
# Project: Detecting Early Signs of Autism using fMRI Scans

## Physics and Informatics of Medical Imaging

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# 1 Introduction

## 1.1 About Autism

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder that affects an individual's ability to communicate, interact socially, and display repetitive behaviors. According to the Centers for Disease Control and Prevention (CDC), ASD affects approximately 1 in 44 children in the United States, with boys being four times more likely to have autism than girls. Over half of those diagnosed with autism are classified as having an intellectual disability or borderline intellectual disability. About 40% of children with autism do not speak. Others might speak, but not until later in childhood. So we can say that the symptoms of autism vary greatly from person to person, and the rate of autism has steadily increased over the last two decades.

## 1.2 Disease Characterization

- Social communication: Autistic children may struggle with nonverbal communication, such as maintaining eye contact, interpreting facial expressions, and using gestures. They may also have difficulty with verbal communication, such as initiating and maintaining conversations, understanding sarcasm or jokes, and taking turns in a conversation.
- Repetitive behaviors: Autistic children may engage in repetitive behaviors, such as hand-flapping, rocking, spinning, or lining up toys. They may also have strict routines and may become upset if their routines are disrupted.
- Sensory processing: Autistic children may be overly sensitive or under-sensitive to sensory input, such as sound, light, touch, taste, and smell. They may become overwhelmed in noisy or crowded environments or may seek out certain types of sensory input, such as spinning or jumping.
- Restricted interests: Autistic children may have very focused interests or may become obsessed with specific topics or objects. They may have difficulty engaging in other activities or may struggle to make friends due to their limited interests.

It's important to note that every autistic individual is unique, and not all autistic children will exhibit all of these characteristics. Additionally, some autistic individuals may have strengths in areas such as pattern recognition, attention to detail, or creative thinking.

## 1.3 Why is Autism known as a Spectral Disorder?

Autism is often referred to as a "spectrum disorder" because of the wide variation in symptoms and severity that individuals with autism can exhibit. The term "spectrum" refers to a range of different abilities, symptoms, and challenges that people with autism can experience, rather than a singular set of characteristics that apply to everyone.

Individuals with autism can have a range of social, communication, and behavioral challenges, which can manifest in different ways and to varying degrees. Some individuals with autism may have difficulty with social interactions and communication, such as making eye contact, initiating conversations, or understanding nonverbal cues. Others may exhibit repetitive behaviors, restricted interests, and sensory sensitivities.

The "spectrum" framework recognizes that autism is a complex and heterogeneous condition, and that there is no single defining feature that applies to all individuals with autism. Instead, it acknowledges that different individuals may have different strengths and challenges, and that their experiences with autism can vary widely. This variability can make diagnosis and treatment challenging, as there is no one-size-fits-all approach to supporting individuals with autism.

## 1.4 Impact of Austism

The impact of this condition on the quality of life extends beyond the affected individual to the entire family. For example, parents of children with ASD report higher stress levels than parents of children with other disabilities. Also, the majority of research regarding autism is based on data from high-income countries. This creates inequities across the world in access to services and support. On the other hand, given the brain's plasticity during the first years of life, early detection paired with early treatment would have considerably stronger benefits than later treatments.

Autism is associated with co-occurring conditions such as seizures, intellectual disability, anxiety, ADHD, and gastrointestinal problems, which can greatly impact an individual's quality of life. People with ASD also have a higher mortality rate, largely due to accidental injury. Additionally, only a small percentage of adults with autism are employed, and supporting individuals with autism can come with a high economic cost. Furthermore, individuals with autism have higher rates of comorbidities such as anxiety, depressive disorders, and bipolar disorder.

# 2 Related Work

Currently, there is no single method that is widely used for detecting early signs of autism. Different methods and techniques have been studied, including behavioral assessments, questionnaires, neuroimaging techniques such as MRI and fMRI, genetic testing, and biomarker analysis. Each method has its strengths and limitations, and the choice of method depends on the specific research question and the population being studied.

Functional magnetic resonance imaging (fMRI) has been used extensively in recent years to study ASD. Studies have used fMRI to examine functional connectivity in the brains of individuals with ASD, and several have shown promising results in using fMRI to identify potential biomarkers for ASD. However, challenges and limitations exist when using fMRI scans for autism diagnosis, including variability in study populations and the high cost of imaging and the need for specialized equipment and trained personnel to interpret the results.

