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Resting EEG Biomarkers: Investigating Energy Asymmetry in Brain Hemispheres for Autism Diagnosis across Gender

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Abstract: Autism spectrum disorder (ASD) is characterized by atypical brain activity, yet early and accurate diagnosis remains challenging. This study proposes a novel EEG-based method to detect ASD by analyzing hemispheric energy asymmetry during the resting state. EEG data were recorded from 44 children (22 ASD, 22 controls) at medical city, Baghdad. Signals were pre-processed using decimation, band-pass filtering, artifact subspace reconstruction, detrending, and normalization. A sliding window (8 s, 12.5% overlap) extracted maximum theta wave energy from each hemisphere. Results revealed greater right-hemispheric energy in ASD children, particularly enhanced in the Theta band. The method achieved 100% ASD detection accuracy for both genders, while control classification yielded 77% accuracy for males and 55.6% for females, resulting in an overall control accuracy of 68.1%. Total accuracy across groups was 84% (88.5% males, 77.8% females). These findings highlight right-hemispheric dominance in ASD and the need for gender-specific considerations in EEG-based diagnosis.

Keywords: Autism Diagnosis; Brain Hemispheres; Brain Hemisphere Imbalance; Diagnostic Biomarkers; Electroencephalography (EEG); Gender Differences

1 INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition influenced by genetic, epigenetic, environmental, and immune factors. It is primarily diagnosed in children and is characterized by difficulties in communication, social interaction, and restricted or repetitive behaviors. The symptoms vary widely among individuals, making ASD a highly heterogeneous disorder [1].

Genetic susceptibility plays a significant role in ASD, with families having a history of autism showing higher occurrence rates. Genetic mutations linked to brain development increase the risk. ASD individuals often exhibit neurochemical and neuroanatomical abnormalities, including atypical brain activity and accelerated early childhood brain growth. Environmental factors like prenatal infections, air pollution, and preterm birth may contribute to ASD risk but typically interact with genetic predispositions rather than acting alone [2].

Given the multidimensionality of ASD, researchers emphasize that development of the disorder results from a combination of genetic, biological, and environmental factors. Due to the multiplicity of causative factors, it is easy to attribute no single cause to the disorder. Identification of such causative factors makes it easier to advance in diagnosis and treatment at an early stage, consequently enhancing the quality of life of people with ASD as well as integration into society [1].

The prevalence of ASD has been steadily increasing around the world. In America, the rate had risen from 1 in 68 children in 2014 to 1 in 36 children in 2018 [3]. Further, ASD is diagnosed roughly 3.9 times more frequently in boys than in females [3]. The World Health Organization (WHO) found that 1 in 100 children in the world has ASD [4]. Similarly, Autism Spectrum Australia (ASA) also noted an increase in the incidence of autism from 1 in 100 in 2014 to 1 in 70 in 2018, a rise of 40% in cases. By 2024, this figure reached 1 in 40, indicating that at least 1 in 40 individuals are on the autism spectrum, a significant increase from the previous estimate of 1 in 70 in 2018 [5].

In South Korea, rates of ASD cases registered have also increased exponentially. They numbered 1,514 as of the year 2000 but rose to a modest 42,700 and above by 2023—a 2,384% increase in just twenty years [6]. Fig.1 illustrates the steady annual rise in ASD cases in South Korea from 2000 to 2023. The graph demonstrates an acceleration pattern of acceleration with the annual growth rate increasing from approximately 1.01 thousand new cases annually in the early 2000s to approximately 2.85 thousand new cases annually in 2016.

This trend suggests an exponential increase in ASD prevalence, emphasizing the urgent need for prevention and intervention strategies. With the assumption that the current trend continues, it is projected that ASD cases in South Korea would be approximately 73.55 thousand in 2030. Based on the current annual increment rate of 2.85 thousand cases, this estimate emphasizes the necessity of understanding the reasons for this rapid increase.

Despite the increasing trend, ASD prevalence is not consistent across all countries, with some countries reporting considerably higher rates compared to others. Differences in diagnostic criteria, awareness, and accessibility of healthcare might explain these variations. It is important to understand the variations in order to formulate effective global measures to manage and alleviate the burden of ASD.

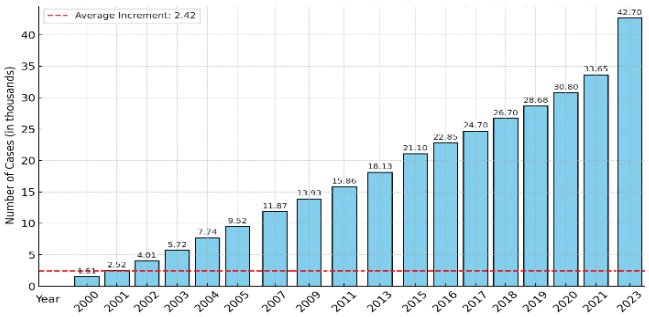


Figure 1 Number of people with ASD in South Korea from 2000 to 2023

Study on infant siblings at high risk of autism shows that some behavioral traits typical of autism start to emerge in the later stages of the 1st and 2nd year of life [7, 8]. ASD severely disables a person from performing daily activities, interacting socially, and succeeding in school and work environments. In addition, people with ASD are constantly exposed to discrimination, abuse, and infringement of their human rights all over the world, as reported by the WHO [4].

