Automated Detection of ASD and Dyslexia

03CS7914 Project (Phase II)

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This is to certify that, this report titled ***Automated Detection of ASD and Dyslexia*** is a bonafide record of the work done by

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student, for the course work in **03CS7914 Project (Phase II)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, M. Tech. Computer Science & Engineering (Image Processing) of **APJ Abdul Kalam Technological University**.

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Shijina T

Acknowledgements

This project would not have been possible without the support of many people.I would like to express my deepest gratitude to my coordinator,**Dr. Jyothi R L**, whose sincerity and encouragement I will never forget. Thank you for your patience, guidance, and support. I have benefited greatly from your wealth of knowledge and meticulous editing. And also I would like to thanks And I would like to express my heartfelt gratitude to my project coordinator **Mr. Ahammed Siraj K K**, Associate Professor in Computer Engineering, for his suggestions and guidance for making of the project.
I express my sincere thanks to **Dr. Smitha Dharan**, Principal, College of Engineering Chengannur and **Dr. Manju S Nair**, Professor and Head of Department of Computer Engineering, for providing constant support.
I will be failing in duty if I do not acknowledge with grateful thanks to the authors of the references and other literature referred for this project. I am indebted to Almighty God for giving me the opportunity to excel in my endeavors in this work.

Shijina T

Abstract

Neurodevelopmental disorders are a group of disorders that affect the development of the nervous system, leading to abnormal brain function which may affect emotion, learning ability, self-control, and memory. The effects of neurodevelopmental disorders tend to last for a person's lifetime.Examples of neurodevelopmental disorders in children include attention-deficit/hyperactivity disorder (ADHD), autism, learning disabilities, intellectual disability (also known as mental retardation), conduct disorders, cerebral palsy, and impairments in vision and hearing.Autism spectrum disorder (ASD) is a psychiatric disorder caused by impairment in brain functions. ASD patients suffer from weakness in verbal and non-verbal communication and difficulty in social activities, which may influence their life quality and interpersonal skills. Dyslexia and autism are two different types of disorders. Dyslexia is a learning disorder that involves difficulty interpreting words, pronunciations, and spellings. The brains of individuals with both autism and dyslexia show minor variations in the cell structure and arrangement compared with an average brain. In both cases, there are issues with the language system. In autism, it is more about not understanding social cues resulting in awkward responses, whereas, in dyslexia, it is more of a struggle decoding and putting together words, their sounds, and meanings. The question is whether a child's learning and language difficulties arise because of autism symptoms or because the child is dyslexic. This work is focused on automated detection of ASD and Dyslexia through a machine learning approach using Brain fMRI data to distinguish between these neurodevelopmental disorders to find out learning disability in a Autstic child.

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Chapter 1

Introduction

One of the most important part in the human body is brain. Brain controls the activities like memory, emotions, skills, thought, emotions, balance, hunger, breathing etc. Brain can be divide into regions and each of these regions will have different functionalities. For examples the frontal lobes are used for problem solving and decision making, the cerebellum is responsible for coordination and balance and thinking and voluntary movements begin in the cortex region. Since the brain can be divide into many parts and each part/regions connected by veins and the blood flowing between these parts makes the functioning in it. If we represent the entire brain as network then we can represent these regions as node and the blood flow levels as connection, each time when we do some action signals passed between these regions as blood flowing rate. Thus using these network we analyses the brain with the adaptation of some machine learning techniques in medical image analysis. Most of brain imaging techniques uses fMRI for get brains functional data and MRI for structural information. BOLD signals are used in fMRI for capturing brain images. Recently for research is done applying machine learning techniques in brain image analysis.

