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IoT-Controlled EEG Monitoring and Decision Support System for Autism Therapy Using Signal Analysis and Embedded Processing

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Abstract: Autism spectrum disorder (ASD) is associated with irregular neural activity that complicates therapy planning when based solely on behavioral observation. This study introduces an Internet of Things (IoT)-based electroencephalography (EEG) analysis system designed to support real-time therapy recommendations for children with ASD. EEG signals were processed using the fast Fourier transform for noise reduction and evaluated through power spectrum density (PSD) using Welch's method to characterize spectral patterns. The system was implemented on a Raspberry Pi platform integrated with an IoT application for remote monitoring and automated therapy notification. EEG recordings were segmented into two 30-s loops from 16 channels with a sampling rate of 256 Hz. Spectral analysis showed dominant Delta activity with frequencies of 1.68 Hz and 1.75 Hz and PSD values reaching up to 1280.31 $\mu V^2/Hz$ across segments. Repeated-measures analysis of variance indicated a statistically significant increase only in the Beta band ($F(1,15) = 10.06$, $p = 0.006$), while other frequency bands remained stable. Based on dominant-band detection, the system generated automated therapy recommendations and transmitted them to the IoT interface in real time. The results demonstrate the technical feasibility of integrating EEG signal analysis, embedded processing, and IoT communication for assistive therapy decision support in ASD management. Future work will extend the framework to multi-subject datasets to improve clinical generalizability.

Keywords: autism spectrum disorder, electroencephalography, therapy recommendation, analysis of variance, Internet of Things

1. Introduction

Autism spectrum disorder (ASD) is a multifaceted neurodevelopmental disorder marked by impairments in social interaction, disruptions in both verbal and non-verbal communication abilities, and atypical patterns of sensory information processing [1–3]. These manifestations often lead to behavioral, language, and learning difficulties that significantly affect the quality of life of both children and their families [4, 5]. Although ASD cannot be cured, numerous behavioral intervention approaches have been designed to help children adapt and function more effectively in daily life as they grow into adulthood [6, 7].

A major challenge in implementing effective therapy for children with ASD lies in the rapid and unpredictable fluctuations of emotional and behavioral states, which may manifest as aggression, object destruction, or self-injury [8–10]. Nowadays, conventional therapeutic decision-making is typically based on visual observation of behavior, which may lead to subjective interpretation and suboptimal intervention outcomes. Therefore, objective and quantitative neurophysiological measurement methods are required to support therapists in assessing treatment readiness and monitoring progress [11, 12].

Electroencephalography (EEG) offers a noninvasive approach for observing real-time brain dynamics by measuring voltage variations generated through neural oscillations within distinct frequency ranges [13, 14]. Each EEG frequency band, including Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–40 Hz), corresponds to specific cognitive functions and behavioral conditions [15]. In this context, EEG-based signal analysis offers a promising approach to evaluate therapeutic responsiveness in children with ASD, particularly

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through frequency-based interpretation rather than subjective observation.

This study employs a secondary EEG dataset from individuals with ASD obtained from King Abdulaziz University (KAU) [16]. The recorded signals are analyzed through the application of the fast Fourier transform (FFT) algorithm for noise removal and through power spectral density (PSD) via Welch's periodogram to determine dominant brainwave components [17, 18]. Further, analysis of variance (ANOVA) is applied to validate frequency stability and statistical differences across EEG channels and time segments [19, 20]. The computational implementation was developed in Python and deployed on a Raspberry Pi 4B integrated with the Blynk Internet of Things (IoT) platform to enable real-time remote monitoring and therapy notification via smartphone.

The main contributions of this study are summarized as follows. First, designing a fully embedded and portable EEG analysis system that integrates an IoT-enabled architecture with real-time processing capability, enabling continuous monitoring and therapy recommendation for autistic children in practical environments without relying on high-cost clinical equipment. Second, developing a multi-stage signal-processing pipeline that combines FFT, PSD analysis, and statistical validation using ANOVA, providing a more reliable and consistent assessment of EEG frequency stability across repeated segments compared to conventional single-method approaches. Third, establishing a cross-disciplinary control-oriented framework that links engineering computation with behavioral therapy indicators, enabling automated therapy decision support through remote-access IoT notification. This integration demonstrates a novel bridge for ASD management.

Recent advances in neuroengineering and Internet of Medical Things technologies have enabled the development of intelligent monitoring systems capable of supporting clinical decision-making processes. EEG-based analysis has been widely explored for detecting neurological abnormalities and monitoring cognitive states in individuals with ASD. Several studies have investigated EEG signal-processing methods, including machine learning and deep learning approaches, to classify emotional states, detect seizure patterns, and identify neural biomarkers associated with ASD. However, many of these studies rely on high-performance computing resources or offline data analysis environments, which limit their applicability in real-time therapeutic contexts.

