject with the results from all iterations. If the probability of being autistic is higher than that, the algorithm returns as positive, and else it will return negative.

Algorithm.py

```
Procedure Calculate(result,storedResult)
    for all subjects in Subjcts
        Set yesPercentangeSMRI to value of autism_SMRI
Set noPercentangeSMRI to value of control_SMRI
Set yesPercentangeFMRI to value of autism_FMRI
Set noPercentangeFMRI to value of autism_FMRI
                Let yesTotal be sum of yesPercentangeSMRI and yesPercentangeFMRI
Let noTotal be sum of noPercentangeSMRI and noPercentangeFMRI
If yesTotal > noTotal
    Set result to 1
    Append 1 to storedResult
Else
    Set result to 2
                Append 2 to storedResult

Procedure FinalResult(finalResult)
    For all elements in storedResult
        Set key to element
        Let autismCount to 0
        Let controlCount to 0
            For all elements in storedResult[key]
                If element is 1
                    Compute autismCount = autismCount+1
                If element is 2
                    Compute controlCount = controlCount+1

                If autismCount > controlCount
    Set finalResult to 1
Else
    Set finalResult to 2
```

Figure 4.5: Our proposed algorithm for fusion

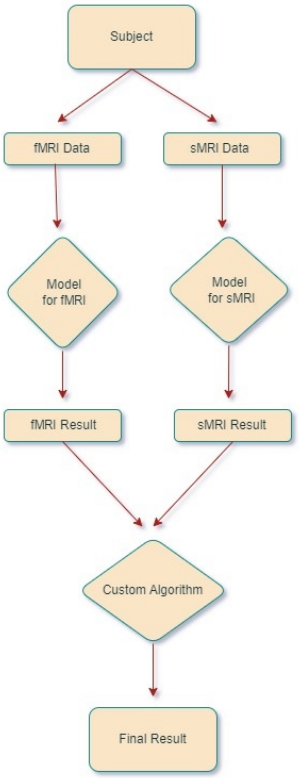

Figure 4.6: fusion of sMRI and fMRI

Chapter 5

Results and Discussion

We have implemented our models according to the implementation chapter of our research for training. After training for a certain epoch we got some decent results. We used the mentioned slices from chapter 3 for sMRI data and we used our proposed pipeline for extracting fMRI data. First, we created a training, testing, and validation part using the dataset. We use to split the dataset with a 60% to 20% to 20% ratio of training, testing, and validation. Then we feed the data to our model. No further prepossessing was needed as deep learning based usually performs badly with Noise reduction or histogram stabilization. We also re-scaled the image according to the model's requirements. For every model under a phase, we used the same dataset. Even splitting seed was the same. We used binary cross-entropy as a loss function with an 'adam' optimizer for all of our models. Then we used different model evaluation metrics.

5.1 Model evaluation metrics

There are different evaluation metrics available to understand how a model is performing. It also shows its strengths and weaknesses. Model Evaluation is a must thing for finding out the efficiency of a model. The main metrics to see how a model is doing are the Accuracy and Confusion matrix.

5.1.1 F1-Score Equation

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{5.1}$$

Here F1 score is a measured metric. It tells us about the model's accuracy for a dataset. This technique is used for binary classification techniques. it combines precision and recalls for a model.

5.1.2 Accuracy Equation

Accuracy is another metric for measuring a deep learning model's performance. Accuracy means the ratio of correct prediction to the total number of predictions of a model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.2}$$

in 5.1, 5.2 and 5.1 tp means true positive, Fn means false negative and Fp means false positives by the model.

5.1.3 Confusion Matrix

A confusion matrix is often known as an error matrix. It helps to visualize the performance of a model. It counts the number of successful and unsuccessful predictions during testing.

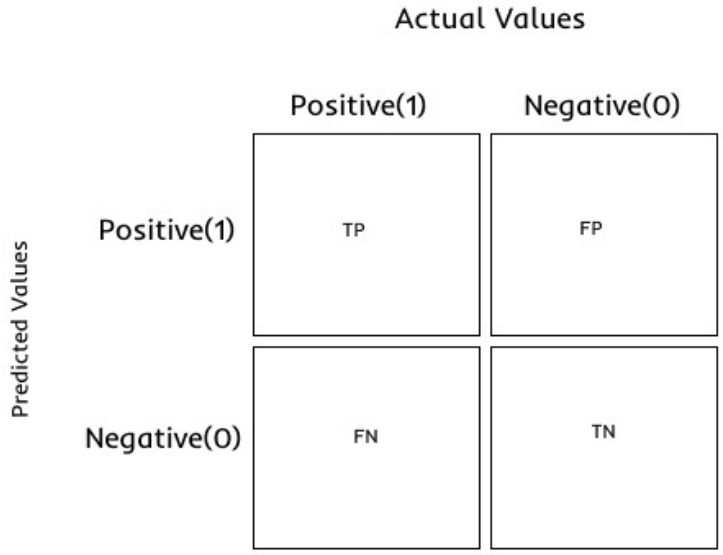

Figure 5.1: Confusion Matrix Example

5.2 Classification using ResNet, VGG, and Inception using transfer learning

Pre-trained models gave very bad results. As they were trained with different features and they can classify thousands of objects. That's why a pre-trained model was not an ideal way to go for complex image datasets like MRI. That's why we used transfer learning according to chapter 3.
After training with ResNet50, VGG16, and Inception-V4 model we got results with our slice-selecting method and transfer learning approach. For measuring results.

5.2.1 Results using ABIDE I

5.2.1.1 sMRI based result

Model	ResNet-50	VGG16	Inception-V4
Accuracy	78.93%	77.69%	74.03%
F1 score	76.01%	73.98%	73.89%

Table 5.1: Result with ResNet50, VGG16 And Inception-V4 using sMRI scans of ABIDE I

ResNet-50:

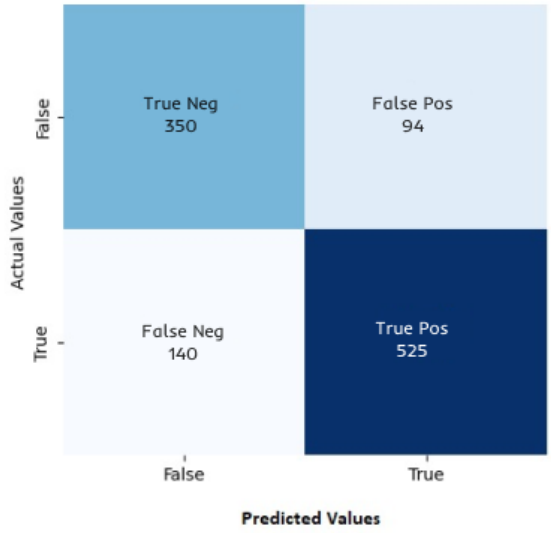

Figure 5.2: Confusion Matrix of ResNet50 using sMRI scans of ABIDE I

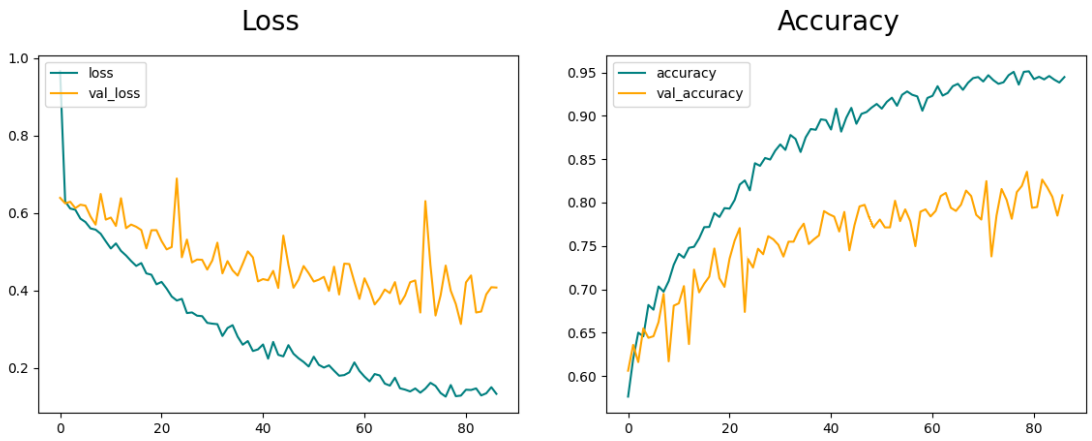

Figure 5.3: Model Loss and Accuracy Graph for Training and Validation of ResNet50 using sMRI scans of ABIDE I

from 5.2 we can see that the ResNet model worked very well without a dataset. It did correct prediction for 78.93% of the whole testing dataset. This model is working quite well compared with other results. It had a balanced performance for finding true positives and true negatives. Its error was also balanced for false positives and negatives.

VGG-16:

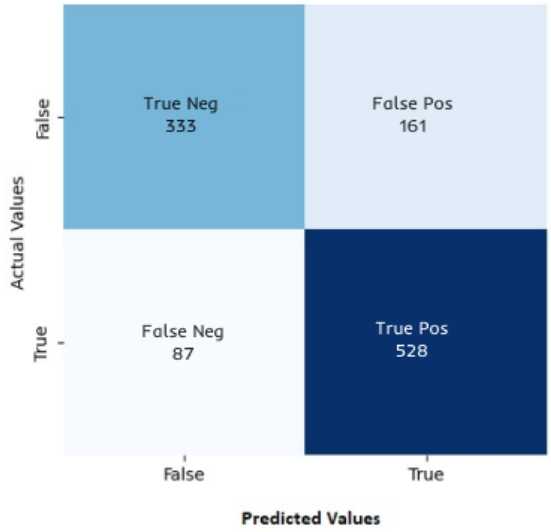

Figure 5.4: Confusion Matrix of VGG16 using sMRI scans of ABIDE I

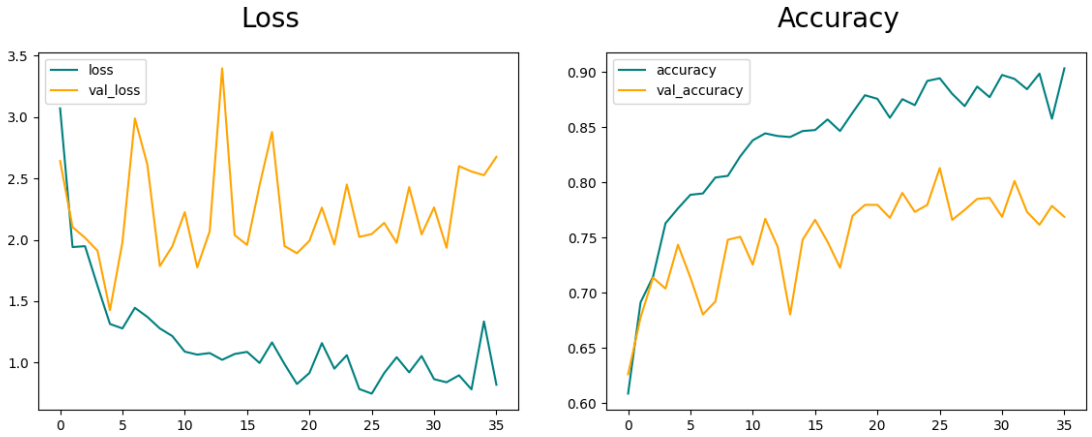

Figure 5.5: Model Loss and Accuracy Graph for Training and Validation of VGG-16 using sMRI scans of ABIDE I

From 5.4 we can see that VGG-16 also did quite well. It achieved 77.69% accuracy during testing. This architecture had good results in finding true values. But it had more trouble finding false positives than false negatives. So, this model was incorrectly labeling images as autistic when it wasn't.

Inception-V4:

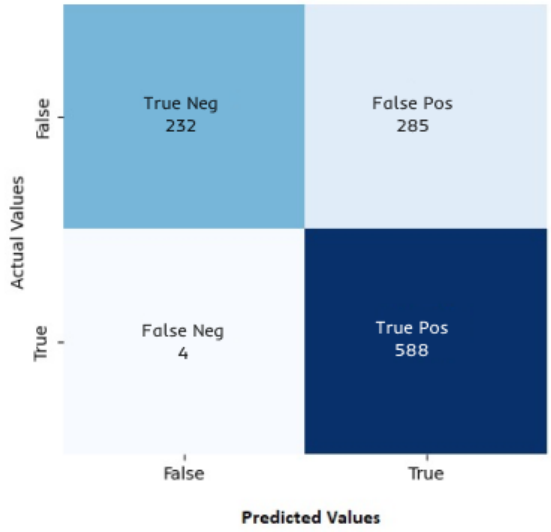

Figure 5.6: Confusion Matrix of Inception-V4 using sMRI scans of ABIDE I

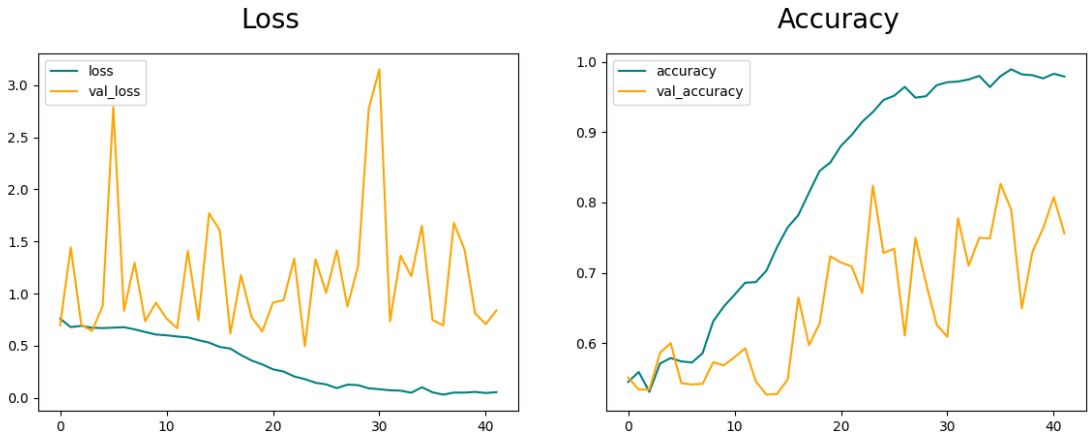

Figure 5.7: Model Loss and Accuracy Graph for Training and Validation of Inception-V4 using sMRI scans of ABIDE I

From 5.6 we can see that inception also did quite well. It achieved 74.03% accuracy during testing. This model performed worst compared with the other two. It was almost labeling every healthy subject's MRI as autistic. from 5.7 we can see that there are a lot of spikes during training and validation. There might be some bias during the training of the data. As we used mini-batch size, it may also introduce noises.

sMRI Analysis of ABIDE I:

Here all of our models are performing close to our expectations. But with tuning and some slight modification to the dataset this result can be improved. We got this result by stopping the training using the Early Stopping feature of Keras. Moreover, we used raw data from the dataset. Slices choosing can play a vital role in better results. We chose slices according to the Data prepossessing of our paper. We compared the results of selecting different slices and came up with selected slices. The main problem with this model is spikes. It can be seen from the graph that there are a huge number of spikes during training.

