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ENHANCING THE RESTING-STATE FMRI DATA FOR DETECTION OF AUTISM SPECTRUM DISORDER USING DEEP LEARNING

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Abstract— Autism Spectrum Disorder (ASD) is an intricate and progressive neurodevelopmental condition. It affects several behavioural domains including social, linguistic competence, stereotyped and repetitive actions. Most of the existing methods utilize the non-clinical data, Low generalization is sacrificed for high accuracy when detecting ASD with a restricted dataset. In relation to clinical data most of the methods uses the structural (fMRI) and leveraging functional Magnetic Resonance Imaging (fMRI) for ASD prediction with a restricted dataset achieves commendable accuracy but falters in terms of broader generalization. To address these constraints and improve the efficacy of automated autism diagnosis, this paper introduces a novel approach: detecting ASD through the utilization of functional connectivity features derived from resting-state fMRI data. The increasing application of deep learning models offers the possibility of early diagnosis for a variety of human ailments by utilizing a range of physiological and health attributes. Our Proposed model utilize the deep learning approach to detect the ASD using resting-state fMRI data. Neural Network classifiers are utilized in order to complete the task of classification. According to the findings, the proposed model outperforms the most advanced techniques available today in terms of accuracy. This model outperforms the state-of-the-art techniques used today with an 87% mean accuracy and other outstanding measures including a 96% AUC, 87% sensitivity, and an 86% F1-score that demonstrate its superiority. An extensive comparison research utilizing several scoring methodologies continuously supports the superior performance of the CC200 atlas over other atlases in Distinguishing between individuals diagnosed with Autism Spectrum Disorder (ASD) and those in the control group. The results offer promise for improving diagnostic accuracy and treatment approaches as well as a deeper comprehension of the brain mechanisms behind ASD.

Keywords: Autism spectrum disorder , Diagnostic accuracy , Brain atlas , Neurodevelopmental condition, functional interconnectedness, Resting-state fMRI data , Brain mechanisms , Neural Network classifiers.

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I. INTRODUCTION

A spectrum of neuro-developmental abnormalities that last a lifetime, Restrictive and repetitive behavioural patterns, in addition to challenges with social interaction and communication, are hallmarks of Autism Spectrum Disorder (ASD) [1]. The World Health Organization (WHO) approximated that globally, one out of every 160 children are affected by Autism Spectrum Disorder (ASD). It is linked to a wide range of behavioural symptoms, some of which might become severe If the assessment is conducted put off. Despite the signs are frequent throughout infancy, the majority instances include a delay in diagnosis. It's because the present method for diagnosing ASD involves only subjective interviews and requires a doctor to review a child's behaviour and developmental history. Though these methods are quite accurate, they are definitely comprehensive and call for specialized knowledge that might not exist in many health institutions.

Autism is commonly described as a disorder that exists along a spectrum due to the wide range of symptom severity and kind that individuals may encounter. Diagnoses of autism spectrum disorders can be made for individuals of any gender, colour, ethnicity, or socioeconomic status. A person's symptoms and everyday functioning can be improved by therapies and programs, even though ASD can be a lifelong disorder. Although the main causes of ASD are unknown, research indicates that environmental factors and a person's genes may interact to influence development in ways that result in ASD.

As a result of recent technological advancements, a sizable number of research are exploring the possibility of automating computer-aided diagnosis of autism in addition to developing interactive tools to aid in the recovery and care of people with autism. Reducing subjectivity and increasing diagnostic availability and reproducibility are two benefits of such automated methods. It would also be crucial in guaranteeing an early diagnosis. Magnetic resonance imaging (MRI) is helpful in diagnosing a variety of diseases of the nervous system and brain: It can be utilized to correlate changes or analyze brain anatomical patterns utilizing structural MRI data in the functional architecture of the brain in relation to mental health disorders. These ailments may include Autism, ADHD, schizophrenia, dementia and other associated disorders.

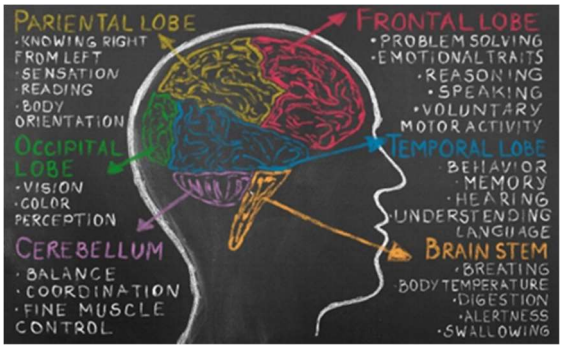

Figure 1:. Autistic Brain Vs Non-Autistic Brain

II. Purpose of Paper

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This research aims to address the current obstacles in the assessment for Autism Spectrum Disorder (ASD) by presenting a novel approach that incorporates Analysis of fMRI data collected during periods of inactivity disclosed discernible functional connectivity patterns. Social interaction, language proficiency, and repetitive, stereotyped behaviours are just a few of the behavioural domains that are affected by ASD, which is recognized for its complexity and degenerative nature. Present approaches struggle with the trade-offs between limited generalization and high accuracy, and they either rely on narrow datasets from fMRI and sMRI imaging or non-clinical data. Our suggested model uses a deep learning methodology, concentrating on resting state fMRI data, to overcome these drawbacks.