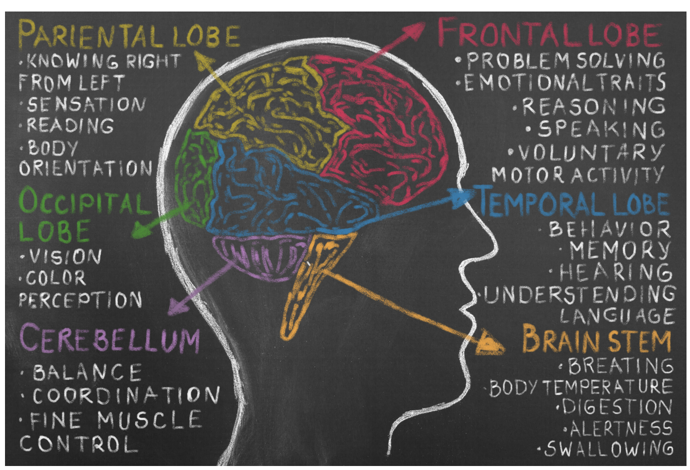

Figure 1.1: Brain fMRI for Healthy and Autistic

A groups of disorders the affect brain functional activities is commonly known as Neurodevelopmental disorders (NDD). NDDs effects in persons emotions, learning abilities, memory, controls etc. Most of these kind of disorders not curable and disorders tend to last for a person's lifetime. Early detection of some of the NDDs is quite difficult since there no a single medical test for diagnosing these disorders. Diagnosis of NDDs are done commonly by timely observation and contact with patients, patients behavioral change, professional therapy, pharmaceuticals, and home- and school-based programs. But these diagnosing become complex due to lack of corporations from patient's side and also the time taking process.Autism , ADHD(Attention Deficit Hyperactivity Disorder), Speech and language disorders, Schizophrenia, are the examples of NDDs. These not only affect someone's personal life but also with the social life also.This project is mainly concentrated on ASD and Dyslexia.
Autism spectrum disease, often known as ASD, is a neurological illness in which the brain perceives sound and colour differently from the usual brain. The autistic brain network differs from the conventional healthy human brain network due to Autistic behaviours. The commonly showed symptom of ASD is repetitive behaviour, lack of communication skill, difficulty expressing emotions, anger,insomnia,lack of eye contact.Whereas Dyslexia is a learning disability characterised by difficulties comprehending words, pronunciations, and spellings. People with dyslexia often have normal brains and eyesight. With tutoring or a specialised education program, most children with dyslexia can succeed in school. Difficulties deciphering words are a crucial indicator of dyslexia. This is the ability to associate letters with sounds. Children may also struggle with a more fundamental skill known as phonemic awareness. This is the capacity to distinguish word sounds. Phonemic awareness issues might appear as early as preschool. There is no one test that can be used to diagnose dyslexia. Questionnaires, your child's growth, educational challenges, and medical history, hearing and brain (neurological) examinations, testing reading and other academic skills are all taken into account. The cell structure and organisation in the brains of people with dyslexia and autism differ slightly from those of people without these conditions. There are problems with the linguistic system in both situations. In dyslexia, it is more difficult to decode and piece together words, their sounds, and meanings, but in autism, it is more about not comprehending social cues, leading to uncomfortable replies.

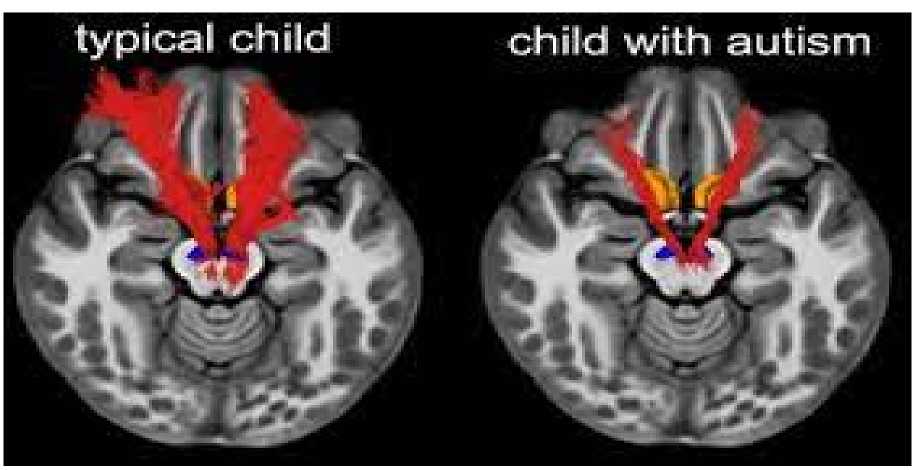

Figure 1.2: Brain fMRI for Healthy and Autistic

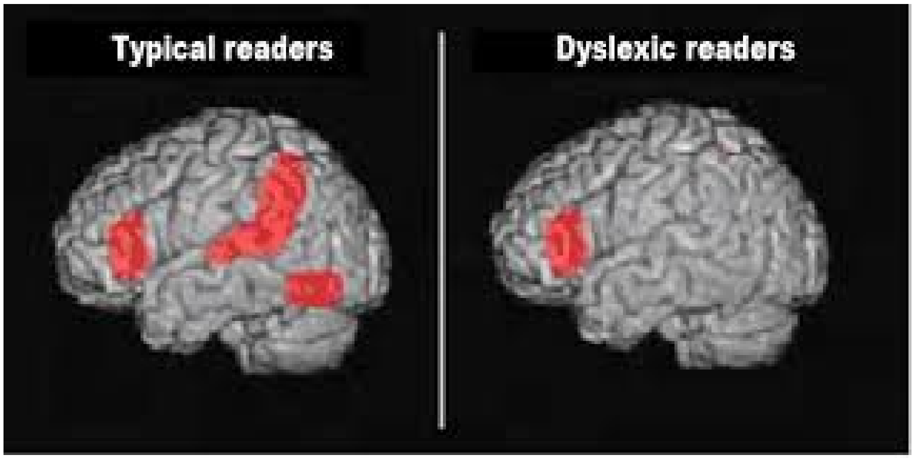

Figure 1.3: Brain fMRI for Healthy and Dyslexic

1.1 Proposed Project

This project mainly focuses on detection of ASD and Dyslexia in children using ABIDE dataset with a machine learning approach so that to find learning disability in an Autistic child. A CNN based approach is used to detect both ASD and Dyslexia. The important task of this project is construction of functional connectivity (FC) networks of brain from fMRI brain images.

1.1.1 Problem Statement

Automated detection of ASD DYSLEXIA through Brain fMRI
Distinguish between ASD DYSLEXIA to find out learning disability in a Autistic child

1.1.2 Proposed Solution

Machine learning techniques for fMRI analysis to construction of FC network of brain for classification.

1.1.3 Motivation

The social-life of a person who has ASD or Dyslexia is difficult due to their lack of communication between other peoples. Typically the responsive of these people were too slow or no response. They tempt to show anger in their behaviour or aggressive manner behaviour towards others. Due to these kind of situations these people were cornered by others and also they life leads into the depressive state. The main motivation of this project is find a qualified solution to diagnose these disorders in early stage so that they can proper treatment or meditation therapies to their social-life. Most of the cases, the autistic individuals are categorized as they shows the learning disorders. This work is to find the learning disabilities in an autistic person, since not all autistic shows these kind of learning disabilities.

