EEG based Diagnosis

Mental Health

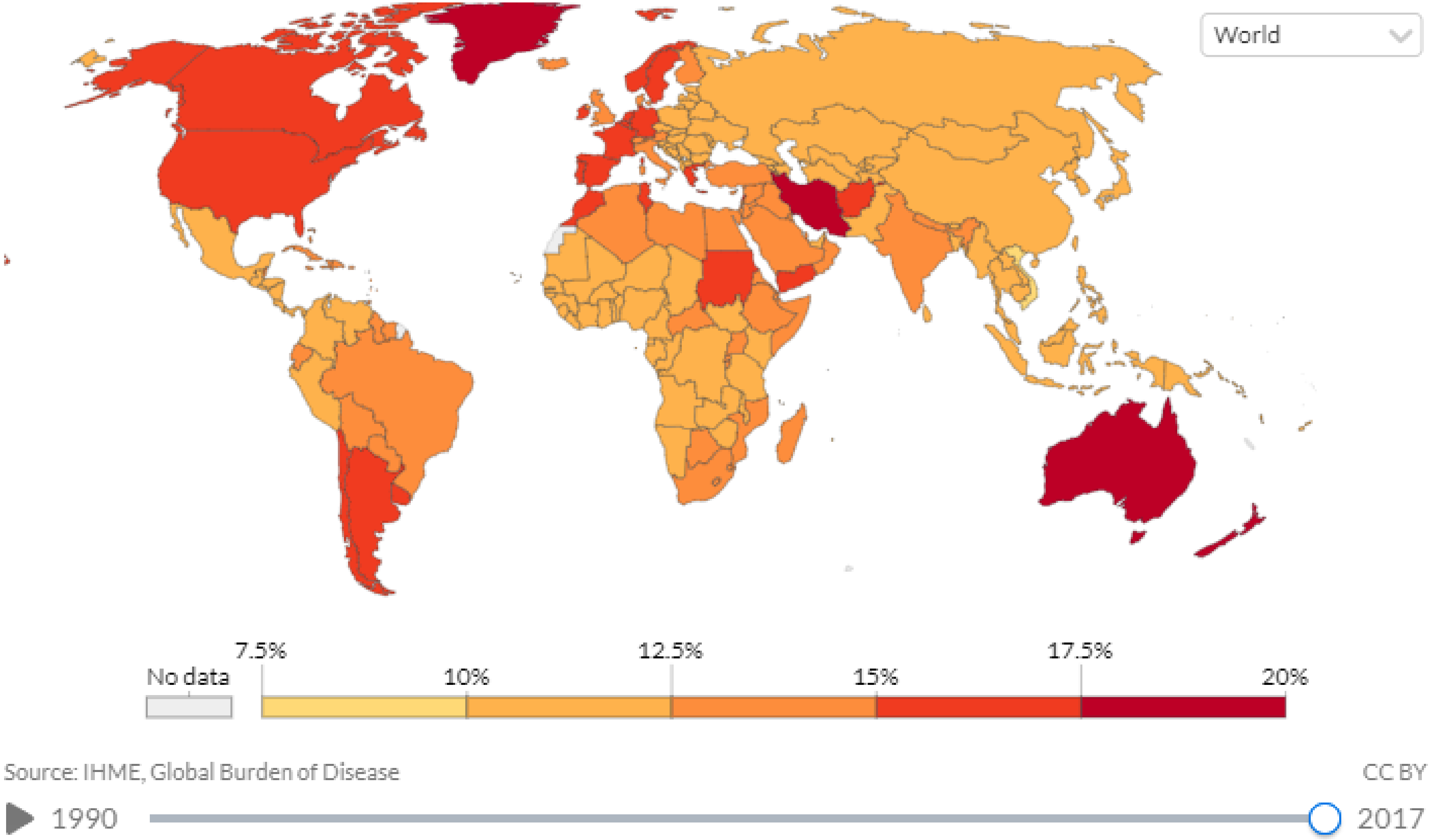
- Mental health includes our emotional, psychological, and social well-being.
- It is an important component of human health which describes the manner in which people think, feel and act.
- Good mental health is highly essential for building a healthy and progressive society.
- Globally, there has been a rapid increase in the people who are suffering from certain type of mental health disorder.
- In 2017, an estimated 11.2 million adults in the U.S., or about 4.5% of adults, had a severe psychological condition, according to the National Institute of Mental Health (NIMH).
- This poses a big challenge for each and every country as huge economic and social burdens are associated with mental disorders which impact the quality of life of individual and the society.