Central to Our strategy is grounded in the utilization of deep neural networks, which are sophisticated models that can extract complicated patterns from large amounts of data. The ability of deep neural network classifiers to identify subtle correlations across functional connectivity features is a critical component in the ASD detection challenge. These features, which were taken from the resting-state fMRI data, show complex patterns of interactions between various brain regions when there is neural activity unrelated to a task. The unique aspect of our model is the integration of areas of interest (ROIs) and brain atlases into the deep neural network architecture, which focuses the analysis on particular brain regions linked to ASD. This tailored strategy increases the accuracy of ASD detection by concentrating on specific brain regions.

In addition, our methodology incorporates brain atlases that partition the brain into discrete regions and define ROIs, so enhancing the study to critical regions associated with ASD. The model performs robustly in part because of its concentrated approach, which allows for a more sophisticated investigation of functional connectivity patterns within certain brain regions. As demonstrated by the stimulation results reported in this study, the combination of deep neural networks, brain atlases, and ROIs enables our suggested model to outperform state-of-the-art techniques.

Our research offers a greater knowledge of the neurological basis of ASD, which is significant beyond the field of ASD identification. Our methodology improves both the accuracy of diagnosis and the efficacy of therapeutic interventions by focusing on functional connectivity aspects and utilizing sophisticated computational models that include brain atlases and ROIs. Results from this research could change the way ASD is identified and managed, leading to a new phase of early and more precise therapies for those with this complicated neurodevelopmental disease.

III. Literature Review

Assessing individuals with developmental conditions has experienced widespread use of fMRI in numerous research studies. While these studies achieve high accuracy, the challenges of limited datasets often result in poor generalization. This section undertakes a comparative analysis of different studies, delving into controversial aspects to identify key gaps. This exploration is

critical for framing the problem statement and underscoring the significance of our proposed research on An Advanced Learning Model for ASD Prediction through Varied Resting-State fMRI Data.

Several investigations[2] have demonstrated the efficacy of fMRI in ASD detection, showcasing commendable accuracy. However, the common challenge across these studies lies in the limited dataset sizes, prompting the need for approaches that enhance generalization[3]. This forms the foundation for our proposed model, which aims to address this specific limitation.

In contrast, studies focusing on the use of different modalities, such as electroencephalography (EEG) or structural MRI, present alternative perspectives. While these modalities offer unique insights, they often face challenges related to interpretability and specificity in ASD diagnosis [4]. Comparing these approaches sheds light on the strengths and limitations of different diagnostic modalities, emphasizing the continued relevance of fMRI in this context.
The choice of brain atlases is another pivotal aspect. Commonly used atlases like CC200 and AAL have been prevalent [5]. However, the lack of diversity in atlas selection across studies limits the exploration of different brain connectivity patterns. Our proposed model introduces rarely used atlases like BASC and Power, seeking to enrich the feature space and enhance the understanding of functional connectivity features relevant to ASD.

Controversial aspects arise when considering the incorporation of deep learning in ASD diagnosis. While some studies endorse its potential for discerning intricate patterns , others highlight concerns about interpretability and the black-box nature of deep learning models . Addressing these controversies is crucial for refining the methodology and ensuring the clinical applicability of the proposed deep learning approach.

Furthermore, the challenges associated with multisite resting-state fMRI data introduce complexities in data harmonization and model generalization. Previous studies often struggle to overcome these challenges , emphasizing the need for approaches that can robustly handle the heterogeneity of data across different imaging sites.

In conclusion, the comparative analysis of various studies reveals a nuanced landscape in ASD diagnosis. The proposed research aims to bridge key gaps by leveraging a deep learning approach, addressing dataset limitations, exploring diverse brain atlases, and navigating the complexities of multisite resting-state fMRI data. By critically examining controversial aspects, this study aims to contribute to the advancement of ASD diagnostic methodologies, providing a more inclusive and effective tool for clinicians and researchers.