The availability of publicly accessible Autism Brain Imaging Data Exchange (ABIDE) datasets has led to an increased interest in detecting biomarkers from fMRI datasets for ASD diagnosis. Numerous studies have been conducted using a subset or the full ABIDE dataset, utilizing various machine learning techniques. The accuracy of these models ranged from 52% to 95%, but their generalizability remains unknown for children.

Overall, while fMRI has shown promise in identifying potential biomarkers for ASD, more research is needed to overcome the challenges and limitations associated with its use. Additionally, the field would benefit from larger, more diverse study populations and standardized approaches to fMRI data collection and analysis. Behavioral assessments, questionnaires, genetic testing, and biomarker analysis are also promising avenues for early detection of autism, but more research is needed to identify specific markers that can reliably predict the development of the disorder.

# 3 Methodology of Autism Detection

In addition to MRI techniques, other types of brain data, including electroencephalography (EEG) and computed tomography (CT), have been used to study ASD. However, MRI is preferred because it is a safe method that involves low radiation exposure.

Table 1: Comparison of Imaging Techniques

| **Imaging Technique** | **Detection Rate** | **Time to Get Results** |
|---|---|---|
| sMRI | 75% - 85% | Few days to a week |
| fMRI | 80% - 90% | Few days to a week |
| EEG | 60% - 70% | Within few hours |
| PET | 75% - 85% | Few days to a week |
| DTI | 80% - 85% | Few days to a week |
| CT | 70% - 80% | Within few hours |
| Consulting a Doctor | 50% - 60% | 1-2 months |

## 3.1 MRI

During the 1990s, MRI techniques underwent significant advancements, including structural MRI (sMRI), functional MRI (fMRI) and Diffusion Tensor Imaging (DTI). Each technique provides distinct information about the brain. sMRI produces different images, such as T1 and T2 weighted, and T2-weighted Fluid Attenuated Inversion Recovery (FLAIR), which can be used to study brain structures and track brain growth over time. On the other hand, fMRI tracks changes in blood flow to brain regions that stimulate neurons and comes in two forms: rs-fMRI and task fMRI.

Figure 1: MRI machine used for fMRI & sMRI scans

### 3.1.1 sMRI

Structural magnetic resonance imaging (sMRI) is a popular modality for examining brain structure in ASD research. Its high sensitivity and resolution, coupled with its lack of ionizing radiation exposure, make it particularly suitable for use with children and adolescents. This method produces different sequences of brain tissue images, such as T1, T2, and FLAIR, by adjusting excitation and repetition durations to visualize various brain regions. Several sMRI-based techniques have been developed for autism detection, including voxel-based morphometry (VBM), cortical thickness measurement, and surface-based morphometry (SBM). These techniques have the advantage of being able to measure brain morphology with high spatial resolution and contrast sensitivity.

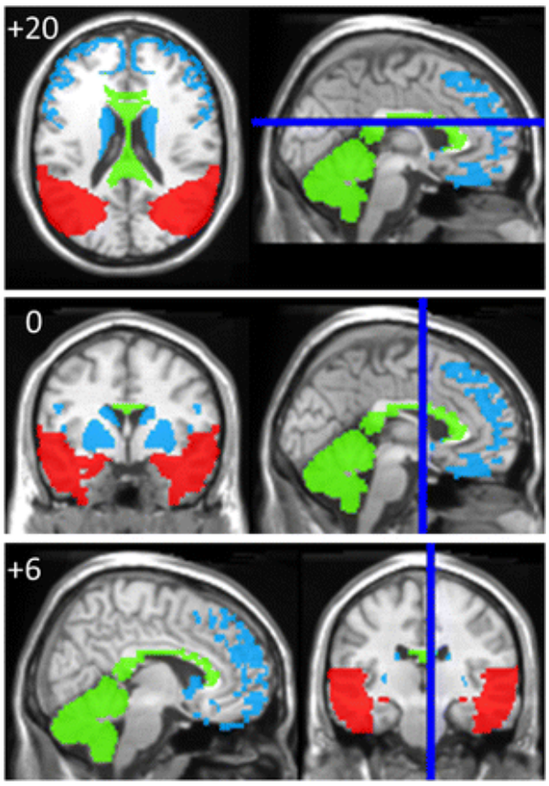


Figure 2: A summary of ASD and ADHD structural MRI findings. Light blue indicates regions where ASD predominately shows volumetric increases compared to controls and ADHD shows decreases; these regions include the prefrontal cortex and basal ganglia. Green indicates regions where ASD and ADHD display similar abnormalities including cerebellum and corpus callosum. Red indicates regions implicated predominately in ASD. These regions include the amygdala and temporal lobe.