Psychiatric Disorders

- Psychiatric disorder refers to a mental illness that interferes with the way a person behaves, interacts with others and functions in daily life.
- Presently, mental health professionals diagnose mental illness as per criteria specified in the Diagnostic and Statistical Manual of Mental Disorders (DSM) published by the American Psychiatric Association (APA) and International Classification of Diseases (ICD) produced by World Health Organization (WHO).
- Some categorically defined mental disorders are anxiety disorder, Attention Deficit Hyperactivity Disorder (ADHD), autism, bipolar mood disorder, conduct disorder, depression, dementia, schizophrenia, sleep disorder etc.
- Some of the causes of mental disorders are trauma, highly stressful life experiences, biochemical imbalances, differences in brain structure, and other genetic, biological and social factors.

Share of population with mental health and substance use disorders, 2017

Share of population with any mental health or substance use disorder; this includes depression, anxiety, bipolar, eating disorders, alcohol or drug use disorders, and schizophrenia. Due to the widespread under-diagnosis, these estimates use a combination of sources, including medical and national records, epidemiological data, survey data, and meta-regression models.



Source: IHME, Global Burden of Disease

Attention Deficit Hyperactivity Disorder (ADHD)

- Attention Deficit Hyperactivity Disorder (ADHD) is a mental condition defined by the presence of high levels of hyperactive, impulsive and inattentive behavior.
- It is one of the most common childhood disorder and is estimated to affect around 5% of children worldwide.
- Longitudinal studies have shown that approximately 65% of children with ADHD continue to show symptoms in adulthood.
- Adults with ADHD experience difficulties like academic underachievement, poor driving records, greater relationship discord, and a high risk of drug abuse.
- Neuropsychological studies have shown executive dysfunctions in individuals diagnosed with ADHD.

ADHD Diagnosis

- The Diagnostic and Statistical Manual of Mental Disorders-5th edition (DSM-5) criteria for the ADHD diagnosis emphasize the importance of gathering behavioral information.
- The diagnosis of adult ADHD involves subjective assessment of the comprehensive history of childhood functioning and current symptoms using rating scales.
- *Wender Utah Rating Scale (WURS)* is used to assess childhood ADHD symptoms and *Adult ADHD Self Report Scale (ASRS)* is utilized to assess current symptoms of ADHD.
- If score of subject is higher than clinically significant levels on two rating scales, then further psychiatric evaluation is done by a doctor to confirm the ADHD diagnosis.

Challenges in ADHD Diagnosis

- Presently, the only way for ADHD diagnosis is a verbal description of abnormality of behavior in specific terms, defined by manuals such as DSM.
- Sometimes, ADHD cases remain unidentified because of misreporting by family members and uncertainty of data.
- Although ADHD is consistently associated with a wide range of social, environmental, neurobiological, and genetic variables, none of these is sufficiently sensitive or specific to predict the syndrome in clinical practice.
- The subjective nature of ADHD diagnosis hinders its effective treatment.
- So, there is a need of objective assessment of the brain dysfunction. The use of biological markers has potential to assist in this important process.

Use of EEG to detect ADHD

- US Food and Drug Administration (FDA) has approved Electroencephalography (EEG) as the first medical device to assist in diagnosis of ADHD.
- The EEG records the brain's electrical activity at the surface of the scalp generated by neuronal ensembles of the cerebral cortex.
- Electrodes are placed over prefrontal, frontal, central, temporal, parietal and occipital region of the brain according to 10/20 system.
- It offers high temporal resolution, non-invasive and relatively inexpensive as compared to other neurophysiological methods.