There is no cure available for ASD to date, yet early intervention is reported to produce a positive influence on brain growth, improving learning, social, and communication functions. With increased cases of ASD across the world, it is imperative to devise an accurate, effective, and highly efficient diagnosis system

The rising prevalence of autism is a big challenge to human health and the quality of education. As the number of ASD cases increases, the most potent way to improve outcomes is early detection and intervention. Therefore, high priority must be accorded to early identification to ensure timely intervention and treatment of individuals with ASD.

Early ASD detection plays a crucial role in mitigating the challenges associated with autism. The following objectives outline the importance of timely diagnosis:

- Improving Developmental Gains: Early diagnosis of ASD allows children to receive interventions during the critical period of brain development (before age 3). This helps improve social, communication, and cognitive development, enabling greater independence as they grow [9].
- Reducing Long-term Costs and Burdens: Early intervention minimizes the need for costly therapies, reducing the financial and emotional burden on families and the healthcare system. Children diagnosed early are more likely to succeed in regular educational settings, reducing the need for specialized programs.
- Facilitating Social and Communication Development: Early diagnosis enhances communication and socialization skills, helping children build essential interpersonal abilities. This promotes better academic engagement and integration into society [9].
- Personalized and Efficient Treatment Strategies: Early identification allows tailored interventions involving pediatricians, therapists, and educators. This individualized approach enhances developmental outcomes and addresses areas of difficulty effectively [9, 10].

2 RELATED WORKS

With the advancements in technology and computing, artificial intelligence (AI) has achieved numerous successes across various fields. Additionally, AI has been employed for the early detection of autism in several studies [11, 12]. However, studying and analyzing the energy distribution in both hemispheres of the brain for different genders is of great importance, as it helps highlight differences and draw valuable conclusions that should be considered in future studies.

However, in this study, a quantitative analysis of brain wave energy distribution between the right and left hemispheres, as well as gender-based differences in control and ASD children, is emphasized. This approach establishes a robust foundation for understanding neurophysiological divergences between these groups.

A study by [13] explores gender differences in brain function and structure, highlighting variations in cognitive processing, emotional regulation, and neurological susceptibility. These differences are attributed to genetic, hormonal, and environmental influences rather than inherent superiority. Understanding these distinctions aids in developing gender-specific strategies for treating neurological disorders.

Research by [14] investigates sex differences in brain-behavior correlations during early childhood using resting-state fMRI. Findings indicate that significant functional connectivity differences exist between males and females, particularly in the prefrontal cortex and temporal pole, influencing cognitive and emotional development at later stages.

A study by [15], examined how the native language influences brain connectivity. Using MRI and diffusion-weighted imaging, they compared brain scans among 94 native speakers of Arabic and German. The findings indicated more connectivity between the left and right hemispheres in Arabic speakers due to the complex semantic and phonological processing of Arabic. Conversely, the German speakers exhibited more left-hemisphere integration, possibly because of German's syntactically complex nature. The study illustrates how early language exposure affects brain structure and cognitive processing.

The study in [16] examines neural abnormalities in vocal pitch perception in children with ASD through magnetoencephalography (MEG). Results reveal atypical pitch processing in ASD, particularly in the left hemisphere, suggesting abnormal neural mechanisms that affect auditory perception.

Similarly using MEG, [17] investigates auditory processing deficits in children with specific language impairment (SLI). Findings indicate an enhanced left-hemisphere auditory response in SLI children, deviating from the typical right-hemisphere dominance, suggesting a compensatory neural mechanism for delayed language development.

In [17], the neural basis of phonological deficits in developmental dyslexia is examined through MEG. Results show atypical left-hemispheric specialization in at-risk children, affecting phonological processing and efficient word learning.

Language lateralization development is explored in [18] using fMRI, revealing strong right-hemisphere activation in young children, which diminishes with age. This suggests a compensatory mechanism for language recovery following left-hemisphere injury.

Authors in [19] examine hemispheric dominance in bimanual movements, supporting left-hemisphere control in symmetric movements. However, asymmetric movements do not show definitive hemispheric dominance, indicating task-dependent lateralization.

The classical left-brain/right-brain theory introduced by [20] posits that each hemisphere governs different cognitive styles. Though outdated, this theory provides a foundation for

understanding hemispheric specialization in analytical and creative tasks.