5.2.1.2 fMRI based result

Model	ResNet-50	VGG16	Inception-V4
Accuracy	80.01%	69.21%	74.04%
F1 score	81.04%	70.98%	73.95%

Table 5.2: Result with ResNet50, VGG16 And Inception-V4 using fMRI scans of ABIDE I

ResNet-50:

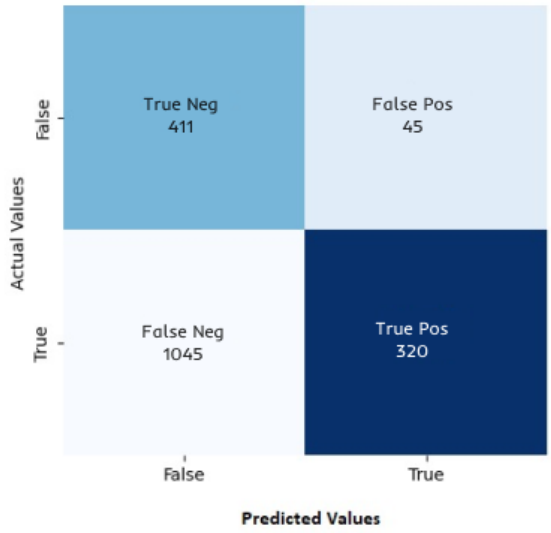

Figure 5.8: Confusion Matrix of ResNet50 using fMRI scans of ABIDE I

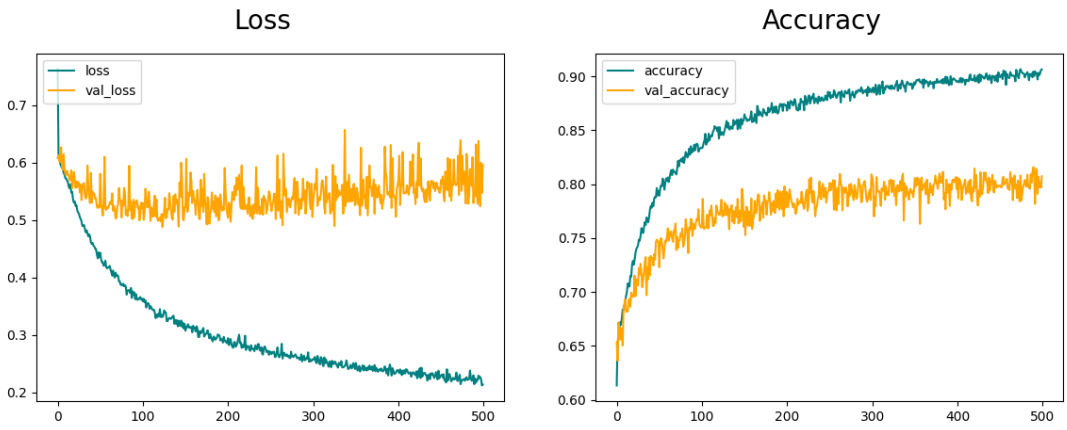

Figure 5.9: Model Loss and Accuracy Graph for Training and Validation of ResNet50 using fMRI scans of ABIDE I

VGG-16:

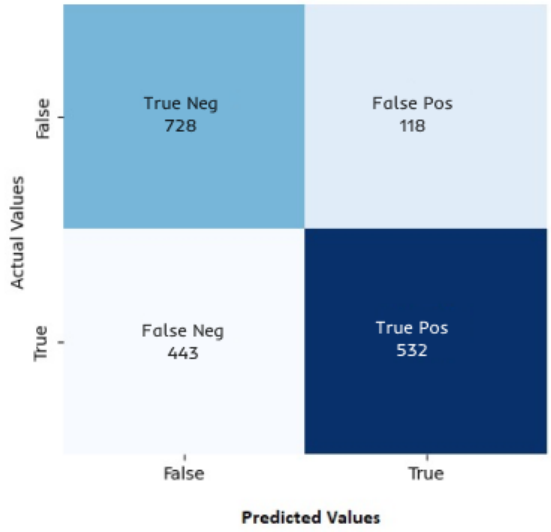

Figure 5.10: Confusion Matrix of VGG-16 using fMRI scans of ABIDE I

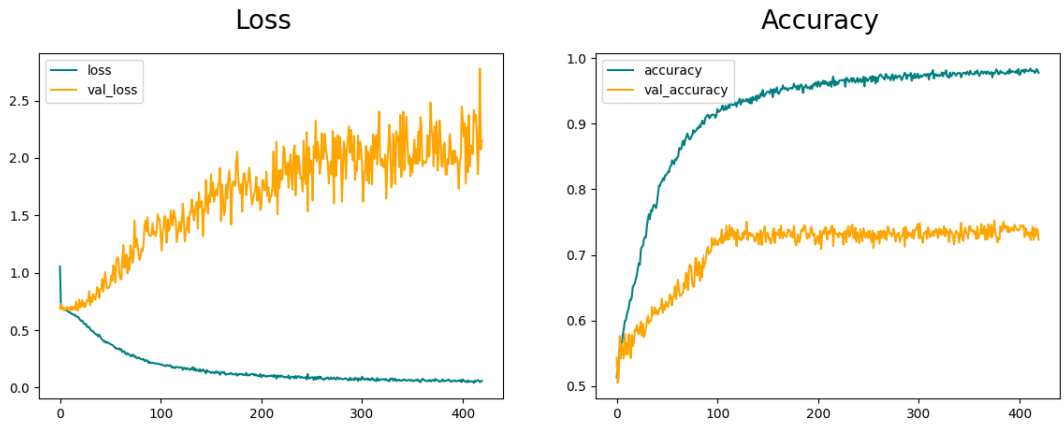

Figure 5.11: Model Loss and Accuracy Graph for Training and Validation of VGG-16 using fMRI scans of ABIDE I

Inception-V4:

