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# Statistical Analysis Of EEG Data For Attention Deficit Hyperactivity Disorder

**Swapnali A. Chaudhari[1*], Dr. Bharti W. Gawali[1] and Dr. Omprakash S. Jadhav[2]**

*[1]Department of Computer Science, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad,* swapnali.waghulade@gmail.com
*[1]Department of Computer Science, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad,* drbhartirokade@gmail.com
*[2]Department of Statistics, Dr. Babasaheb Marathwada University, Aurangabad,* drjadhavop@gmail.com

**Abstract:**

The "psychiatric disorder" has a fine distinction between it and other mental disorders. A psychiatric disorder assessment provides feedback of how a person thinks, feels, reasons, and remembers to a clinician. This behavioral trait of human beings is monitored by the brain, in the form of signals called neuro-electric impulses. EEG is the well-known and effective way for acquiring these brain signals. It is the non-invasive, portable, wireless, easy to use modality and it does not require experience for obtaining brain signals. ADHD (Attention Deficit/ Hyperactivity Condition) is the most frequent and challenging neurobehavioral and mental disorder in children, adolescents, and adults. Research work analyzing EEG data (https://ieee-dataport.org/open-access/eeg-data-adhd-control-children) that has been clinically proven in presented paper. The absolute FFT values of EEG signals are calculated in Python using NumPy. The features obtained are then analyzed statistically. An implementation of statistical techniques (Tukey's post hoc test) marked clear distinction in ADHD and control group.

**Keywords:** Mental disorder, ADHD, EEG, FFT, statistical approach, ANOVA, Tukey's Post Hoc Test

## 1. Introduction:

An individual suffering from a mental disorder is unable to lead a happy, healthy, productive life because their thoughts, feelings, and behaviors are affected. The term "psychiatric disorder" does not necessarily refer to a "mental disorder," but there is a distinction to be made between it and "other medical disorders"[1]. It is possible for a behavior or mental pattern to cause great suffering or impair one's ability to function. It include neuro developmental disorders, schizophrenia spectrum disorders, bipolar disorders, depressive disorders, anxiety disorders, obsessive-compulsive and related disorders, trauma and stress-related disorders, dissociative disorders, neuro-cognitive disorders, personality disorders, and behavioural and emotional disorders in children[2, 3]. A psychiatric disorder assessment provides doctors, a picture of how a person thinks, feels, reasons and remembers. A physical examination and series of questions to measure one's emotional well-being are included in the mental health test. Various approaches to the examination of such disorders have been employed for many years, are discussed as follows.

### 1.1 Psychological Approach for assessment of psychiatric disorder

All the psychiatric disorders are related to mental health; hence these are assessed through psychology. Patients are examined psychologically for psychiatric disorders using a variety of rating scales, screening tests or questionnaires. These rating scales will aid professionals and patients in determining the effects of treatment. Some of the most often used rating scales, screening exams, and questionnaires are listed in Table 1[4].

**Table 1 Rating scales, screening exams, and questionnaires for Psychiatric Disorders**

| Sumptoms | Scale name |
|---|---|
| Depression | Hamilton Depression Rating Scale – 17-item version |
| | Montgomery Asberg Depression Rating Scale |
| | Quick Inventory of Depressive Symptomatology (16-item, self-report version) |
| | Zung Self-Rated Depression Scale |
| Children (any disorder) | Brief Psychiatric Clinical Rating Scale for Children |
| Cognitive Functioning | Draw a Clock Test |
| | Trail Making Test |
| Anxiety | Panic Disorder Severity Scale |
| | Liebowitz Social Anxiety Scale |
| | Hamilton Anxiety Rating Scale |
| | Yale-Brown Obsessive Compulsive Scale |
| | Short PTSD Rating Scale |
| Bipolar disorder | Hamilton Depression Rating Scale – 31-item version |
| | Young Mania Rating Scale |
| | Internal State Scale |
| | Clinical Monitoring Form |
| Personality disorder | Five Factor Model Rating Form |
| | Inventory of Interpersonal Problems |
| | Standardized Assessment of Personality – Abbreviated Scale |
| ADHD | Adult ADHD Self-Report Scale |
| Schizophrenia | Psychotic Symptoms Rating Scale |
| | Quality of Life Scale |
| | Abnormal Involuntary Movements Scale |
| | Brief Psychiatric Rating Scale |
| Psychotherapy practice | Schwartz Outcome Scale |
| | Outcome Rating Scale |
| | Session Rating Scale (Version 3.0) |