Hemispheric attention differences are investigated in [21], suggesting the right hemisphere processes both contralateral and ipsilateral stimuli, whereas the left hemisphere primarily processes contralateral stimuli. EEG findings support right-hemisphere dominance for attention.

The development of functional brain asymmetry in childhood is further explored in [22] through cerebral blood flow studies. Initial right-hemisphere dominance in early childhood shifts to left-hemisphere dominance by age three, aligning with the evolution of visuospatial and language functions.

The right hemisphere's role in emotional processing is analyzed in [23] through behavioral and physiological measures. Results indicate strong physiological responses to emotional stimuli in the right hemisphere, suggesting its primary contribution to emotional regulation rather than cognitive processing.

These studies collectively indicate the presence of significant hemispheric and gender differences in brain function, supporting the hypothesis that ASD involves distinct patterns of brain wave energy distribution. The current study builds upon this foundation by quantitatively comparing energy differences between hemispheres in autistic and control children, further delineating the neurophysiological distinctions between these groups.

3 DATASET DESCRIPTION

The study, conducted from March 5, 2021, to July 11, 2023, data collected from the Children's Welfare Teaching Hospital at Medical City, Baghdad, Iraq.

EEG signals were recorded using the 10/20 international electrode system [24], employing a 19-channel scheme with a sampling frequency of 0.5 kHz, ensuring channel resistance remained below 10 kΩ. All EEG data consisted of real signals to obtain accurate and practical results. The EEG machine used in this study was manufactured by Nihon Kohden Company, Japan. Fig. 2 illustrates electrode connections using 19 channels based on the 10/20 international electrode placement system.

Subjects underwent EEG recording during induced sleep, with the chloral hydrate group receiving specified doses of the drug. The study included 44 children: 22 diagnosed with ASD (mean age: 3.9 ± 1.7 years) and 22 control children (mean age: 4.8 ± 3.1 years). The recording duration ranged from 28 to 42 minutes, with an average of 32.8 minutes. Autism diagnoses were subsequently confirmed using the medical history, and clinical assessments conducted by child and adolescent psychiatrists. The DSM-5 [25] criteria at the National Autism Center, using standardized assessments by child and adolescent psychiatrists.

The control group was selected from the pediatric department of the Child Welfare Teaching Hospital, EEG unit. Anonymization techniques were applied to maintain confidentiality and adhere to ethical standards.

The dataset indicates that parents did not report any instances potentially linked to epileptic seizures among the cases.

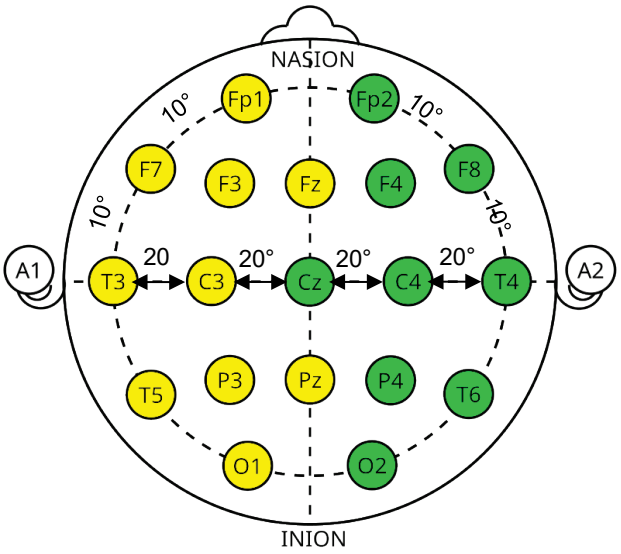


Figure 2 Illustration of electrode connections using 19 channels based on the 10/20 international electrode placement system

4 PROPOSED METHOD

The pre-processing stage included some significant steps. Data downsampling of data was initially performed in to reduce the sampling frequency from 0.5 kHz to 0.25 kHz for quicker processing. Filtering was subsequently performed utilizing linear-phase Finite Impulse Response (FIR) Band-Pass Filter (BPF) to remove frequencies less than 0.2 Hz and greater than 48 Hz. The aim of this step was to remove 50 Hz low-frequency artifacts and baseline noise. The filter was a Hamming-window design with heuristic order and transition bandwidth estimation, conducted automatically in EEGLAB [26].