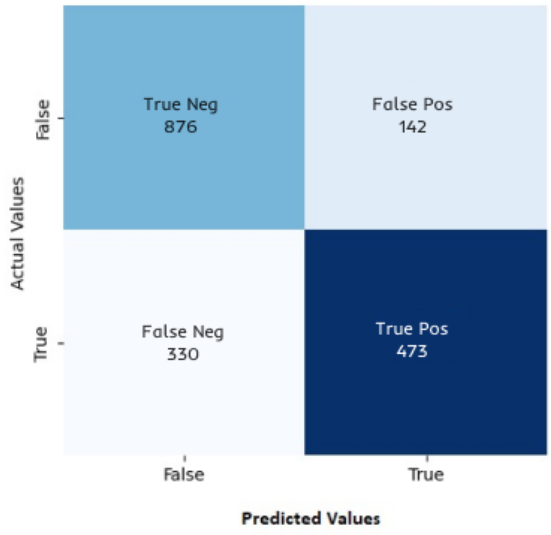

Figure 5.12: Confusion Matrix of Inception-V4 using fMRI scans of ABIDE I

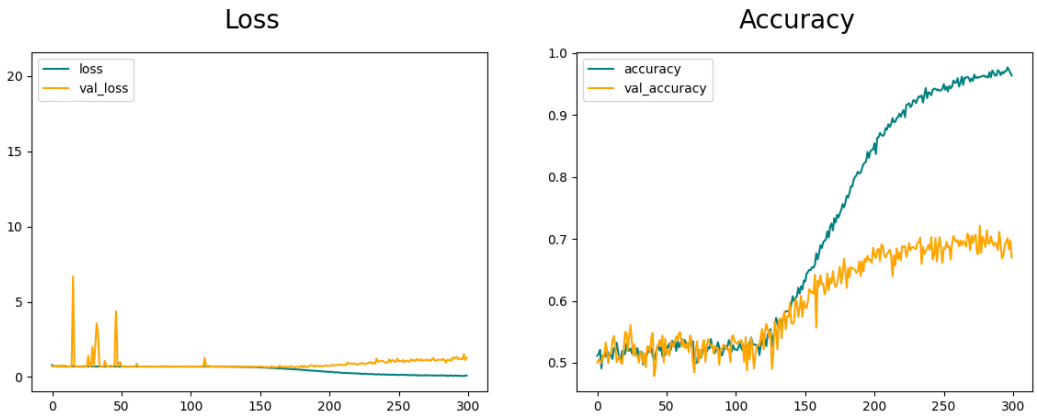

Figure 5.13: Model Loss and Accuracy Graph for Training and Validation of Inception-V4 using fMRI scans of ABIDE I

fMRI Analysis of ABIDE I:

As already mentioned, ABIDE has both fMRI and sMRI data for every patient. fMRI data contains very less information about the brain. It only consists of the functional activity of the brain. We the help of EPI image plotting we extracted mean MRI images of the whole brain. Surprisingly this approach gave almost save the output as sMRI data. We think the subjects were the same. The models already learned the features it can learn. So, giving new features of the same brain did not do anything good in terms of accuracy.

5.2.2 Results using ABIDE II

5.2.2.1 sMRI based Result

Model	ResNet-50	VGG16	Inception-V4
Accuracy	70.56%	72.21%	75.71%
F1 score	67.01%	73.25%	75.07%

Table 5.3: Result with ResNet50, VGG16 And Inception-V4 using sMRI scans of ABIDE II

Resnet-50:

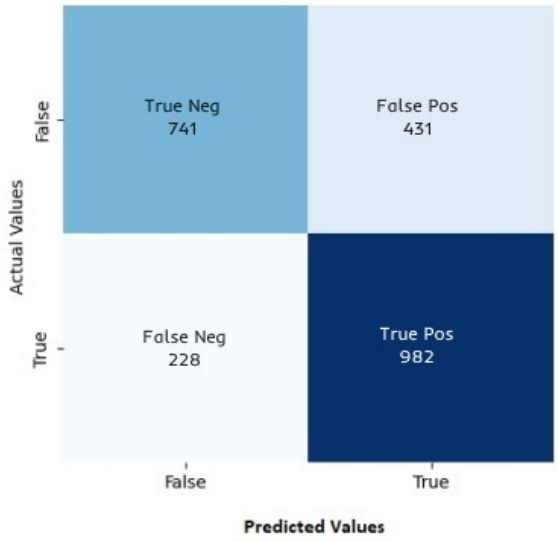

Figure 5.14: Confusion Matrix of Resnet-50 using sMRI scans of ABIDE II

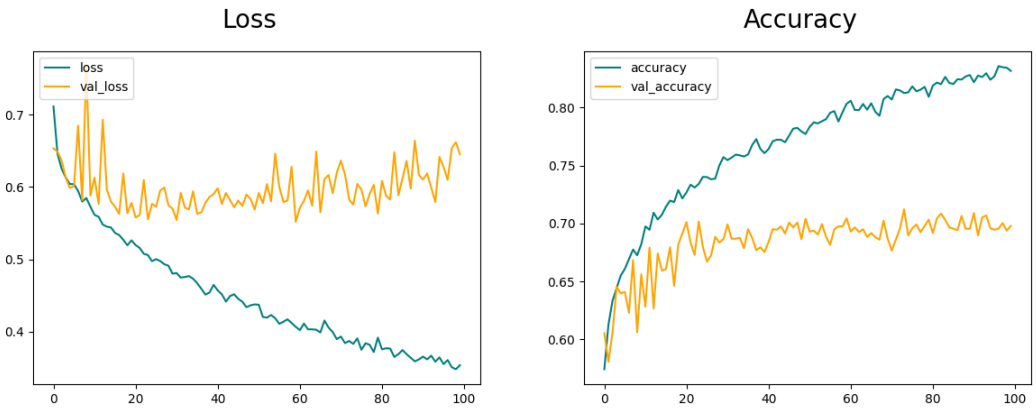

Figure 5.15: Model Loss and Accuracy Graph for Training and Validation of Resnet-50 using sMRI scans of ABIDE II

VGG-16:

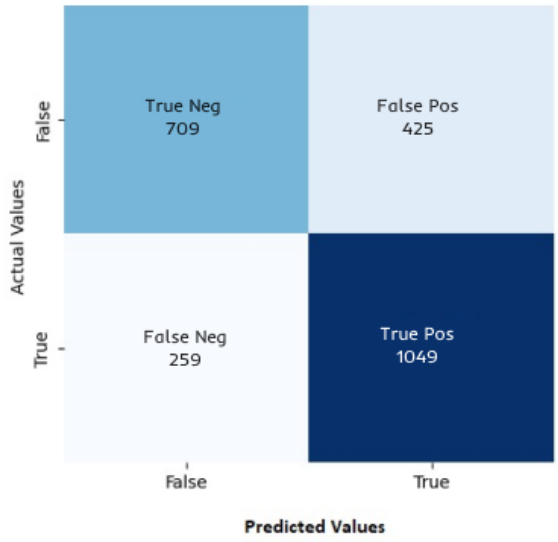

Figure 5.16: Confusion Matrix of VGG-16 using sMRI scans of ABIDE II

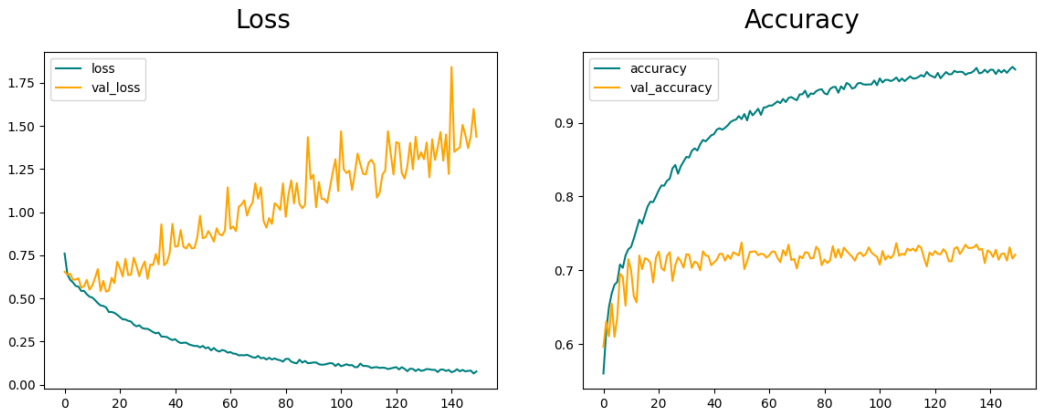

Figure 5.17: Model Loss and Accuracy Graph for Training and Validation of VGG-16 using sMRI scans of ABIDE II