IV. Proposed Methodology

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Investigating regional interactions during periods of inactivity, the application of resting-state fMRI (rs-fMRI) serves as a neuroimaging methodology. Research in this field typically heavily depends on having Availability to unprocessed data from fMRI images. However, using original data has drawbacks as well, like high dimensionality by nature and significant processing time requirements that increase the chance of overfitting. In response to these problems, we support the use of functional connectivity characteristics obtained from pre-processed fMRI data in a sophisticated deep learning method intended to identify Autism Spectrum Disorder (ASD). Figure 2 shows the suggested procedure, which breaks down each important phase of this novel strategy. We seek to improve the effectiveness and precision of ASD identification by concentrating on pre-processed data and utilizing deep learning techniques. This providing a more reliable and efficient substitute for conventional techniques that rely on unprocessed fMRI data.

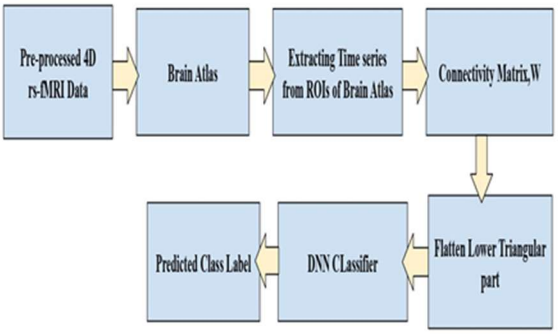

Figure 2: Proposed Architecture for ASD Detection.

Data Collection:

The ABIDE program has compiled data from various labs, encompassing both structural and neuroimaging information worldwide to expedite our comprehension of the neurological underpinnings of autism. The ABIDE effort, which comprises two large-scale collections, ABIDE I and ABIDE II, aims to ultimately facilitate discovery science and cross-sample comparisons[6].Open science principles, such as those underlying The Global Neuroimaging Data Collaboration Initiative, These collections are made available to researchers worldwide in accordance with the philosophy of global accessibility. Each collection was formed by aggregating independently collected datasets across over 24 international brain imaging laboratories.

In the pursuit of comprehensive insights into Autism Spectrum Disorder (ASD) diagnosis, our research paper strategically leveraged the ABIDE initiative for data collection. ABIDE, a pioneering initiative, stands at the forefront of facilitating in-depth investigations into the complexities of ASD, contributing significantly to the advancement of our understanding and diagnostic approaches in this critical field.

We utilized resting-state fMRI brain imaging data for our project implementation, selecting it due to the prevalence of key parameters essential for our objectives. Our focus was on functional brain

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imaging data sourced from the NYU Langone Medical Centre's extensive collection within ABIDE I. This dataset encompasses 172 patient profiles, including details such as age, gender, and DX_GROUP classification. The DX_GROUP categorization distinguishes between the control group (representing individuals with normal health) and the autistic group (comprising individuals with disorder).

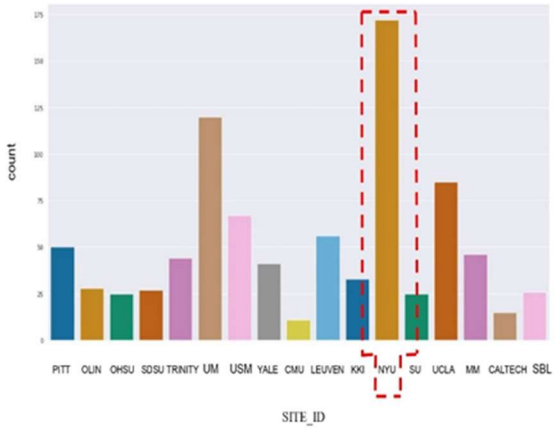

Figure 3: ABIDE Dataset site_id and patients_count

b)Data pre-processing:

Data from ABIDE were pre-processed by five teams utilizing the Connectome Computation System (CCS), the Data Processing Assistant for Resting-State fMRI (DPARSF), the Configurable Pipeline for the Analysis of Connectomes (CPAC), and the Neuro-Imaging Analysis Kit, according to their preference. To address debates over Filtering signals within a specific frequency range and regression of the global signal, each pipeline used four preprocessing options (Both employing and not employing signal filtering, and both applying and not applying global signal correction). CPAC application computed the outcomes of each processing pipeline's statistical analysis and strategy, guaranteeing that output variation was limited primarily due to preprocessing.

The ABIDE repository's pre-processed fMRI dataset was acquired from the pre-processed Project for Connectome Research (PCR). The CPAC's preprocessing involved correcting slice timing, motion, and intensity, while eliminating nuisance signals such as respiration, heartbeat, scanner drifts, global mean signal, and head motion. The data underwent band-pass filtering (0.01-0.1 Hz) and was spatially mapped to a standardized template. ABIDE I Pre-processed provides In-depth details on Computational methods, tactics, Settings applied and applications used deployed.