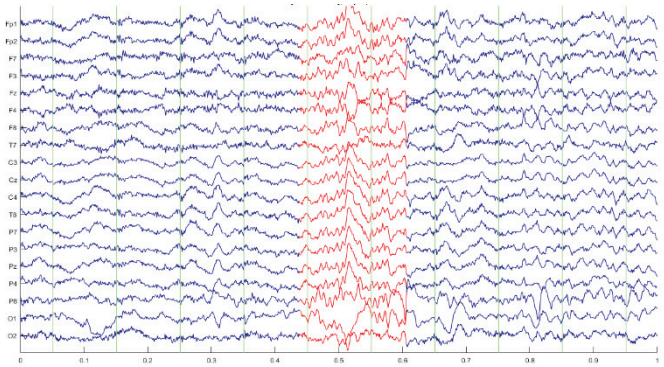


Figure 3 The work of ASR red color presented excluded segment of EEG

A key pre-processing step was Artifact Subspace Reconstruction (ASR), a technique that removes artifacts from EEG signals. ASR had three steps: 1st extracting reference data from raw EEG signals, 2nd estimating thresholds for identifying artifact components, and 3rd rejecting artifact components and reconstructing the cleaned data [27]. ASR effectively removes artifacts and reconstructs

the remaining EEGs, enhancing the quality and reliability of subsequent analysis and interpretation. Fig. 3 shows the rejected EEG signal segments identified by ASR in red and the reconstruction of the remaining segments in blue color.

Detrending is used to removes offsets or linear trends from time-domain input-output EEG data after artifact removal. It helps in detrend the data to eliminate systematic biases or drifts that may be operating it and ensures that the data is zero-centered or follows a stationary trend. While dealing with EEG signals, baseline shifts or slow linear trends are very common, which may distort the interpretation and analysis of the data. Detrending is done to eliminate these trends and focus on the dynamics of interest [28]. The technique involves estimating the trend component in the data and subtracting it to obtain detrended data. Fig. 4(B). An example of an output signal after detrending, shows a clear difference compared to Fig. 4(A), which representing the input EEG signals.

Following Amplitude Normalization (AN) was employed to increase the interpretability, removes the DC component, reliability, and effectiveness of EEG signal analysis for a broad spectrum of applications, e.g., neuroscience studies, clinical diagnosis, and brain-computer interface development [29]. The AN range was +1 to -1. Fig. 4(C). An example of an output signal after AN shows, a clear difference compared to Fig. 4 (A and B), representing the input EEG signals.

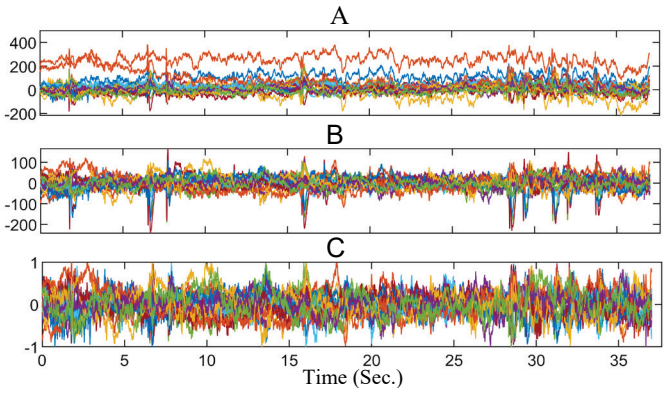


Figure 4 (A) Input EEG signals after the downsampling step, (B) output signal after detrending the input EEG signals, and (C) output signal after amplitude normalization

The EEG signal was then decomposed into sub-frequency bands using five BPFs, each implemented as a 6th-order Infinite Impulse Response (IIR) Chebyshev Type II filter and designed to extract specific EEG bands: [Delta (Δ): 0.2 – 4.0 Hz, Theta (θ): 4.0 – 8.0 Hz, Alpha (α): 8.0 – 13.0 Hz, Beta (β): 13.0 – 28.0 Hz, and Gamma (Γ): 31.0 – 48.0 Hz] as displayed in Fig. 5 a five decomposed frequency bands obtained using Fast Fourier Transform (FFT), shown in the frequency domain.

FFT is an efficient algorithm to compute the Discrete Fourier Transform (DFT), which is mathematically defined in Eq. (1):

$$X_h = \sum_{n=0}^{N-1} f(n) \cdot \mathrm{e}^{-j2\pi\frac{hn}{N}} \tag{1}$$

Where, X_h is the DFT of the sequence $f(n)$, $f(n)$ is the EEG signal in the time domain, $n = 0, 1, 2, \ldots, (N-1)$ is the time-domain sample index, $h = 0, 1, 2, \ldots, (N-1)$ represents the frequency index, and $\mathrm{e}^{-j2\pi\frac{hn}{N}}$ is the complex exponential, with j representing the imaginary unit. Fig. 5 illustrates an output of input EEG data.

