AUTISM SPECTRUM DISORDER CHARACTERIZATION AND INTERVENTION USING BRAIN COMPUTER INTERFACE DATA AND DEEP LEARNING

A PROJECT REPORT

Submitted by

PADMA PRAVIN E (1920106063)

PRAVEEN N (1920106069)

PRAVIN P (1920106070)

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

IN

INFORMATION TECHNOLOGY

SONA COLLEGE OF TECHNOLOGY

SALEM-5(Autonomous)

ANNA UNIVERSITY : CHENNAI 600025

NOVEMBER 2023

BONAFIDE CERTIFICATE

Certified that this project report "**AUTISM SPECTRUM DISORDER CHARACTERIZATION AND INTERVENTION USING BRAIN COMPUTER INTERFACE DATA AND DEEP LEARNING"** is the bonafide work of **"PADMA PRAVIN E (1920106063), PRAVEEN N (1920106069) PRAVIN P(1920106070)"** who carried out the project work under my supervision.

SIGNATURE

Dr. J. Akilandeswari

Professor

HEAD OF THE DEPARTMENT

Department of Information Technology

Sona College of Technology

Salem- 636 005.

SIGNATURE

Mr. J.L.Aldo Stalin

Assistant Professor

SUPERVISOR

Department of Information Technology

Sona College of Technology

Salem- 636 005.

Submitted for mini project viva voce examination held from 16/11/2023 to 18/11/2023

INTERNAL EXAMINER **EXTERNAL EXAMINER**

ACKNOWLEDGEMENT

First and foremost, we thank to **power of almighty** for showing us inner peace and for all blessings .Special gratitude to our parents, for showing their support and love always.

We express our sincere thanks to chairman **Sri.C.VALLIAPPA** and principal **Dr.S.R.R.SENTHILKUMAR** for providing adequate facilities to complete the project.

We are immensely grateful to our Head of Information Technology Department, **Dr.J.AKILANDESWARI for** the continue encouragement to complete the project.

We heartfully thank our project coordinator **Dr.P.SHANMUGARAJA** for all of his support and guidance throughout this project. Your leadership has been instrumental in our success.

We express our heartfelt thanks to our project supervisor **Mr.J.L.ALDO STALIN** for his valuable guidance and fruitful discussions throughout the course of the project work.

We feel proud in sharing this success with all our department Faculty, Staff members and friends who helped directly and indirectly to completing this project successfully.

ABSTRACT

Autism is a complex spectrum disorder that is characterized by a range of symptoms, skills, and levels of disabilities. It is typically diagnosed in early childhood, often around the age of 2 to 3 years. The symptoms of autism can vary widely form person to person, but they generally include difficulties in social interaction, communication challenges and restricted or repetitive behaviours. Some individuals can have excellent skills in certain areas, such as memory or math, while struggling with social interactions. Where others struggling with sensory sensitives, repetitive behaviours.

For years scientists believed that cerebellum's main function is to coordinate movements. But increasing evidence has shown that the cerebellum also plays an important role in cognition and social skills. There's evidence that it not only regulates movements, but maybe cognition, wide range of other functions.

Autistic brains often show a loss of specialized brain cells called "Purkinje cells", which are responsible for carrying the signals out of cerebellum. This research focuses on harnessing Brain Computer Interface (BCI) data and deep learning techniques to enhance the understanding of autism and develop targeted interventions. The project is to leverage electroencephalogram(EEG) numerical data obtained through BCIs to uncover distinctive neural patterns associated with ASD.

By collecting and analyzing EEG signals from both neuro-typical individuals and those with ASD, we aim to identify specific neural signatures linked to social interaction difficulties, sensory sensitive, repetitive behaviour. Deep Learning methods, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), will be employed to learn complex patterns within EEG data. These models will be trained to recognize subtle differences in brain activity that correlate with various ASD characteristics.

Additionally, the project seeks to develop real-time algorithms capable of detecting momentary changes in neural patterns during social interactions or sensory experiences. The outcomes of this project hold significant implications for autism intervention. By deciphering neural markers associated with specific ASD traits, personalized interventions can be designed.

These interventions may involve real time feedback mechanisms delivered through wearable devices or interactive applications, aiding individuals with ASD in recognizing and navigating social situations, managing sensory sensitivities, and reducing repetitive behaviors.

LIST OF FIGURES

LIST OF ABBREVIATIONS

ASD – Autism Spectrum Disorder

BCI – Brain Computer Interface

DL – Deep Learning

CNN – Convolutional Neural Network

RNN – Recurrent Neural Network

LSTM – Long-Short Term Memory

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND STATEMENT OF THE PROJECT

Autism spectrum disorder (ASD) is a neurodevelopmental disorder that affects communication, social interaction, and behavior. It is called a spectrum disorder because the symptoms and severity can vary widely from person to person. Some individuals with ASD may have difficulty with social interaction and communication, while others may have repetitive behaviors or highly focused interests. The causes of ASD are not yet fully understood, but research suggests that a combination of genetic and environmental factors may be involved. There is no known cure for ASD, but early intervention and therapy can help individuals with ASD to improve their skills and quality of life. ASD is typically diagnosed in early childhood and affects about 1 in 54 children in the United States. The symptoms of ASD can range from mild to severe, and may include difficulty with social interaction, communication, and behavior. Some individuals with ASD may have difficulty making eye contact, understanding social cues, or engaging in conversation. Others may have difficulty with repetitive behaviors or may be highly sensitive to sensory input such as sounds or textures. Brain computer interface (BCI) technology has been explored as a potential tool to help researchers better understand autism spectrum disorder (ASD). A BCI is a system that allows direct communication between the brain and a computer, typically by measuring brain activity and translating it into a signal that can be used by a computer. BCI technology could also potentially be used to develop new interventions for individuals with ASD. For example, BCIs could be used to train individuals with ASD to regulate their own brain activity, which could help to improve their ability to focus and reduce symptoms such as anxiety or hyperactivity. Deep learning algorithms can be trained on large datasets of clinical and behavioral data to

identify patterns that are associated with ASD. For example, deep learning algorithms have been used to analyze brain scans and identify differences in brain activity between individuals with and without ASD. They have also been used to analyze speech patterns and identify differences in language use between individuals with and without ASD. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are types of deep learning algorithms that have been explored as potential tools for diagnosing and treating autism spectrum disorder (ASD). CNNs can be used to analyze images, such as brain scans, and identify patterns that are associated with ASD. For example, CNNs have been used to analyze functional magnetic resonance imaging (fMRI) scans and identify differences in brain activity between individuals with and without ASD. This could potentially help clinicians to diagnose ASD earlier and more accurately. LSTMs, on the other hand, are particularly useful for analyzing sequential data, such as speech or movement patterns. They have been used to analyze speech patterns and identify differences in language use between individuals with and without ASD. LSTMs have also been used to analyze movement patterns and identify differences in gait and posture between individuals with and without ASD.

1.2 PROJECT OBJECTIVE AND SIGNIFICANCE

The objective of this project is to develop a system for the characterization and intervention of Autism Spectrum Disorder (ASD) using brain computer interfaces (BCIs) and deep learning. The goal is to identify patterns in brain activity that are associated with specific ASD symptoms and develop targeted interventions based on these patterns. The significance of this project lies in the potential for earlier and more personalized interventions for individuals with ASD. Currently, diagnosis of ASD is based on behavioral observations and can be difficult to make, especially in young children. By using BCIs to identify patterns in brain activity, we may be able to identify individuals with ASD earlier and provide interventions before symptoms become more severe. Additionally, the use of targeted interventions based on brain

activity patterns may be more effective than current one-size-fits-all interventions. By tailoring interventions to specific symptoms and behaviors, we may be able to improve outcomes for individuals with ASD and their families. Overall, this research project has the potential to make significant contributions to the field of ASD characterization and intervention, and ultimately improve the lives of individuals with ASD. Additionally, the use of targeted interventions based on brain activity patterns may be more effective than current one-size-fits-all interventions. By tailoring interventions to specific symptoms and behaviors, we may be able to improve outcomes for individuals with ASD and their families. Overall, this research project has the potential to make significant contributions to the field of ASD characterization and intervention, and ultimately improve the lives of individuals with ASD. Overall, this project has the potential to make significant contributions to the field of ASD research and improve the lives of individuals with ASD and their families. It may also pave the way for further research and development of BCI and deep learning-based interventions for other neurological and developmental disorders.