## 1.2 Neurofeedback Approach for assessment of psychiatric disorder

Neurofeedback is a technique that detects brain waves and sends feedback signals [5]. Neurons in the human brain communicate with one another via neuro-electric impulses. This information is represented by a pattern of brain waves that varies depending on the individual's cognitive processing ability. A combination of brain waves is used to describe brain activity in general using brain waves [6].

Electrical signals are controlled by different lobes of the brain as they travel around the brain and throughout the body. PET (Positron Emission Tomography), fMRI (frequency Magnetic Resonance Imaging), CT (computed tomography),MEG(magneto electroencephalography) , and EEG (electroencephalography) are some of the brain imaging techniques used for medical and research purposes. During last two decades, EEG has become one of the most popular procedures [7, 8].The EEG is the only non-invasive, lightweight, portable, wireless, easy to use, and it does not require experience for obtaining brain signals from the scalp[9, 10]. Some EEG acquisition devices are InterAxon Muse, Neurosky MindWave, OpenBCI, Emotive Insight, and Epoc[11].

## 1.3 EEG based diagnosis of ADHD

ADHD is the most common and challenging neurobehavioral and mental disorder in children, adolescents, and adults. ADHD children are hyperactive, impulsive, and inattentive. Adults with ADHD may struggle with time management, organisation, goal-setting, and job retention, as well as relationships, self-esteem, and reliance [12, 13].

A chemical imbalance in the brain, poor nutrition, illness, smoking, drinking, hyperthyroidism, lead exposure, and chemical imbalance in the brain cause ADHD. The severity of ADHD is determined by factors such as parents, schools, stressful events and exposure to lead and other poisons [14, 15].

ADHD has been estimated to affect between 1.6 and 17.9% of Indian children. ADHD was discovered in 12.66% of primary school children [16]. ADHD is becoming more prevalent for a variety of reasons, including genetic disorders, environmental factors such as maternally related prenatal risks in pregnancy, such as drinking, smoking, or using drugs while pregnant, increased maternal stress, obesity, and birth complications, and a lack of nutritional factors [17]. As a result, identifying and treating ADHD in its early stages is critical to avoiding catastrophic adult consequences.

Since, ADHD is a brain-based behavioural disorder can be monitored via brain signals. The sole non-invasive technique is EEG, portable, wireless and inexpensive EEG equipment makes it more user-friendly [18].

The diagnosis of ADHD is very crucial and may have misjudgement in diagnosing it. Advantages of using EEG make it to be best option to use it for evaluation of ADHD. When the EEG data recorded, generally it is vast volumes of data with diverse categories over a long period of time. And hence automated methods are required to analyse and classify the data in order to extract information from such a massive volume of data. Since EEG signals contribute so much to biological science, a detailed assessment of the data is required to provide useful information and increase comprehension, and this is achieved using automatic classification algorithms for EEG signal [19]. From statistical point of view, high dimensionality of EEG, repeated inspection of subjects for ensuring the treatment effects and also no specific functionality for the evolution of EEG over time data makes it tough to analyze the data[20].Various statistical approaches used for the assessment of ADHD are elaborated in section 1.4.

### 1.4 Statistical Approach

To study and analyze the EEG data, researchers used a wide range of linear and nonlinear approaches. To analyse EEG markers in the time domain, linear approaches such as the ARMA (Autoregressive Moving Average) and MVAR (multi-variate AR) are utilised. Non-linear, non-parametric techniques include the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) technique, as well as Burg Method, Durbin Recursion, LORETA (low-decision electromagnetic tomography) , and Yule-Walker. The spectral domain sign is provided using the STFT (Short Time Fourier Transform) approach. It has been proven that wavelet transform possesses good localization properties in frequency domain whereas PCA (Principal Component Analysis) is used for reduction of data [21]. In the proposed work we have suggested the multidisciplinary study which involves the computational as well the statistical approaches explained the forthcoming section.