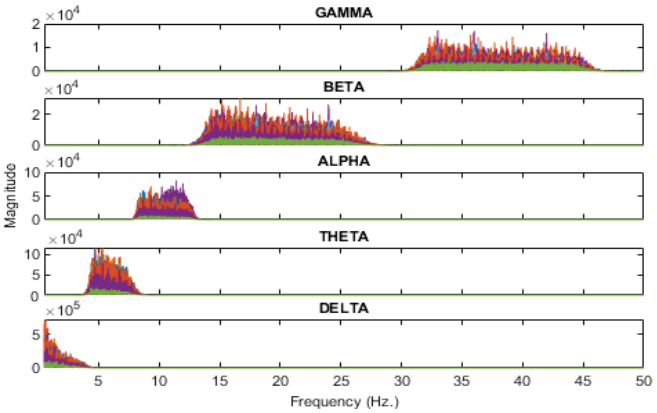


Figure 5 The FFT for the decomposed EEG bands

For analysis, EEG channels were grouped into two categories based on brain hemispheres: 1) Right hemisphere channels - Fp2, F4, C4, P4, O2, F8, T4, T6, and Cz. 2) Left hemisphere channels - Fp1, F3, C3, P3, O1, F7, T3, T5, Fz, and Pz, see Fig. 2 for the green and yellow channels, respectively.

The peak envelope method [30] was used to derive signal envelopes for all sensors. This process resulted in 10 envelope signals for the left hemisphere and 9 for the right hemisphere, as illustrated in Fig. 6. The mean of these envelopes was computed for each frequency band, generating a single envelope signal for each brain hemisphere.

The energy values were computed using a sliding window method on the mean envelope of each brain hemisphere for each decomposed band separately. The envelope signals denoted as ($\hat{H}_{\text{band, hemisphere}}[n] = \Psi$) were divided into overlapping windows. Define the index of a window as W denotes the window index and N the window length, experimentally set to 2×10^3 samples (~8 seconds), which is considered sufficient based on prior studies [11] and [29] suggests that an 8-second window provides informative data for EEG analysis.

Different overlap ratios, ranging from 12.5% to 87.5% with a step size of 250 samples, were tested to determine the most effective overlap, providing a measure of signal energy for each EEG band and hemisphere. The windowed signal envelope $E_{\text{band, hemisphere}}[n]$ is defined by the following Eq. (2):

$$E_{\text{band, hemisphere}} = \sum_{n=0}^{N-1} \left| \Psi\left[n + W(N - \Phi)\right] \right|^2 \tag{2}$$

Where Φ is the overlap in samples. The envelope energy in a window, $E_{\text{band, hemisphere}}$ is given by the sum of the squared envelope values over the window, $n = 0, 1, 2, \ldots, (N-1)$ is

the time-domain sample index within each window, and N is the total number of samples in the window.

Overlapping windows ensure continuity of the EEG signal and prevent the loss of valuable features between adjacent windows. Overlap improves feature extraction and enhances model performance. Mild overlapping allows the model to capture temporal patterns that might otherwise be overlooked without overlapping strides. Overlapping sliding windows have been shown to significantly improve classification accuracy [11]. In contrast, non-overlapping windows treat each segment as independent, potentially missing transitional features.

The proposed method is displayed in Fig. 6.

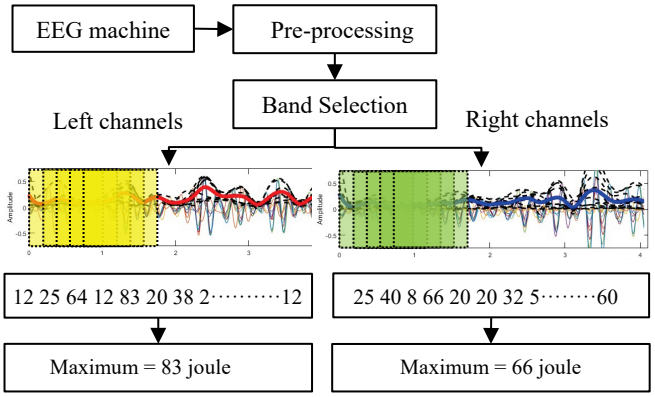


Figure 6 The proposed methodology for measuring energy in both brain hemispheres

5 RESULTS AND DISCUSSION

The experiments were conducted on a Microsoft Windows 10 Pro (22H2) operating system, with MATLAB® + plugin EEGLAB [26] on an Intel® CoreTM i7-7500U CPU @ 2.70-2.90 GHz, RAM 12.0 GB computer. The EEG signals were processed with EEGLAB V2023.1. With the help of the Automated artifact rejection tool in EEGLAB, employing the "Clean raw data" EEGLAB plugin, bad data segments were automatically excluded.

The study aimed to investigate hemispheric differences in EEG energy as potential biomarkers for ASD. The energy values were compared between the right and left hemispheres. In ASD cases, energy levels were generally higher in the right hemisphere (Left < Right), whereas in control cases, the left hemisphere exhibited higher energy (Left > Right).

Accuracy was calculated as the ratio of correctly classified samples to the total number of samples to quantify the discriminative power of these hemispheric energy differences. Specifically, for the Theta band, a stride of 250 samples was used, and the maximum energy within each window was selected as the feature for classification. Using this approach, the classification accuracy reached 100% for the ASD group and 68.18% for the control group, resulting in an overall accuracy of 84%, as presented in Tabs. 1 and 2. This demonstrates that hemispheric energy asymmetry can effectively differentiate between ASD and control subjects.