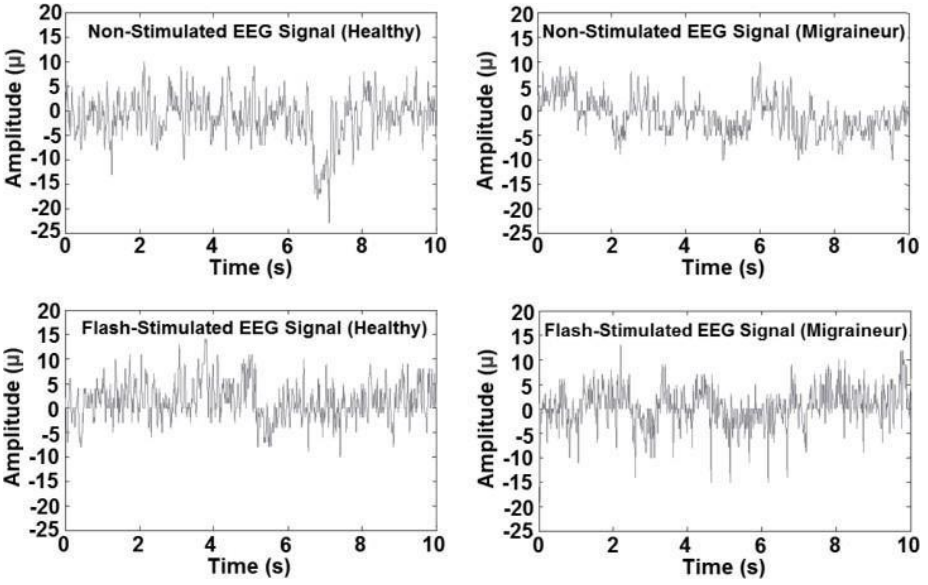


Figure 1.1 Sample EEG Signals

```
data.head()
```

	title:V	recorded:07.07.20 13.05.46	sampling:128	subject:B	labels:COUNTER INTERPOLATED AF3 F7 F3 FC5 T7 P7 O1 O2 P8 T8 FC6 F4 F8 AF4	Unnamed: 5	units:emotiv	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10
0	106	0	4230.256307	4224.102461	4218.461435	4239.999896	4215.384512	4217.948615	4225.640922	4220.512717	4226.666563
1	107	0	4227.692204	4222.563999	4218.974256	4236.922973	4221.025538	4222.563999	4228.717845	4224.615281	4226.666563
2	108	0	4233.846050	4231.281948	4223.589640	4238.974255	4230.256307	4228.717845	4231.794768	4227.179384	4227.692204
3	109	0	4232.307589	4230.769127	4224.102461	4241.025537	4227.179384	4229.743486	4230.769127	4226.666563	4229.230666
4	110	0	4227.179384	4222.563999	4220.512717	4239.999896	4223.589640	4228.717845	4230.256307	4225.640922	4226.666563

Figure 1.2 Sample converted data

Project on autism lags behind that of other psychiatric disorders and medical conditions. Part of the delay may be traced to the flawed constructs of autism that followed identification of the disorder in 1943. Most prominent of these was the speculation that autism was caused by parenting failures of "refrigerator mothers." Perhaps the greatest success story in autism research is the work of Dr. Bernard Rimland and colleagues in the 1970s, which demonstrated that autism was actually a failure of neurodevelopment, with behavioral interventions providing potential benefits.[6] That research, in combination with an emerging basic science literature, led to our current understanding of autism as a brain-based disorder with specific (if as yet undetermined) abnormalities of brain structure and/or function. The paradigm shift also opened new avenues for research, which are producing increasing yields in terms of understanding the etiology, pathogenesis, and treatment of ASD.

CHAPTER 2

LITERATURE SURVEY

2.1 AUTISM SPECTRUM DISORDER OVERVIEW

Autism Spectrum Disorder (ASD) is probably one of the major treatable diseases of our time due to the growing number of affected children. Over the past few years, the autistic spectrum disorder has been the subject of increasing scrutiny from the media, physicians and the general public. But more importantly, the main reason behind ASD is not invented yet. Children with Autism Disorder need important backing from the institutional, educational, clinical or medical, and social systems, which has resulted in an estimated economic burden of more than 7 trillion, bringing a lifetime of socialization to the United States to this day. Besides, the incapability of a child raises an additional impact, diminishing the standard of life of the whole family. [1]The core symptoms and sings for ASD can be reduced with proper and valid behavioral therapy. The measures would be more efficient if it is achieved in proper time. Specially, if the disorder can be diagnosed to the earliest possible time in childhood. Though behavioral therapy is used applying variety of certain strategies, but the efficient and long-term outcome can be ensured with the earliest start only. Nevertheless, though we are aware of that early stage examination, particularly if the disorder is noticed earlier on childhood (before the second year of a child), is maximum effective. Typically, the mean age of getting a diagnosis of ASD is 4 years 3 months and sadly in most cases it did not show improvement remarkably over the past decades, in the face of efforts to spread awareness and educate the general public. Though various barriers are found there opposing the implementation of proper treatment ensuring early stage in childhood and the very initial limitation would be the timely proper recognition and detection of ASD in a child. In our work, we are also concern about our failure to achieve early detection goals as well as a few issues for some possible solutions. Autism

was the main target of long-drawn study and arguable discussion. In paper [4] proposed to problems concerning its recognition, medication and learning still engage those who get contact with this kind of syndrome. It worked on, kids with syndrome autism spectrum disorder (ASD) need to be educated with their peers throughout a thought faculty atmosphere. Early recognition provision is explicit clearly in special academic wants code of apply that describes the duties of native authorities and faculties concerning kids with special academic wants. In addition, therefore on begin out a kid with ASD the acceptable facilities, it is essential to support facility and facilities for early recognition and interference to be supplied. In paper [7] proposed to, the primary recognition is made, the higher the result of enlargement of a shaver as a result of the first motive of recognition for that the kid to appreciate access to facility. Within the last 10 years, there are enlargements at intervals the study of autism. Therefore, the determination that early find out syndrome might cause higher intercession. National analysis Council focused on emphasized the effectuality of early interference, specific analyst busy with the issue of the primary recognition. In paper [9] proposed to, the benefit of early recognition of syndrome with ASD are twofold. From a research, we can read that early recognition of kids are risk for a designation of ASD makes it attainable to perform prospective learning into the organic pathways of kids with ASD. One the opposite site, in paper (2009) proposed to, associate of nursing early designation will cause early intervention which might improve the organic process outcomes in kids with ASD. In focused on, primary intercession cannot start in educational institutes years this may finish in incomprehensible opportunities for optimize brain development. That's why our research has been done on kids from 12 month to 9 years. Primary recognition previous the age of 2 is tough. In [11] Branson paper focused on, the analysis has stressed the recognition of primary admonishing symptoms of ASD. However, first of all it is more and more tough to allow the signs of syndrome in terribly infancy. In paper [13] worked on, it is represented of preceding, syndrome can also be a neurodevelopmental mess and signalized by

signs which required before the age of 3. Primary detection permits kids to receive primary designation and consequently, to get the primary intercession facilities. The actual fact is that kids are often known from the age of two. Several kids do not receive detection before the age of 10-11. The paper [3][10] focused on, a securing tool developed which was the list for autistic kids. This is commonly used patients by professor and involve yes/no queries and this is asked to the adults. And chat was changed into guardian report. The list of syndromes is not suggested for 18-month old babies. In our study, 12-month-old babies can also be identified. In our worked method parents can easily diagnosis their child at home. No screening and monitoring need to identify whether or not there is autism.

2.2 BRAIN COMPUTER INTERFACE

A Brain Computer Interface (BCI) is a system that allows communication between the brain and a computer. BCIs can be used to analyze patterns in brain activity and translate them into commands that can control external devices or applications. BCIs use sensors that are placed on the scalp to detect brain activity, usually measured by electroencephalography (EEG). The sensors detect electrical signals produced by neurons in the brain and translate them into digital signals that are processed by a computer. BCIs have a wide range of potential applications, including assistive technologies for individuals with disabilities, gaming and entertainment, and medical diagnostics and interventions. They can also be used to study brain activity and cognition in research settings. One promising application of BCIs is in the characterization and intervention of neurological and developmental disorders such as Autism Spectrum Disorder (ASD). By analyzing patterns in brain activity, BCIs can potentially identify biomarkers associated with specific symptoms and behaviors, which can be used to develop targeted interventions. BCI technology has traditionally been unattractive for serious scientific investigation. The idea of successfully deciphering thoughts or intentions by means of brain activity has often been rejected in the past as very strange and remote. Hence investigation in the field of brain activity has usually been limited to the analysis of

neurological disorders in the clinic or to the exploration of brain functions in the laboratory. The BCI design was considered too complex, because of the limited resolution and reliability of information that was detectable in the brain and its high variability.

