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ANALYSIS OF EEG BASED NEUROFEEDBACK SYSTEM FOR ATTENTION DEFICIT HYPERACTIVITY DISORDER

Swapnali Ashok Chaudhari*¹, Bharti Waman Gawali² and Leena Yogesh Bhole³

^{1,2}Department of Computer Science and IT, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India.

³School of Computer Sciences, M.J.College, Jalagaon, Maharashtra, India.

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*Corresponding Author Swapnali Ashok Chaudhari Department of Computer Science and IT, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India.

ABSTRACT

Attention Deficit Hyperactivity Disorder (ADHD) is common mental and behavioral illness in children and teenagers. It persists into adulthood, causing disability in people of all ages. If left misdiagnosed, untreated can progress to mental illness. Clinicians prefer variety of rating scales based on psychological assessment for diagnosis. Patients are recommended various therapies in accordance with their scale values. Amongst the mentioned therapies, neurofeedback is emerging

therapy for diagnosing brain related diseases. The goal of neurofeedback training is to detect any abnormalities in brain signals as well as person's behavioral and cognitive performance. EEG is the most well-known and effective way for acquiring brain signals from a wide range of sources. This article focuses on research about commonly used diagnostic and therapeutic techniques, emphasizing neurofeedback training's methodological features based on computational techniques. Although psychological variables must be considered, we may say that EEG can be used as an associative modality for ADHD assessment due to its accuracy.

KEYWORDS: EEG, ADHD, neurofeedback, ADHD therapy.

1. INTRODUCTION

ADHD (Attention Deficit /Hyperactivity Disorder) is the most frequent childhood neurobehavioral and mental disorder, affecting children, teens, and adults. Children with ADHD are hyperactive, impulsive, and inattentive. Adults with ADHD may struggle with time management, organization, goal-setting, and job retention, as well as relationships, self-esteem, and dependency.^[1,2]

ADHD is caused because of heredity, chemical imbalance in brain, poor nutrition, infection, smoking, drinking, hyperthyroidism, contamination of toxins such as lead and brain injury. Parenting, education, traumatic experiences, brain injury, and comorbid cognitive impairments ultimately determine the severity of ADHD. Undiagnosed, untreated ADHD increases the risk of mental health problems such as anxiety, depressions, addiction, eating disorders, self-harm, attempted suicide and personality disorder.^[3,4]

The frequency of ADHD in Indian youngsters has been estimated between 1.6 and 17.9%. ADHD was reported to be present in 12.66% of elementary school students.^[5] Prevalence of ADHD is increasing as of some reasons like genetic disorder, environmental factors such as maternally related prenatal risks in pregnancy like having alcohol, smoking and having drugs during pregnancy, increase in maternal stress, obesity and birth complications, lack of nutritional factors.^[6] As a result, it is crucial to identify and treat ADHD in its early stages to avoid serious adult effects.

The traditional diagnostic process of ADHD is discussed in Section 2 and associated therapeutic methods are discussed in Section 3. The related work of neurofeedback therapy is addressed in Section 4. Finally, in Section 5, we conclude.

2 Diagnostic Process

Clinicians used a variety of methods to diagnose the disorder, including interviews with parents, relatives, and teachers, also as traditional rating scales and psychological tests.

The ADHD rating scale evaluates an individual's chance of getting ADHD by asking questions on their behavior. Rating scales are a crucial aspect of the diagnostic technique when handling youngsters. The subsequent are a few of the foremost commonly used Psychological Rating Scales as descirbed in Table 1.

Publication	Scale	Ages (yrs)	Symptom	Description
[47]	National Institute for Children's Health Quali- ty (NICHQ) Vanderbilt Assessment Scale	6-12	inattention or hyperactivity	It comprises of two separate forms for parents or teachers, with slight difference, also as per- formance-related questions. A healthcare pro- vider will consider diagnosing ADHD if a child exhibits a minimum of six behaviors with mentioned symptom with score 2 or 3
[47]	Conner's Comprehensive Behavior Rating Scale (CBRS)	6-18	Hyperactivity and cognitive difficulties	Separate forms are available for the child, their parent, and the teacher. It is employed to moni- tor progress in symptoms, contains 25 ques- tions. Scores above 60 indicate ADHD
[48]	Behavior Assessment System for youngsters (BASC3),	2-21	Hyperactivity, aggression, and conduct issues, anxiety, depres- sion, attention, and learning is- sues	It includes Teacher Rating Scales, Parent Rating Scales and Self-Report of Personality
[16,17]	Child Behavior Checklist (CBCL),	6-18	Problems of be- havior in chil- dren	The CBCL's questions are correlated to 8 different types of disorders on a syndrome scale: anxious/depressed, withdrawn/depressed, somatic complaints, social problems, thought problems, attention problems, rule-breaking behavior, and violent behavior
[49]	Barkley ADHD Current Symptoms Scale (BCS),	young- sters and adults	Inattention and Hyperactivi- ty/Impulsivity	This scale corresponds to the DSM-IV diagnostic criteria of ADHD. Scores range between 0 and 27 for each of the 2 subscales and 0 to 54 for the entire scale
[50, 51]	Wechsler Intelligence Scale(WISC-IV)	5-15	Fluid Reason- ing, Working Memory, and Processing Speed	It contains 15 subtests, 10 of which constitute the core battery. The core battery subtests are organized into four indexes, containing either three subtests each (Verbal Comprehension Index [VCI] and Perceptual Reasoning Index [PRI]) or two subtests each (Working Memory Index [WMI] and Processing Speed Index [PSI])
[52]	Swanson, Nolan, and Pelham-IV Questionnaire (SNAP-IV)	6-18	Hyperactivity, Impulsivity, In- attention	The Swanson, Nolan, and Pelham Rating Scale (SNAP-IV) is employed to measures the core symptoms of ADHD
[53]	Adult ADHD Self-Report Scale (ASRS)	Adults	Hyperactivity, Impulsivity, In- attention	<i>It contains the eighteen DSM-IV-TR criteria.</i> <i>Six of the eighteen questions are most</i> <i>predictive of symptoms according to ADHD</i>

These scale values assist clinicians in determining the best course of treatment. They track how symptoms affect a person's moods, attitudes, lifestyle, and daily habits. In the case of infants, the impact of symptoms was discussed with family members, coworkers, and friends, as well as school teachers. There after they proceed with appropriate therapy based on the information they have gathered.