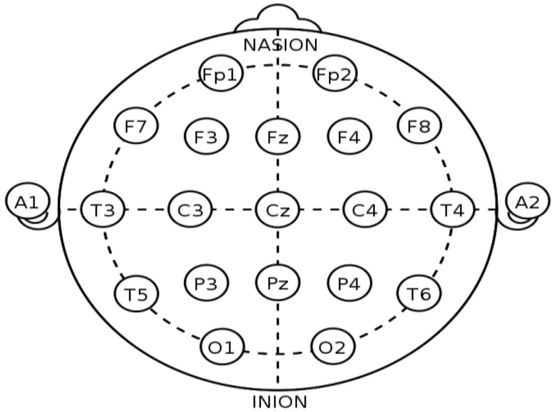


Fig. 1: 10/20 montage system

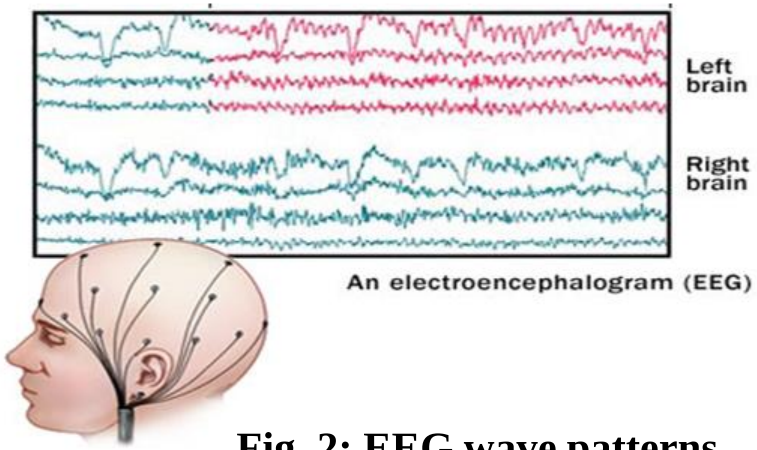


Fig. 2: EEG wave patterns

Problem Formulation

- To study and analyze electrical activity of brain in a sample of ADHD patients and age-matched control group in order to identify abnormal wave patterns in ADHD.
- To examine the diagnostic utility of EEG in ADHD using deep learning based classification algorithms to differentiate between ADHD and control subjects.

Dataset Description

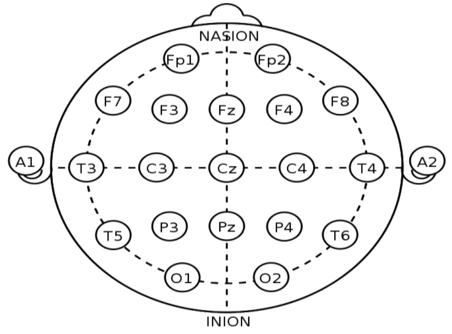
- Participants were 61 children with ADHD and 60 healthy controls (boys and girls, ages 7-12). The ADHD children were diagnosed by an experienced psychiatrist to DSM-IV criteria, and have taken Ritalin for up to 6 months. None of the children in the control group had a history of psychiatric disorders, epilepsy, or any report of high-risk behaviors.
- EEG recording was performed based on 10-20 standard by 19 channels (Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, O2) at 128 Hz sampling frequency. The A1 and A2 electrodes were the references located on earlobes.

- https://ieee-dataport.org/open-access/eeg-data-adhd-control-children

- Since one of the deficits in ADHD children is visual attention, the EEG recording protocol was based on visual attention tasks.
- In the task, a set of pictures of cartoon characters was shown to the children and they were asked to count the characters. The number of characters in each image was randomly selected between 5 and 16, and the size of the pictures was large enough to be easily visible and countable by children. To have a continuous stimulus during the signal recording, each image was displayed immediately and uninterrupted after the child’s response.
- Thus, the duration of EEG recording throughout this cognitive visual task was dependent on the child’s performance (i.e. response speed).

DATASET FILES

- ADHD_part1.zip (8.69 MB)
- ADHD_part2.zip (7.88 MB)
- Control_part1.zip (6.93 MB)
- Control_part2.zip (7.85 MB)
- Standard-10-20-Cap19new.zip (522 bytes)
- Channel_Labels.zip (9.36 kB)



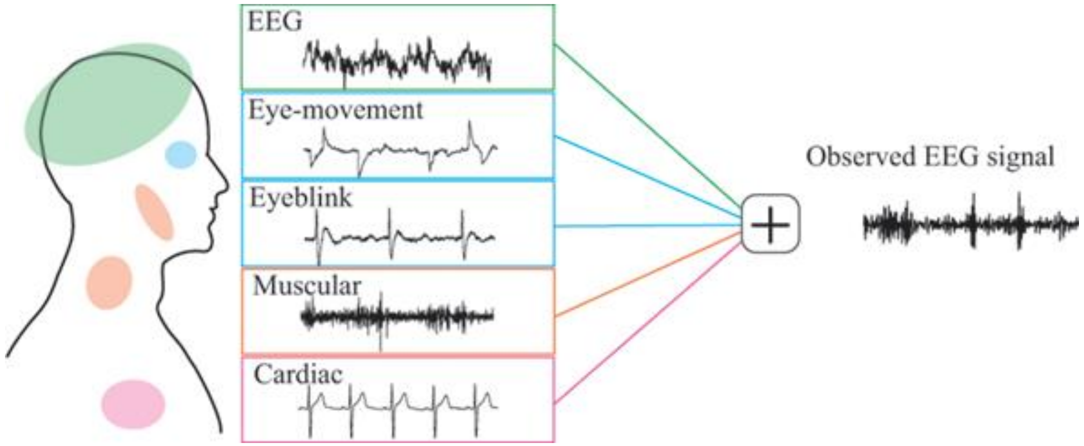
Channel Number	labels
1	Fp1
2	Fp2
3	F3
4	F4
5	C3
6	C4
7	P3
8	P4
9	O1
10	O2
11	F7
12	F8
13	T7
14	T8
15	P7
16	P8
17	Fz
18	Cz
19	Pz