VBM is a popular method used to detect gray matter (GM) differences between individuals with ASD and healthy controls. VBM involves the segmentation of the brain into GM, white matter, and cerebrospinal fluid, followed by normalization to standard space and voxel-wise statistical analysis to detect GM differences between groups. GM alterations in regions such as the cerebellum, temporal lobes, and frontal lobes have been observed in individuals with ASD using VBM.

Cortical thickness measurement involves measuring the distance between the gray and white matter surfaces across the cortical ribbon. This technique can detect differences in cortical thickness between individuals with ASD and healthy controls. Cortical thickness measurements have revealed alterations in several brain regions, including the prefrontal cortex, temporal lobes, and cingulate gyrus, in individuals with ASD.

SBM is a technique used to analyze cortical surface properties such as gyrification and sulcal depth. SBM can provide a more detailed view of surface changes in the brain, which are often associated with specific functional or structural changes. For example, alterations in gyrification in the medial temporal lobe have been observed in individuals with ASD using SBM.

The advantages of using sMRI-based techniques for autism detection include their non-invasiveness, high spatial resolution, and the ability to visualize brain regions that are difficult to image using other techniques. Additionally, sMRI can provide information on brain structure that is related to specific behaviors and cognitive abilities.

Despite its advantages, there are also some disadvantages associated with sMRI scans like its inability to capture dynamic brain function and its susceptibility to noise artifacts that may affect image quality. sMRI scans are expensive, making them less accessible to lower-income families. Additionally, sMRI scans require patients to remain still for an extended period of time, which can be difficult

for young children or individuals with sensory issues. Another limitation of sMRI is that it only provides information about brain structure and not function, which may be important in understanding ASD. Finally, the interpretation of sMRI results can be challenging, requiring skilled specialists to analyze and interpret the images.

#### 3.1.2 fMRI

fMRI has been used in various studies to investigate differences in brain function between individuals with ASD and typically developing individuals. The underlying theory is that differences in brain function in individuals with ASD may be related to the core symptoms of the disorder, such as social communication difficulties and repetitive behaviors. Studies have used fMRI to investigate a variety of brain functions in individuals with ASD, including social cognition, language processing, executive function, and sensory processing. Some studies have reported differences in brain activation patterns in individuals with ASD compared to typically developing individuals, while others have found no differences. More about this is written in Section 4.

### 3.2 EEG

Electroencephalography (EEG) is a non-invasive neuroimaging technique that measures the electrical activity of the brain through electrodes placed on the scalp. EEG-based techniques have been used for ASD detection by analyzing brain activity and connectivity.

One feature commonly used in EEG-based studies is event-related potentials (ERPs), which are changes in electrical activity in response to specific stimuli. Studies have shown that individuals with ASD exhibit altered ERPs compared to neurotypical individuals, particularly in response to social and emotional stimuli. Additionally, measures of connectivity, such as coherence and phase synchronization, have been used to investigate the functional connectivity between different brain regions in individuals with ASD.

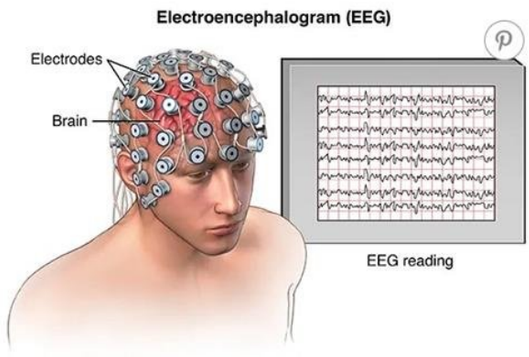


Figure 3: EEG and brain waves

One of the advantages of EEG is its high temporal resolution, as it can measure changes in brain activity in real-time. It is also non-invasive and relatively inexpensive compared to other neuroimaging techniques. However, EEG has limited spatial resolution, as it only measures electrical activity on the surface of the scalp, which can make it difficult to accurately localize the source of brain activity.

## 4 fMRI

### 4.1 Introduction

In the context of early detection of autism, fMRI has been used to study brain function in individuals with autism compared to typically developing individuals. Studies have found differences in the patterns of brain activation between these groups, which may be indicative of underlying neural abnormalities associated with autism.

One study by Weng et al. (2010) used fMRI to compare brain activity in children with and without autism during a social task. The researchers found that children with autism showed reduced activation in several areas of the brain that are involved in social processing, such as the amygdala and superior temporal sulcus.