Table 1 Energy values for each hemisphere in Theta waves for the control group with a stride of 250 samples

ID	Gender	Left brain energy	Right brain energy	Left > Right
1	male	193.13	151.76	TRUE
2	male	113.85	92.52	TRUE
3	male	309.81	303.79	TRUE
4	male	157.84	147.53	TRUE
5	Female	184.92	187.41	FALSE
6	Female	192.28	176.64	TRUE
7	Female	184.70	202.92	FALSE
8	Female	182.92	177.72	TRUE
9	male	159.37	118.98	TRUE
10	male	110.27	125.66	FALSE
11	male	169.01	178.70	FALSE
12	male	139.19	145.49	FALSE
13	male	148.94	138.49	TRUE
14	male	168.17	161.15	TRUE
15	male	137.06	125.13	TRUE
16	male	215.52	179.88	TRUE
17	Female	129.69	180.37	FALSE
18	Female	158.48	178.18	FALSE
19	Female	285.15	212.42	TRUE
20	Female	193.20	174.88	TRUE
21	male	171.63	166.42	TRUE
22	Female	146.56	140.24	TRUE

Table 2 Energy values for each hemisphere in Theta waves for the ASD group with a stride of 250 samples

ID	Gender	Left brain energy	Right brain energy	Left < Right
1	male	121.54	180.96	TRUE
2	male	153.02	224.93	TRUE
3	male	151.69	178.93	TRUE
4	male	77.61	126.62	TRUE
5	male	143.91	198.98	TRUE
6	male	109.45	152.27	TRUE
7	male	125.24	162.18	TRUE
8	male	68.69	95.57	TRUE
9	male	169.67	284.28	TRUE
10	male	120.16	168.84	TRUE
11	male	72.19	127.10	TRUE
12	male	195.37	229.88	TRUE
13	Female	89.80	113.62	TRUE
14	male	110.95	170.70	TRUE
15	male	187.82	274.40	TRUE
16	male	133.56	160.57	TRUE
17	male	138.46	162.36	TRUE
18	male	139.37	188.63	TRUE
19	Female	84.84	99.54	TRUE
20	Female	97.35	213.04	TRUE
21	male	115.20	164.22	TRUE
22	Female	177.47	200.02	TRUE

The concept of comparing both brain hemispheres has been spurred by evidence showing that the right hemisphere is more active when psychotherapy occurs [31]. The right hemisphere has the capacity for implicit, integrative processing of affective, nonverbal, intuitive, and social information, which provides insight into relational aspects of the neurobiology of psychotherapy. This concurs with the relational psychotherapy model, which stipulates that right hemisphere processes that are collaboratively activated by both the therapist and the client lie at the center of change during psychotherapy.

In Tab. 3 presents the total accuracy calculated across both ASD and control groups, where accuracy is defined as the ratio of correctly classified samples for both groups to the total number of samples. Each value corresponds to a specific

EEG band and overlap ratio, and the results summarize performance in each case.

Table 3 Overall EEG band results with seven overlap ratios (total accuracy across ASD and control groups), showing the Theta band is dominant with a lower stride

Window length	Strid	Γ	β	α	θ	Δ
2000 Samples	250	52.2	72.7	75.0	84.1	65.9
	500	52.3	72.7	75.0	81.8	61.4
	750	54.5	72.7	77.2	84.0	68.1
	1000	54.5	72.7	75.0	77.3	63.6
	1250	50.0	72.7	75.0	81.8	70.4
	1500	54.6	70.5	77.3	79.5	65.9
	1750	50.0	72.7	75.0	75.0	68.2

Theta achieves the highest accuracy (84%) at stride 250 with 87.5% overlap, showing strong performance with high overlap. Its lowest value (77.3%) is at stride 1000 (50% overlap), suggesting a slight decline with decreasing overlap.

Fig. 7 shows the results of the theta band for a stride length of 250 samples, showing a summary of the differences across the 44 equally divided total samples for both groups including both genders. For ASD participants, assuming the right hemisphere had higher energy than the left, the difference was calculated as right minus left; for controls, the opposite was applied. The resulting differences are plotted to highlight group-specific patterns. These results emphasize the importance of the current study in focusing on feature extraction in future studies, considering both brain hemispheres and gender.