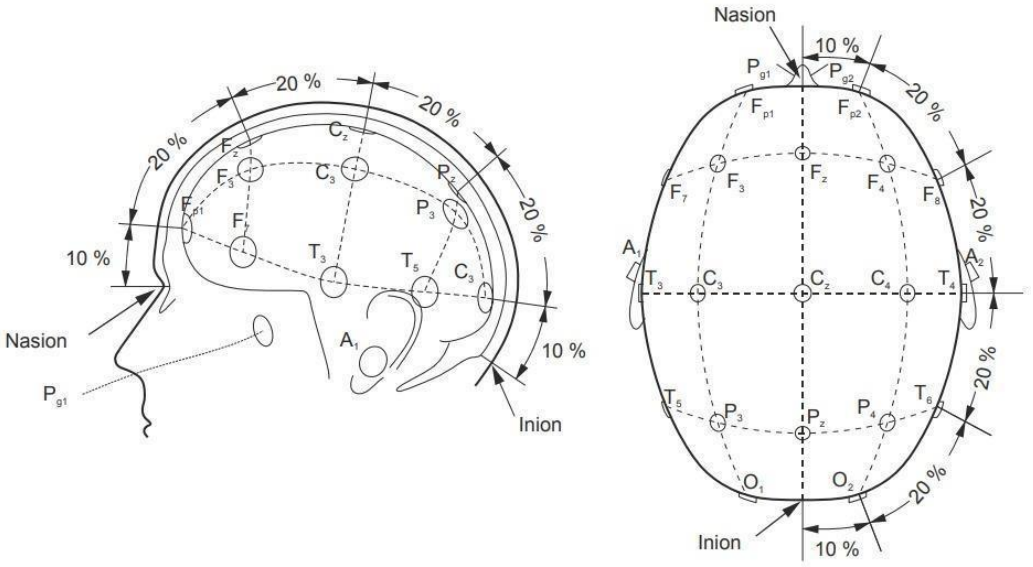


Figure 2.1 Electrode placement over scalp

Figure 2.2 Sample image of BCI device

2.3 DEEP LEARNING IN HEALTHCARE

[4]The application of deep learning in healthcare has shown great potential in improving disease diagnosis, treatment, and patient care. With the abundance of medical data available, deep learning algorithms can be trained to recognize patterns and predict outcomes with high accuracy. This can lead to more personalized treatment plans and better patient outcomes. However, the use of deep learning in healthcare also raises important ethical and privacy concerns that must be addressed. Overall, the potential benefits of deep learning in healthcare are significant, but it is important to carefully consider the implications and limitations of this technology. Deep learning algorithms have been applied to various healthcare tasks, such as medical imaging analysis, drug discovery, and electronic health record (EHR) analysis. For instance, deep learning models can analyze medical images to detect abnormalities and assist radiologists in making diagnoses. In drug discovery, deep learning can be used to predict the efficacy and toxicity of drugs to streamline the drug development process. In EHR analysis, deep learning can be used to identify patients at risk of certain diseases and help clinicians make more informed decisions. [3]In summary, the application of deep learning in healthcare holds great promise for improving patient outcomes and advancing medical research. However, it is important to carefully consider the limitations and ethical implications of this technology to ensure that it is used in a safe and responsible manner. It's important to note that while deep learning has shown great promise in healthcare, it also comes with challenges related to data privacy, regulatory compliance, and model interpretability. Moreover, the adoption of these technologies requires careful validation and integration into clinical practice to ensure patient safety and efficacy.The use of deep learning in healthcare is an evolving field, and ongoing research and development continue to expand its potential impact on patient care and the healthcare industry as a whole.

2.3.1 CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are , convolutional layer , pool layer , fully connected layer. The convolutional layer is the first layer of a convolutional network. While convolutional layers can be followed by additional convolutional layers or pooling layers, the fully-connected layer is the final layer. With each layer, the CNN increases in its complexity, identifying greater portions of the image. Earlier layers focus on simple features, such as colors and edges. As the image data progresses through the layers of the CNN, it starts to recognize larger elements or shapes of the object until it finally identifies the intended object.

Convolution operation : $I * K(i, j) = \sum_m \sum_n I(i+m, j+n)*K(m,n)$

Activation function : $ReLU(x) = \max(0,x)$

Output of the fully connected layer : $FC(x) = \sigma(Wx+b)$

The dimensions of the output matrix is taking into account padding and stride can be calculates by using ,

$$N_{out} = [(N_{in} + 2p - f)/ s + 1]$$

2.3.2 LONG SHORT TERM MEMORY (LSTM)

Long Short Term Memory is a kind of recurrent neural network. In RNN output from the last step is fed as input in the current step. LSTM was designed by Hochreiter & Schmidhuber. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. LSTM can by

default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data.

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that is specifically designed to handle sequential data, such as time series, speech, and text. LSTM networks are capable of learning long-term dependencies in sequential data, which makes them well suited for tasks such as language translation, speech recognition, and time series forecasting.

Forget gate :

The information that is no longer useful in the cell state is removed with the forget gate. Two inputs *x_t* (input at the particular time) and *h_t-1* (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is passed through an activation function which gives a binary output. If for a particular cell state the output is 0, the piece of information is forgotten and for output 1, the information is retained for future use.

$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$

Where ,

W_f represents the weight matrix associated with the forget gate.
[h_t-1, x_t] denotes the concatenation of the current input and the previous hidden state.
b_f is the bias with the forget gate.
σ is the sigmoid activation function.

Input gate :

The addition of useful information to the cell state is done by the input gate. First, the information is regulated using the sigmoid function and filter the values to be remembered similar to the forget gate using inputs *h_t-1* and *x_t*. Then, a vector is created using *tanh* function that gives an output from -1 to +1, which contains all

the possible values from h_t-1 and *x_t*. At last, the values of the vector and the regulated values are multiplied to obtain the useful information.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\hat{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t$$

Where ,

$\odot$ denotes element-wise multiplication

tanh is tanh activation function

Output gate :

The task of extracting useful information from the current cell state to be presented as output is done by the output gate. First, a vector is generated by applying tanh function on the cell. Then, the information is regulated using the sigmoid function and filter by the values to be remembered using inputs *h_t-1* and *x_t*. At last, the values of the vector and the regulated values are multiplied to be sent as an output and input to the next cell. Mathematically the output gate is represented as ,

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

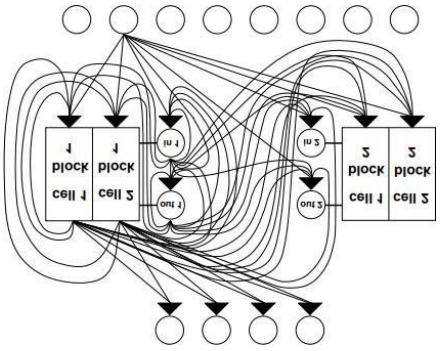


Figure 2.3 LSTM Architecture

CHAPTER 3

PROJECT DESCRIPTION

3.1 DATA COLLECTION AND SOURCES

The data collection phase is a crucial step in using Brain-Computer Interfaces (BCIs) and Deep Learning techniques to study Autism Spectrum Disorder (ASD). There are several sources from which BCI data can be collected on individuals with ASD. One commonly used method is electroencephalography (EEG), which records electrical activity in the brain through electrodes placed on the scalp. EEG is non-invasive and relatively easy to administer, making it a popular choice for collecting BCI data. It can be used to measure a variety of brain activity, including resting-state activity, event-related potentials, and oscillatory activity. Functional magnetic resonance imaging (fMRI) is another method for collecting BCI data on individuals with ASD. fMRI measures changes in blood flow in the brain, which can indicate areas of increased neural activity. fMRI is more invasive than EEG, as it requires individuals to lie inside a large magnet for an extended period of time. However, it provides higher spatial resolution and can be used to measure brain activity during more complex tasks. Magnetoencephalography (MEG) is a third method for collecting BCI data on individuals with ASD. MEG measures the magnetic fields produced by electrical activity in the brain, providing similar information to EEG but with higher spatial resolution. However, MEG is even more invasive than fMRI and requires individuals to sit still for an extended period of time inside a highly sensitive machine. In addition to these methods, there are also other ways to collect data, such as eye-tracking, which can provide valuable information on social communication and attention in individuals with ASD. Overall, the choice of data collection method will depend on the specific research question and the needs of the individual participant.