Chapter 2

Report of Preparatory Work

2.1 Literature Survey Report

ASD

Autism spectrum disorder is a condition related to brain development that impacts how a person perceives and socializes with others, causing problems in social interaction and communication. The disorder also includes limited and repetitive patterns of behavior.According to National Institute of Mental Health (2015), Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by a wide range of symptoms and levels of impairment or disability in children. These symptoms range from difficulties or deficiencies in social communication and social interaction, restricted, repetitive patterns of behavior, or significant impairment of social functioning (National Institute of Mental Health, 2015).
Early detection and treatment are most important steps to be taken to decrease the symptoms of autism spectrum disorder problem and to improve the quality of life of ASD suffering people.Current ASD diagnosis is a two step process. General screening during routine health checkups provide pediatricians insight into potential developmental problems. Children who demonstrate potential problems are referred to experts for additional evaluation. This second stage is an evaluation by a team of experts and medical professionals who may diagnose the child with ASD or another developmental disorder (from National Institute of Mental Health, 2015). However, there is no procedure of medical test for detection of autism. ASD Symptoms usually recognized by observation. A brain-tissue study suggests that children affected by autism have a surplus of synapses, or connections between brain cells. Thus brain images can be used for detecting chances of having ASD. Recent time it has been research area to find a better and accurate automated machine learning technique for detection of ASD.The performance of machine learning algorithms depends on the features or bio-markers such as structural properties of brains,phenotype information,behavioral attributes that are used for the classification.

Dyslexia

Dyslexia is a specific type of learning disability characterized by difficulties with accurate and/or fluent word recognition when reading, along with poor spelling and decoding ability. The problem with reading in people with dyslexia is often unexpected in relation to their intellectual ability. Dyslexia is the most common learning disability in children. It lasts throughout life.Dyslexia is defined by the international classification ICD-10 as "A cognitive disorder characterized by an impaired ability to comprehend written and printed words or phrases despite intact vision" (2019 ICD-10-CM Diagnosis Code F81.0). Unfortunately, dyslexia is a genetic life long issue which tends to run through family members, and may lead to the social exclusion of the affected person if it is not addressed properly. It is necessary to assert that dyslexia does not have to do with intelligence. Children with dyslexia are just as smart as other children with functional reading and writing abilities.There's no single test that can diagnose dyslexia. A number of factors are considered, such as: Your child's development, educational issues and medical history, home-life, questionnaires, vision, hearing and brain (neurological) tests, psychological testing , testing reading and other academic skills, etc.

Related Works

In recent years neurodevelopmental disorders such as ASD have been diagnosed based on machine learning techniques. Most of these type detection is based on brain fMRI data. Maryam Akhavan Aghdam1 , Arash Sharifi1 and Mir Mohsen Pedram , present the intelligent model to diagnose ASD in young children based on resting-state functional magnetic resonance imaging (rs-fMRI) data using convolutional neural networks (CNNs). They were used samples ranging in age from 5 to 10 years from global Autism Brain Imaging Data Exchange I and II (ABIDE I and ABIDE II) datasets were for this research. This proposed method can be applied to analyzing rs-fMRI data related to brain dysfunctions.B.J. Bipin Nair, N. Shobha Rani, S. Saikrishna, and C. Adith et al study on Experiment to Classify Autism through Brain MRI Analysis deals with the Classification the ASD from the Brain MRI using PCA feature extraction technique and naïve Bayesian theorem. Taban Eslami, and Vahid Mirjalili, study targeted the problem of classifying subjects with ASD disorder from healthy subjects using ASD-DiagNet framewprk. ASD-DiagNet, is based on using the most correlated and anti-correlated connections of the brain as feature vectors and using an autoencoder to extract lower dimensional patterns from them. The autoencoder and a SLP are trained in a joint approach for performing feature selection and classification. They used fMRI data provided by ABIDE consortium, which has been collected from different brain imaging centers.
Automated detection of Autism Spectrum Disorder Using a Convolutional Neural Network is proposed by Zeinab Sherkatghanad, et al using most common resting-state functional magnetic resonance imaging (fMRI) data from a multi-site dataset named the Autism Brain Imaging Exchange (ABIDE). The proposed approach was able to classify ASD and control subjects based on the patterns of functional connectivity. Another approach used to detection of ASD, implementation deep neural network (DNN) models to classify autism spectrum disorder (ASD) patients and typically developing (TD) participants. Study of Kaushik Vakadkar,Diya Purkayastha, and Deepa Krishnan ,on detection of Autism Spectrum Disorder in children using Machine Learning techniques. It focuses on determine if the child is susceptible to ASD in its nascent stages, which would help streamline the diagnosis process. It discussed on various machine learning such as Support Vector Machines (SVM), Random Forest Classifer (RFC), Naïve Bayes (NB), Logistic Regression (LR), and KNN. There is also ASD detection using Eigen values computed from brain pattern. Another approach for detection of ASD is convolutional neural network combined with a prototype learning (CNNPL) framework by Yin Liang , Baolin Liu , and Hesheng Zhang.
Brain image analysis for finding Dyslexia will leads to automatic recognition of children with dyslexia.fia Zahia, Begona Garcia-Zapirain proposes an approach for Dyslexia detection using 3D convolutional Neural Networks and fMRI. Laura Tomaz Da Silva gives study on Visual Explanation

for Identification of the Brain Bases for Developmental Dyslexia on fMRI Data.
This project mainly focuses on detection of ASD and Dyslexia in children using ABIDE dataset with a machine learning approach so that to find learning disability in an Autistic child.

2.2 System Study Report

ABIDE Dataset

Figure 2.1: ABIDE Dataset

Autism Brain Imaging Data Exchange (ABIDE) initiative has aggregated functional and structural brain imaging data collected from laboratories around the world to accelerate our understanding of the neural bases of autism. With the ultimate goal of facilitating discovery science and comparisons across samples, the ABIDE initiative now includes two large-scale collections: ABIDE I and ABIDE II. Each collection was created through the aggregation of datasets independently collected across more than 24 international brain imaging laboratories and are being made available to investigators throughout the world, consistent with open science principles, such as those at the core of the International Neuroimaging Data-sharing Initiative. For details about these initiatives visit the collection specific pages: ABIDE I and ABIDE II.