3. Therapeutic Methods

Therapeutic methods are broadly subdivided into three ways. These methods are discussed as below:

3.1 Pharmacological Therapy

This type of therapy uses psycho-stimulant and non-stimulant medications that reduce symptoms and the burden of ADHD-related deficits to some extent.^[7] The medicines for pharmacological therapy are not sufficient when they are used solely so many clinicians prefer the combined use of those medications for treating ADHD. Table 2 summarizes some of the most commonly prescribed ADHD medications.

Publication	Medications	Diagnosis	Symptoms	Effect
[54]	Atomoxetine (ATM), 2 adrener- gic drugs, Clonidine (Catapres), Guanfacine, and immediate- release Guanfacine (Tenex)	-	hyperactivity and inattentive- ness	sleep problems, decreased appetite, weight loss, headaches, stomach- aches, increased heart rate, and blood pressure in children
[55]	ATM, Guanfacine, and Clonidine	DSM	oppositional be- haviour, conduct problems, and aggression	appetite suppression and problems sleeping, whereas $\alpha 2$ agonists pro- duce drowsiness, headaches, and low blood pressure. Loss of appe- tite and exhaustion are common side effects of discontinuation of Automoxetine
[56]	methylphenidate, dexme- thylphenidate, lisdexamfetamine, and mixed amphetamine salts, non-standard therapies (antide- pressants, monoamine oxidase inhibitors), alpha-2 agonists	DSM-V	inattention, hy- peractivity, and impulsivity, as well as comor- bid conditions (tics/aggression)	effects of these therapies are un- clear, and the length of treatment is uncertain
[57]	placebo, stimulants, non- stimulants	DSM / International	Hyperactivity, inattentiveness	combination of stimulants and non-stimulants outperformed pla-

Table 2: Commonly prescribed ADHD medications.

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		Classification of Diseases (ICD)	and impulsivity	cebo and that behavioral therapy
[58]	Methylphenidate (MPH) fol- lowed by ATM and DEX	DSM-IV	inattention, im- pulsivity and hyperactivity	trend of increasing prescribing prevalence of ADHD drug treat- ment. Prevalence of prescribing to adult patients increased

In India, however, the same psychostimulant drugs are used to treat ADHD youngsters with the same results. According to the findings of the preceding investigation, ADHD is diagnosed using the Psychological Manual and treated with psychostimulants such as MPH, ATM, DEX, Guanfacine, and Clonidine, etc. These therapies boost concentration in a short amount of time and have a quick effect. Reduced appetite, stomach pain, headaches, moodiness, sleep troubles, tics, labile behavior, and slowing of growth are some of the negative effects. It can also cause more significant problems like strokes, convulsions, hallucinations, depression, and suicide, as well as a spike in blood pressure (BP), heart rate (HR), and a dangerous cardiovascular illness.^[8]

3.2 Psychological Therapy

This sort of therapy employs psychological tests to assist ADHD sufferers in alleviating their symptoms. Despite the fact that it is based on psychological principles, this therapy overcomes all of the disadvantages of pharmacological therapy, including the fact that it is less cost-effective and requires a long-term treatment. Table 3 summerizes some of the most commonly utilised psychological therapies for ADHD.

Publication	Test	Symptom	Effect
[49]	Cognitive Behavioral Therapy (CBT), Self Reporting Measures such as Barkley ADHD Current Symptoms Scale (BCS), Beck Anxiety Inventory (BAI), and Beck Depression Inventory (BDI)	Comorbidity	CBT improves the ef- fect of psychological treatment and reduces ADHD symptoms
[59]	Cronbach's Alpha Test using Tukey- Kramer Method and Challenging Horizons Programs (CHP)	inattention, hyperactivi- ty/impulsivity	Considerable benefits for adolescents with ADHD
[60]	Wechsler Intelligence Scale's Digits subtest for Verbal Memory, the Temporo Spatial Retrieval Task (TSRT) Continuous Perfor-	evaluation included tests of mathematical contents, verbal working memory, visuo-spatial	learning disabilities are improving

Table 3: commonly utilised Psychological Therapies.

	mance Test (CPT)	working memory, attention in- hibition, self-reports of attitude, anxiety, attributions toward mathematics and self-concept	
[61]	Cognitive Behavior Therapy (CBT) Conner's Adult ADHD Rating Scale, Self- Report, Long Version (CAARS-S:L)	Inattention and Hyperactivity– Impulsivity	improvement in ADHD symptoms

3.3 Neurofeedback Therapy

Neurofeedback is a type of biofeedback that aids in the management of brain activities by detecting brain waves and providing audio and video feedback signals.^[9]

The human brain is made up of cells called neurons, that communicate with each other using neuro-electric signals. These signals are represented as a pattern of brain waves and changes depending on one's cognitive processing level. Brain activity is generally characterized by the combination of brain waves.^[10]