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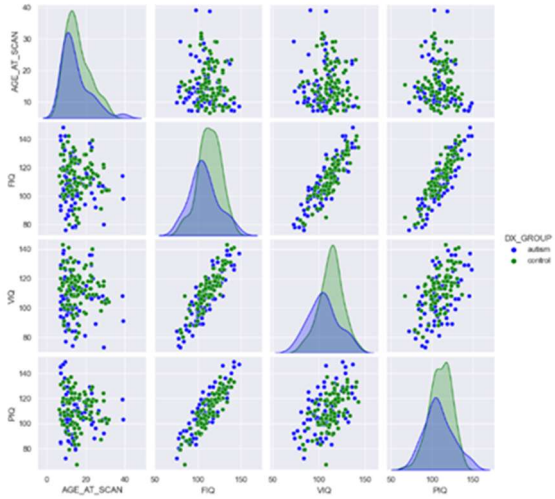

Figure 4: Pair plot of different features in ABIDE dataset of NYU site

c) Extraction of temporal sequences from Regions of Interest (ROIs) using a Brain Atlas:

A dynamic 4D time-series dataset is created using fMRI, which records the changing three-dimensional images of Neural activity across a temporal span. These pictures show Modifications in hemodynamic signals (BOLD) signal strength, which are useful measure to correlate with brain functions. Subjects stay in the MRI scanner during the scan without performing any particular tasks, which results in a series of temporal representations of the BOLD signal. This last dataset captures the important factor of time in addition to three spatial dimensions.

Specifically, we employed four conventional brain atlases to designate our areas of interest (ROIs) and did not deal with the complete time series across all brain voxels in our research. With the use of these atlases, we were able to extract mean time-series signals from voxels inside the specified ROIs: Craddock-200 (CC200), Craddock-400 (CC400), Harvard-Oxford, and Dosenbach160. The atlases for CC200, CC400, Harvard-Oxford, and Dosenbach160 have 200, 400, 110, and 160 ROIs, in that order. This focused method improves our analysis and gives us a more complex picture of how the brain functions in important areas.

d) Selecting Key Atlases for Analysis:

(i) CC200: The entire brain was homogenized sliced spectrally clustered into 200 spatially limited zones Exhibiting consistent functional activity to create the CC200 cerebral partitioning map [7].

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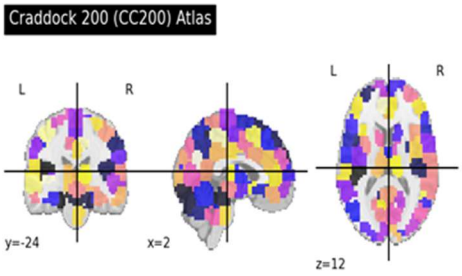

Figure 5: Craddock 200(CC200) Atlas

CC400: The process used to generate the CC400 functional brain parcellation atlas is the same as that of the CC200 brain atlas; the primary distinction is that 400 regions were duplicated in place of 200 spatially constrained zones of homogenous functionality activity.

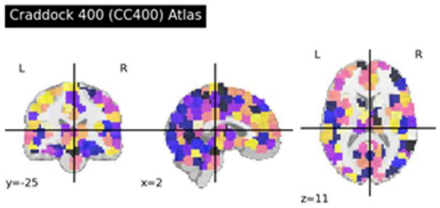

Figure 6: Craddock 400(CC400) Atlas

Dosenbach 160: We utilised a set of 160 ROIs that were derived from extensive Analyses that consolidate findings from functional activations, utilising the Dosenbach-160 functional brain parcellation atlas[8].Through a thorough Examining the modular organization of resting-state fMRI data, this detailed study permitted the categorization of these ROIs into six different networks: Operational, front and back brain, default mode (DMN), sensory and motor, visual, and cerebellum functional networks.

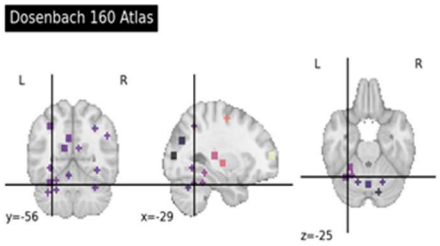

Figure 7: Dosenbach 160 Atlas

Harvard-Oxford: The Harvard-Oxford atlas embodies precision, featuring 110 ROIs meticulously derived from 48 cortical and 21 subcortical structural areas. Crafted from high-

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fidelity structural data, these ROIs underwent a transformative synthesis, honed to functional precision through the adept application of nearest-neighbour interpolation techniques.