Inception-V4:

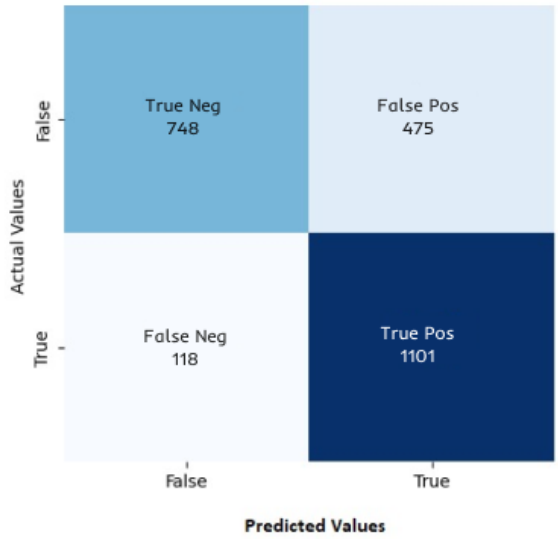

Figure 5.18: Confusion Matrix of Inception-V4 using sMRI scans of ABIDE II

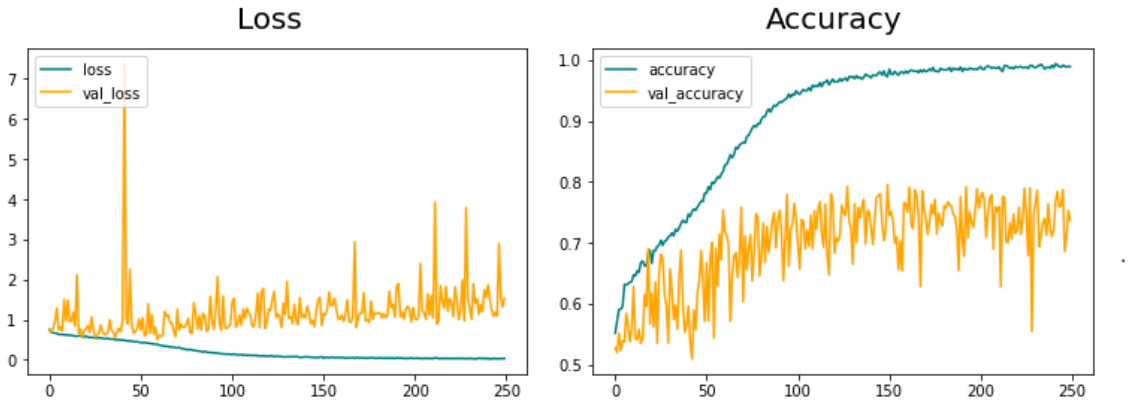

Figure 5.19: Model Loss and Accuracy Graph for Training and Validation of Inception-V4 using sMRI scans of ABIDE II

sMRI analysis of ABIDE II:

With ABIDE II sMRI data, we trained it with the same models as ABIDE I. But surprisingly this time the model performed badly compared with the previous result from 5.1. This performance degradation came from sMRI images. The Reason might be ABIDE II consist of more children than ABIDE I. As a result, children's brains are not fully developed. So comparing the structural similarities of children with an adult will give bad results for testing. If we only trained our model for children's age group, it would have given a better performance. Also, it looks like the model is overfitting for the training data. More on this issue will be discussed after analyzing the fMRI data of ABIDE II.

5.2.2.2 fMRI based Result

Model	ResNet-50	VGG16	Inception-V4
Accuracy	73.94%	77.76%	82.22%
F1 score	74.01%	77.92%	81.67%

Table 5.4: Result with ResNet50, VGG16 And Inception-V4 using fMRI scans of ABIDE II

Resnet-50:

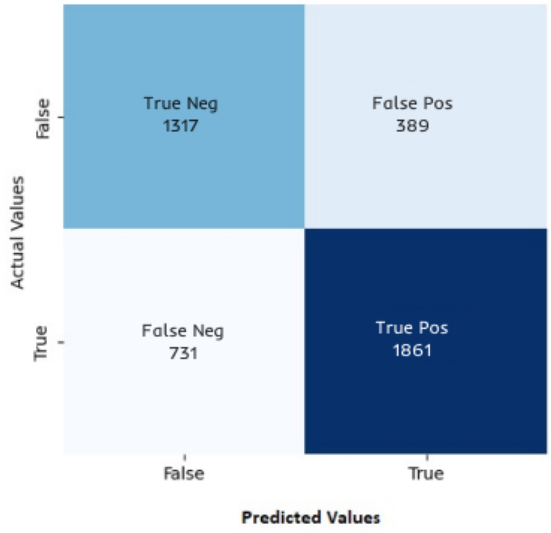

Figure 5.20: Confusion Matrix of ResNet50 using fMRI scans of ABIDE II

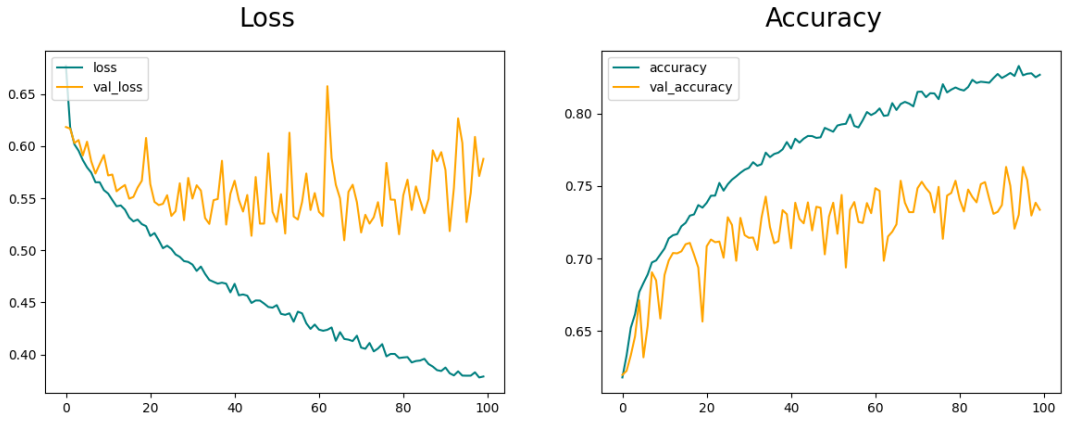

Figure 5.21: Model Loss and Accuracy Graph for Training and Validation of ResNet50 using fMRI scans of ABIDE II