Preprocessing fMRI data.

Preprocessing fMRI data is a two step method. The first is cleaning the raw acquisition data. fMRI images are noisy and sometimes do not resemble brains. It is necessary to filter the noise and warp the brain volume to fix movement or other scan errors.
The second step is transforming fMRI data into the desired data type. While technically data, fMRI files can be gigabytes in size and most classification algorithms cannot use the file type. Therefore, the researchers must determine how to process the data into a structure that can be used.

CNN combined with prototype learning (CNNPL) framework

This model combined the advantages of CNN and prototype learning strategy to further promote the feature learning and enhance the classification performance. CNN was employed as basic feature extractor and multiple prototypes were automatically learnt for each category. A generalized prototype loss based on distance cross-entropy can be used to make the CNN feature extractor and the prototypes jointly learn.(Y. Liang, B. Liu and H. Zhang , 2021)

GCN:Graph convolutional network

Motivated by breakthroughs of deep learning on grid data, efforts have been made to extend CNN to graphs, a natural way to represent many forms of data including fMRI data. Two categories of graph convolutional networks (GCNs)—spectral GCNs and spatial GCNs—have been proposed. For spectral GCNs, graphs can be decomposed into spectral bases associated with graph-level information according to spectral graph theory . In contrast, spatial GCNs imitate the Euclidean convolution on grid data to aggregate spatial features between neighboring nodes. Although spectral GCNs have achieved great success on both structural and functional MRI applications, spatial models are preferred over the spectral ones because of their efficiency, generalization, and flexibility and they have gained increasing interest in the community.

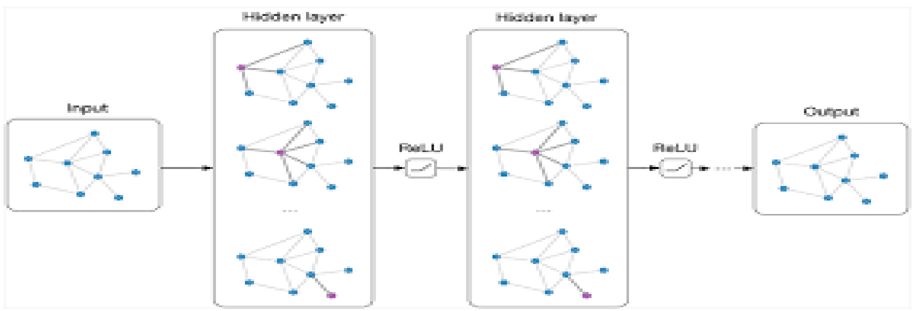

Figure 2.2: GCN Architecture

Chapter 3

Project Design

The this project work related to implementation classification model for ASD from healthy brain network and then check whether the Autistic is Dyslexic or not. According to the reference taken for Dyslexic brain, in the dyslexic brain, there is more activity in the frontal lobe and less activity in the parietal and occipital areas of the brain. So we need analyse the correlation values in these regions.

3.1 Workflow

Firstly , the 4D fMRI image is loaded from the data set. The an appropriate brain atlas were selected for the generation of FC. Then the we go through the classification networks. The networks trains with ASD and TDC(Typical Development Control) to generate a classification model. The new input is tested with the trained model to check whether the input belongs to ASD or TDC. Then output should be visualized in brain network. It should be noted that the classification networks are trained with 2D fMRI image so that, if we taken 3D/4D fMRI we should change into 2D image. After finding autistic input we go for an analyse to check whether the patient have Dyslexia or not.

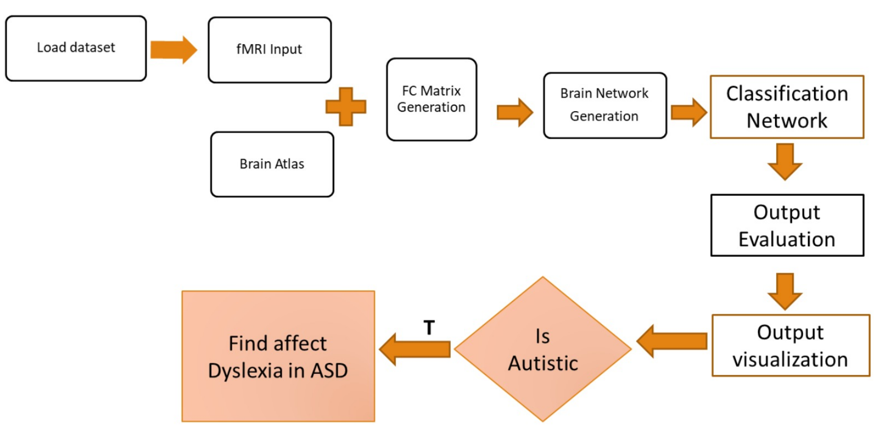

Figure 3.1: Overall Project Design

3.2 Data Acquisition And prepossessing

In this work, rs-fMRI data were obtained from the Autism Brain Imaging Data Exchange . This dataset aggregated collections of both functional and structural MRI data from 17 international imaging sites. The Preprocessed Connectomes Project (PCP) is pleased to announce the public release and open sharing of preprocessed neuroimaging data from the Autism Brain Imaging Data Exchange (ABIDE). Data from ABIDE was preprocessed by five different teams using their preferred tools. Functional preprocessing was performed using: the Connectome Computation System (CCS), the Configurable Pipeline for the Analysis of Connectomes (CPAC), the Data Processing Assistant for Resting-State fMRI (DPARSF) and the NeuroImaging Analysis Kit. In this work CCS pipeline is choosed.