Furthermore, most existing EEG-based ASD studies focus primarily on classification accuracy or diagnostic prediction rather than providing practical decision-support mechanisms for therapy planning. The integration of embedded systems with IoT connectivity for real-time neurophysiological monitoring remains relatively underexplored. This research addresses this gap by developing an embedded EEG signal analysis framework implemented on a Raspberry Pi platform and connected to an IoT-based monitoring system. By combining FFT-based filtering, PSD spectral analysis, and statistical validation, the proposed system aims to provide a lightweight and accessible assistive tool that can support therapists in identifying neural states and receiving automated therapy recommendations based on dominant EEG frequency patterns.

2. Literature Review

2.1. EEG of autistic children

To diagnose autism, EEG is a potential physiological test for diagnosing autism since it measures the electrical activity of brain waves [21, 22]. Brain waves are electrical impulses originating from many neurons that communicate with each other, forming waves of varying frequency and amplitude that represent a person's behavior, emotions, and ideas. The brain wave frequencies include Delta ($\triangle$), Theta (θ), Alpha (α), Beta (β), and Gamma (γ) [23, 24]. Signals are obtained from various brain regions to evaluate brain electrical activity [25–27]. Brain–computer interface (BCI) represents EEG signals in frequency form so that further analysis can be carried out [28, 29]. Table 1 presents the brain wave frequencies scale and their corresponding conditions.

Table 1
Brain wave frequencies scale and conditions

Frequencies	Scale (Hz)	Conditions
Delta	0.5–4	Relaxation and deep sleep
Theta	4–8	Meditation, creativity, and drowsiness
Alpha	8–13	Relaxed reflection
Beta	13–30	Focus, active thinking, problem solving
Gamma	>30	Heightened awareness, stress

2.2. Therapy for autistic children

Brain waves have varying frequencies for each emotional condition, so different therapies are needed. Established clinical practice guidelines for ASD management recognize multiple therapeutic modalities including behavioral interventions, speech-language therapy, occupational and physical therapy approaches, and nutritional support strategies. The following are several therapies that can be given to autistic children based on brain wave frequencies.

Behavior therapy aims to increase desired behavior and reduce undesirable behavior in autistic children. This therapy uses techniques based on Applied Behavior Analysis. This study recommends that this therapy be applied at the Alpha frequency due to the calm and creative condition of autistic children [24]. Speech-language therapy aims to improve children's verbal skills, such as speech rhythm, sentence structure, and vocabulary. This study recommends that this therapy be applied during the Beta frequency, which facilitates concentration, critical thinking, decision-making, and problem-solving [24, 30].

Physical and occupational therapy aims to build motor skills such as posture, coordination, balance, and muscle control [31]. This study recommends that this therapy be applied at the Theta frequency because the child is in a state of deep relaxation, meditation, and receptiveness, facilitating the delivery of therapeutic guidance [24]. Nutritional therapy aims to help ensure that children with autism follow a healthy eating pattern, especially when they are picky about food, by offering similar taste or texture [32]. This study recommends that this therapy be applied during the Theta frequency because the mind is most receptive to suggestions during the Theta state, optimizing the formation of consistent eating patterns [24].

Cognitive behavior therapy aims to help autistic children understand how thoughts influence behavior by showing children how to recognize, reevaluate, and regulate emotions such as anxiety [33]. This study recommends that this therapy be used when children are in the Gamma frequency because, at this frequency, autistic children carry out cognitive actions. Prolonged

Gamma frequency activity may cause stress, anxiety, and excessive alertness [24]. Music therapy aims to help improve emotional relationships and serves as a therapeutic intervention to relieve insomnia and promote relaxation [34, 35]. This study recommends that this therapy be used when the Theta frequency is lowest toward the Delta frequency because autistic children transition from drowsiness to deep sleep by listening to calming music for relaxation, promoting good quality sleep [24, 34].

2.3. Theoretical framework

The integration of neurophysiological measurement with behavioral intervention requires a theoretical foundation that bridges objective brain activity monitoring with clinical decision-making processes. In the context of ASD therapy, the selection and timing of interventions are influenced by multiple factors including the child's current neural state, therapist expertise, and environmental constraints. This study adopts a data-driven approach where quantified EEG frequency patterns serve as empirical indicators for therapy readiness, rather than relying solely on behavioral observation, which may be subjective and inconsistent.

The proposed framework operates on the premise that specific brainwave patterns correspond to distinct cognitive and emotional states that are differentially receptive to particular therapeutic modalities. For instance, dominant Delta activity signaling deep relaxation may create optimal conditions for music therapy, while elevated Beta activity indicating active cognitive processing may be more suitable for speech-language interventions. This correspondence between neural signatures and therapy types forms the core rationale for the automated recommendation system developed in this research. The IoT-enabled architecture further enhances this framework by providing real-time accessibility to neural state information, enabling therapists to make timely and evidence-based intervention decisions that align with the child's momentary neurophysiological condition.