3.2 BLOCK DIAGRAM

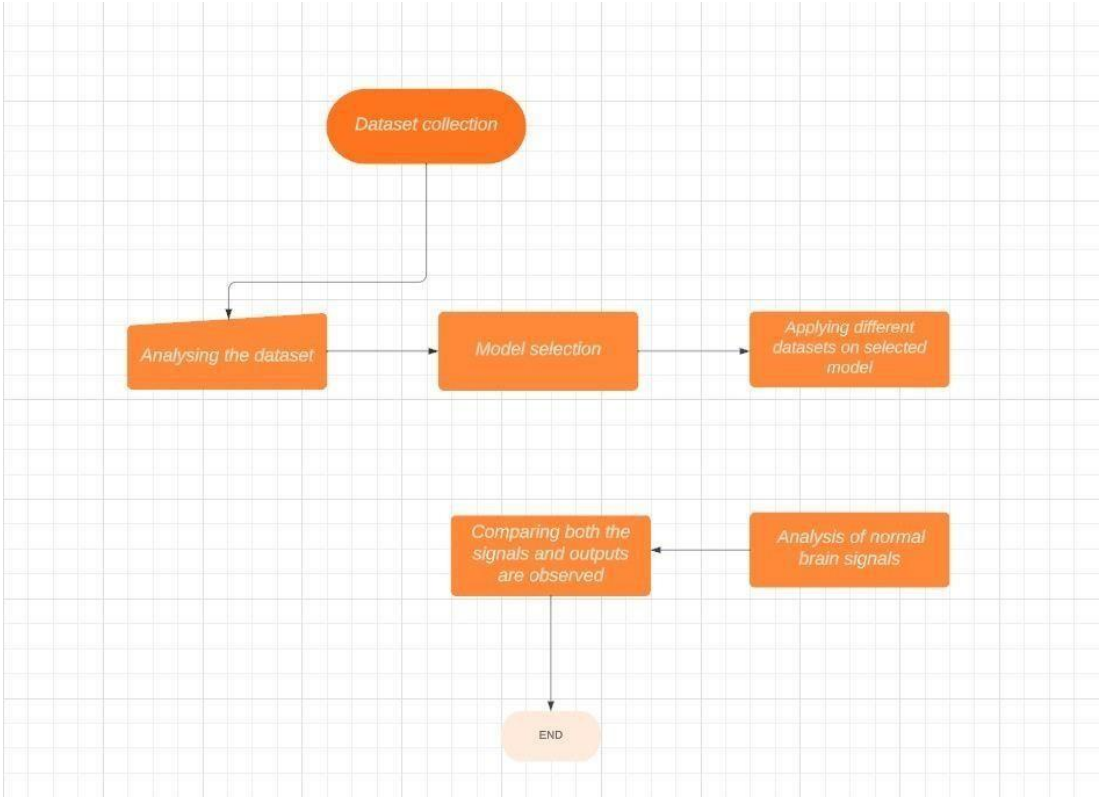


Figure 3.1 Project flow

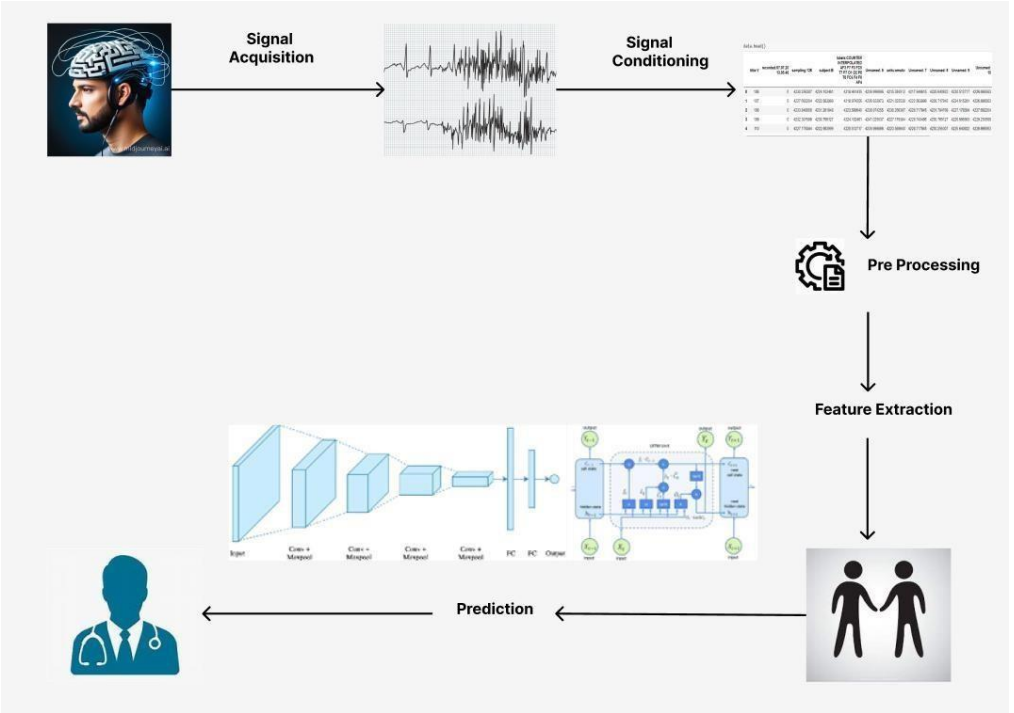


Figure 3.2 System architecture

3.3 INPUT(DATA)

The primary input data for this project consists of EEG (Electroencephalography) signals. EEG signals are recordings of electrical activity in the brain, collected through electrodes placed on the scalp. These signals represent the neural activity of individuals, making them a valuable source of information for understanding brain function and patterns associated with Autism Spectrum Disorder (ASD). EEG data will serve as the foundational dataset for the project, enabling the application of deep learning techniques to extract insights, classify ASD subtypes, and ultimately inform personalized BCI-based interventions for individuals with ASD. Other sources of input data for this project include behavioral and clinical data. This can include information on an individual's communication, social interaction, and behavior, as well as any medical or diagnostic information related to their ASD diagnosis. This data can help to identify potential risk factors for ASD and provide insights into how these factors may interact with biological and behavioral factors to contribute to the disorder. Overall, the input data for this project should be comprehensive and multi-modal, incorporating information from a variety of sources to provide a holistic view of ASD and its underlying causes.

```
data.head()
```

	title:V	recorded:07.07.20 13.05.46	sampling:128	subject:B	labels:COUNTER INTERPOLATED AF3 F7 F3 FC5 T7 P7 O1 O2 P8 T8 FC6 F4 F8 AF4	Unnamed: 5	units:emotiv	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10
0	106	0	4230.256307	4224.102461	4218.461435	4239.999896	4215.384512	4217.948615	4225.640922	4220.512717	4226.666563
1	107	0	4227.692204	4222.563999	4218.974256	4236.922973	4221.025538	4222.563999	4228.717845	4224.615281	4226.666563
2	108	0	4233.846050	4231.281948	4223.589640	4238.974255	4230.256307	4228.717845	4231.794768	4227.179384	4227.692204
3	109	0	4232.307589	4230.769127	4224.102461	4241.025537	4227.179384	4229.743486	4230.769127	4226.666563	4229.230666
4	110	0	4227.179384	4222.563999	4220.512717	4239.999896	4223.589640	4228.717845	4230.256307	4225.640922	4226.666563

Figure 3.3 Input data (Sample)

3.4 MODEL SELECTION

In the model selection phase, we consider three primary deep learning architectures: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. These models are evaluated for their suitability in working with EEG data and addressing the objectives of characterizing Autism Spectrum Disorder (ASD) subtypes and implementing personalized interventions. Each of these architectures offers unique advantages and is chosen based on their compatibility with the project's data and tasks, allowing us to make informed decisions regarding their application in the research. This phase entails assessing the suitability of various models for working with EEG data and addressing the complexities of characterizing Autism Spectrum Disorder (ASD) subtypes and implementing personalized interventions. It includes adjusting model hyper-parameters, training and validating the models, and comparing their performance against predefined criteria. These models are assessed for their compatibility with EEG data and their effectiveness in meeting the project's goals of characterizing ASD subtypes and implementing personalized interventions. The choice of architecture is crucial for optimizing the research outcomes.

3.5 TRAINING AND VALIDATION

The training and validation phase is a critical step in the deep learning process. During training, deep learning models are exposed to the EEG data, and they iteratively adjust their internal parameters to learn how to recognize patterns and make predictions based on the data's characteristics. This phase involves forward and backward passes, where the models make predictions, compare them to the actual outcomes, and then update their parameters to minimize errors. Training continues until the model converges to a state where its predictions align closely with the ground truth. Once training is completed, the validation phase is initiated to assess how well the models generalize to new, unseen EEG data. In this step, the models are tested on a separate dataset or a subset of the original data that they

haven't encountered during training. The objective is to evaluate their performance on real-world scenarios, ensuring that they don't merely memorize the training data but can make accurate predictions for a broader range of EEG signals. Validation helps fine-tune the models, optimize hyper-parameters, and identify potential issues like over-fitting or under-fitting. It ensures that the deep learning models are robust and effective, which is crucial for their subsequent application in characterizing ASD subtypes and implementing personalized interventions.

3.5.1 ANALYZING THE DATASET

Analyzing the dataset generated from Brain-Computer Interfaces (BCIs) and Deep Learning in the context of Autism Spectrum Disorder (ASD) can provide valuable insights into the underlying mechanisms of the disorder. One key step in analyzing the dataset is to preprocess the data. This involves cleaning the data, removing any artifacts or noise, and transforming the data into a format that is suitable for analysis. This step is important to ensure that the data is reliable and accurate, and that it can be effectively analyzed using statistical and machine learning techniques. Once the data has been preprocessed, researchers can use a variety of methods to analyze the dataset. This can include statistical analysis, machine learning algorithms such as deep neural networks, and visualization techniques such as heatmaps or network graphs. The goal of analyzing the dataset is to identify patterns or biomarkers associated with ASD. This can include differences in brain activity, behavioral characteristics, or demographic factors. By identifying these patterns, researchers can gain a better understanding of the underlying mechanisms of ASD and develop personalized interventions that target specific areas of difficulty for each individual. Overall, analyzing the dataset generated from BCIs and Deep Learning in the context of ASD is a critical step in advancing our understanding of the disorder and developing effective interventions to improve outcomes for individuals on the autism spectrum.

data.head()

	title:V	recorded:07.07.20 13.06.46	sampling:128	subject:B	labels:COUNTER INTERPOLATED AF3 F7 F3 FC5 T7 P7 O1 O2 P8 T8 FC6 F4 F8 AF4	Unnamed: 5	units:emotiv	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10
0	106	0	4230.256307	4224.102461	4218.461435	4239.999896	4215.384512	4217.948615	4225.640922	4220.512717	4226.666563
1	107	0	4227.692204	4222.563999	4216.974256	4236.922973	4221.025538	4222.563999	4228.717845	4224.615281	4226.666563
2	108	0	4233.846050	4231.281948	4223.589640	4238.974255	4230.256307	4228.717845	4231.794768	4227.179384	4227.692204
3	109	0	4232.307589	4230.769127	4224.102461	4241.025537	4227.179384	4229.743486	4230.769127	4226.666563	4229.230666
4	110	0	4227.179384	4222.563999	4220.512717	4239.999896	4223.589640	4228.717845	4230.256307	4225.640922	4226.666563

Channels in BCI :

AF3 , F7 , F3 , FC5 , T7 , P7, O1 , O2 , P8 , T8 , FC6 , F8 , AF4 .