3.3 Brain Atlas Selection

An atlas is a set of reference files based on knowledge accumulated through past experiences. A brain atlas, in this review, consists of a brain template image or a set of brain template images with various types of boundaries drawn on them. Traditionally, such boundaries were based on existing knowledge about features of brain anatomy, pathology, and functions. The human brain contains hundreds of anatomically and functionally distinct cortical and subcortical structures, accurately defining these parcellations and mapping their functions and connections pose massive challenges.The human brain atlases that allow correlating brain anatomy with psychological and cognitive functions are in transition from ex vivo histology-based printed atlases to digital brain maps providing multimodal in vivo information.

3.4 Construction of Brain Functional Connectivity Networks

Human brain can be represented as network with a graph structure with nodes and edges.Brain nodes may be individual neurons or entire brain regions, depending on the measurement technique. Edges can take on binary or weighted values, and they can be directed or undirected, depending on how interactions are estimated from empirical data. The selection of appropriate graph theory methods for modeling and analyzing empirical data requires that the nature of the edge representation is taken into account. Functional connectivity is defined as the temporal dependency of neuronal activation patterns of anatomically separated brain regions. The most frequently employed FC analysis strategy is to compute pairwise correlations between the region-averaged rs-fMRI signals for each brain region pair . A conventional correlation-based FC network is generated by computing the Pearson correlation between the average time series for each pair of ROIs.For each subject, we defined $x_i(t), x_j(t) \in R^M$ the average rs-fMRI signals for the brain regions i and j at the time point t(t=1,2,...,T) . M and T denote the total number of ROIs and total number of time points, respectively. The FC_{ij} can be defined as,

$$FC_{ij} = \frac{\Sigma_{t=1}^{T}(x_i(t) - \bar{x}_i)(x_j(t) - \bar{x}_j)}{\sqrt{\Sigma_{t=1}^{T}(x_i(t) - x_i)^2}\sqrt{\Sigma_{t=1}^{T}(\bar{x}_i(t) - \bar{z}_i)^2}} \tag{3.1}$$

HOFC networks may provide additional information to describe high-level relationships among brain regions. Therefore, we also constructed HOFC networks in this study to examine whether proposed framework is robust for the classification of high-level brain functionality organization.

The generation of HOFC based on the calculation of the "correlation's correlation" to capture high-level functional interactions across brain regions.

$$HOFC_{ij} = \frac{\Sigma_k (FC_{ik} - \bar{FC_i})(FC_{jk} - \bar{FC_i})}{\sqrt{\Sigma_k (FC_{ik} - \bar{FC_i})^2} \sqrt{\Sigma_k (FC_{jk})(\bar{FC_j})^2}} \tag{3.2}$$

3.5 Classification Network

After the generation FC network we have to classify between ASD and Typically Development controls(TDC).For that we can develop different network models for this classification.This work tries to develop different approach then select suitable. Here mainly tried to implement a simple CNN ,VGG16,LSTM and GCN.

3.5.1 CNN and VGG

A new 2 layer fully-connected binary classification CNN architecture is considered. For classification purpose we need to convert the fMRI into 2d image format then given to model for classification. This same step repeated with Different VGGNET classifier.

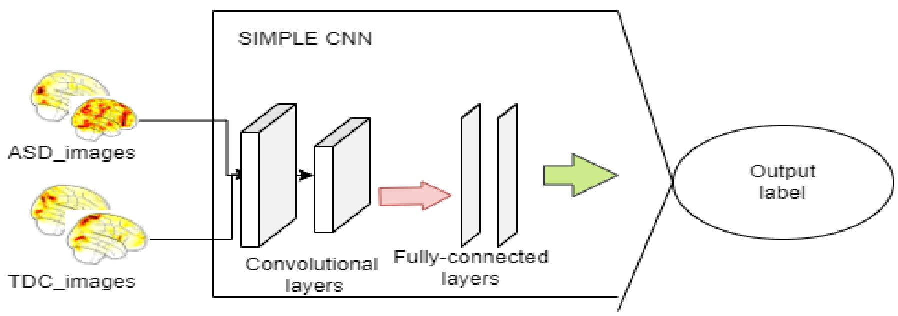

Figure 3.2: Simple CNN for classification

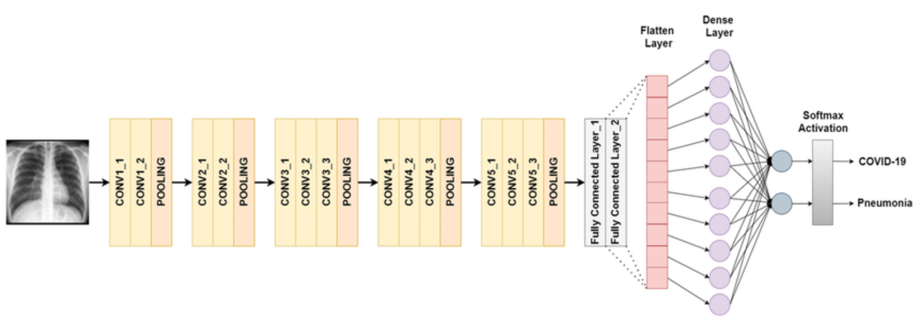

Figure 3.3: VGG16 architecture designed for binary classification

3.5.2 LSTM

Type of recurrent neural network capable of learning order dependence in sequence prediction problems is called LSTM(Long Short-Term Memory).Long Short-Term Memory. This model can be used for fMRI analysis based on the time series data.