## 2. Related Work

Comparison between morphological features (absolute amplitude, positive region, negative region, zero crossing point), time domain features (mean value, energy, entropy, asymmetry and flattening), frequency, time-frequency features (discrete wavelet transform (DWT)), and nonlinear features (fractal size, Lyapunov exponent, approximate entropy, degree complex Lempel-Ziv) in [22] claims that non-linear features domain gives more accuracy (91.2 ± 2.9 train, 86.4 ± 3.45 test, 91.78 sensitivity, 81.1 specificity ) compared to other four criteria. Whereas 4-level wavelet decomposition used to obtain sub-bands and non-linear feature synchronisation likelihood among all electrodes and between electrode pairs distinguishes the ADHD and control group; is confirmed by using one-way ANOVA at 1% level of significance [23]. The authors of [24], employs one-way ANOVA to assess the performance of EEG data from electrodes implanted in the frontal, central, and parietal regions. The Bonferroni-Holm correction T-test post hoc used for pair-wise comparisons of two groups revealed that the ADHD-C (ADHD Combines) and ADHD-I

(ADHD Inattentive) groups had significantly higher reaction time variability than the control group (control vs. ADHD-I: t(26) = -3.32; p (corr.) =0.009; control vs. ADHD-C: t(32) = -2.61; The ADHD-I group had a GROUP effect for median reaction times compared to the control group (control vs. ADHD-I: t(26) = 3.71; p (corr.) = 0.003), as did the ADHD-C group (ADHD-C vs. ADHD-I: t(22) = 2.36; p (corr.) = 0.05) [25].

## 3. Methodology

### 3.1 EEG Data for ADHD / Control Children

A clinically proven online EEG dataset (https://ieee-dataport.org/open-access/eeg-data-adhd-control-children) is used for the proposed experiment. It includes EEG data of 61 ADHD children (48 boys and 13 girls with an average age of 9.61.75 years) and 60 healthy children (50 boys and 10 girls with an average age of 9.85 1.77 years). An experienced child and adolescent psychiatrist diagnosed the ADHD youngsters using DSM-IV criteria. Normal children from elementary school were recruited, with the exclusion criteria including a history of substantial neurological diseases, brain injury, major medical sickness, learning or speech difficulties, other psychiatric illnesses, and use of benzodiazepine and barbiturate medicines.

The EEG data is captured by using SD-C24 machine with 19 channels. The electrodes are placed on the scalp by following 10-20 standards. Figure 1 shows the 10-20 standards for EEG Recording electrode positions. Where Frontal (F3, F4, F7, F8), Central (C3,C4), Occipital (O1,O2), Temporal (T3, T4, T5, T6), Parietal (P3, P4), Prefrontal (Fp1,Fp2) and Ground (Fz, Cz, Pz)are the positions and corresponding names of electrodes [26]. While collecting the data the sampling frequency was set to 128 Hz. Visual attentions is one of the weaknesses in ADHD children hence, EEG data recording approach was based on visual attention activities. The children were shown a series of cartoon character photos and asked to count the figures. Each image had a random set of characters range from 0 to 16, and also the images were large enough so that children can view and count them easily. Each image was flashed instantly and without delay after the child's response during data capture to provide continual stimulation. As a result, the length of the EEG recording was determined by the child's performance during this cognitive visual activity (i.e. response speed) [27].

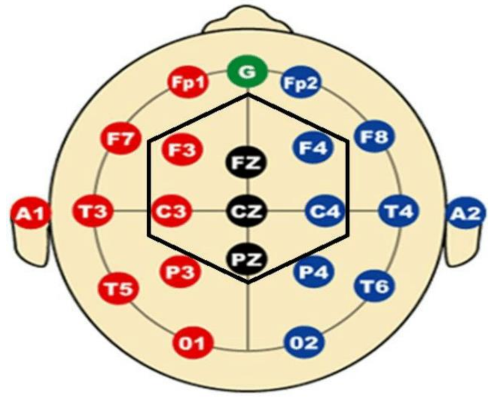


**Fig. 1 10-20 standard for EEG Recording electrodes positions**

### 3.2 Applied Computational Techniques

EEG data is more prone to errors known as artefacts; these artefacts must be removed through a procedure known as data pre-processing. It is intended to be the first step in the data processing, followed by feature extraction and classification. A unique measurement that extracts the structural components of a signal is referred to as a feature [28]. The EEG data we have is pre-processed using FIR (Finite Impulse Response) Butterworth band pass filter (order 7) with cut-off frequency at 0.3 and 70 Hz and Notch filter of 50 Hz for noise and inference cancellation. The primary goal of this study is to determine how ADHD children's EEG frequency bands change across different brain regions compared to the normal children. As a result, the data must be transformed into the frequency domain for which the FFT algorithm was used, with absolute values as features.