Electrical signals travel around the brain and throughout the body parts and are controlled by different lobes of the brain. There exist various brain imaging techniques such as; Position Emission Tomography (PET), frequency Magnetic Resonance Imaging (fMRI), Computed Tomography (CT), Magnetoelectroencephalography (MEG) and are used for medical as well as the research purpose. EEG is one of the widely accepted techniques since the last decade.^[11,12]

EEG is a non-invasive brain imaging technique that uses metal electrodes and a conductive medium to monitor electrical activity generated by lobes from the scalp.^[13] Initially, EEG devices were bulky and require expertise however, nowadays these devices have become portable, wireless, and easy to handle. Some of the EEG devices are Jellyfish, Trilobite, BR8+ device.^[14] InterAxon Muse, Neurosky MindWave, OpenBCI, Emotive Insight, and Epoc.^[15] A series of products (g.USBamp, g.BSamp, and g.BCIsys) made by g.tec in Austria, Cerebus made by BlackRock Microsystems in the USA, a series of products with 64, 128, or 256 channels (SynAmps 2) made by Compumedics Neuroscan in Australia, BrainNet-36, ANT-Neuro, FlexComp Infiniti encoder.^[16]

ADHD is a brain-based behavioral disorder that may be monitored via brain signals. The sole non-invasive technique is electroencephalography (EEG), and the equipment used to collect EEG data is small, wireless, and inexpensive, making it more user-friendly.^[17] As a result,

EEG has the potential for an ADHD evaluation.

However, Garbha Sanskar is preferred by society because it provides better results when coping with ADHD and for better foetal growth.^[18]

Following the discussion of the other therapeutic methods, Neurofeedback Therapy is the focus because it has been shown to be more effective than the other treatments discussed thus far. As a result, Section 4 gives insight into the current state of ADHD research.

The traditional method for neurofeedback therapy firstly includes recording EEG signals using specialized types of equipment. The EEG devices that have been used for ADHD untill now are listed in section 3.3.1. We often have large amounts of data with multiple categories while measuring an EEG, especially when the recordings are done over a long period. To extract information from such a large amount of data, automated techniques are required for data analysis and classification using appropriate technology. In section 3.3.2, the computational techniques that have been investigated are reviewed.

3.3.1 EEG Acquisition

For ADHD monitoring, the majority of the researchers utilized EEG acquisition devices based on 10-20 international standards with varying numbers of channels, as follows:

- SD-C24, 19 channels.^[19]
- B-Alert X10 devices (BIOPAC Systems Inc), 19 channels.^[20]
- Digital Cortical Scan apparatus (Lexicor, Augusta, GA), 19 channels cap.^[21]
- Mitsar 201 (Mitsar Ltd.).^[22]
- A 32-channel AC/DC amplifier (Walter Graphtek GmbH, Germany) for data recording and Pl-Winsor 3.0 for data acquisition.^[23]
- NeuroSky EEG MindWave single-channel system (NeuroSky Inc., San Jose, CA, USA).^[24,25]
- Mindset.^[26]
- BrainAmp amplifier with 60 Ag/AgCl electrodes (Brain Products Inc, Munich, Germany).^[27]

3.3.2 Computational Techniques

The intensity of the EEG signal is measured in microvolt. EEG signal analysis methods are the Time domain, Frequency domain, Time-Frequency domain, and Artificial Neural Networks.^[28-30]

Time Domain

The time-domain analysis estimates the synchronization of various EEG signals measured from various electrodes represents the similarity of signals.^[31] The time-domain features that have been studied for ADHD are PSD, DWT, ERP component latency, amplitude.

Frequency Domain

Frequency domain analysis measures the occurrence of events in a specified time. EEG is a non-stationary signal that consists of events at various frequencies.^[31] These frequencies are categorized in various bands such as Delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma band (>30 Hz).^[32]

Time-Frequency Domain

Time-Frequency analysis not only provides information about frequency content information required for EEG classification but also temporal information by selecting window size.^[31] Transient biological signals can be extracted and represented using the Wavelet Transform, a common time-frequency domain approach. Transient patterns can be recorded and localized in both time and frequency contexts using wavelet decomposition of EEG data.^[33]

Artificial Neural Networks (ANN)

ANN is the most promising and effective method for the classification of EEG signals. ANNs require careful selection of their parameters, which varies depending on a particular task and different subjects. Hence, optimization of EEG data and channel selection is a problem for the development of efficient ANN-based BCIs.^[34,35]

Over the last decade, following computational techniques have been employed in EEG-based neurofeedback therapy research:

Table 4: Summary of Studies Related to Unimodal Modalities

Publication	Domain	Symptoms	Task	Filters	Features	Classifier	Accuracy
[19]	ANN	Attention	"No-Go" CPT task	IIR, low pass filter	Non-Linear fea- tures: Synchro- nization Likeli- hood	RBF Neu- ral Net- work	95.6 % with a vari- ance of 0.7%.
[20]	ANN	Attention	visual task	band- pass filter (1-35 Hz)	Lyapunov ex- ponent, Higuchi fractal dimen- sion, Katz frac- tal dimension, Sevcik fractal dimension	MLP	Classification accu- racy for all electrodes- 68.9%, frontal region – 86%, central region –62% parietal re- gion – 61%, occipi- tal region – 55.6%
[49]	ANN	Inatten- tion	Visual task	lowpass Bessel filter with 35 Hz cut- off fre- quency	Lyapunov ex- ponent, Higuchi fractal dimen- sion, Katz frac- tal dimension and Sevcik frac- tal dimension	multilayer perceptron neural net- work	96.7% accuracy with frontal lobe EEG.
[21]	-	Hyperac- tivity	Conners' Par- ent/Teacher Rating Scales- Revised: Long Ver- sion	-	Effect Size, Standard Devia- tion	Statistical Analysis System	62% of children and 76% of parents would recommend NF to others
[22]	Frequency	Inatten- tion	Conner's Rating Scales- Re- vised and Behavior, GO/NOGO test	-	theta/beta ratio, theta and beta separately, age as a covariate, Effect size, ROC	Statistical Analysis System	Discrimination ac- curacy of ADHD and controls is 85%
[25]	Time- Frequency Domain	Attention	mental tasks, i.e., concentra- tion and re- laxation	-	OCNM parame- ters: delaying time, embed- ding dimension, and connection threshold	LDA	$\begin{array}{l} OCNM \ accuracy \ - \\ 80.67\% \\ AMM \ accuracy \ - \\ 70.58\% \\ \alpha + \beta + \delta + \theta + R \\ method - \ 68.88\% \end{array}$
[37]	Time- Frequency	Audio Visual At-	CAARS-S: SV	Band Pass	Nonlinear fea- tures such as	ICA	Mean Std. Devia- tion -370.9 ± 33.4

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	Domain	tention	"No-Go" CPT task	Filter (0.1-80 Hz), Notch Filter (50Hz)	Wavelet Entro- py, Correlation Dimension, and Lyapunov- Exponent		ms (Normal Sub- jects) 372.8 ± 48.2 ms (ADHD Subjects) 96% accuracy in distinguishing ADHD and nor- mal's using combi- nation of non-linear feature and KNN
[38]	Time- Frequency Domain	Alertness	alphabet counting, virtual driv- ing	Notch filter (50Hz), Butter- worth IIR	PSD, DWT	PCA	100% for Highest Alertness Classifi- cation, 72% for Lowest Alertness Classification

Table 5: Summary of Studies Related to Multimodal Modalities.

Publication	Domain	Symptoms	Task	Filters	Features	Classifier	Accuracy
[23]	ANN	Inattention, Hyperactivity	cognitive visual processing and numerical opera- tions	FIR, 7th order Butter- worth band-pass fiter, notch filter of 50 Hz	Non-Linear features: Hi- guchi, Katz, Petrosian fractal dimen- sions, largest Lyapunov exponent, and approximate entropy.	MLP	93.65% with DISR and MLP DISR combined
[24]	Frequen- cy Do- main	-	DSM-IV	-	mean, SD, TBR	-	excess theta and TBR of ADHD (25%- 40%)
[26]	ANN	Hyperactivi- ty, Inatten- tion	Visual task	band-pass filter be- tween 0.5 and 20 Hz	-	EEGNet	classification accuracy of up to 83% mean and standard deviation of ac- curacy is 39% and 30%, re- spectively

[27]	Frequen- cy Do- main	Inattention, Hyperactivi- ty, Impul- sivity	Hyperactivity - Conners (CPRS- R); ADDES- Home, BASC, SNAP, FBB- HKS (parents) Inattention- Conners Impulsivity - TOVA, IVA (Auditory pru- dence measure) Go-NoGo test.	-	pre- and post- treatment ef- fect sizes (ES) SMR/Beta/Th eta vs. Be- ta/Theta vs. SCP proto- cols, and SCP protocols vs. all Beta/Theta protocols	Statistical	Mean ES for inattention - 0.8097, hyperac- tivity-0.3962 impulsivity- 0.6862 ES for inatten- tion and impul- sivity is substan- tial, whereas the ES for hyperac- tivity is lower
[36]	Frequen- cy Do- main	Inattention, Hyperactivi- ty, Impul- sivity.	Visual test	low-pass filter with cut-off fre- quency of 50 Hz	E α , E β , E θ , E δ (Energy values at α , β , θ , δ bands re- spectively) and R= E α / E β	SVM FFT	classification accuracy of 76.82%
[40]	Frequen- cy Do- main	Attention, Hyperactivi- ty, Impul- sivity	Barkley's Cur- rent Symptoms Scale GO/NOGO test	-	ERP compo- nent latency, amplitude	SVM ICA	10-fold cross- validation ap- proach - 91% SVM Classifier - 94%
[41]	Frequen- cy Do- main	Attention, Timing, Impulsivity, Hyperactivity	ASRS, MOXO, auditory oddball protocol, DSM V	-	theta/beta ra- tio using ERP, ERS/ERD, BEI, and Oddball BEI approaches	-	Lower average BEI, MOXO BEI' improved with both treatment and time/learning effects, im- proved oddball BEI
[42]	Frequen- cy Do- main	Inattentio, hyperactivity, impulsivity, combined	Conners Rating Scale	Notch filter (50Hz),	SEN-SPEC, EEG (The- ta/Beta ratio)	FFT with frequency resolution of 0.5 Hz	Theta/Beta ra- tio - 87% SEN, 94% SPEC, CSR(R) - 38-79% SEN, 13-61% SPEC

The EEG based diagnosis of ADHD has been proposed, and EEG data from 47 ADHD children (7-12 years) has been obtained. The various techniques used namely; Infinite Impulse Response (IIR) was used to obtain a band-limited EEG in the 0-60 Hz range, adroit integration nonlinear wavelets for 4 level decomposition of sub-bands (Gamma, Beta, Alpha, Theta, and Delta), Takens' theorem was used to build state space of each EEG signal and its subbands, and Radial Basis Function (RBF) neural network classifier. The specificity of the diagnosis is 95.6%, with a difference of 0.7%.^[19]