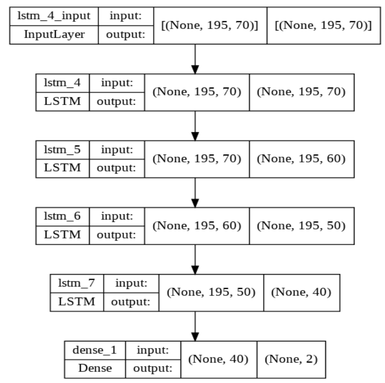

Figure 3.4: LSTM architecture designed for binary classification

3.5.3 Connectivity-based graph convolutional network (cGCN)

Mapping the relational data into graphs,the topological structures can be encoded to model the connections among nodes,and provide more promising perspectives underlying the data. Inspiring by this mechanism, GCN is successfully implemented in deep learning research. The various approaches in modeling GCNs fall into two categories, including spatial and spectral approaches. Spatial approaches use graph theory to define the nodes and edges for entities on data. Interestingly, spectral approaches analyze the constructed graph in the frequency domain . The spectral approach usually leverages the Laplacian eigen-vector to transform a graph in the time domain to in frequency domain, potentially resulting in large computation cost. In this work, adopts a connectivity-based graph convolutional network (cGCN), a spatial GCN architecture, for fMRI analysis by Lebo Wang , Kaiming Li , and Xiaoping P. Hu were ROIs were considered to be graph nodes with the blood oxygen level–dependent (BOLD) signals of each frame as their attributes. Convolutions were performed within neighbors defined by the k-NN graph based on the groupwise FC matrix. Combined with prototype learning for classification.

Working

- Generate FC matrix based on correlation analysis.
- A k-NN graph was generated by retaining only the top k edges in terms of their connectivity strength (i.e., average correlation coefficient) for each node.
- Generation of the convolutional neighborhood defined by the shared k-NN graph across convolutional layers, time frames, and subjects.

  The cGCN architecture consisted of 5 convolutional layers.The FC-based k-NN graph was used to guide the convolutional operations with functional connectivity–based neighborhoods. For simplicity, the same graph was shared by all subjects and at all time frames. Although each node had a few neighbors, the convolution field of each layer was extended by stacking multiple convolutional layers in the architecture. Between convolutional layers, skip connections were added from the prior convolutional layers to the last one, providing multilevel feature fusion for classification and accelerating the model training by alleviating the vanishing gradient problem.

from the convolutional layers were followed by a temporal average pooling layer to generate temporal evolutions by combining spatial representations from all frames.

- A Softmax layer was used at the end for the final classification.

3.6 Valuation and Visualization

The outputs are visualized accordingly so that we can visually verify. Different plotting techniques can be used to show the fMRI data or Grad-CAM class activation visualization like can be implemented. The affect of Dyslexia in Autistic brain can be evaluated by the correlation values between specific brain regions. The evaluation of classification model accuracy can be also done accordingly.

3.7 Resource Requirements

Disk Storage : 100GB or above
Platform : Google COLAB

3.8 Hardware & Software Requirements

Operating System : Windows 10
Supporting software : Python , Tenserflow , Keras ,Opencv ,Nilearn
Processor : Intel Core i5 10th GEN
RAM : 8GB

3.8.1 Data Requirements

Dataset : http://preprocessed-connectomes-project.org/abide/

Chapter 4

Implementation

This section describes this entire project workflow done. For the implementation of this work , the very first step is familiarizing with the ABIDE data. We will get preprocssed fMRI images with original phenotypic file from ABIDE dataset with specified preprocessing pipelines like CCS(Connectome Computation System),NIAK(Neuroimaging Analysis Kit),CPAC(Configurable Pipeline for the Analysis of Connectomes),DPARSF(Data Processing Assistant for Resting-State fMRI). The preprocessing steps implemented by the different pipelines are fairly similar. What varies most are the specific algorithms used for each of the steps, their software implementations, and the parameters used. Due to the limitation in the Dyslexic fMRI dataset , firstly the the classification between ASD(Autism Spectrum Disorder) and TDC(Typical Developing Control) is done. For that classification network is implemented using various machine learning techniques like CNN,VGG16 etc. For simple binary image classification model the CNN and VGG Net is used. The input for these are taken by converting the 4D fMRI images into 2D in different directions(like axial(z)or coronal(y),or sagital(x),sagittal left hemisphere only(l),sagittal right hemisphere only(r)). Similarly for LSTM model we can use time-series data and for GCN brain network can be used. After the classification we can easily identify the ASD patients, as a next phase identification of Dyslexic has to be done. For that purpose, considers the brain regions like frontal areas and consider the activation rate their.As a final outcome the entire system predicts the learning dis ability in Autistic.

- Dataset downloading
  The implementation step start with ABIDE data-set downloading. The preprocessed ABIDE data can easily downloaded using Nilearn.dataset.fetch_abide_pcp() module or by a script.
- Brain Atlas selection
  A deterministic atlas is a hard parcellation of the brain into non-overlaping regions, that might have been obtained by segmentation or clustering methods. These objects are represented as 3D images of the brain composed of integer values, called 'labels', which define the different regions. In such atlases, and contrary to probabilistic atlases, a voxel belongs to one, and only one, region. Here selected the an automated anatomical parcellation (AAL) which returns image has shape (91, 109, 91) and contains 117 unique integer values defining the parcellation.