Another study by Ecker et al. (2013) used fMRI to investigate differences in brain function between adults with autism and typically developing adults. The researchers found that individuals with autism showed reduced activation in the dorsal anterior cingulate cortex, a region of the brain that is involved in social and emotional processing.

### 4.2 Resting state fMRI

Resting-state functional magnetic resonance imaging (rs-fMRI) is a non-invasive technique that measures brain activity by detecting changes in blood oxygen levels. In recent years, rs-fMRI has gained attention as a potential tool for the early detection of ASD.

The idea behind rs-fMRI is that even when a person is not performing any specific task, the brain remains active and communicates with different regions. This ongoing activity is known as the default mode network (DMN) and is believed to be related to various cognitive processes such as self-referential thinking, social cognition, and memory consolidation. In individuals with ASD, studies have shown altered connectivity patterns within the DMN, suggesting that it may be a biomarker for the disorder.

Several studies have used rs-fMRI to investigate the connectivity patterns in individuals with ASD. For example, a study by Anderson et al. (2011) found decreased connectivity between the posterior cingulate cortex (PCC) and medial prefrontal cortex (mPFC) in children with ASD compared to typically developing children. Similarly, a study by Supekar et al. (2013) showed reduced connectivity between the DMN and the frontoparietal network in children with ASD.

Other studies have investigated the use of machine learning algorithms to analyze rs-fMRI data for early detection of ASD. For example, Khosla et al. (2018) used a deep learning approach to classify children with ASD and typically developing children based on rs-fMRI data. They reported high accuracy in identifying children with ASD using this method.

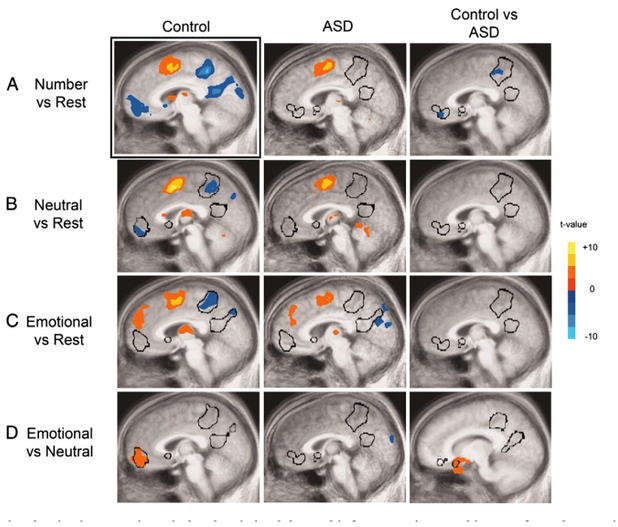


Figure 4: The study looked at brain activity in typical and autistic adults while counting words or at rest. Control subjects showed brain activity during the task, but autistic individuals did not, indicating difficulty in using the necessary brain regions. The data is presented as t values, with negative values showing decreased activity during rest.

Despite promising results, there are several challenges associated with using rs-fMRI for the early detection of ASD. One limitation is the lack of standardized methods for acquiring and analyzing rs-fMRI data, which can lead to variability in results across studies. Additionally, there is a need for larger and more diverse study populations to ensure the generalizability of findings.

## 4.3 Signal generation

### 4.3.1 Introduction

In both fMRI and rs-fMRI, the signal being measured is related to changes in blood flow and oxygenation levels in the brain. Specifically, fMRI measures changes in the blood oxygen level-dependent (BOLD) signal, while rs-fMRI measures correlations in spontaneous fluctuations of the BOLD signal between different brain regions.

The BOLD contrast in fMRI is related to the difference in magnetic properties between oxygenated and deoxygenated blood. When neurons in a certain area of the brain become active, they consume more oxygen, leading to an increase in blood flow to that area. The oxygenated blood has weaker magnetic susceptibility than deoxygenated blood, leading to a local distortion in the magnetic field that can be detected by the fMRI scanner.

On the other hand, rs-fMRI measures the correlation in the BOLD signal between different regions of the brain during rest, without any explicit task or stimulus. This technique is based on the concept of functional connectivity, which refers to the temporal correlation of neural activity between different regions of the brain.

Neither fMRI nor rs-fMRI measure the diffusion of molecules or proton density. However, diffusion MRI (dMRI) is a related technique that measures the diffusion of water molecules in the brain, which provides information about the microstructure of white matter pathways. This technique has been used to investigate white matter abnormalities in individuals with autism. The proton density is a parameter that reflects the number of protons in a given tissue, which is related to its water content. However, proton density imaging is not commonly used in fMRI or rs-fMRI as the BOLD signal is a more sensitive and specific measure of neural activity.