VGG-16:

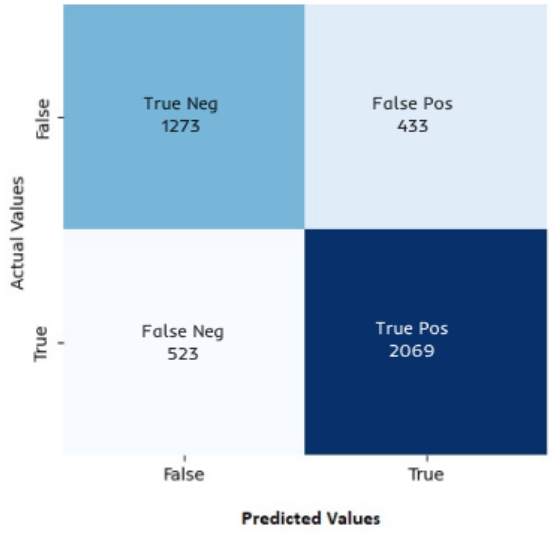

Figure 5.22: Confusion Matrix of VGG-16 using fMRI scans of ABIDE II

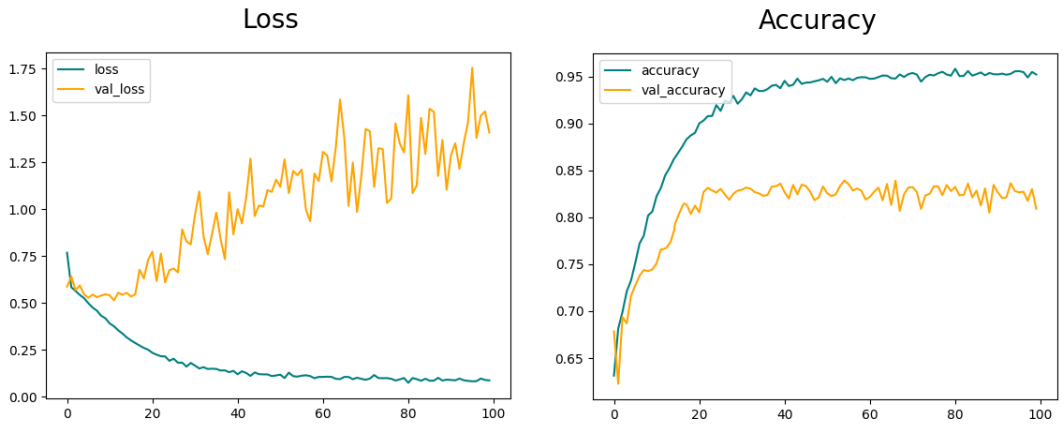

Figure 5.23: Model Loss and Accuracy Graph for Training and Validation of VGG-16 using fMRI scans of ABIDE II

Inception-V4:

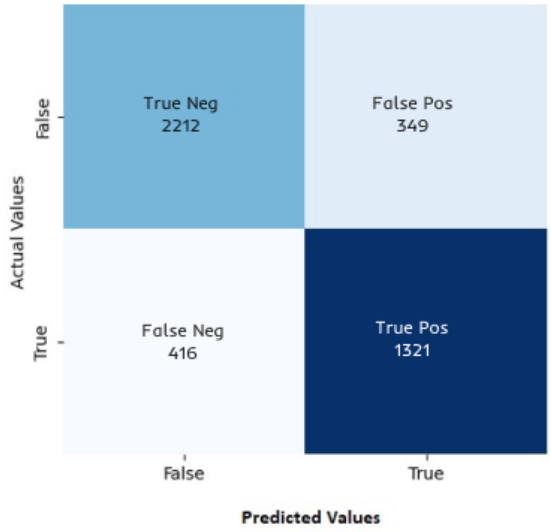

Figure 5.24: Confusion Matrix of Inception-V4 using fMRI scans of ABIDE II

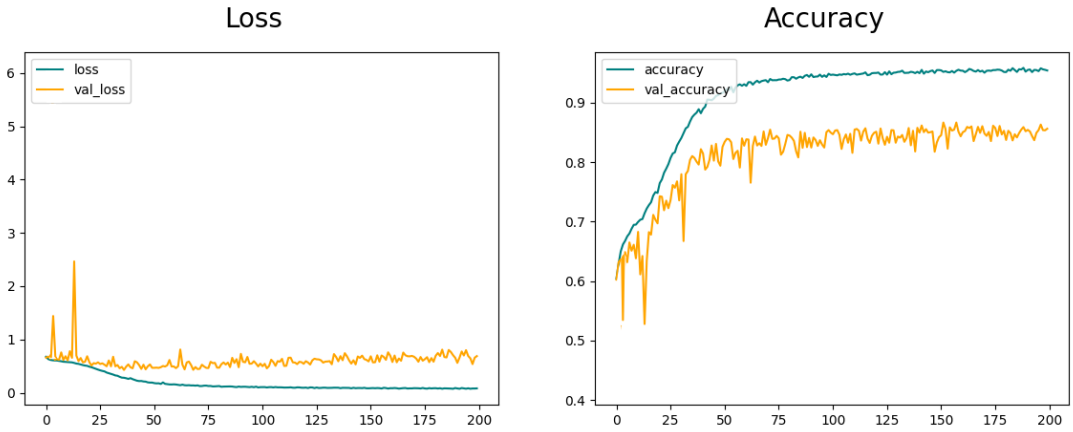

Figure 5.25: Model Loss and Accuracy Graph for Training and Validation of Inception-V4 using fMRI scans of ABIDE II

fMRI Analysis of ABIDE II:

Here the models performed quite well compared with ABIDE I data. The overall performance was good. But the data again overfitted. Here, the reason behind the performance increase is fMRI data do not have any structure information. It contains functional information about the brain. Children and adults both have

similar regions activated during a task or thinking process. Not all the activation of regions is the same. But a child, on average has a 60% greater extent of activation than an adult [38]. That's why we see better accuracy than sMRI data.

Overall Analysis of ABIDE I and ABIDE II:

But one thing is noticeable between both sMRI and fMRI images. They both are overfitting. As training accuracy increases but validation accuracy stays almost the same. This is a case of overfitting. Adding regularization or dropout layers during training can avoid this situation. The model can not properly generalize and it gets fits too closely to the training data. It may happen because of not enough data samples.

	ABIDE I			ABIDE II		
MRI Type	Resnet50	VGG-16	Inception v4	Resnet50	VGG-16	Inception v4
sMRI	78.93 %	77.69 %	74.03 %	70.56 %	72.21 %	75.71 %
fMRI (EPI)	80.01 %	69.21 %	74.04 %	73.94 %	77.76 %	82.22 %

Table 5.5: comparison between different model and dataset

5.2.3 Overall analysis of our three models with transfer learning:

ABIDE I is very old compared with ABIDE II. Both consist of almost the same number of subjects. But still, the data is quite different. The complexity of brain connections and the wide range of characteristics of ASD subjects made it harder to do deep learning tasks. To gain more characteristics and more information about brain connections, ABIDE II was introduced. ABIDE II consists of more variable data. That's why the model trained with ABIDE II data gave better results compared with ABIDE I for certain scenarios. From table 5.5, we can see that ABIDE II was better than ABIDE I for Different models. Now moving on to a more detailed description. The inception model performed far better for ABIDE II than I. The inception model's layer depth is much deeper than normal. This resulted in much slower training time but with better accuracy. Compared with that VGG-16 did well despite having fewer layer counts.