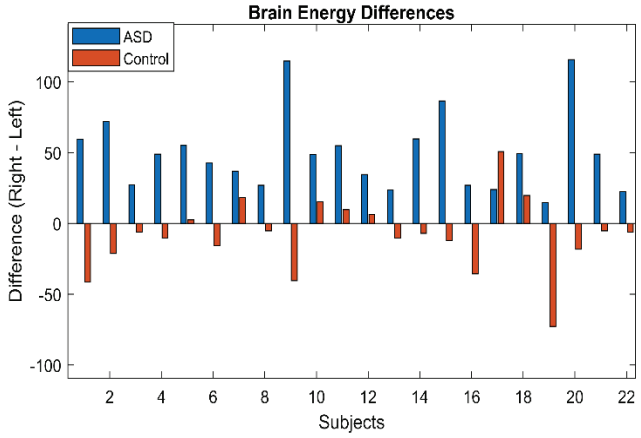


Figure 7 The results of brain energy differences, including both genders

The study examines gender differences in brain energy distributions between ASD and control groups using boxplots (Fig. 8 and 9). The boxplots illustrate the right-minus-left brain energy differences across ASD males, ASD females, control males, and control females, providing key statistical insights.

Each boxplot represents crucial statistical elements: the red line inside each box marks the median energy difference for that group, while the blue box captures the interquartile range (IQR), encompassing the middle 50% of the data. The whiskers extend to the minimum and maximum values within 1.5 times the IQR, and red crosses beyond the whiskers indicate outliers.

In the 2D visualizations (Fig. 10), male groups exhibit more apparent separation, whereas females display greater overlap, suggesting non-linear separability. The boxplots further confirm this trend, as ASD males show a positive median energy difference, indicating right-brain dominance with low variability, while ASD females exhibit stronger right-brain dominance but with higher variability and more outliers. Control males demonstrate a balanced energy distribution, whereas control females tend to have left-brain dominance with greater fluctuation.

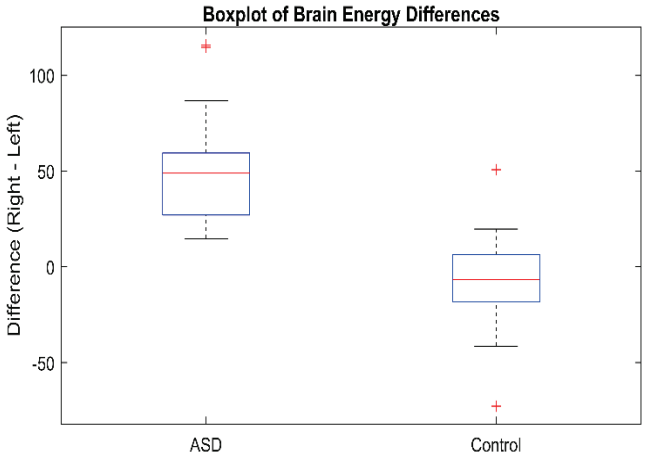


Figure 8 The results of the boxplot of brain energy differences, including both genders (male and female)

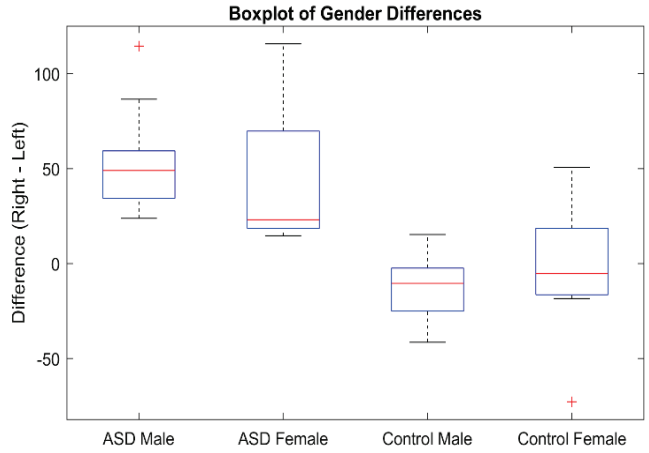


Figure 9 The results of the boxplot of brain energy differences separately for each gender (male and female)

Additionally, the energy quantities were plotted in joules, with the *X*-axis representing the left hemisphere and the *Y*-axis representing the right hemisphere (see Fig 10). This visualization helps in analyzing the energy distribution across brain hemispheres for a comprehensive assessment of ASD-related differences, shows both groups' differences and clearly highlights the error samples in the control group.

ASD participants consistently exhibit right-brain dominance, while control groups show a more balanced or left-leaning distribution. Gender differences influence variability, with females in both groups showing wider distributions and more pronounced differences.

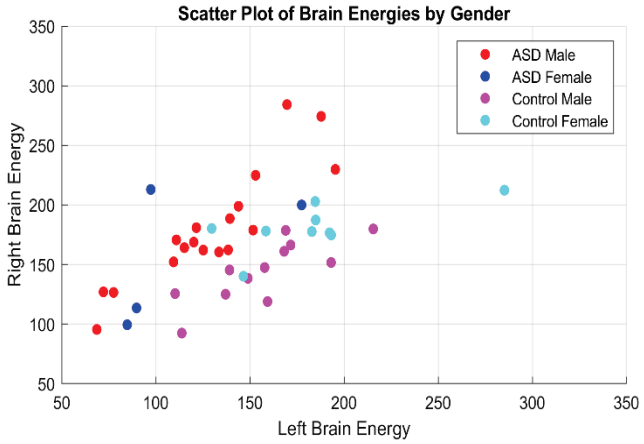


Figure 10 Two-dimensional feature representation of ASD and control groups plotted in 2D for each gender independently, the data is categorized into four groups: ASD Male, ASD Female, Control Male, and Control Female

From a diagnostic perspective, determining the best results depends on whether the focus is on consistency or group separation. If consistency is prioritized, ASD males provide the most reliable results due to lower variability and fewer outliers. However, suppose the goal is to maximize separation between the ASD and Control groups. In that case, ASD females offer the strongest distinction, as their median difference is significantly higher than that of Control females, though their greater variability may impact classification reliability.