### 4.3.2 Physics of signal generation

The BOLD signal is typically measured using a T2*-weighted echo planar imaging (EPI) sequence. In this sequence, a series of gradient-echo images are acquired with a very short echo time (typically less than 30 ms). The gradient-echo images are sensitive to changes in the magnetic field caused by the BOLD effect, and the time course of the signal can be used to infer changes in neuronal activity.

BOLD signal fluctuations are thought to represent intrinsic functional connectivity between different brain regions, which can provide insights into functional networks involved in various brain processes. The underlying physics of rs-fMRI signal generation involves the use of strong magnetic fields and radiofrequency (RF) waves to manipulate the magnetic properties of hydrogen nuclei in water molecules, which are abundant in the brain. This leads to changes in the alignment and relaxation of these nuclei, resulting in the emission of a signal that can be detected and reconstructed into an image.

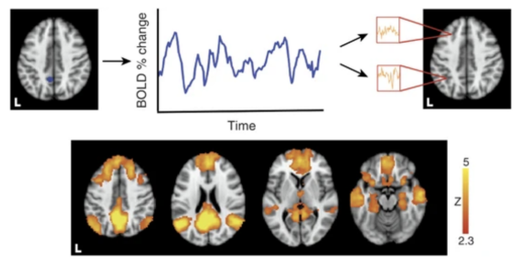


Figure 5: Seed-based functional connectivity. The average BOLD signal time series is extracted from a seed region (eg, the precuneous). The time series of activity from this seed region is then correlated with the time series of activity of all other voxels in the brain, yielding maps of coactivating brain areas. Brain areas represented in these maps are inferred to be part of the same functional brain network, as activity in these regions is highly correlated with one another.

During rs-fMRI, the patient lies in a magnetic field, which causes the alignment of protons in water molecules in the brain. A radiofrequency pulse is then applied, which causes the protons to flip, and when the pulse is turned off, the protons return to their original alignment. This generates a signal that can be measured by the MRI machine. As the protons return to their original alignment, they emit radiofrequency signals that are used to create an image of the brain. The BOLD signal is typically quantified using the percent signal change ($\%S_C$), which is calculated as the difference between the signal intensity during the task or resting state period and the baseline signal intensity, divided by the baseline signal intensity, and multiplied by 100: $\%S_C = (S - S_0)/S_0$x100 where $S$ is the signal intensity during the task or resting state period and $S_0$ is the baseline signal intensity.

The BOLD signal is often described using the general linear model (GLM), which is a statistical framework for modeling the relationship between an observed signal and a set of predictor variables. In the case of fMRI, the predictor variables are typically convolved with a hemodynamic response function (HRF), which describes the time course of the BOLD response to a brief neural stimulus. The GLM can then be used to estimate the magnitude and temporal characteristics of the BOLD signal associated with different experimental conditions or task events.

The BOLD signal is influenced by a number of factors, including physiological noise, motion artifacts, and scanner drift. To correct for these factors, various preprocessing steps are typically performed on the fMRI data, including motion correction, slice-timing correction, spatial smoothing, and high-pass filtering. In addition, several denoising techniques have been developed to further remove noise from the fMRI data, including independent component analysis (ICA) and regression-based methods.

Overall, the physics of signal generation in rs-fMRI is complex and involves multiple factors, such as cerebral blood flow, metabolism, and neurovascular coupling. While there are still some technical challenges and limitations in using rs-fMRI for clinical applications, recent advances in data analysis methods and machine learning techniques have shown promise in improving the sensitivity and specificity of this technique for early detection and diagnosis of autism and other neurological disorders.

## 4.4 Characterization of Autism Through rs-fMRI

rs-fMRI has been extensively used for the characterization of ASD. As mentioned earlier, rs-fMRI measures the intrinsic activity of the brain by detecting the BOLD signal. In contrast to task-based fMRI, which requires the presentation of a stimulus, rs-fMRI is performed when the subject is at rest, i.e., not performing any specific cognitive or motor task.

The rs-fMRI data is acquired over a period of time, typically between 5 to 15 minutes. The data is then preprocessed to remove artifacts and to reduce the effects of noise. The preprocessed data is then analyzed using various methods, including seed-based correlation analysis, independent component analysis, and graph

theory analysis.