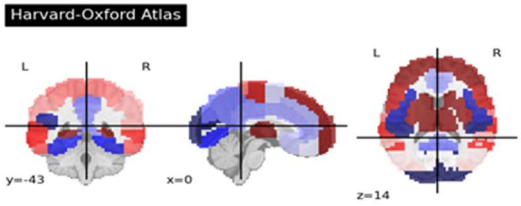

Figure 8: Harvard-Oxford Atlas

Neural Insights: Precision in 4D fMRI ROI Timeseries:

In the intricate landscape of functional MRI analysis, conceptualizing the application of a brain atlas to 4D fMRI scans reveals a transformative process resembling the overlay of dynamic 3D grids. These grids, acting as masks, selectively sample voxels at each time point, leading to the conversion of original 4D fMRI data (with dimensions H, W, D, T) into a concise 2D representation (T, N). Here, H, W, D, T, and N denote spatial dimensions, temporal aspects, and the number of regions of interest (ROIs), respectively.

The necessity to extract mean time-series signals by applying a brain atlas to pre-processed rs-fMRI data encounters significant memory challenges. In response to hardware limitations, our study pioneers a prudent approach by utilizing pre-extracted time-series data from the Pre-processed Connectomes Project (PCP). The study uniquely explores the comprehensive analysis of mean time-series signals related to CC200, CC400, Harvard-Oxford, and Dosenbach-160 defined ROIs. This strategic use optimally shapes the (T, N) dimensions in our investigation, showcasing an innovative blend of efficiency, resourcefulness, and impactful exploration within the contemporary constraints of hardware and memory capabilities.

Visualization of Functional Connectivity Matrix:

Embarking on an exploration of cerebral intricacies, we harnessed the (T, N) dimensional data to forge dynamic functional connectomes. These matrices, pulsating with the vitality of neural interactions, unfolded into powerful dimensions — (200, 200), (400, 400), (110, 110), and (160, 160). Defined by eminent brain atlases such as CC200, CC400, Harvard-Oxford, and Dosenbach-160, these connectomes stand as formidable reckonings, vividly encapsulating the nuanced correlations and dynamic interplay among distinct regions within the vast landscape of the brain. Figure illustrates functional connectivity matrices as an embedded connectome, revealing notable variations in connectivity among different brain regions.

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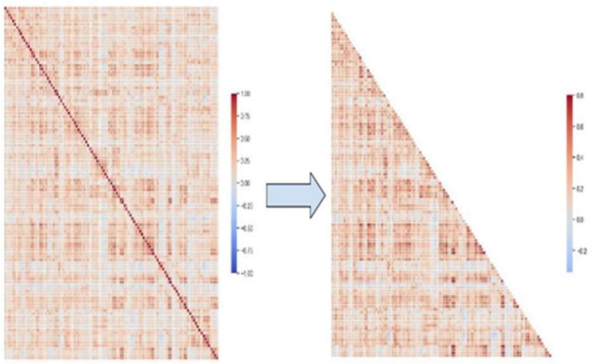

Figure 9: Connectivity maps of individuals randomly selected from the ASD and control cohorts

g) Employing a deep neural network classifier for the purpose of classification: Deep neural network classification has been described as follows.

1. First, the bottom Values arranged in a triangular pattern were recovered as indicated in Figure 9 and the higher triangular patterns—including the principal diagonal—were eliminated in order to reduce dimensionality.
2. The lower triangular part of each connectivity matrix was flattened into 1D feature vectors, resulting in sizes of 19,900, 19,900, 6,105, and 12,880 for CC200, CC400, Harvard-Oxford, and Dosenbach-160 atlases, respectively, across individual subjects.
3. A deep neural network classifier (DNN) housing 32 neurons per hidden layer was fed feature vectors. A 0.8 dropout probability dropout layer was put purposefully in between these layers to prevent overtraining.
4. Rectified Linear Unit (ReLU) activation functions were employed in the hidden layers, which resulted in outputs that fell between 0 and ∞. The sigmoid activation function was employed in the final output layer, which was tasked with binary classification (ASD vs. control), producing probability values ranging from 0 to 1.
5. The activation of the (i + 1) hidden layer (z_{i+1}) was calculated through the equation
   $z_{i+1}F(w_i x_i b_i)$,
   where x_i denotes the input, b_i is
   the bias value, and w_i is the weight vector linking nodes in hidden layer
   (i) to those in hidden layer
   (ii) (i + 1).
6. Xavier and He weight initializers were selectively applied with sigmoid and ReLU activations, respectively, optimizing the network's weight initialization for each activation function.
7. The Adam optimizer, featuring a learning rate of 0.0001 and default parameters, efficiently facilitated the training of the network.
8. The binary cross-entropy loss function was chosen for the binary classification task Expressed as

$j = \frac{1}{m}\sum_{i=1}^{m} y_i \log\big(P(y_i)\big)\,(1 - y_i)$, where m represents the total number of samples, y signifies the label, and p indicates the probability of y belonging to the autism or control group.