ABIDE II seemed to be overfitted. Also, its sMRI score is quite lower. We concluded that, because ABIDE II contains more MRI of children, it performed badly as sMRI data contains brain structural information. As children's and adult brain structure is different, the model performed badly when testing with random subjects between the age of 2 to 65. On the other hand, fMRI scored Better because of functional similarities between adults and children. According to [38] children's brains are 60% more functionally active than an adult's. That's why with a variation of data of ABIDE II, it performed well among the two datasets.

5.3 Classification using ResNet and VGG using Healthy Block:

Model	ResNet-50	VGG16
Accuracy	84.04%	83.20%

Table 5.6: Result with ResNet50 and VGG16 using fMRI scans of ABIDE II

For simplicity, we used ABIDE II data for this analysis. Here with the traditional models, we added our healthy block to solve the problem we faced during traditional model training. The main problem was overfitting and not being able to learn complex features. So, with our healthy block, we wanted to solve the overfitting problem.

Resnet-50:

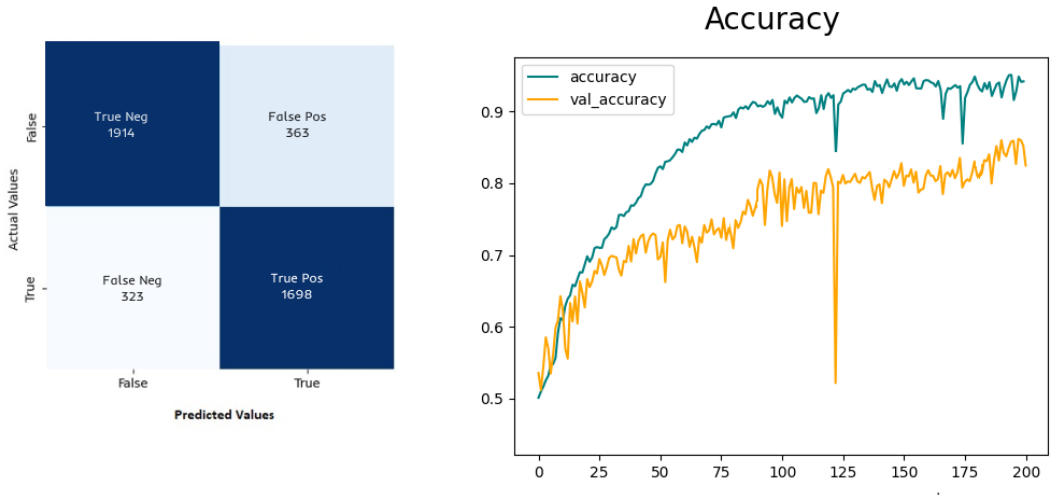

Figure 5.26: Confusion Matrix and accuracy graph of Resnet-50 with healthy block using fMRI scans of ABIDE II

VGG-16:

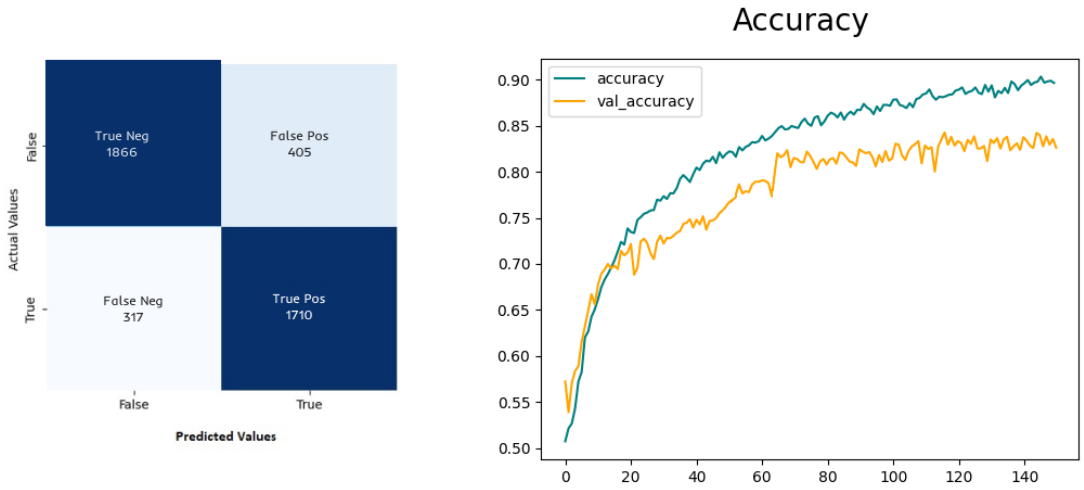

Figure 5.27: Confusion Matrix and accuracy graph of VGG16 with healthy block using fMRI scans of ABIDE II

It can be seen that our model is performing slightly better for similar epoch numbers. Also, there is no overfitting present. Our custom block reduces the overfitting problem with the dropout layer. Then we are also getting slightly better results with the same epoch because of batch normalization. Then more dense layer helped us to get better classification results for two classes of autism and control. Though there is a sudden drop in training accuracy, it happens because of the batch training and drop-out layers. Drop-out layers make training performance worse. But it makes test performance to be better. Because of dropout layers, weights have less chance for collusion and making overfitting. Our model was performing the same as inception without the deeper layers and high training epoch of the Inception model. Also, the Inception model takes a long time to train. That's why we didn't add a custom block on Inception. Also as already stated before, sMRI gives less accuracy for ABIDE II because of the large child sample. That's why we also excluded that part. fusionFail

5.4 Label fusion with sMRI and fMRI data:

After applying the procedure, we didn't notice any major changes. Both the sMRI and fMRI models gave us variations of results in each iteration and the accuracy was inconsistent. The reason for this was the models were giving some wrong results on some subjects in some cases and the same subjects were predicted correctly in some iterations. For that reason, our accuracy which was initially 84% became inconsistent meaning sometimes we were getting higher accuracy and sometimes the accuracy wasn't near as perfect. So, the algorithm couldn't predict the correct decision every time hence the final result wasn't satisfactory enough. From 5.28, it can be seen that the result is not fixed. It is very much unpredictable.