ASD males and females achieve 100% classification accuracy, indicating a strong and reliable pattern in brain energy asymmetry. In the Control group, males reach 77% accuracy, while females have a lower accuracy of 55.56%, reflecting greater variability in their energy distributions. Overall, ASD classification remains highly accurate, whereas Control classification is more challenging, resulting in a total accuracy of 84%.

These findings highlight the potential of Theta band energy asymmetry as a biomarker for ASD diagnosis, demonstrating clear gender-specific trends. ASD individuals exhibit strong right-brain dominance, while Control participants tend to have more balanced energy distributions. Additionally, gender differences suggest that males provide more consistent data, whereas females exhibit greater variability but stronger group separation. Understanding these patterns can help refine diagnostic tools and improve the reliability of ASD classification using resting EEG data.

Theta performs best with high overlap and smaller strides (250 with 87.5% overlap), suggesting that shorter strides with larger overlaps optimize EEG feature detection (Tab. 3). The theta band is the most reliable across all conditions, consistently producing high accuracy values. While Gamma and Delta perform strongly under certain conditions, Beta exhibits the highest variability, particularly with a 62.5% overlap.

In practice, high overlap combined with small stride lengths enhances accuracy in Theta and Alpha bands, whereas Delta performs best at moderate strides with lower overlaps. These findings guide EEG data analysis, particularly in determining optimal windowing parameters for diagnostic applications like ASD detection.

The theta band demonstrated the most consistent performance across the ASD and Control groups. Energy level analysis between hemispheres revealed significant differences in functional connectivity across genders. In the Control group, most participants (15 out of 22) exhibited greater left hemisphere energy, suggesting left-hemisphere dominance (Tab. 1).

In the ASD group, right-hemisphere dominance was more prevalent (22 out of 22 participants -100%) compared to the Control group, suggesting imbalances in functional connectivity that may contribute to ASD-related challenges. ASD males and females exhibited stronger right-hemisphere dominance (Tab. 2).

The theta band emerges as the most reliable indicator of brain-behavior correlations. Male subjects, particularly those in the Control group, exhibited peak performance. These findings emphasize the role of gender-specific hemisphere energy dominance in cognitive function, particularly in ASD diagnosis.

The lower classification accuracy in the control group, especially among females, highlights the challenge of distinguishing ASD from controls. These results support the argument that ASD in females presents unique characteristics that complicate diagnosis. The higher classification accuracy in ASD and control males suggests that the method may be more effective at detecting ASD in males while underscoring the need for further research into ASD in females and improvements in diagnostic procedures.

The limitations of the current study include the relatively small sample size (44 participants), which may limit generalizability, although it is comparable to other studies in the field, with some having fewer participants and others the same sort of sample. The data set was treated rather than being split into test sets and training sets as AI based methods. While non-arbitrary in its approach, it may have a somewhat negative impact on predictive accuracy. Gender imbalance, because of the higher prevalence of ASD among males, also has an effect, as ASD in females has more subtle behavioral and neural patterns. Another limitation is that children were sedated using chloral hydrate, which contaminates EEG signals and distorts them by inducing low-frequency, high-amplitude activity that might mask or imitate actual neural features.

Future studies should focus on increasing the sample size and diversity to improve generalizability, exploring additional EEG frequency bands for a more comprehensive understanding of ASD, and developing gender-specific models, particularly for females. Longitudinal studies that track symptom progression and integrating the current features with AI technologies could further enhance diagnostic precision.

6 CONCLUSIONS

This study presents a new EEG-based method for diagnosing autism through hemispheric energy asymmetry in resting states. The approach showed excellent potential for segregating ASD from controls, particularly when accounting for gender-patterned trends. The uniform right-hemispheric energy dominance among ASD subjects, as opposed to the more random energy distribution in controls,

highlights the significance of lateralized neural activity in neurodevelopmental disorders.

The findings validate the use of hemispheric energy analysis as an input in diagnostic processes, with particular attention being placed on the Theta band as a reliable biomarker. Furthermore, the evidence of gendered differences underscores the importance of differential diagnostic models. Future work should prioritize the improvement of feature extraction algorithms and larger datasets to maximize diagnostic accuracy and generalizability.

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