v1p <12258x19 double>

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	85	-407	200	191	420	457	310	310	16	1009	531	126	457
2	-266	-55	-20	367	163	384	-20	310	494	1193	494	236	236
3	-90	-19	126	437	420	568	347	457	-131	1156	384	384	494
4	-90	-160	163	473	384	494	310	384	457	1340	494	420	310
5	-301	-336	-20	473	200	531	89	420	200	1156	310	494	273
6	85	-336	273	402	494	641	457	457	-20	1156	420	494	420
7	-160	191	89	508	236	568	126	457	494	1304	457	568	126
8	15	297	200	508	384	715	200	568	-241	1083	384	604	347
9	191	121	347	402	457	604	273	494	200	1193	568	457	310
10	-55	-55	126	367	273	531	89	531	200	1046	384	420	273
11	297	-266	347	226	568	568	457	457	-167	862	420	310	494
12	-19	-125	126	226	273	347	89	273	384	936	384	236	163
13	-90	-90	89	156	273	347	163	347	-241	678	200	273	347
14	156	-55	273	85	457	273	384	236	163	825	420	200	347
15	-19	50	89	121	200	163	52	200	273	715	384	163	126
16	437	85	347	15	494	236	310	163	-241	531	384	126	347
17	367	367	236	50	273	89	89	89	420	715	457	126	52
18	226	367	126	15	200	89	16	163	-57	494	236	163	200
19	402	191	273	-55	384	89	236	126	89	531	347	126	273
20	85	297	-20	-19	89	52	-131	89	347	494	200	163	16

Methodology

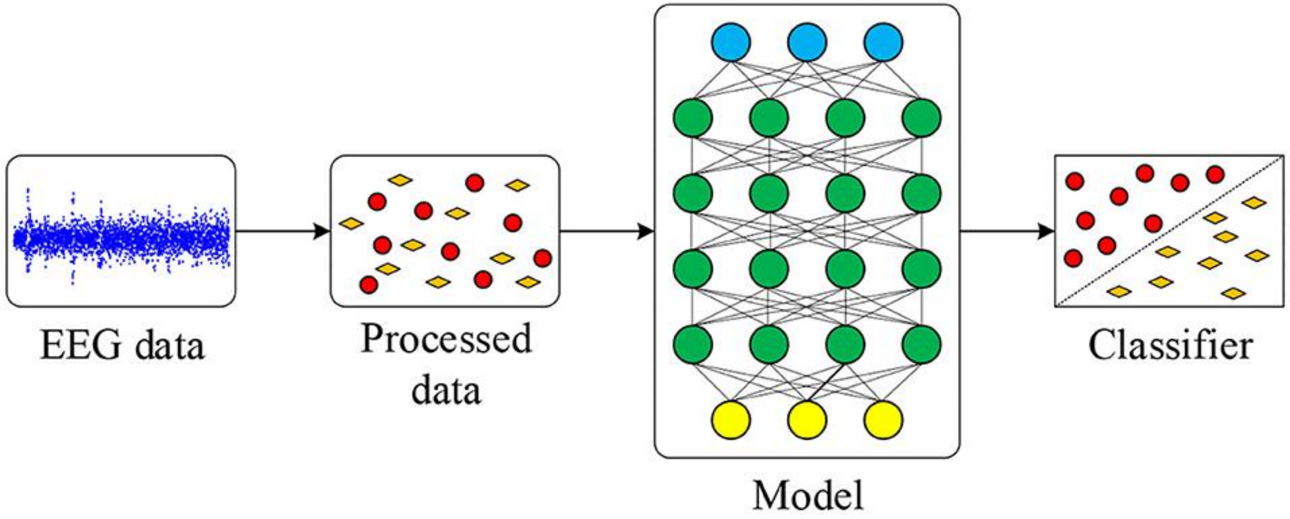
- EEG Data Preprocessing to remove artifacts