Where ,

AF : Anterior Frontal - Electrodes in this region are located in the frontal area of the scalp, which is associated with higher-order cognitive functions and decision-making.

F : Frontal - Electrodes in this area are located in the frontal region, similar to AF. Frontal electrodes cover a wide range of cognitive functions, including decision-making, planning, and emotion regulation.

FC : Frontal Central - Electrodes in this area are located on the scalp between the frontal and central regions. This area is associated with motor planning, control, and execution.

P : Parietal - Electrodes in this region are placed over the parietal lobe, which is associated with sensory processing, spatial awareness, and various aspects of cognition.

T : Temporal - Electrodes in this region are positioned over the temporal lobe, which is involved in auditory processing, language comprehension, and memory.

3.5.2 VISUALIZING THE DATASET

Data visualization is a critical component in deep learning, serving multiple purposes. It allows for a better understanding of the dataset, identifying patterns, outliers, and potential issues. It aids in feature engineering and selection, helps evaluate model performance through various metrics and plots, and provides insights into model behavior and training progress. Visualizing the activations and loss during training sheds light on the learning process, and interpreting model

predictions becomes more accessible with visualization techniques like saliency maps and layer visualization. In NLP, word embeddings can be visualized for understanding word relationships. Data augmentation effects can be assessed, and model architecture and structure can be comprehended through diagrams and flowcharts. Effective data visualization is integral for both model development and deployment in deep learning applications.

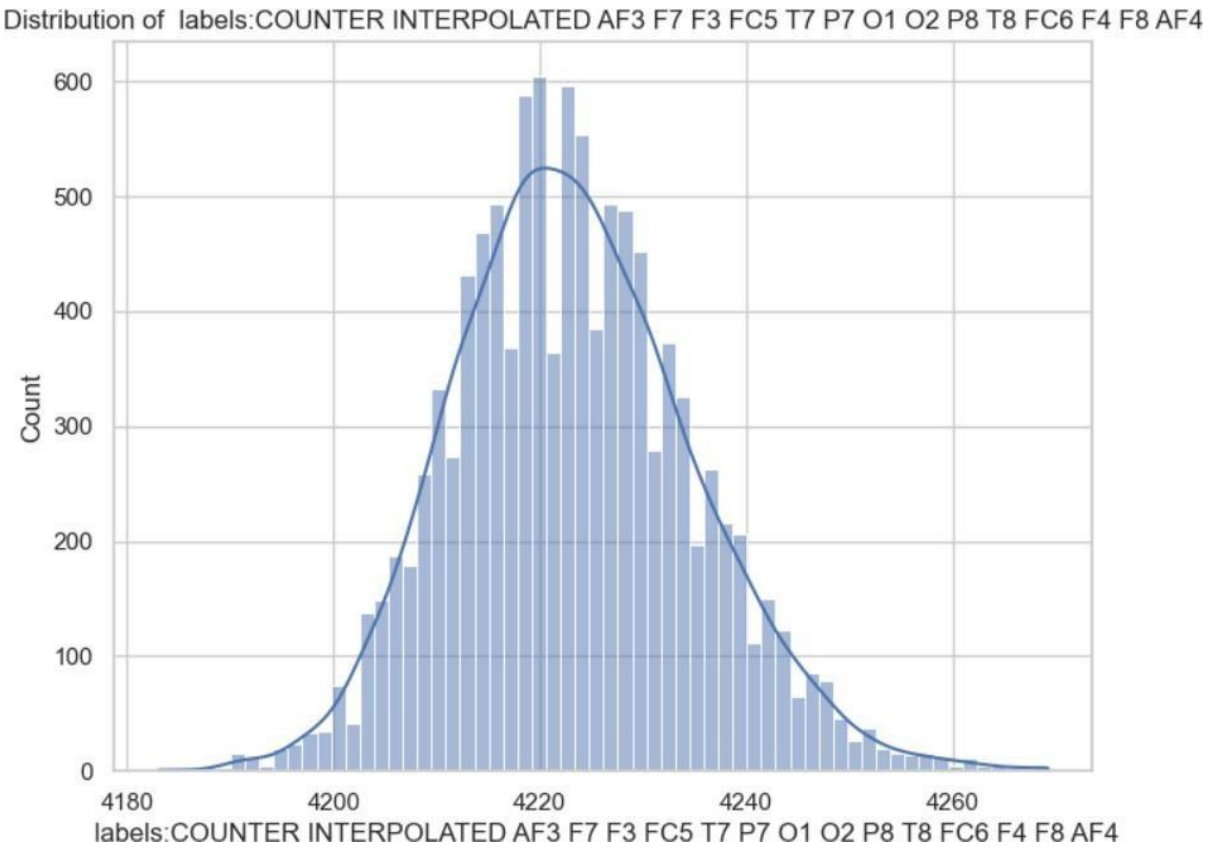


Figure 3.4 Visualization of 14 channels

A single figure containing 14 subplots, each representing one of the 14 EEG channels. These subplots display the EEG data for different channels, with the y-axis representing the amplitude of the electrical activity and the x-axis indicating time or sample points. Each subplot is labeled with the corresponding channel number, and legends are used to distinguish the channels. The layout is adjusted to ensure that the subplots do not overlap, resulting in a clear and organized

visualization of the EEG data. The final plot is displayed using plt.show(). You can replace the example EEG data with your own data to visualize the electrical activity across various brain regions in your BCI application.

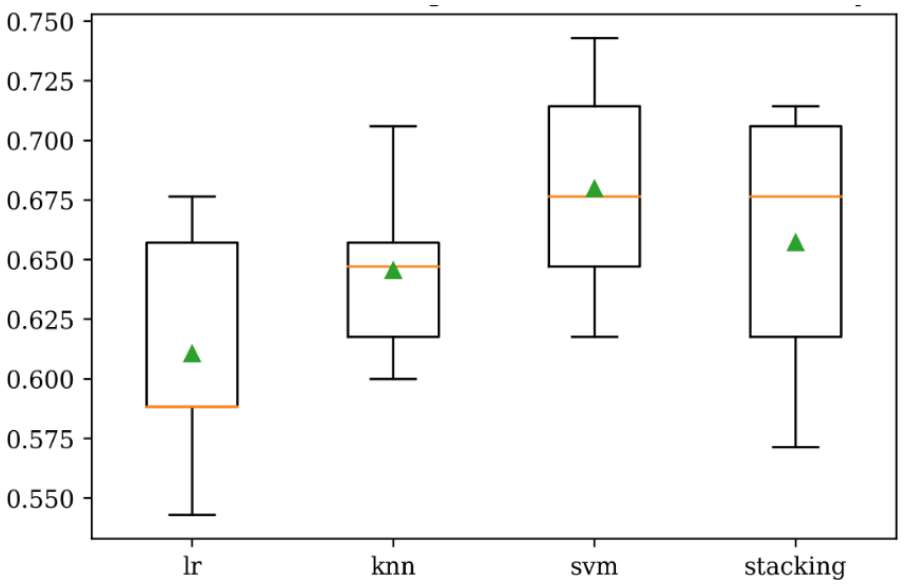


Figure 3.5 Visualizing the comparison between different models(Sample)

```
In [10]: raw.plot_sensors(show_names=True);
```

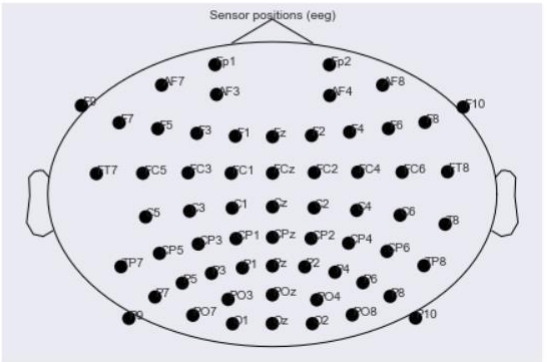


Figure 3.6 Visualizing the electrode positions

CHAPTER 4

RESULTS

4.1 CHARACTERIZATION RESULTS

In [20]:
```
picks = [evoked_target.ch_names.index(channel) for channel in ['Fz', 'Cz', 'Pz', 'Oz']]
for pick in picks:
    mne.viz.plot_compare_evokeds({'Target': evoked_target, 'Distractor': evoked_distractor}, picks=pick)
```