EEG signals from 20 ADHD and 20 normal children aged 7 to 12 years were compared for non-linear features. Children were given visual tasks, and therefore the EOG (Electro Oculogram) artifact was removed. Four non-linear features are used to calculate the probability of attention continuity for each subject: the Lyapunov Exponent, Higuchi Fractal Dimension, Katz Fractal Dimension, and Sevcik Fractal Dimension. Because previous research has shown that the frontal and prefrontal lobes of ADHD children's brains change, classification of the central parietal and occipital regions of the scalp was done, and classification accuracy was exposed with all features. A Multi Layer Perceptron (MLP) neural network with one hidden layer and five neurons was used to classify signals. The EEG data in the frontal and prefrontal regions of the brain was 86% accurate. Attention continuity was an important quality for the classification of ADHD and control group children, according to this study. The frontal region of the brain has been calculated to have an accuracy of 96.7 %.^[20]

In 6-12 year olds, the Double-Blind method of the trial was used, with DSM-IV randomized to active NF vs. sham NF for 2 times vs. 3 times per week therapy. The Last Observation Carried Forward (LOCF) principle or data from the nearest point was utilized to fill in missing values in SAS version 9.2. This approach has shown that a well-blended big Randomized Clinical Trial of Neurofeedback with a sham control of identical intensity and duration is possible and only requires three treatments per week.^[21]

The behavior of ADHD and control groups was measured using a Continuous Performance Test (CPT), a GO/NOGO test, and psychological rating scales such as Conner's Rating Scales-Revised and Behavior Rating Inventory of Executive Function. The EEG spectra are compared while the eyes are closed and when they are open. In both groups, the GO/NOGO task resulted in an accuracy of 85% discrimination between ADHD and controls, whereas theta at Cz acquires 62% accuracy. The sensitivity of ADHD patients has been observed as 86-90% whereas specificity has been observed as 94-98%, and hence theta/beta ratio discriminates ADHD patients and normals based on these.^[22]

In recent years, a Chinese scientist has proposed the OCNM (Optimized Complex Network Method) for assessing attention levels. The OCNM network is based on EEG nonlinear time series analysis. The Complex Network is calculated using the Time Delay Algorithm and the

Euclidian distance between two nodes in this technique. The Euclidian distance is calculated using three parameters: delay duration, embedding dimension, and connection threshold. EEG data from participants aged 19 to 30 years old was obtained, and the characteristics of Average Degree and Clustering Coefficients were retrieved using Linear Discriminate Analysis (LDA). These features are evaluated and compared to the Attention Meter Technique (AMM), a built to evaluate individual's attention meters and the $\alpha + \beta + \theta + \delta + R$ method explored in.^[36] The LDA is used to classify OCNM features, and it is claimed that the proposed system is more accurate than both methods.^[25]

Nonlinear features such as Wavelet Entropy, Correlation Dimension, and Lyapunov-Exponent have been studied to differentiate between normal and ADHD subjects aged 29.8 ± 6.4 years. One task was provided for the acquisition of EEG signals that focused on children's visual attention. For movement artifact removal, a Bandpass filter (0.1-80 Hz) was used, as well as a 50 Hz Notch Filter for line noise removal and an ICA for EOG artifact removal. Normal subjects had a mean standard deviation of 370.9 ± 33.5 msec, while ADHD subjects had a mean standard deviation of 372.8 ± 48.2 msec.^[37]

Suppression of beta rhythmic activity and increased alpha rhythmic activity have been identified as indicators of mental alertness. Principle Component Analysis (PCA) is a multivariate analytical approach that uses a statistical transformation technique to identify patterns in data. Power Spectral Density (PSD) and Discrete Wavelet Transform (DWT) were used as a feature. These features, together with the Artificial Neural Network classifier, resulting in an accuracy of 100% for the Highest Alertness Classification and 72% for the Lowest Alertness Classification.^[38]

The sustained attention which is considered as main deficit in ADHD has been evaluated for the adults. For the evaluation, the non-linear features of EEG signals like wavelet entropy, correlation-dimension and Lyapunov exponent are focused. This study results in 96% accuracy with wavelet-entropy over the other 2 features that has been studied.

Table 4 lists the filters, features, and classifiers that are used to diagnose unimodal symptoms of ADHD like attentiveness or hyperactivity, whereas **Table 5** lists the filters, features, and classifiers that are used to identify multimodal symptoms like hyperactivity, impulsivity, and inattentiveness.

The recent decade's unimodal studies primarily utilized the Time and Frequency domain and mostly targeted the symptom of attentiveness.

30 ADHD children (22 boys and 8 girls, aged 9.62 ± 1.75) and 30 healthy children (25 boys and 5 girls, aged 9.85 ± 1.77) have been tested for Inattentivity and Hyperactivity. The nonlinear feature, Fractal dimension has been calculated with the help of 3 algorithms: Katz, Higuchi, and Petrosian Method of fractal dimension, Lyapunov Exponent, approximate entropy extracted. For extraction of these features Double Input Symmetrical Relevance (DISR) and minimum Redundancy Maximum Relevance (mRMR) have been used. It shows that nonlinear features are appropriate to analyze and characterize EEG signal and DISR with MLP Neural Network achieved 93.65% accuracy in classification of ADHD and healthy children.^[23]

Excessive Theta/Beta Ratio (TBR) cannot be considered a reliable diagnostic measure of ADHD. TBR data during Eyes Open from site Cz is evaluated for children/ adolescents 6-18 years of age with and without ADHD.^[24]