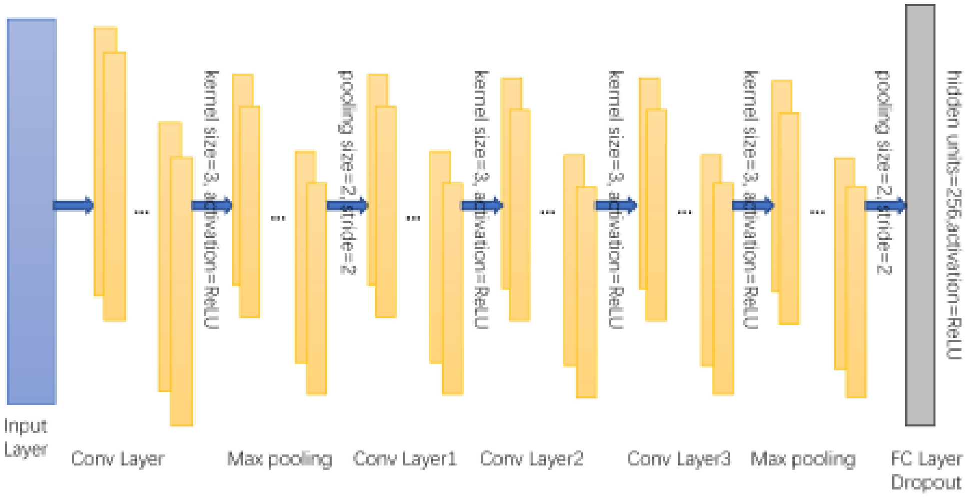


Notch filter (60 Hz)
Bandpass filter (0.1-50 Hz)
StandardScaler method

- Apply Deep Learning Model to classify ADHD/Control
- Performance Evaluation

Deep Learning





Sample network structure

https://github.com/SuperBruceJia/EEG-DL

Performance Evaluation Metrics

In this study, four evaluation indicators are used to evaluate the performance of the architecture: accuracy, F1-score, precision and recall. These performance metrics are briefly described below:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (10)$$

Accuracy represents the ratio of the number of correct decisions to all the decisions.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (11)$$

Precision refers to the proportion of correctly predicted positive samples to all predicted positive samples.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (12)$$

Recall, also known as sensitivity or hit rate, refers to the proportion of positive samples that are correctly predicted.

$$\text{F1-score} = \frac{2(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (13)$$

The F1-score is an indicator of the comprehensive consideration of accuracy and recall rate.

Project Evaluation (5 marks)

✓Presentation

(Network structure, Results for different parameter settings)

✓Submit File and Code

(File - Proposed framework, Results and discussion)

Presentation Schedule

Group	Roll Number	Name	DL Model	Date
1	202201029	Rahul Bajaj	Thin Residual Convolutional Neural Networks	20-Nov-2023
	202201033	Riya		
	202201036	Sanskriti Gupta		
	202201038	Saurabh Mishra		
2	202201022	Mitul Chaudhary	Deep Residual Convolutional Neural Networks	20-Nov-2023
	202201020	Mayank Goyal		
	202201051	Vibha		
	202201058	Alisha		

Presentation Schedule

Group	Roll Number	Name	DL Model	Date
3	202201026	Omkar Goyal	Densely Connected Convolutional Neural Networks	22-Nov-2023
	202201063	Vedansh Khurana		
	202201031	Rakshit Khosla		
	202201053	Myansha		
4	202201042	Shubhojeet Ghosh	Bidirectional Recurrent Neural Networks	22-Nov-2023
	202201008	Astha Bhatia		
	202201046	Tanvi Puri		
	202201064	Kanubha Mohindru		

Presentation Schedule

Group	Roll Number	Name	DL Model	Date
5	202201018	Lovepreet Sood	Attention-based Recurrent Neural Networks	24-Nov-2023
	202201027	Poojan		
	202201003	Abhishek Singh		
	202201002	Abhishek Dhiman		
6	202201004	Aishvarya Vardhinee	Bidirectional Long-short Term Memory	24-Nov-2023
	202201006	Aman Jindal		
	202201009	Ayush Sharma		
	202201034	Saksham Bansal		

Presentation Schedule

Group	Roll Number	Name	DL Model	Date
7	202201057	Himanshi	Fully Convolutional Neural Networks	27-Nov-2023
	202201045	Tanu		
	202201043	Sidhant		
	202201011	Bipan		
8	202201040	Shlok Aggarwal	Graph Convolutional Neural Networks	27-Nov-2023
	202201007	Anmol Pawa		
	202201054	Khuwaish Rani		