#### 3.2.1 Significance of FFT absolute values

DFT is the most extensively used discrete transform in digital signal processing, which translates a sequence into the frequency domain[29]. Fourier analysis transforms a signal from its native domain (time or space) to a frequency domain representation which in turn are very useful in solving problems [30]. FFT is a computationally efficient way of creating a Fourier Transform.

The fundamental benefit of FFT is speed, which reduces the amount of calculations required to analyse a waveform. The values returned after applying the FFT to the EEG signal are negative. When compared to a positive result, any negative value represents a phase shift. A negative real component means that the input waveform appears to vary in the opposite direction of the related cosine function, going largely low while the cosine increases and vice versa. As a result, absolute FFT values are obtained for EEG signals.

FFT values are computed using Python's NumPy module. The NumPy Python library aims to provide array objects that are up to 50 times faster than normal Python lists. In NumPy, the array object is named ndarray, and it includes a plethora of methods to work with it. The one-dimensional discrete n-point discrete Fourier Transform is computed using Numpy's fft.fft() function (DFT). The one-dimensional discrete Fourier Transform is computed using the Numpy fft.fft() function. Using the efficient Fast Fourier Transform (FFT) algorithm, the numpy fft.fft() method computes the one-dimensional discrete n-point discrete Fourier Transform (DFT) [31].The acquired traits are then statistically analysed.

### 3.2.2 Statistical analysis of dataset

The human brain is divided broadly 5 lobes, including the frontal, central, parietal, temporal, and occipital [32]. The frequencies of EEG data are divided into five bands in the frequency domain: Delta (0.5Hz - 4Hz), Theta (4Hz - 8Hz), Alpha (8Hz - 13Hz), Beta (13Hz - 30Hz), and Gamma (30Hz - 50Hz) [33]. According to the frequency bands, the absolute FFT values of the EEG data are divided into groups. Measures of central tendencies are estimated for all lobes and frequency bands. These statistical parameters are computed using IBM SPSS Statistics 22.

The Null Hypothesis ($H_0$) for proposed work is "There is no significant difference between the FFT absolute values of frequency bands across various brain lobes for ADHD children" while the Alternate Hypothesis ($H_1$) is "There is significant difference between the FFT absolute values of frequency bands across various brain lobes for ADHD children." Table 2 shows p-values at the 0.05 level of significance. As a result, $H_0$ is rejected and $H_1$ is accepted. That instance, for ADHD children, there is a considerable variance in the FFT absolute values of frequency bands across different brain lobes.

We have compared means within and between the groups like ADHD All region Alpha, Control All Region Alpha, ADHD All region Beta, Control All Region Beta, ADHD All region Theta, Control All Region Theta, ADHD All region Delta, Control All Region Delta, ADHD All region Gamma, Control All Region Gamma. Table 3 shows the mean and standard deviation of the respective bands across various brain regions.

When an analysis of variance (ANOVA) F test is significant, post hoc tests are employed to evaluate specific differences between the group means after the Alternate Hypothesis is accepted [34]. There are various post hoc tests like: Bonferroni Procedure, Duncan’s new multiple range test (MRT), Dunn’s Multiple Comparison Test, Fisher’s Least Significant Difference (LSD), Holm-Bonferroni Procedure, Newman-Keuls Rodger’s Method,
Scheffé’s Method, Tukey’s Test [35, 36].

As the Tuckey's Post Hoc Test is usually used to figure out which groups in sample differ, also it uses the “Honest Significant Difference,” a number that represents the distance between groups, to compare every mean with every other mean. In this work, Tukey’s Post Hoc test is utilised to determine which pairs exhibit a significant difference. According to the results of the descriptive analysis of post hoc test, two distinguishable groups for ADHD and Controlled children are clearly observed as shown in Fig. 2.