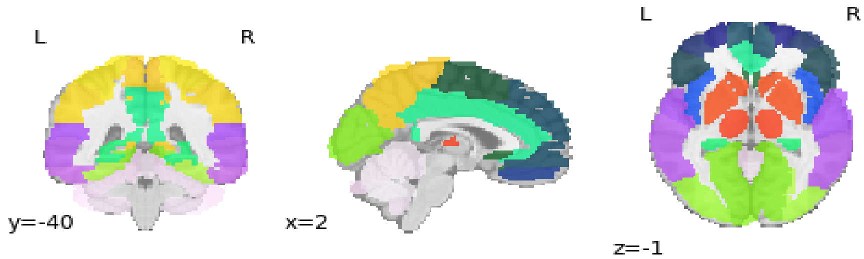

Figure 4.1: Example of an automated anatomical parcellation (AAL) brain atlas

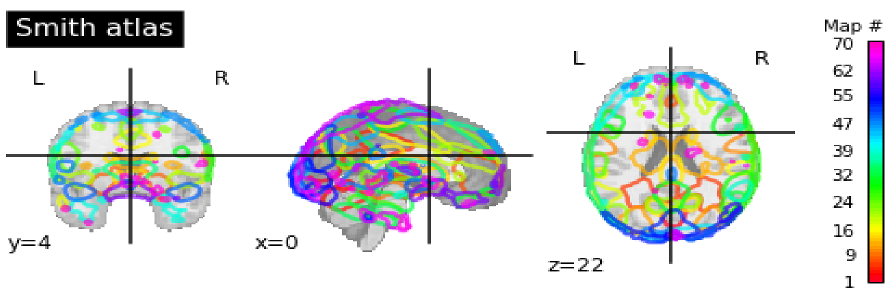

Figure 4.2: Example of the smith (ICA based)brain the smith (ICA based) mask atlas

- FC Network generation based on Brain atlas The Functional connectivity is generated on correlation measure of time-series signals in different regions.
- Classification Using binary CNN or VGG16 model or LSTM

- For GCN classification we need extract graph with respect to the FC network. And train the GCN model with these.
- To find the learning disablity in an Austic person, we have to identify the regions affected by the Dyslexia, then need to analyse the value in correlation matrix of particular individual based on the region which can be identified by the atlas choosen.

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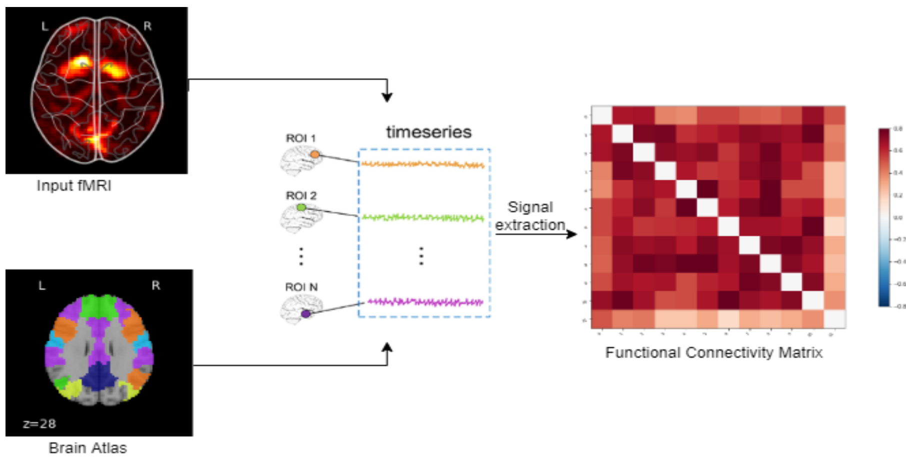


Figure 4.3: FC Network generation based on Brain atlas

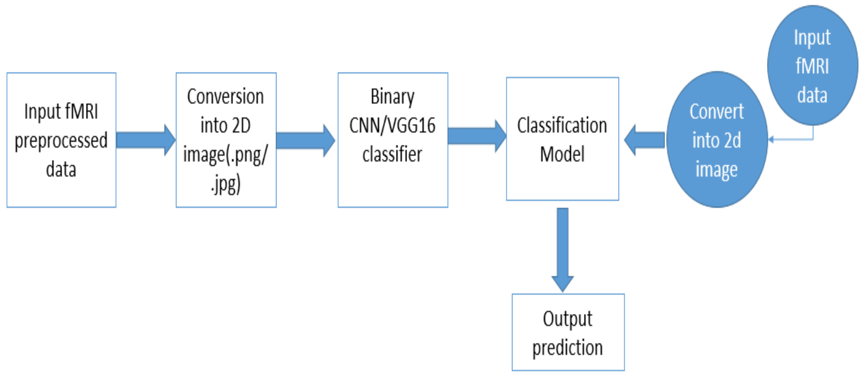


Figure 4.4: Classification Model

Chapter 5

Results & Conclusions

5.1 Result

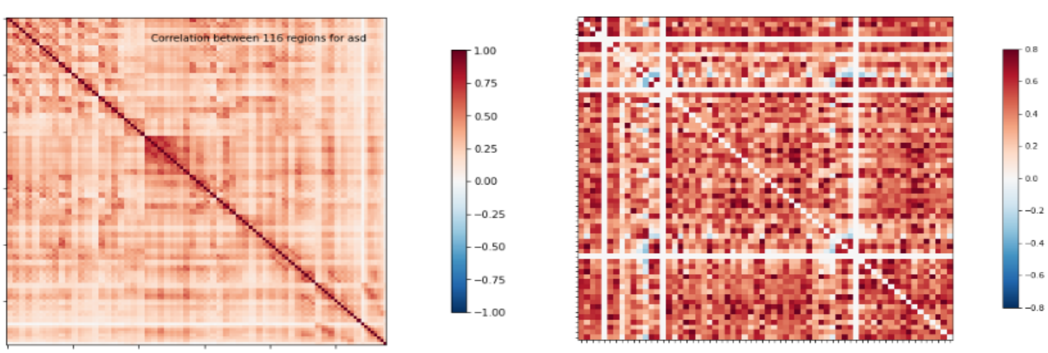
5.1.1 Result for Classification

This project mainly focused on different classification models for ASD classification. Compare these models and replace with better accuracy model. The classification model is implemented by variations in simple CNN and VGG16. And these models gives above 0.91 testing accuracy. By using time-series information for classification, the LSTM model get upto .8 accuracy. From the perform analysis of these models, LSTM approach takes more time than others. It may also observed that the CNN models leads into an over-fitting case.