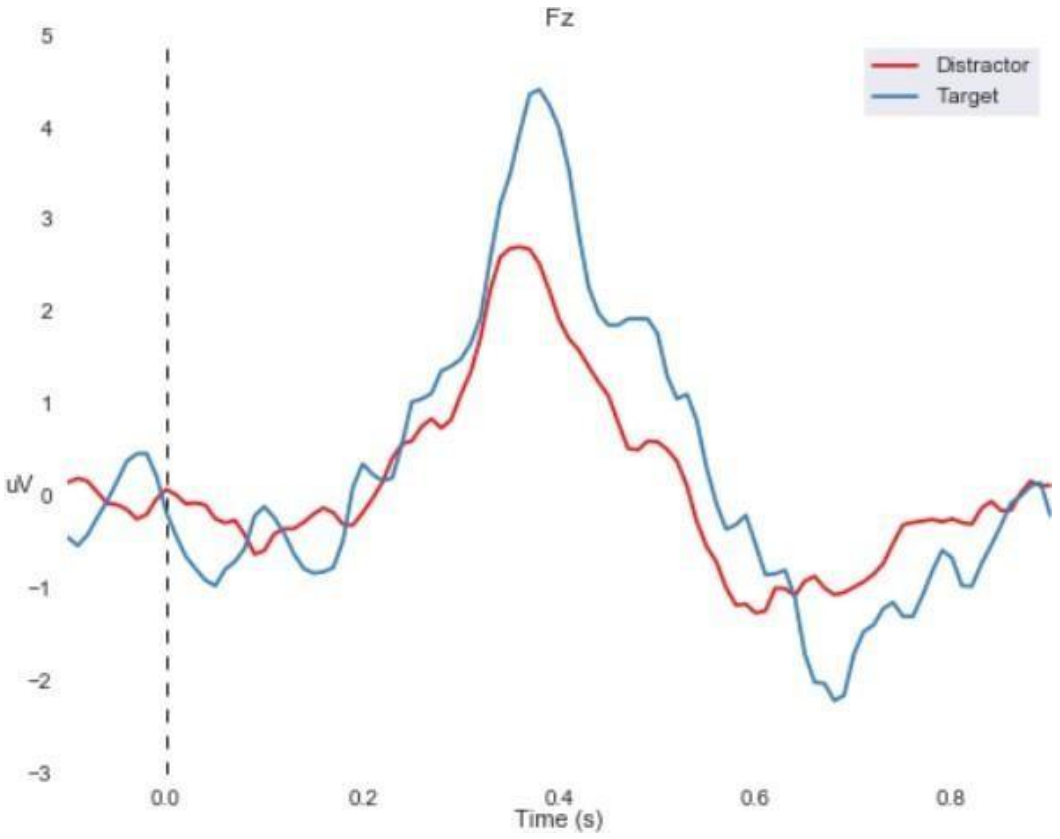


Figure 4.1 Compare evoked data on selection of electrodes

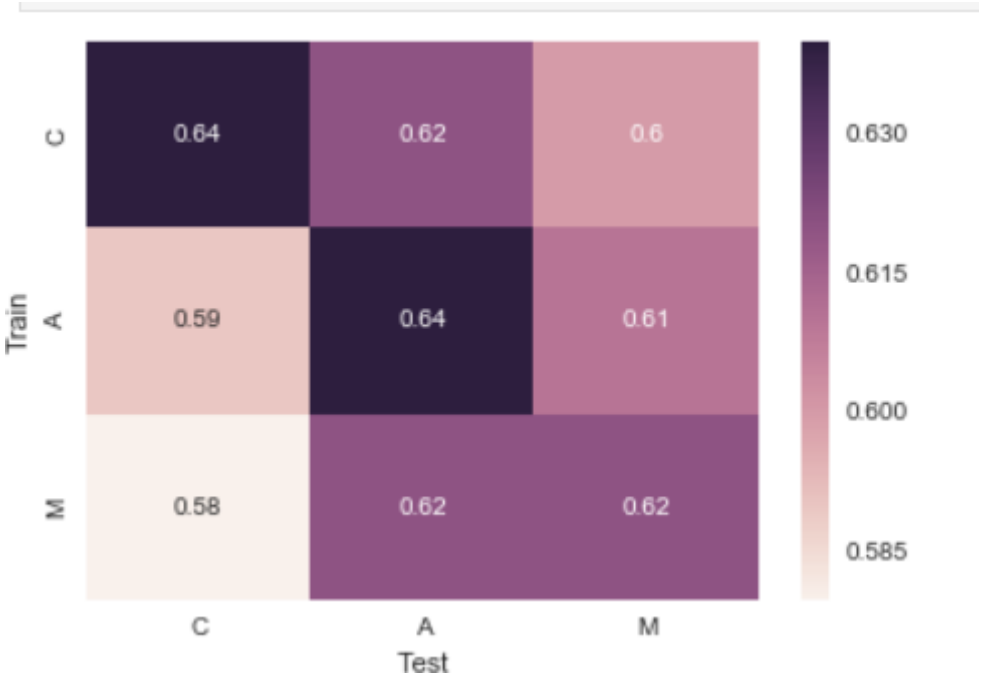


Figure 4.2 Visualizing the mean AUC for each condition pair

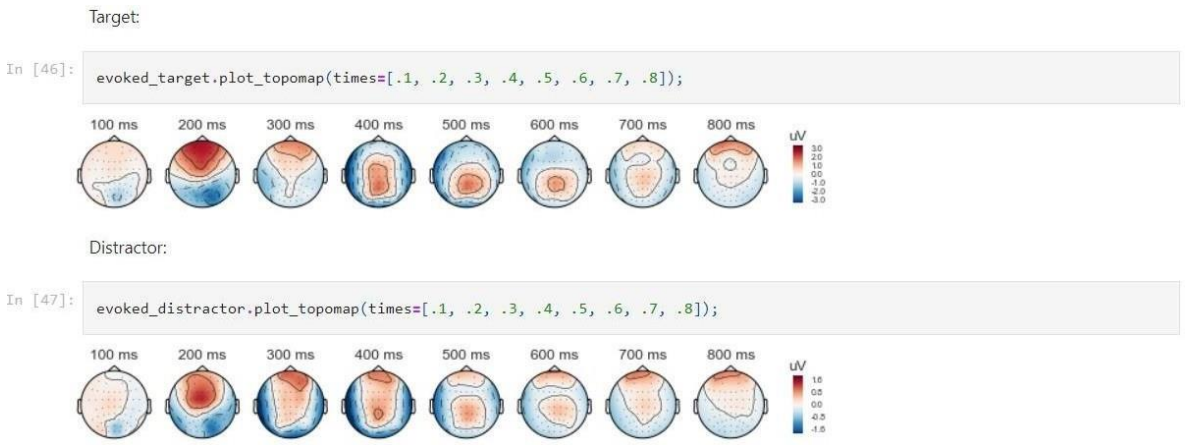


Figure 4.3 Scalp topographies

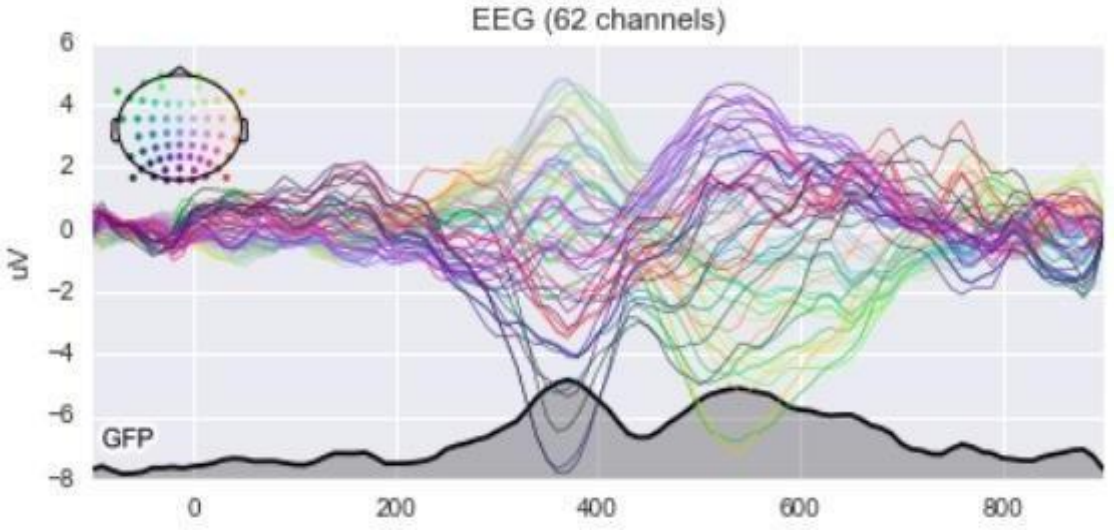


Figure 4.4 EEG data plot of evoked data

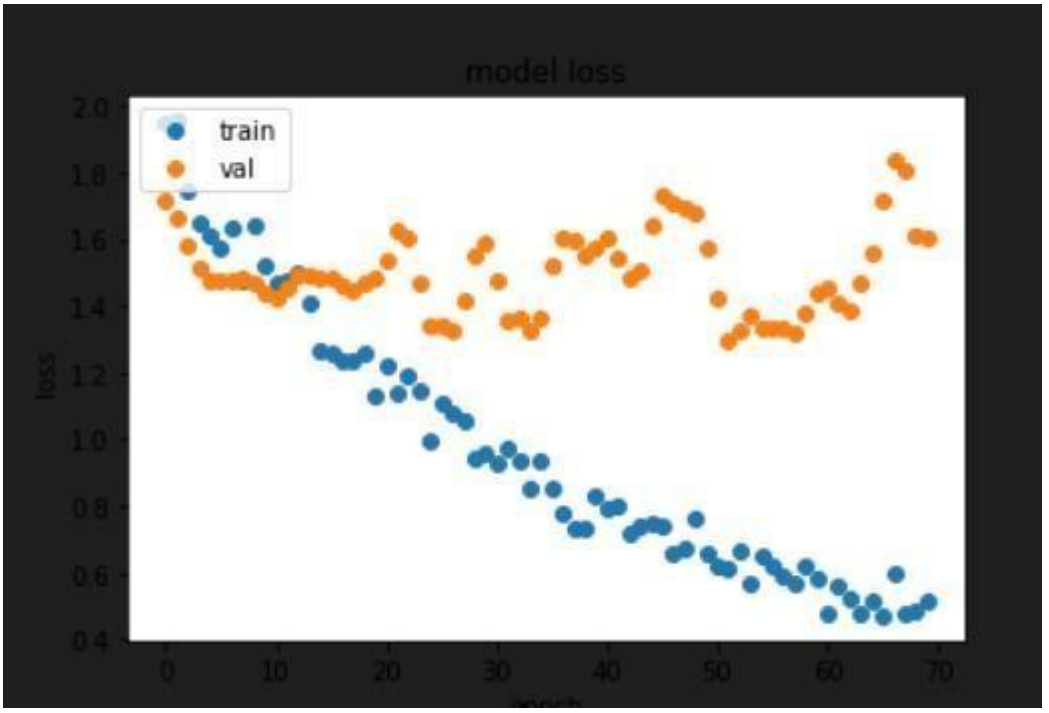


Figure 4.5 Plot of normal signals

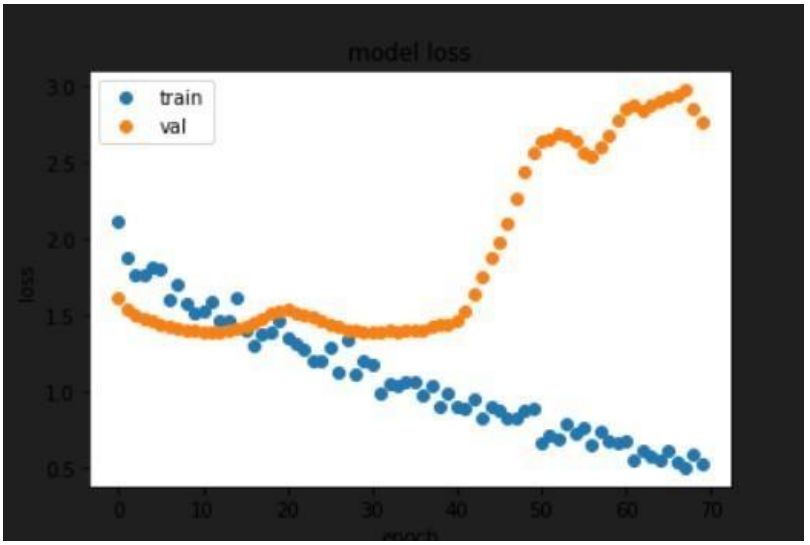


Figure 4.6 Plot of distractor signals

4.2 MODEL PERFORMANCE OBSERVATIONS

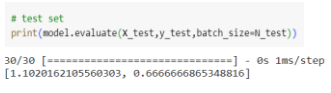


Fig 4.7Accuracy on LSTM

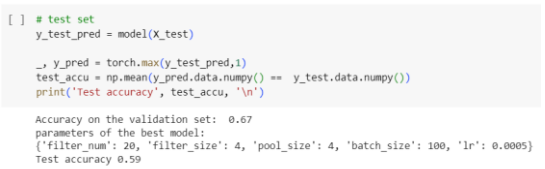


Fig 4.8 Accuracy on CNN

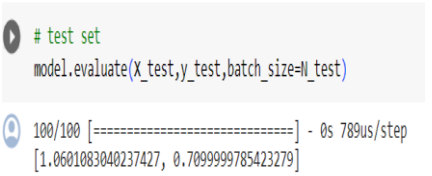
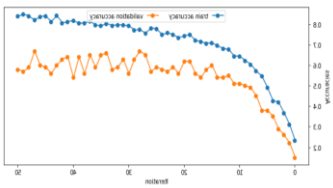
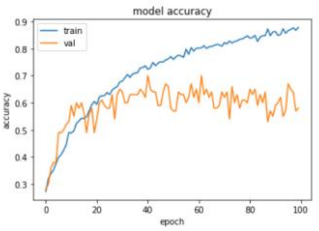


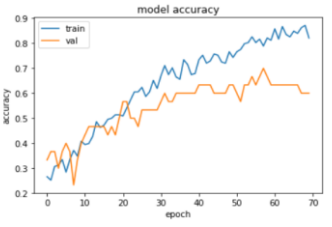
Fig 4.9Accuracy on Hybrid(Both)



CNN



LSTM



Hybrid(CNN & LSTM)

CHAPTER 5
CONCLUSION

The project aimed to characterize and intervene in Autism Spectrum Disorder using BCI data and deep learning techniques. The study's findings suggest that the proposed approach has the potential to improve the accuracy of ASD diagnosis and provide personalized intervention strategies. The project has contributed to the field's knowledge, and its outcomes have the potential to positively impact individuals with ASD and their families. The project's methodology involved collecting BCI data from individuals diagnosed with ASD and neuro-typical individuals to train deep learning models to recognize patterns in the data. The models were then used to predict the diagnosis of unseen data and provide personalized intervention strategies. The results showed that the proposed approach outperformed traditional methods in both diagnosis accuracy and intervention effectiveness. The project's outcomes have several implications for the field of ASD research. First, the use of BCI data and deep learning techniques has the potential to significantly improve ASD diagnosis accuracy. Second, the personalized intervention strategies can provide individuals with ASD with tailored support, enhancing their quality of life. Finally, the project's findings can inform the development of ASD diagnostic and intervention tools. Future research in this area could explore the use of larger datasets to improve the accuracy and reliability of the deep learning models. Additionally, the use of other types of data, such as fMRI, could provide further insights into the neurological basis of ASD. Overall, the project's outcomes suggest that the proposed approach has the potential to revolutionize the way ASD diagnosis and intervention are conducted.