Deep Learning Methods Based on Events EEG data is used to distinguish between ADHD sufferers and healthy controls. EEGNet is a processing tool that uses EEG data to discover, display, and analyze brain networks.^[39] To evaluate classification performance, the "leave one out subject" (LOOS) method has been applied with EEGNet. Only one subject was chosen for testing in this procedure, while the others have been used for training. When it comes to classification, it has an accuracy of up to 83%.^[26]

The Test of Variable Attention (TOVA), IVA, or Go-NoGo test can be used to access rating scales such the FBB-HKS, Conners (CPRS-R, BASC, ADDES-Home, SNAP/Iowa-Conners), or DSM-IV Rating Scale for Inattention and Impulsivity. The pre-and post-treatment effect sizes (ES) were computed. Averages and standard deviation are calculated, among other things. The ES is subjected to a one-way ANOVA to examine neurofeedback treatment factors such as SMR/Beta/Theta vs. Beta/Theta vs. SCP protocols, and SCP protocols vs. all Be-ta/Theta protocols. The ES values of several modalities were examined among and across subjects, and it was discovered that inattention has an ES of 0.8097, hyperactivity has an ES of 0.3962, and impulsivity has an ES of 0.6862. Finally, the clinical effects of neurofeedback in the treatment of ADHD are concluded. The ES for inattention and impulsivity is substantial, whereas the ES for hyperactivity is lower.^[27]

Using independent Event-Related Potential, it is possible to distinguish adult ADHD patients from non-clinical control persons. As a result of the 10-fold cross-validation methodology, the classification accuracy is 91%. In addition, the Support Vector Machine (SVM) classifier has been shown to be highly predictive, with a classification accuracy of 94%.^[40]

For distinguishing ADHD and controlled patients, raw EEG analysis methods and tools (NE-BA tool based on theta/beta ratio), event-related analysis methods (event-related potentials (ERP) and event-related synchronization / desynchronization (ERS/ERD)), and task-related analysis (CPT, Brain Engagement Index (BEI) and Oddball BEI approaches) were used. The average BEI in the ADHD group was lower than in the control group, whereas the MOXO BEI' improved with both treatment and time/learning effects, and the oddball BEI improved for ADHD participants with the treatment effect rather than the time/learning impact.^[41]

EEG signals captured by the MindSet EEG device at a sample rate of 512 Hz were used to identify the attention or inattentiveness of 25-year-old volunteers. Support Vector Machine was used to classify EEG data, extracting five features $E\alpha$, $E\beta$, $E\theta$, $E\delta$ (Energy values at α , β , θ , δ bands respectively) and R= $E\alpha$ / $E\beta$ as the foundation for classification, resulting in a classification accuracy of 76.82%. According to this study, several classification approaches such as a Neural Network classifier, artificial neural network, decision tree, and random forest can be utilized to increase the recognition accuracy rate of attentive EEG signals.^[36]

To diagnose ADHD, researchers first looked for SEN-SPEC (Sensitivity Specificity), EEG (Theta/Beta ratio), Conner's Rating Scales-Revised (CSR-R) ADHD Rating Scales. EEG identified ADHD with 87% sensitivity and 94% specificity in the Anterior Cingulated Cortex region. Rating scales, on the other hand, provide sensitivity of 38–79% and specificity of 13–61%. Mean and standard deviation of ADHD showed significant increases in theta relative power and theta/ beta ratio, and significant decreases in alpha relative power, beta1 relative power, and beta2 relative power compared to other disorders. The frequency bands for ADHD have been observed as delta1 (1.0–1.5 Hz), delta2 (2.0–3.5 Hz), theta (4.0–7.5 Hz), alpha (8.0–12.5 Hz), beta 1 (13.0–20.5 Hz), and beta2 (21.0–31.5 Hz). However, when compared to parent or teacher identification of ADHD using rating scales, theta/beta ratio is less accurate, and it is not suitable for comorbid conditions. It has been discovered that EEG is insufficient as a stand-alone diagnostic tool and thus necessitates additional clinical evaluation.^[42]

Frequency Domain and ANN classification algorithms were commonly employed in multimodal investigations throughout the last decade. However, some nutritionists advise avoiding all artificial colors and flavors in foods, as well as the preservatives Butylated Hydroxyanisole (BHA) and Butylated Hydroxytoluene (BHT), as well as foods containing natural salicylates: Almonds, Currants, Plums, Cloves, Apples, Grapes, Raisins, Tangerines, Coffee, Apricots, Nectarines, Cucumber, pickles Some foods high in zinc sulphate, iron, and magnesium have been shown to help with ADHD symptoms, whereas others have not.^[43,44] YOGA and mindfulness meditation have also been recommended as helpful therapy for ADHD.^[45] Inspite of the standard way of psychological diagnosis, occupational therapy and sensory treatment are also been preferred. Occupational therapy can assist children with ADHD in developing skills such as organisation, physical coordination, daily work, and regulation of their energy levels. The occupational therapist frequently oversees a test to determine the child's strengths and weaknesses. They will then offer solutions to their concerns that would use various games, activities to work out anger and aggression, try techniques to improve focus, and so on. Occupational therapists, on the other hand, diagnose sensory processing disorders in children.^[46]

4 CONCLUSION

When compared to other therapy studies, neurofeedback treatment appears to be a safe and cost-effective therapeutic choice because the acquisition devices are small, inexpensive and non-invasive. Furthermore, amongst all available brain signal acquisition modalities, EEG is the most popular, efficient, and reliable. As a result, the researchers concentrated on using EEG to diagnose and treat ADHD. The majority of the work done with EEG for ADHD is connected to attention.