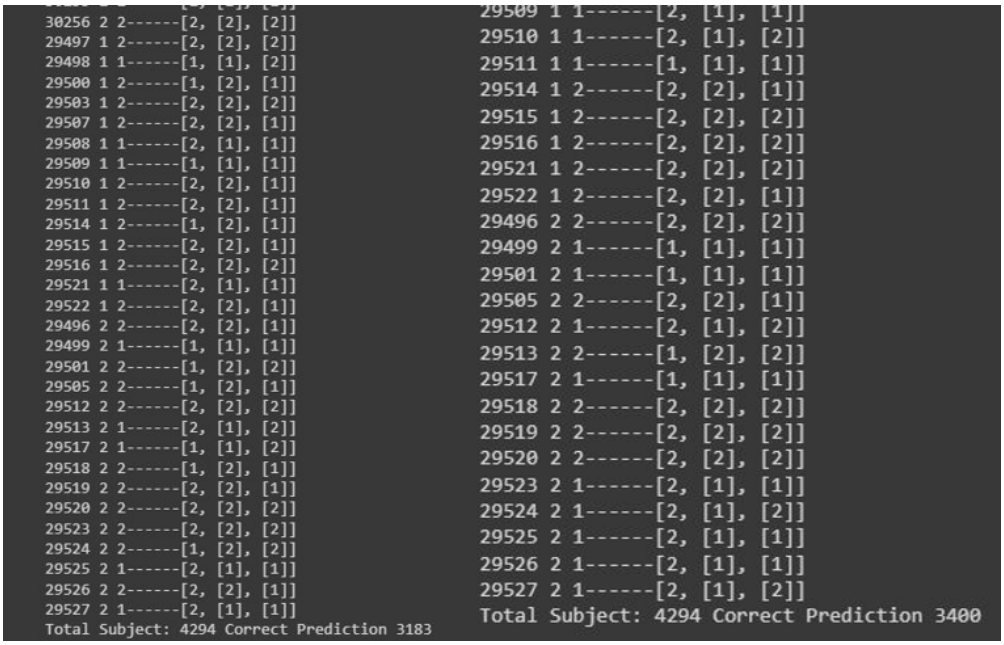

Figure 5.28: Fusion results

5.5 Performance of different approaches

Our modified model is working quite well compared with others. With simple blocks, we achieved higher accuracy than other researchers. With traditional models and simple prepossessing our model is performing almost the same and sometimes better than other complex models. We achieved an accuracy of 84.04% with very less epochs. Moreover, most of the researchers used specific parts of the ABIDE dataset to achieve higher accuracy. But very less researchers used a full dataset of ABIDE to get classification results. After comparing with different models and different sorts of data, we came up with some insights about ABIDE dataset.

- ABIDE I contains fewer children's MRI scans. Which gives better accuracy for sMRI scans. While ABIDE II contains a variety of data with more children's MRI scans. Because of that ABIDE II gives better results with fMRI data.

- We came up with a simple algorithm to fusion sMRI and fMRI data to get better accuracy. But it failed due to the complexity of both data formats. Also, the models were giving close values for different subjects. This resulted in bad performance. It was quite unpredictable because one model can sometimes give a false call to a subject and while another model can give a false call to another random subject. This made the fusion unpredictable. This approach of ours was not a success from an accuracy perspective. But it gave us some insight into future work.

- Our healthy block improved accuracy slightly while reducing the overfitting problems and faster convergence. In detail comparison of our model with different pre-existing complicated models can be found below in table 5.7.

- we found out that Resnet performed better with modified layers and normal layers if we think of the overall accuracy.

- from table 5.7 it is visible that our model is performing quite well compared with other complex models. It is getting better accuracy or almost the same level for ABIDE I and ABIDE II datasets.

Study	Dataset	Technique	Accuracy
[13]	ABIDE I	first-level high-order FC networks	81%
[24]	ABIDE I	Siamese verification framework with path signature features	83%
[28]	ABIDE I	Functional Brain Networks with deep learning	79.2%
[23]	ABIDE I	Support vector machine and logistic regression	75%
[27]	ABIDE I	Multiclass class activation mapping models with sMRI biomarkers	80.2%
[27]	ABIDE I	CNN based approach	83.8%
[27]	ABIDE I	RNN based approach	83.1%
[25]	ABIDE I	Deep leaning approach using VGG-16 and Resnet-50	63.01% 87.0%
[32]	ABIDE I ABIDE II	VGG 19 Inception V3 DenseNet based model	70.22%, 57.75% 57.61%
Our model	ABIDE II	Modified Resnet-50 VGG-16	84.04% 83.20%
Our model	ABIDE I	Resnet-50 VGG-16 Inception-v4	80.01% 77.89% 74.04%
Our model	ABIDE II	Resnet-50 VGG-16 Inception-v4	73.94% 77.76% 82.22%

Table 5.7: accuracy of different research

Chapter 6

Conclusion And Future works

6.1 Conclusion

In this thesis, we looked into different deep-learning approaches for the diagnosis of Autism using MRI scan data. In chapter 1, we analyzed our problem. What were the obstacles to this problem and how this research can solve an issue in our society. After defining the objective of our research, we found a platform to get data. We also did background studies for different architecture and researched some pre-existing research papers to find out how people are dealing with this classification problem. In chapter 3, we introduced the ABIDE database. We analyzed and found out that it was one of the most complicated datasets to deal with. We showed how we extracted data from a huge platform. We mentioned our pipeline of extracting sMRI and fMRI data for each subject. Then how we split our dataset to train models. For fMRI images, we used a technique to export EPI samples. We used these EPI images to train our model.
In chapter 4, we tested different approaches and architectures to get better accuracy. We also tried deep-learning models with transfer learning and without transfer learning. We also added some layers on top of existing layers to get better results. We trained our model with ABIDE I and ABIDE II datasets. Lastly, we discussed and compared these results with existing results.

The number of individuals with autism is increasing day by day. Although early intervention does not cure autism, it can assist a child in developing the required abilities to function in society. An individual with autism finds it very hard to deal with the world. After studying different literature, it can be observed that many researchers used different approaches to solve the problem of autism detection. From using an advanced algorithm to observing behavior to get data, all these techniques had the same goal of detecting ASD accurately. This is why our research is an attempt to solve the problem of detecting ASD properly and accurately.

In this study, we first started with doing related research studies. By which we found how people tried to deal with this problem. Then we selected a dataset known as ABIDE. Then we extracted some specific slices among the 256 slices per subject. After prepossessing our dataset, we studied different architecture and models to train. We came up with some solutions and some decent results. To make our research effective and consistent with other researchers we used the worldwide used

dataset of ABIDE. So, far our research can be said to be effective and going in the right direction.

6.2 Future Work

Our research is not finished. This topic can be explored further to determine better results. Our proposed models and findings can be improved further using different approaches.

- One of the key improvements can be found in using the whole brain MRI as a 3d image instead of using a 2D image.
- The behavioral pattern along with MRI images can be also used to get a better classification.
- As GPU capabilities are increasing day by day, there are more advanced architectures like R-CNN, and many more are coming into the picture. These models promise higher accuracy for more complex datasets. We couldn't implement those models due to hardware and time constraints. Then fusion of different MRI data can be trained together to work with complex brain structures and find better results.
- There are also different planes available for the brain. These planes can be used to create a more vast dataset. 3 different planes will give 3 different planes to extract brain features. After combining these features, a better result can be found.
- One of the major future work to do will be to set up a supplemental online service. Where users can come and upload their MRI images and get diagnoses. In this way, users will be able to get benefits from the system without meeting doctors. This will also help to collect MRI images of patients with their consent. Data is the key to the future. Collecting MRI using an online portal while helping others will help us to develop a rich database for MRI scans. It will also help us to create a large database for the Bangladeshi people.

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