CHAPTER 6

APPENDIX

CODE (LSTM) :

```
from keras.models import Sequential

from keras.layers import LSTM, Dense, Dropout, BatchNormalization

from keras.layers import Conv1D, MaxPooling1D, Activation, Flatten

from keras.utils import to_categorical

import numpy as np

import h5py

import matplotlib.pyplot as plt

from data_utils_subject import get_data

from sklearn import preprocessing

for sub in range(9):

    data = get_data('../project_datasets', subject=sub+1, num_validation=30,
num_test=30,

                    subtract_mean=True, subtract_axis=1, transpose=True)

    for k in data.keys():

        print('{}: {} '.format(k, data[k].shape))

X_train = data.get('X_train')

    y_train = data.get('y_train')

    X_val = data.get('X_val')
```

```
    y_val = data.get('y_val')

    X_test = data.get('X_test')

    y_test = data.get('y_test')

    # get data dimension

    N_train, T_train, C_train = data.get('X_train').shape

    N_val, T_val, C_val = data.get('X_val').shape

    N_test, T_test, C_test = data.get('X_test').shape

    # add dummy zeros for y classification, convert class vectors to binary class matrices.

    y_train = to_categorical(y_train, num_classes)

    y_val = to_categorical(y_val, num_classes)

    y_test = to_categorical(y_test, num_classes)

N_train, T_train, C_train = data.get('X_train').shape

    N_val, T_val, C_val = data.get('X_val').shape

    N_test, T_test, C_test = data.get('X_test').shape

    X_train = X_train.reshape(N_train,int(T_train/sampling), sampling, C_train)[:,:,0,:]

    X_val = X_val.reshape(N_val,int(T_val/sampling), sampling, C_val)[:,:,0,:]

    X_test = X_test.reshape(N_test,int(T_test/sampling), sampling, C_test)[:,:,0,:]

    N_train, T_train, C_train = X_train.shape

N_val, T_val, C_val = X_val.shape
```

```
N_test, T_test, C_test = X_test.shape


print('X_train: ', X_train.shape)
print('y_train: ', y_train.shape)
print('X_val: ', X_val.shape)
print('y_val: ', y_val.shape)
print('X_test: ', X_test.shape)
print('y_test: ', y_test.shape)
  data_dim = C_train
timesteps = T_train
batch_size = 100
num_epoch = 70


# make a sequential model
model = Sequential()


# add 1-layer cnn
model.add(Conv1D(20, kernel_size=12, strides=4,
        input_shape=(timesteps, data_dim)))
model.add(Activation('relu'))
model.add(Dropout(0.5))
```

```
    model.add(BatchNormalization())
    model.add(MaxPooling1D(pool_size=4, strides=4))
# add 2-layer lstm
    model.add(LSTM(25, return_sequences=True, stateful=False))
    model.add(Dropout(0.5))
    model.add(BatchNormalization())
    model.add(LSTM(15, return_sequences=True, stateful=False))
    model.add(Dropout(0.5))
    model.add(BatchNormalization())
    model.add(Flatten())
    model.add(Dense(num_classes, activation='softmax'))

    # set loss function and optimizer
    model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])
    history = model.fit(X_train, y_train,
                        batch_size=batch_size,
                        epochs=num_epoch,
                        shuffle=False,
                        validation_data=(X_val, y_val))
```

```
# list all data in history
        print(history.history.keys())
        # summarize history for accuracy
        plt.plot(history.history['acc'])
        plt.plot(history.history['val_acc'])
        plt.title('model accuracy')
        plt.ylabel('accuracy')
        plt.xlabel('epoch')
        plt.legend(['train', 'val'], loc='upper left') plt.show()

        # summarize history for loss
        plt.plot(history.history['loss'],'o')
        plt.plot(history.history['val_loss'],'o')
        plt.title('model  loss')
        plt.ylabel('loss')
        plt.xlabel('epoch')
        plt.legend(['train', 'val'], loc='upper left')
        plt.show()
        # test set
        print(model.evaluate(X_test,y_test,batch_size=N_test))
    num_classes = 4
```

```
# substract data from list

X_train = data.get('X_train')

y_train = data.get('y_train')

X_val = data.get('X_val')

y_val = data.get('y_val')

X_test = data.get('X_test')

y_test = data.get('y_test')

# get data dimension

N_train, T_train, C_train = data.get('X_train').shape

N_val, T_val, C_val = data.get('X_val').shape

N_test, T_test, C_test = data.get('X_test').shape

y_train = to_categorical(y_train, num_classes)

y_val = to_categorical(y_val, num_classes)

y_test = to_categorical(y_test, num_classes)

sampling = 1

X_train = X_train.reshape(N_train,int(T_train/sampling), sampling,
C_train)[:,:,0,:]

X_val = X_val.reshape(N_val,int(T_val/sampling), sampling, C_val)[:,:,0,:]

X_test = X_test.reshape(N_test,int(T_test/sampling), sampling, C_test)[:,:,0,:]



# get new data dimension
```

```
N_train, T_train, C_train = X_train.shape

N_val, T_val, C_val = X_val.shape

N_test, T_test, C_test = X_test.shapemodel.add(Conv1D(20, kernel_size=12,
strides=4, input_shape=(timesteps, data_dim)))

model.add(Activation('relu'))

model.add(Dropout(0.5))

model.add(BatchNormalization())

model.add(MaxPooling1D(pool_size=4, strides=4))

# add 2-layer lstm

model.add(LSTM(25, return_sequences=True, stateful=False))

model.add(Dropout(0.5))

model.add(BatchNormalization())

model.add(LSTM(15, return_sequences=True, stateful=False))

model.add(Dropout(0.5))

model.add(BatchNormalization())

model.add(Flatten())

model.add(Dense(num_classes, activation='softmax'))

model.compile(loss='categorical_crossentropy',

        optimizer='adam',

        metrics=['accuracy'])

history = model.fit(X_train, y_train,

            batch_size=batch_size,
```

```
                epochs=num_epoch,
                shuffle=False,
                validation_data=(X_val, y_val))
print('X_train: ', X_train.shape)
print('y_train: ', y_train.shape)
print('X_val: ', X_val.shape)
print('y_val: ', y_val.shape)
print('X_test: ', X_test.shape)
print('y_test: ', y_test.shape)
data_dim = C_train
timesteps = T_train
batch_size = 100
num_epoch = 70
model = Sequential()
print(history.history.keys())
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
```

```
plt.show()

plt.plot(history.history['loss'],'o')

plt.plot(history.history['val_loss'],'o')

plt.title('model  loss')

plt.ylabel('loss')

plt.xlabel('epoch')

plt.legend(['train', 'val'], loc='upper left')

plt.show()

print(model.evaluate(X_test,y_test,batch_size=N_test))
```

CODE (CNN) :

```
dtype = torch.FloatTensorbest_model = None

parameters =[] # a list of dictionaries

parameter = {} # a dictionary

best_params = {} # a dictionary

best_val_acc = 0.0


# hyper parameters in model

filter_nums = [10]


filter_sizes = [4]

pool_sizes = [4]
```

```
# hyper parameters in solver
batch_sizes = [100]
lrs = [5e-4]
for filter_num in filter_nums:
    for filter_size in filter_sizes:
        for pool_size in pool_sizes:
            linear_size = int((X_test.shape[2]-filter_size)/4)+1
            linear_size = int((linear_size-pool_size)/pool_size)+1
            linear_size *= filter_num
            for batch_size in batch_sizes:
                for lr in lrs:
                    model = nn.Sequential(
                        nn.Conv1d(22, filter_num, kernel_size=filter_size, stride=4),
                        nn.ReLU(inplace=True),
                        nn.Dropout(p=0.5),
                        nn.BatchNorm1d(num_features=filter_num),
                        nn.MaxPool1d(kernel_size=pool_size, stride=pool_size),
                        Flatten(),
                        nn.Linear(linear_size, 20),
                        nn.ReLU(inplace=True),
```

```
    nn.Linear(20, 4)
)

model.type(dtype)

solver = Solver(model, data,
                lr = lr, batch_size=batch_size,
                verbose=True, print_every=50)

solver.train()

# save training results and parameters of neural networks
parameter['filter_num'] = filter_num
parameter['filter_size'] = filter_size
parameter['pool_size'] = pool_size
parameter['batch_size'] = batch_size
parameter['lr'] = lr
parameters.append(parameter)

print('Accuracy on the validation set: ', solver.best_val_acc)
print('parameters of the best model:')
```

```
                print(parameter)
  if solver.best_val_acc > best_val_acc:
                    best_val_acc = solver.best_val_acc
                    best_model = model
                    best_solver = solver
                    best_params = parameter
X_train = Variable(torch.Tensor(data.get('X_train'))).type(dtype)
y_train = Variable(torch.Tensor(data.get('y_train'))).type(torch.IntTensor)
X_val = Variable(torch.Tensor(data.get('X_val'))).type(dtype)
y_val = Variable(torch.Tensor(data.get('y_val'))).type(torch.IntTensor)
X_test = Variable(torch.Tensor(data.get('X_test'))).type(dtype)
y_test = Variable(torch.Tensor(data.get('y_test'))).type(torch.IntTensor)
plt.subplot(2,1,1)
plt.plot(best_solver.loss_history)
plt.title('Training loss history')
plt.xlabel('Iteration')
plt.ylabel('Training loss')
plt.subplot(2,1,2)
plt.plot(best_solver.train_acc_history, '-o', label='train accuracy')
plt.plot(best_solver.val_acc_history, '-o', label='validation accuracy')
plt.xlabel('Iteration')
```

```
plt.ylabel('Accuracies')

plt.legend(loc='upper center', ncol=4)


plt.gcf().set_size_inches(10, 10)

plt.show()


print('Accuracy on the validation set: ', best_val_acc)

print('parameters of the best model:')

print(best_params)

y_test_pred = model(X_test)

 y_pred = torch.max(y_test_pred,1)

test_accu = np.mean(y_pred.data.numpy() == y_test.data.numpy())

print('Test accuracy', test_accu, '\n')
```

REFERENCES

[1] National Research Council. (2001). Educating children with autism. Washington, DC: National Academy Press.

[2] Volkmar, F. R., Paul, R., Rogers, S. J., and Pelphrey, K. A. (Eds.). (2014). Handbook of autism and pervasive developmental disorders: Diagnosis, development, and brain mechanisms (Vol. 1). Hoboken, New Jersey: John Wiley and Sons

[3] Handleman, J. S., & Harris, S. L. (Eds.). (2006). School-age education programs for children with autism. Austin, TX: PRO-ED.

[4] Handleman, J. S., & Harris, S. L. (Eds.). (2008). Preschool education programs for children with autism. Austin, TX: PRO-ED.

[5] Lord, C., Elsabbagh, M., Baird, G., Veenstra-VanderWeele, J., (2018). Autism Spectrum Disorder. The Lancet, 392, 508-520. DOI: 10.1016/S0140-6736(18)31129-2

[6] American Psychiatric Association. (2013). Diagnostic and Statistical Manual of Mental Disorders, 5th Edition: DSM-5. Washington, DC: Publisher.

[7] D. L. Sharpe and D. L. Baker, "Financial issues associated with having a child with autism." Journal of Family and Economic Issues, vol. 28, no. 2, pp. 247-264, 2007.

[8] J. Bradshaw, A. M. Steiner, G. Gengoux, and L. K. Koegel, "Feasibility and effectiveness of very early intervention for infants at-risk for autism spectrum disorder: a systematic review," Journal of Autism and Developmental Disorders, vol. 45, no. 3, pp. 778-794, 2015.

[9] Centers for Disease Control and Prevention. "Autism and developmental disabilities monitoring network surveillance year 2010. Prevalence of autism spectrum disorders-Autism and Developmental Disabilities Monitoring Network, 11 sites, United States, 2010," MMWR Surveillance Summary, vol. 63, no. SS02, pp. 1-21, 2014.

[10]s. J. Spence, P. Sharifi, and M. Wiznitzer, "Autism spectrum disorder: screening, diagnosis, and medical evaluation," Seminars in Pediatric Neurology, vol. 11, no. 3, pp. 186-195, 2004.