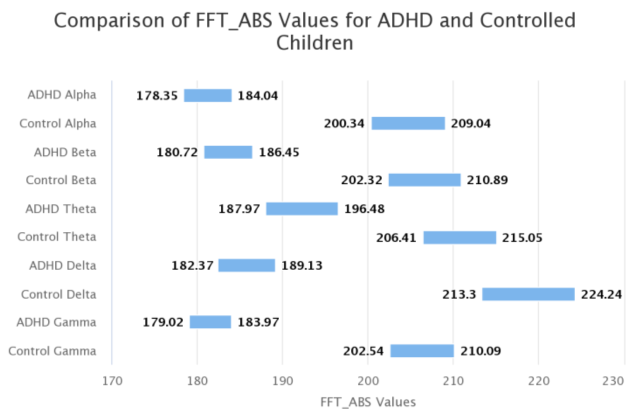


**Fig. 2 distinguishable groups for ADHD and Controlled children**

**Table 2 ANOVA Table**

| | Sum of Squares | Df | Mean Square | F | Significant value (p-value) |
|---|---|---|---|---|---|
| **Between Groups** | 1960571.408 | 9 | 217841.268 | 48.400 | .000 |
| **Within Groups** | 51265119.821 | 11390 | 4500.888 | | |
| **Total** | 53225691.228 | 11399 | 222342.2 | | |

**Table 3 Mean and Standard Deviation of various bands across various brain regions**

| Bands | Region Criteria | Frontal | Temporal | Central | Parietal | Occipital |
|---|---|---|---|---|---|---|
| **Alpha** | **ADHD** | 209.7484±79.9601 | 207.9825±84.2177 | 196.5651±65.5096 | 200.6728±70.7124 | 205.9546±68.8549 |
| | **Controlled** | 187.3696 ± 50.9355 | 176.1265 ± 43.0203 | 178.6297±36.1590 | 174.8392±45.9840 | 184.4084±66.0795 |
| **Beta** | **ADHD** | 212.8201±78.6973 | 195.5338±65.9522 | 198.9060±66.3832 | 203.1593±72.2472 | 205.3232±66.1349 |
| | **Controlled** | 193.1491 ± 58.7815 | 177.1783 ± 37.7332 | 180.6732±37.0866 | 174.5812±39.0510 | 183.4055±55.7050 |
| **Theta** | **ADHD** | 213.3126±71.8158 | 208.6406±82.2729 | 198.2968±58.5286 | 205.7924±72.7022 | 209.6781±64.4945 |
| | **Controlled** | 200.5834 ± 74.5809 | 193.2002 ± 89.5242 | 189.7080±69.7430 | 181.5105±63.0535 | 192.5494±76.6667 |
| **Delta** | **ADHD** | 231.0365±107.7565 | 217.5197±90.8973 | 205.1234±70.0157 | 211.9103±88.7302 | 214.6926±86.6955 |
| | **Controlled** | 195.7102 ± 67.2470 | 178.3103± 50.9798 | 182.3856±45.5529 | 176.2615±51.9199 | 187.0707±57.4897 |
| **Gamma** | **ADHD** | 231.0365 ±107.7565 | 206.9231±66.0937 | 197.5236±57.4620 | 202.6346±62.6084 | 203.6267±51.7530 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | **Controlled** | 190.2606 ± 47.0792 | 176.9957± 36.6399 | 177.9851±32.5903 | 173.3852±36.6661 | 181.0752±52.9450 |

(Significant at 5% level of significance)

## 4. Conclusion

ADHD is a tough disorder to diagnose. Apart from psychological and neurofeedback approaches EEG can be efficient candidate technique to be used for the diagnosis of ADHD. FFT absolute values of the EEG signal are the inputs for comparative analysis of ADHD and Normal data. Fourier analysis converts a signal from its native domain to a frequency domain representation. The speed of FFT is its key advantage, as it decreases the amount of calculations required to analyse a waveform. The difference between these values throughout all regions of the brain of controlled and an ADHD child is confirmed using one-way ANOVA after the FFT absolute values have been extracted. The statistical significance difference between the controlled and ADHD groups is calculated using Tukey's post hoc test at a 5% significance threshold, indicating that both groups are statistically distinct.

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