9. The primary objective of the DNN was to minimize the binary cross-entropy loss function (j), ensuring optimal performance in accurately classifying subjects into Autistic and Non-Autistic groups.

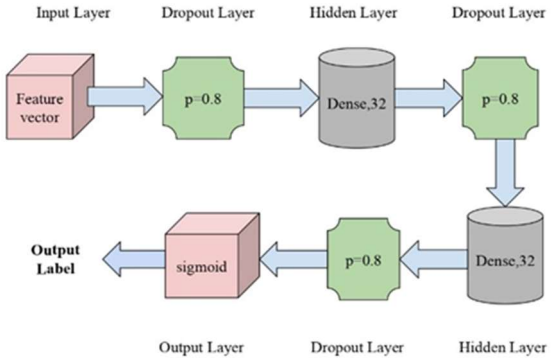

Figure 10: Cutting-Edge model for ASD Identification.

Finally, We used Incorporation of regularization techniques and the utilization of a very small batch size of 10 during training because our input vector was high dimensional. This allowed our model to perform better on unseen data and generalize effectively.

V. Results and Discussion:

The process of fine-tuning the DNN classifier required a lot of experimentation with different hyperparameters. We investigated performance using two hidden layers, each with 32 neurons, and four distinct atlases. The objective of this comprehensive method was to capture subtle differences in classifier performance.

In the rigorous evaluation of our neural networks, we maintained a balanced representation of participants in each target class autistic and Non-Autistic throughout the 5-fold cross-validation process. Our research focused exclusively on the NYU site, leveraging a dataset comprising 172 patient records. The data was meticulously partitioned, allocating 80% for model fitting and validation, with the outstanding 20% reserved for evaluation. Within the training set, 20% was further earmarked for validation, while 80% supported the model's training. This strategic division is visually represented in Figure 11, depicting the conceptual framework of data splitting. This meticulous approach, involving diverse data subsets for testing and training, underscored the reliability of our model assessment.

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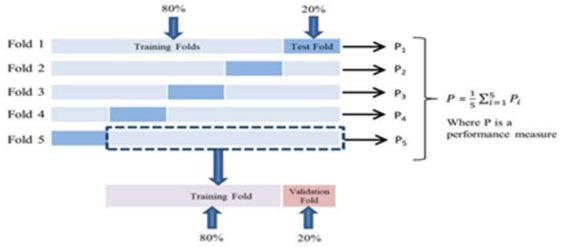

Figure 11: Utilizing a stratified 5-fold cross-validation strategy.

Comparative accomplishment Assessment Across Various Atlases:

Craddock 200 (CC200) Atlas:

Table 1 represents, while utilizing the suggested model, the CC200 atlas obtained the highest performance measure out of all performance measurements. Our model's classification matrix is shown in Figure 12.

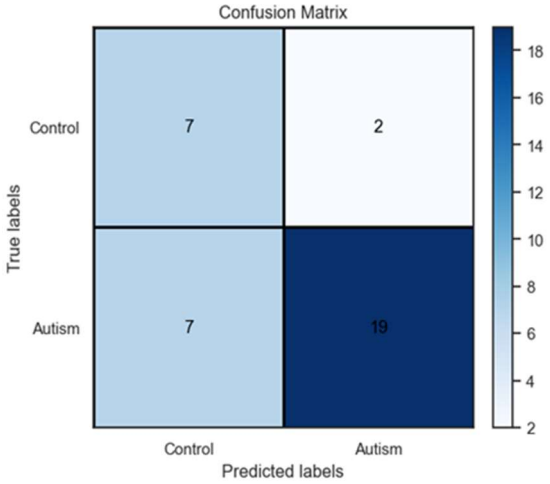

Figure 12: classification matrix for CC200 atlas using our Model

Craddock 400 (CC400) Atlas:

The network configurations from Table 1 were used to analyze the mean performance assessment, and the results showed that CC400 had The peak accuracy and F1-score achieved in our proposed model. However, the model's sensitivity and AUC were the greatest. Accuracy and F1 score, however, were comparatively decrease. Overall, our algorithm performed rather well according to all performance metrics. Using the suggested Model, the classification matrix is shown in Figure 13.