Seed-based correlation analysis involves selecting a region of interest (ROI) based on previous knowledge of the brain regions involved in a specific cognitive or behavioral process. The correlation between the activity of the ROI and the rest of the brain is then computed. This method has been used to study the functional connectivity between different brain regions in individuals with ASD.

Independent component analysis (ICA) is a data-driven approach that identifies patterns of functional connectivity in the brain without a priori selection of regions of interest. This method has been used to identify the functional networks involved in ASD, such as the default mode network (DMN), salience network (SN), and the executive control network (ECN).

Graph theory analysis involves the construction of a graph where the nodes represent brain regions, and the edges represent the functional connectivity between them. This method has been used to study the network properties of the brain in individuals with ASD, such as the small-worldness, modularity, and global efficiency.

Several studies have used rs-fMRI to investigate the differences in functional connectivity between individuals with ASD and typically developing individuals. These studies have reported alterations in the functional connectivity of several brain regions, including the amygdala, anterior cingulate cortex, and the insula, among others. These findings suggest that individuals with ASD have altered functional connectivity in brain regions involved in social communication, emotion processing, and sensory integration.

### 4.4.1 Connectivity Abnormalities

Studies have consistently reported altered connectivity patterns in various brain regions and networks in individuals with ASD compared to typically developing individuals. For instance, a meta-analysis by Di Martino et al. (2014) found that individuals with ASD show decreased functional connectivity in the default mode network (DMN), which is a network of brain regions that is active during rest and self-referential thinking, and increased functional connectivity in the fronto-parietal network (FPN), which is involved in executive functions and attentional control.

Other studies have also found abnormalities in the connectivity of the salience network, which is involved in detecting and filtering relevant sensory and emotional information, and the social brain network, which is important for social cognition and communication.

Moreover, several studies have reported a correlation between the severity of ASD symptoms and the degree of connectivity abnormalities, suggesting that rs-fMRI measures could potentially serve as biomarkers for ASD diagnosis and prognosis.

However, there are also challenges and limitations associated with rs-fMRI-based connectivity analyses in ASD. For instance, the interpretation of connectivity abnormalities can be confounded by factors such as head motion, age, and comorbidities. Moreover, the spatial resolution of rs-fMRI is limited, which can make it difficult to identify specific brain regions or circuits that are implicated in ASD.

### 4.4.2 Anatomic Perturbations

In addition to connectivity abnormalities, rs-fMRI studies have also shown anatomic perturbations in the brains of individuals with autism. For example, studies have found that the gray matter volume is reduced in several brain regions, including the amygdala, hippocampus, and superior temporal gyrus, in individuals with autism compared to typically developing individuals (Ecker et al., 2013). Other studies have reported changes in the white matter integrity in several tracts, including the corpus callosum, superior longitudinal fasciculus, and inferior longitudinal fasciculus (Khosla et al., 2018).

Such anatomic perturbations may be related to the cognitive and behavioral symptoms associated with autism. For instance, reduced gray matter volume in the amygdala and hippocampus, which are involved in emotion processing and memory, respectively, may contribute to the social and communication deficits as well as the repetitive behaviors and restricted interests observed in individuals with autism (Ecker et al., 2013). Similarly, changes in white matter integrity in the corpus callosum, which connects the two hemispheres of the brain, may affect the integration of information between the two hemispheres, potentially contributing to the difficulties in social communication observed in individuals with autism (Khosla et al., 2018).

### 4.4.3 Abnormal Growth Patterns

rs-fMRI has been used to investigate the neural underpinnings of abnormal growth patterns in autism. Studies have shown that children with autism exhibit abnormal patterns of functional connectivity in several brain regions compared to typically developing children.

In particular, studies have identified abnormalities in functional connectivity within the default mode network, which is a set of brain regions that are active during rest and self-referential processing. Other studies have identified alterations in connectivity in regions involved in social cognition, language, and executive function.

Furthermore, rs-fMRI has also been used to investigate the relationship between abnormal growth patterns and clinical symptoms in autism. For example, studies have shown that decreased connectivity within the default mode network is associated with increased social and communication deficits.

# 5 ABIDE Dataset and Machine Learning Algorithm

## 5.1 ABIDE

The ABIDE Preprocessed dataset is a subset of the Autism Brain Imaging Data Exchange (ABIDE) initiative, which aims to facilitate the sharing and analysis of brain imaging data from individuals with autism and typically developing controls.