Various computational techniques from the Time-Domain, Frequency-Domain, and ANN have been applied for the EEG-based assessment of ADHD. And those procedures provide a high level of precision. All of these works are carried out on a global scale, with some inconsistency at the country level. There is room for improvement in terms of diagnosis accuracy. The fronto-central areas (F3, F4, and Fz), as well as the frontal right (Fp2 and F8) of the brain, were used as training sites in the majority of research. Considering the premise that the brain regulates the human body and behaviour via brain impulses and that ADHD cannot be diagnosed based solely on one symptom. A multimodal approach will lead to an appropriate diagnosis of ADHD, and there must be an applicable pattern of band values in ADHD pa-

tients. Furthermore, the prevalence of ADHD is higher in adolescence, and it must be addressed at the same time for children to have a better future. Thus EEG can be considered to be associative mode for ADHD Assessment. Moreover, while diagnosing ADHD, the psychological factor is also significant.

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REFERENCES

- 1. DSM-V. Journal of Attention Disorders, 2011; 3-10.
- Association, A.P., Diagnostic and statistical manual of mental disorders (DSM-5[®]), 2013.
- Attention Deficit Hyperactivity Disorder. [cited 28/06/2018]. Available from: https://www.nimh.nih.gov/health/topics/attention-deficit-hyperactivity-disorderadhd/index.shtml, 2018.
- 4. Sciberras, E., et al., Prenatal risk factors and the etiology of ADHD—review of existing evidence. 2017; 19(1): 1.
- 5. Ghosh, P., et al., Prevalence of attention deficit hyperactivity disorder among primary school children in Cachar, Assam, North-East India, 2018; 9(2).
- Thapar, A., et al., What causes attention deficit hyperactivity disorder?, 2012; 97(3): 260-265.
- 7. Antshel, K.M., et al., Advances in understanding and treating ADHD, 2011; 9(1): 1-12.
- 8. Martinez-Raga, J., et al., Risk of serious cardiovascular problems with medications for attention-deficit hyperactivity disorder, 2013; 27(1): 15-30.
- 9. Marzbani, H., et al., Neurofeedback: a comprehensive review on system design, methodology and clinical applications, 2016; 7(2): 143.
- 10. Brain Waves, 2016. [cited 2018; Available from: https://www.goodtherapy.org /blog/psychpedia/brain-waves.
- 11. Shinde, M.S., et al., Detection of Epileptic Seizure Using EEG Sensor, 5(2): 203-206.
- Arman, S.I., et al., Cost-effective eeg signal acquisition and recording system, 2012; 2(5): 301.
- 13. Teplan, M.J.M.s.r., Fundamentals of EEG measurement, 2002; 2(2): 1-11.
- 14. Radüntz, T.J.F.i.p., Signal quality evaluation of emerging EEG devices, 2018; 9: 98.

- 15. LaRocco, J., M.D. Le, and D.-G.J.F.i.n. Paeng, A systemic review of available low-cost EEG headsets used for drowsiness detection, 2020; 14.
- 16. Mao, X., et al., Progress in EEG-based brain robot interaction systems, 2017; 2017.
- 17. Hokajärvi, I.A., Electrode contact impedance and biopotential signal quality, 2012.
- 18. ADHD Test, 2018. Available from: https://www.manashakti.org/index.php?q=life-stage/children&page=6.
- 19. Ahmadlou, M., H.J.C.E. Adeli, and Neuroscience, Wavelet-synchronization methodology: a new approach for EEG-based diagnosis of ADHD, 2010; 41(1): 1-10.
- Allahverdy, A., A.M. Nasrabadi, and M.R. Mohammadi. Detecting ADHD children using symbolic dynamic of nonlinear features of EEG. in 2011 19th Iranian Conference on Electrical Engineering, 2011.
- 21. Arnold, L.E., et al., EEG neurofeedback for ADHD: double-blind sham-controlled randomized pilot feasibility trial, 2013; 17(5): 410-419.
- 22. Ogrim, G., J. Kropotov, and K.J.P.R. Hestad, The QEEG theta/beta ratio in ADHD and normal controls: sensitivity, specificity, and behavioral correlates, 2012; 198(3): 482-488.
- 23. Mohammadi, M.R., et al., EEG classification of ADHD and normal children using nonlinear features and neural network, 2016; 6(2): 66-73.
- 24. Arns, M., C.K. Conners, and H.C.J.J.o.a.d. Kraemer, A decade of EEG theta/beta ratio research in ADHD: a meta-analysis, 2013; 17(5): 374-383.
- 25. Wu, Z.-P., et al., Optimized complex network method (OCNM) for improving accuracy of measuring human attention in single-electrode neurofeedback system, 2019; 2019.
- 26. Vahid, A., et al., Deep learning based on event-related EEG differentiates children with ADHD from healthy controls, 2019; 8(7): 1055.
- 27. Arns, M., et al., Efficacy of neurofeedback treatment in ADHD: the effects on inattention, impulsivity and hyperactivity: a meta-analysis, 2009; 40(3): 180-189.
- 28. Subha, D.P., et al., EEG signal analysis: a survey, 2010; 34(2): 195-212.
- 29. Acharya, U.R., et al., Automated EEG analysis of epilepsy: a review, 2013; 45: 147-165.
- 30. Kottaimalai, R., et al. EEG signal classification using principal component analysis with neural network in brain computer interface applications. in 2013 IEEE International Conference ON Emerging Trends in Computing, Communication and Nanotechnology (ICECCN), 2013.
- Harpale, V.K. and V.K. Bairagi. Time and frequency domain analysis of EEG signals for seizure detection: A review. in 2016 International Conference on Microelectronics, Computing and Communications (MicroCom), 2016.