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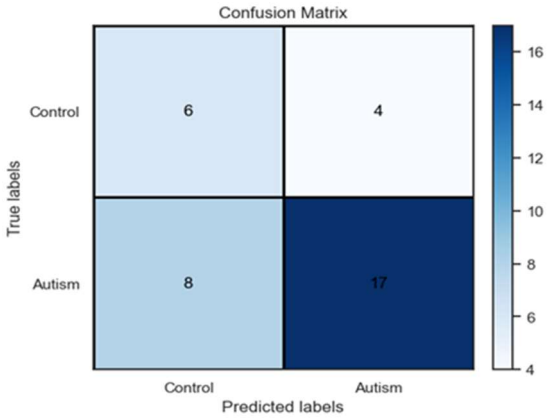

Figure 13: classification matrix for CC400 atlas using our Model

c)Harvard-Oxford Atlas:

According to Table 1, the suggested Model outperformed the others with an F1-score that was higher than 83%. Despite continued weak accuracy and F1-score, our model had the maximum sensitivity. For our model, the AUC value was nearly constant at 95%. The classification matrix created with the suggested algorithm is shown in Figure 14.

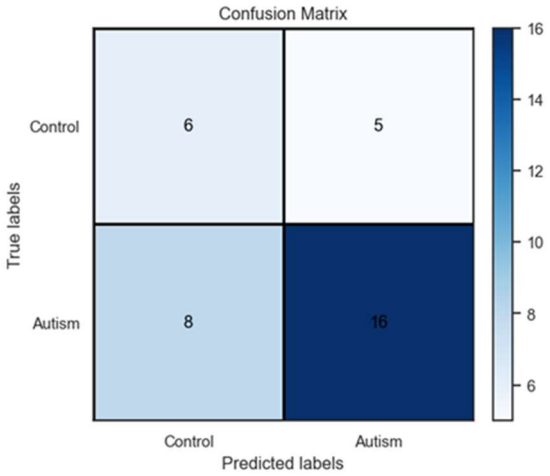

Figure: 14 Confusion matrix for Harvard-Oxford atlas using our Model.

d)Dosenbach-160 Atlas:

Analysis of Table 1 reveals the dynamic performance exhibited by our model across various scoring metrics, particularly notable when employing the Dosenbach-160 atlas. Further insights into the model's performance, depicted in the confusion matrix, are visually conveyed in Figure 15.

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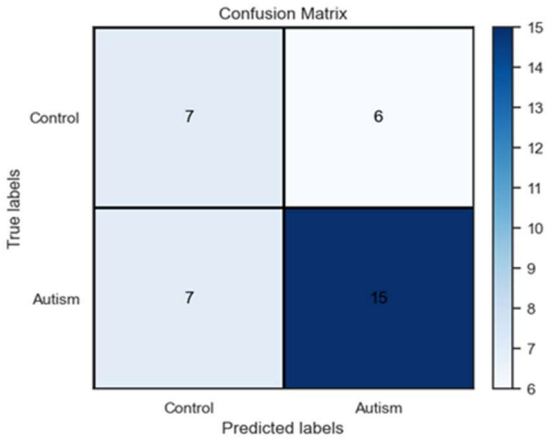

Figure 15: Confusion matrix for Dosenbach-160 atlas using our Model.

Network Configuration			Performance Evaluation using Different Atlases				
Input Layer	Hidden Layer-1	Hidden Layer-2	Accuracy	Acc. Std	Sensitivity	F1-Score	AUC Score
19900	32	32	0.8668	2.38	0.8683	0.8579	0.9571
76636	32	32	0.8533	2.38	0.8633	0.8453	0.9531
12880	32	32	0.8473	1.57	0.9406	0.8510	0.9515
6105	32	32	0.8312	2.73	0.9404	0.8379	0.9509

Table 1: performance evaluation using Different atlases for network configurations.

Comparative Analysis of Performance with Computational Models:

a) Neural Network(ANN):

Throughout our categorization efforts, the Multilayer Perceptron (MLP) classifier played a pivotal role in distinguishing between the Autism and control groups. Notably, among the diverse atlases employed, the CC400 Atlas emerged with the highest accuracy, achieving an impressive score of 65.07%. This noteworthy accuracy for the CC400 Atlas was attained with a specific configuration of one hidden layer and six nodes. The graphical representation of accuracy scores for all atlases, along with a focused depiction of the accuracy metric for CC400, is eloquently illustrated in Figure 16.

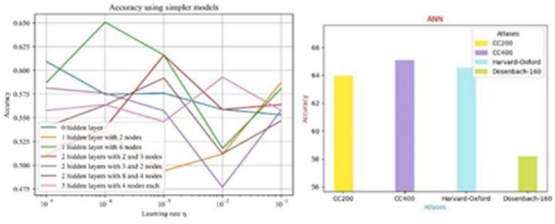

Figure 16: Performance comparison among atlases using ANN.

b)Linear-Support Vector Machine(L-SVM):

One classification system that uses a straight line to divide data into distinct groups is the linear Support Vector Machine (SVM). It works well in scenarios in which there is a distinct boundary that roughly divides the groups. With an accuracy of 69.176, we had achieved the maximum

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accuracy for the CC200.The accuracy bar-graph across all atlases and the accuracy graph with two parameters (C and Gamma) are shown in Figure 17.