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | **Universities** | **Number of time samples** | **MRI Scanner Machine Model** | **Acquisition Time (minutes : seconds )** | **Acquisition Time ( seconds )** | **Bandwidth (Hz/Px)** | **TR ( Repetition time ) ( ms )** | **TE ( Echo Time ) ( ms )** | **Number of Autistic samples** | **Number of Typically developing child samples** |
| 2 | California Institute of technology | 145 | SIEMENS MAGNETOM TrioTim syngo MR B17 | 05:04 | 304 | 2604 | 2000 | 30 | 15 | 14 |
| 3 | Carnegie Melon Institute_a | 235 | SIEMENS MAGNETOM Verio syngo MR B17 | 08:06 | 486 | 1628 | 2000 | 30 | 5 | 7 |
| 4 | Carnegie Melon Institute_b | 315 | SIEMENS MAGNETOM Verio syngo MR B17 | 08:06 | 486 | 1628 | 1500 | 30 | 3 | 3 |
| 5 | Kennedy Krieger Institute | 151 | 3 Tesla Philips Achieva scanner | 06:40 | 400 | 2696 | 2500 | 30 | 16 | 20 |
| 6 | Ludwig Maximilians University Munich_a | 115 | SIEMENS MAGNETOM Verio syngo MR B17 | 06:06 | 366 | 2232 | 3000 | 30 | 4 | 6 |
| 7 | Ludwig Maximilians University Munich_b | 115 | SIEMENS MAGNETOM Verio syngo MR B17 | 06:06 | 366 | 2232 | 3000 | 30 | 5 | 0 |
| 8 | Ludwig Maximilians University Munich_c | 115 | SIEMENS MAGNETOM Verio syngo MR B17 | 06:06 | 366 | 2232 | 3000 | 30 | 2 | 15 |
| 9 | Ludwig Maximilians University Munich_d | 195 | SIEMENS MAGNETOM Verio syngo MR B17 | 10:06 | 606 | 2232 | 3000 | 30 | 10 | 6 |
| 10 | NYU Langone Medical Center | 175 | SIEMENS MAGNETOM Allegra syngo MR 2004A | 06:00 | 360 | 3906 | 2000 | 15 | 65 | 74 |
| 11 | Olin, Institute of Living at Hartford Hospital | 202 | SIEMENS MAGNETOM Allegra syngo MR 2004A | 05:15 | 315 | 4112 | 1500 | 27 | 16 | 13 |
| 12 | Oregon Health and Science University | 77 | SIEMENS MAGNETOM TrioTim syngo MR B17 | 03:32 | 212 | 2298 | 2500 | 30 | 12 | 14 |
| 13 | San Diego State University | 175 | GE 3T MR750 scanner | 06:10 | 370 | | 2000 | 30 | 13 | 16 |
| 14 | Social Brain Lab | 195 | Philips Intera 3T | 7:28.8 | 448 | 1283 | 2200 | 30 | 15 | 15 |
| 15 | Stanford University | 175 | GE SIGNA 3T | 04:12 | 252 | | 2000 | 30 | 15 | 16 |
| 16 | Trinity Centre for Health Sciences | 145 | Philips 3T Achieva MRI Scanner | 06:40 | 400 | 2419 | 2000 | 28 | 22 | 25 |
| 17 | University of California,Los Angeles: Sample 1 | 115 | SIEMENS MAGNETOM TrioTim syngo MR B15 | 06:06 | 366 | 2442 | 3000 | 28 | 35 | 27 |
| 18 | University of California,Los Angeles: Sample 2 | 115 | SIEMENS MAGNETOM TrioTim syngo MR B15 | 06:06 | 366 | 2442 | 3000 | 28 | 13 | 11 |
| 19 | University of Leuven: Sample 1 | 245 | 3.0 Tesla Philips MR scanner | 07:06.7 | 426 | 3208.1 | 1667 | 33 | 14 | 15 |
| 20 | University of Leuven: Sample 2 | 245 | 3.0 Tesla Philips MR scanner | 07:06.7 | 426 | 3208.1 | 1667 | 33 | 12 | 13 |
| 21 | University of Michigan: Sample 1 | 295 | 3 Tesla GE Signa scanner | 10:00 | 600 | | 2000 | 30 | 43 | 36 |
| 22 | University of Michigan: Sample 2 | 295 | 3 Tesla GE Signa scanner | 10:00 | 600 | | 2000 | 30 | 12 | 20 |
| 23 | University of Pittsburgh School of Medicine | 195 | SIEMENS MAGNETOM Allegra syngo MR A30 | 05:06 | 306 | 3126 | 1500 | 25 | 25 | 23 |
| 24 | University of Utah School of Medicine | 235 | SIEMENS MAGNETOM TrioTim syngo MR B17 | 08:06 | 486 | 2894 | 2000 | 28 | 46 | 25 |
| 25 | Yale Child Study Center | 195 | SIEMENS MAGNETOM TrioTim syngo MR B17 | 06:40 | 400 | 2520 | 2000 | 25 | 20 | 20 |