Comparison between models :

	CNN	VGG16	LSTM
MODEL ACCURACY	0.58	0.728	0.625
TEST ACCURACY	0.9	0.93	0.8750

5.1.2 Result for FC



(a) ASD (b) TDC/Control

Figure 5.1: FC Network generated for based on Brain atlas

5.1.3 Result for Brain network

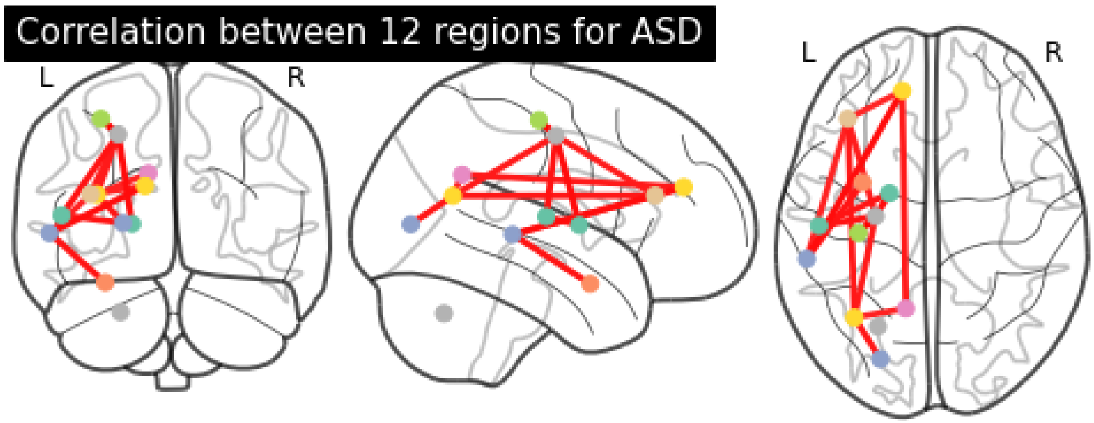


Figure 5.2: ASD

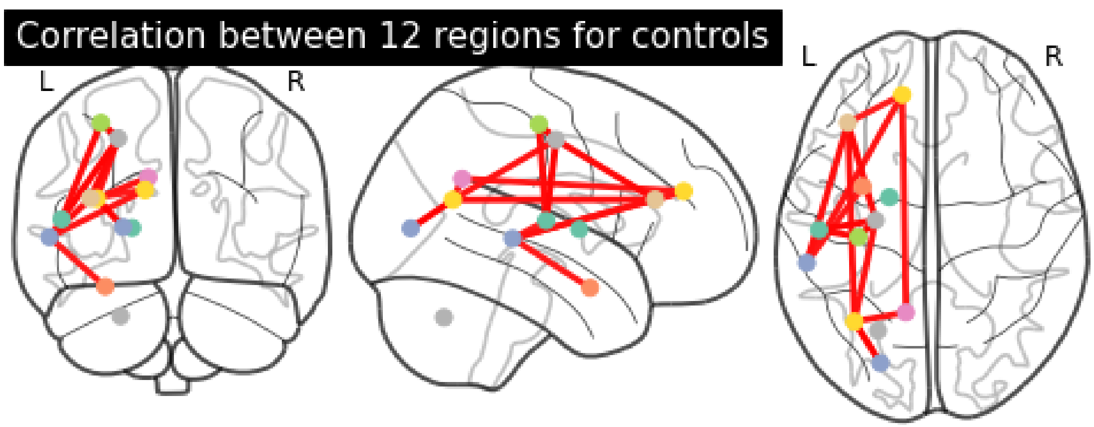


Figure 5.3: TDC

Figure 5.4: Brain Network generated based on Brain Atlas

5.2 Conclusion

This project is mainly aimed to find an system to classify neuro-developmental disorders such as ASD and Dyslexia on the basis of brain network. The fMRI data taken as input. Then system generates the FC network based on the selected Brain Atlas, using these information need to generate machine learning model for the classification.
A simple binary CNN Classifier implemented for ASD and TDC classification. For this image classifier first we have to convert the fMRI into the 2D image, the train the system with these. Here only single slice in axial view. This model correctly classified the test images but also have problem overfitting. similar way VGG16 can also implemented for classification. The LSTM model used for classification is based on the time series information from the fMRI. From these different machine learning approches for classification, need to identify the better version for the ASD clasiification with highest accuracy

After the classification, if the input data classified as ASD then we need to find Dyslexia affect in ASD brain.From referrals, it found that In the dyslexic brain, there is more activity in the frontal lobe and less activity in the parietal and occipital areas of the brain. cerrebellum is the commonly affected region for both. So first we need to setup the threshold for the timseries values in these regions for Dyslexic brain. In this work selected the mean of correlation matrix value. And predicts the chances of having dyslexia.

5.3 Future Scope

For a classification of ASD the the cGCN model implementation with higher accuracy.
Talent identification in ASD patients : If we can easily identify the different brain regions and the activity level in these regions then using machine learning technique we can easily identify skills in a particular individual from their fMRI.

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