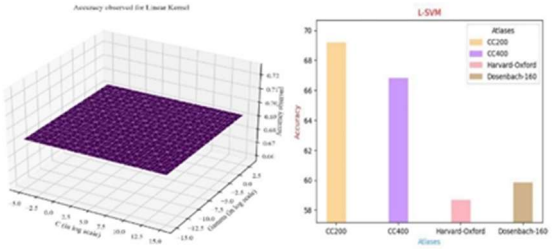

Figure 17: Performance comparison among atlases using L-SVM

c)K-Nearest Neighbour(KNN):

A simple machine learning technique called K-Nearest Neighbours (KNN) classifies a data item according to the majority class of its close neighbours[9]. Manhattan distance and Euclidean distance were the two distance measurements we employed. Applying Euclidean distance metrics to the Harvard-Oxford Atlas yielded an accuracy of 62.82. Figure 18 shows a bar graph for all atlases and an accuracy graph for two data measurements.

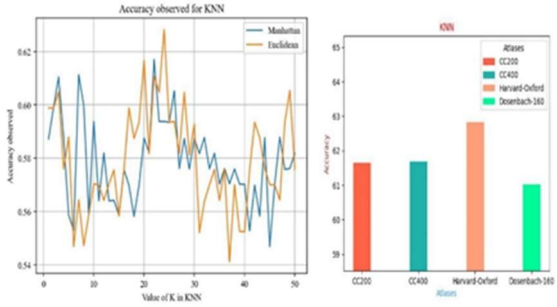

Figure 18: Performance comparison among atlases using KNN

Atlases	ANN	L-SVM	KNN	LR	DNN
CC200	63.94	69.17	61.64	69.00	86.68
CC400	65.07	66.80	61.68	66.80	85.33
Harvard-Oxford	64.52	58.68	62.82	61.00	83.12
Dosenbach-160	58.18	59.84	61.02	57.50	84.73

Figure 19: Comparing Performance Across Machine Learning Algorithms

Comparing performance among Atlas:

The suggested Model is used in Figure 20 to compare all performance indicators across all four atlases and decide which atlas has the most discerning ability in distinguishing between cases of Autistic and Non-Autistic group.

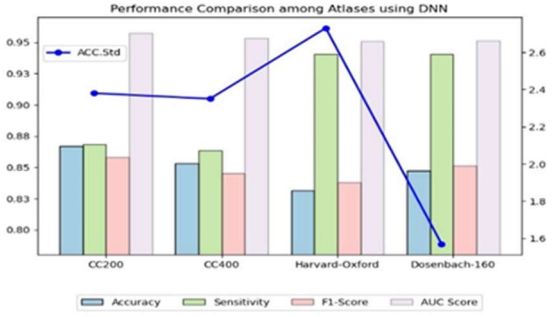

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Figure 20: Assessing atlases using Deep Neural Networks (DNN).

The visual examination above elucidates the following aspects:

The proposed Model showed exceptional performance across accuracy, sensitivity, F1, and AUC score metrics when utilizing the CC200 atlas.

The CC400 displayed mixed findings for several parameters. In terms of sensitivity, which is vital and important for medical diagnosis, it had the lowest value.

Across all metrics, the Harvard-Oxford and Dosenbach-160 atlases exhibited the least predictive efficacy in terms of performance.

The CC200 atlas performs the best across all criteria, as may be inferred from the previously mentioned statements. Its F1 score clearly indicates that it demonstrates The most balanced discriminative capacity.

VI. CONCLUSION

In this groundbreaking research, we introduce an innovatively utilized a deep learning approach with diverse resting-state fMRI data sources. for the transformative prediction of Autism Spectrum Disorder (ASD). Amidst the challenge of ASD detection and the absence of a standardized modelling choice, our study diverges from conventional practices, utilizing pre-processed fMRI data from the CPAC pipeline and exploring four distinct standard brain atlases. The CC200 atlas emerges as a robust biomarker, surpassing CC400, Harvard-Oxford, and Dosenbach-160 atlases in performance. Featuring a fixed hidden layer configuration, our model achieves exceptional results, boasting an impressive 87% accuracy, 87% sensitivity, 86% F1-score, and an outstanding 96% area under the Discrimination curve. Beyond diagnostic capabilities, our approach unravels neural activation patterns in autism and provides a visually compelling Analysis of the functional aspects intricacies within the autistic brain. Through a meticulous examination of the distinction between autistic and Non-Autistic brains, our research unveils the elusive neural and biological underpinnings of ASD, marking a promising advance with far-reaching implications for diagnostic accuracy and the broader landscape of autism and neurobiological research.

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