The ABIDE dataset is a collection of resting-state fMRI data from individuals with ASD and typically developing individuals. The dataset includes data from 20 different universities, each using different fMRI machines and acquisition parameters. Summary of the ABIDE dataset

- Sample sizes:
  The number of time samples collected by each university varies, with the smallest sample size being 77 and the largest being 315. This suggests that some universities may have had more resources or access to more participants than others, which could affect the statistical power of their analyses.

- MRI machine model:
  Each university used a different MRI scanner machine model. While all of the models are from reputable manufacturers (e.g., Siemens, Philips, GE), there may be differences in the quality and accuracy of the data collected by each machine, which could affect the results.

- Acquisition time:
  The time it took to acquire each scan varies across universities, ranging from 3 minutes and 32 seconds

to 10 minutes and 6 seconds. Longer acquisition times may result in more motion artifacts or fatigue in participants, which could affect the quality of the data.

- TR and TE:
  The repetition time (TR) and echo time (TE) parameters used by each university also vary. These parameters can affect the contrast and resolution of the images obtained, and can also affect the sensitivity to certain types of neural activity.

- Autistic vs typically developing samples:
  The number of samples from autistic vs typically developing children also varies across universities. Some universities have more samples from autistic children than typically developing children, while others have more samples from typically developing children. This could affect the statistical power of analyses that aim to compare these groups.

Resampling is a common technique used in fMRI studies to adjust for differences in acquisition rates across different machines or studies. In this case, since each university used a different MRI machine model and the acquisition time varied across studies, it was necessary to resample the data to create a consistent time series that could be analyzed across all studies. There are several ways to resample fMRI data. We decided to interpolate the data to a common sampling rate, which involved estimating the missing values at each time point based on the neighboring values. We also downsampled the data by averaging the signal over multiple time points, which helped to reduce the impact of noise and increase the signal-to-noise ratio.

### 5.2 Machine Learning Algorithm

- We processed and cleaned the data before feeding it into a Support Vector Machine (SVM). The output of the SVM was a weight matrix of 90x90, indicating significant regions in the brain.

- We utilized the fact that different brain regions are correlated with each other to generate a correlation matrix from the weight matrix.

- We then transformed this correlation matrix into a 3D matrix representing RGB channels to enable its use as input for Convolutional Neural Networks (CNNs)

- Finally, we employed various CNN architectures, starting with Lenet 5, to analyze the 3D matrices.

A few notable results from our experiments:

- The study tested seven different neural network models, with varying numbers of epochs, batch sizes, and activation functions.

- The FR2 model was the best-performing model, with an overall accuracy of 73.6%, and an autistic accuracy of 96.8%, and a neurotypical accuracy of 50.4%.

- The LeNet model was the worst-performing model, with an overall accuracy of 47.0%, and an autistic accuracy of 0.0%, and a neurotypical accuracy of 100.0%.

- The accuracy of the models varied considerably depending on the hyperparameters used, suggesting that there is still room for optimization in the design of the neural networks for this task.

- The study found that models with larger numbers of epochs and smaller batch sizes tended to perform better on this task.

## 6 Limitations & Conclusion

rs-fMRI is a promising technique for early detection of ASD. However, its application for early detection has several limitations. One limitation is the variability in the resting-state connectivity patterns in individuals with ASD, making it challenging to identify a consistent biomarker for early detection. Another limitation is the requirement for a high level of expertise in data analysis and interpretation, which may limit its use in clinical settings. Additionally, the cost and availability of MRI machines pose a significant challenge, especially in low-resource settings.

In conclusion, although rs-fMRI holds promise for early detection of ASD, further research is necessary to address the limitations and optimize its potential as a diagnostic tool. Future studies should aim to establish a standardized protocol for data collection and analysis, develop machine learning algorithms to aid in data interpretation, and investigate the feasibility of using other neuroimaging techniques in combination with rs-fMRI for more accurate and reliable early detection of ASD. Ultimately, the development of an effective and accessible early detection tool for ASD would have a significant impact on improving the lives of individuals with ASD and their families.

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