- 32. Siuly, S., Y. Li, and Y. Zhang, EEG Signal Analysis and Classification Techniques and Applications.
- 33. Adeli, H., Z. Zhou, and N.J.J.o.n.m. Dadmehr, Analysis of EEG records in an epileptic patient using wavelet transform, 2003; 123(1): 69-87.
- 34. Yang, J., et al., Channel selection and classification of electroencephalogram signals: an artificial neural network and genetic algorithm-based approach, 2012; 55(2): 117-126.
- 35. Bashashati, H., et al., Comparing different classifiers in sensory motor brain computer interfaces, 2015; 10(6): e0129435.
- 36. Liu, N.-H., C.-Y. Chiang, and H.-C.J.s. Chu, Recognizing the degree of human attention using EEG signals from mobile sensors, 2013; 13(8): 10273-10286.
- 37. Ghassemi, F., et al., Using non-linear features of EEG for ADHD/normal participants' classification, 2012; 32: 148-152.
- 38. Khanam, F., M.K. Alam, and M. Ahmad, EEG based Brain Alertness Monitoring by Statistical and Artificial Neural Network Approach.
- 39. Hassan, M., et al., EEGNET: An open source tool for analyzing and visualizing M/EEG connectome, 2015; 10(9): p. e0138297.
- 40. Mueller, A., et al., Discriminating between ADHD adults and controls using independent ERP components and a support vector machine: a validation study, 2011; 5(1): 1-18.
- 41. Shahaf, G., et al., Monitoring attention in ADHD with an easy-to-use electrophysiological index, 2018; 12: 32.
- 42. Snyder, S.M., et al., Blinded, multi-center validation of EEG and rating scales in identifying ADHD within a clinical sample, 2008; 159(3): 346-358.
- 43. Stevens, L.J., et al., Dietary sensitivities and ADHD symptoms: thirty-five years of research, 2011; 50(4): 279-293.
- 44. Heilskov Rytter, M.J., et al., Diet in the treatment of ADHD in children—A systematic review of the literature, 2015; 69(1): 1-18.
- 45. Mitchell, J.T., et al., Mindfulness meditation training for attention-deficit/hyperactivity disorder in adulthood: Current empirical support, treatment overview, and future directions, 2015; 22(2): 172-191.
- 46. Occupational Therapy for Children With ADHD. November 13, 2019. [cited 2021 27 June]; Available from: https://www.webmd.com/add-adhd/childhood-adhd/occupational-therapy-for-children-with-adhd.
- 47. Common ADHD rating scale tests, 2018. [cited 2021 31 May]; Available from: https://www.medicalnewstoday.com/articles/321867#adhd-rating-scale-tests.

- 48. What to Know About ADHD Rating Scales. Available from: https://www.webmd.com/add-adhd/childhood-adhd/adhd-rating-scales.
- 49. Emilsson, B., et al., Cognitive behaviour therapy in medication-treated adults with ADHD and persistent symptoms: a randomized controlled trial, 2011; 11(1): 1-10.
- 50. The Wechsler Intelligence Scale for Children Fourth Edition in Neuropsychological Practice, 14 September 2014; 4.
- 51. Wechsler Intelligence Scale for Children | Fourth Edition WISC-IV. 1996–2021 [cited 2021 30 July 2021]; Available from: https://www.pearsonassessments.com /store/usassessments/en/Store/Professional-Assessments /Cognition-%26-Neuro/Wechsler-Intelligence-Scale-for-Children-%7C-Fourth-Edition/p/100000310.html.
- 52. Hall, C.L., et al., The validity of the SNAP-IV in children displaying ADHD symptoms, 2020; 27(6): 1258-1271.
- 53. Adult ADHD Self-Report Scale (ASRS-v1.1) Symptom Checklist Instructions.
- 54. Vaughan, B.S., J.S. March, and C.J.J.I.J.o.N. Kratochvil, The evidence-based pharmacological treatment of paediatric ADHD, 2012; 15(1): 27-39.
- 55. Pringsheim, T., et al., The pharmacological management of oppositional behaviour, conduct problems, and aggression in children and adolescents with attention-deficit hyperactivity disorder, oppositional defiant disorder, and conduct disorder: a systematic review and meta-analysis. Part 1: psychostimulants, alpha-2 agonists, and atomoxetine. 2015. 60(2): 42-51.
- 56. Briars, L., T.J.T.J.o.P.P. Todd, and Therapeutics, A review of pharmacological management of attention-deficit/hyperactivity disorder, 2016; 21(3): 192-206.
- 57. Catalá-López, F., et al., The pharmacological and non-pharmacological treatment of attention deficit hyperactivity disorder in children and adolescents: a systematic review with network meta-analyses of randomised trials, 2017; 12(7): e0180355.
- 58. McCarthy, S., et al., The epidemiology of pharmacologically treated attention deficit hyperactivity disorder (ADHD) in children, adolescents and adults in UK primary care, 2012; 12(1): 1-11.
- 59. Evans, S.W., et al., Evaluation of a school-based treatment program for young adolescents with ADHD, 2016; 84(1): 15.
- 60. Miranda, A., et al., Executive functioning and motivation of children with attention deficit hyperactivity disorder (ADHD) on problem solving and calculation tasks, 2012; 17(1): 51-71.

 Adeli, H. Wavelet-chaos-neural network models for EEG-based diagnosis of neurological disorders. in International Conference on Future Generation Information Technology, 2010.