3. Research Methodology

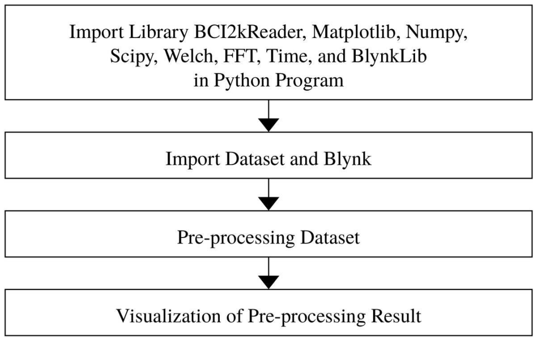
3.1. Research design

This study has employed a cross-sectional study design in order to examine the application of EEG signal processing for therapy recommendation in children with ASD. The study utilized secondary EEG data and focused on developing an IoT-integrated system capable of real-time signal analysis and automated therapy notification. The research was conducted through systematic stages including data preprocessing, frequency analysis, statistical validation, and system integration.

3.2. Brain–computer interface

BCI is a medium used to research, map, assist, or improve human cognitive or sensory functions, which provides a communication and control channel that does not depend on normal brain function [13, 36]. EEG is commonly used in BCI to measure neural activity and restore lost motor control by converting brain signals into system commands [37–39]. This study aims to build a system that automatically reads EEG signal datasets in '.dat' format; therefore, the BCI2kReader library, a Python reader for BCI2000 (.dat) files, was used [40, 41]. Figure 1 presents the block diagram of the preprocessing dataset.

Figure 1
Block diagram of preprocessing dataset



Algorithm 1 presents the basic steps in using the BCI library for EEG data processing.

Algorithm 1: BCI2KReader

Input: BCI2000 EEG data file (.dat)
Output: Visualization EEG data

1. **Load** the BCI2KReader library.

Initialize BCI2KReader with the appropriate settings.
Read the BCI2000 EEG data file (.dat) from file path.
Perform EEG data.
Store the processed EEG data in a variable or data structure.
Close the BCI2000 EEG data file.
Return the processed EEG data.
Configure size with row=2, col=1, size (15, 10) using matplotlib

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3.3. Fast Fourier transform (FFT)

EEG signals generally contain noise due to disturbances from body activity and electronic devices during the recording process, which can change the original signal, damage the amplitude, slow down time, and disrupt the information from the signal [42]. Therefore, the FFT filtering method is used to obtain an EEG signal cleaner than noise by reaching the peak of each signal [43, 44].

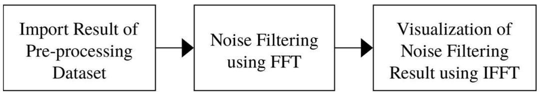
FFT transforms a signal from its time-domain representation into the frequency domain. This operation evaluates the extent to which the original waveform can be represented as a combination of fundamental sinusoidal components without redundant information. A closer fit between the signal and these constituent frequencies indicates a stronger correspondence [45, 46]. Mathematically, FFT is defined in Equation (1) [47]:

$$X(k) = \sum_{n=0}^{N-1} x(m)e^{-j\frac{2\pi km}{N}}, 1 \leq k \leq N-1 \quad (1)$$

where $X(k)$ denotes the transformed signal expressed in the frequency domain, N represents the total number of samples in the dataset, $x(m)$ corresponds to the original time-domain signal, e refers to the complex exponential component, j is the imaginary unit, and n serves as the frequency index spanning from 1 to N. Once the filtering process is completed, the cleaned waveform is reconstructed by applying the Inverse Fast Fourier Transform (IFFT) [36]. IFFT changes the signal from the FFT results from the frequency domain back to the time domain [47].

Figure 2 illustrates the schematic representation of the noise-filtering workflow.

Figure 2
Block diagram of noise filtering



After filtering the noise, the signal is analyzed to determine its frequency power distribution. To save resources, the signal is cut into short segments that reflect dynamic changes. Using PSD is an alternative for analyzing signals based on the frequency band they have. PSD displays the power distribution between frequency components [45, 48].

Although advanced artifact removal techniques such as independent component analysis (ICA) can improve EEG signal preprocessing, this study prioritizes lightweight signal-processing methods compatible with embedded systems. Therefore, FFT-based filtering was selected to maintain computational efficiency and enable real-time processing on the Raspberry Pi platform.

Algorithm 2 presents the basic steps in using FFT to filter noise from EEG signals.

Algorithm 2: FFT Signal Filter

Input:
Signal (x)
Cutoff Frequency (cutoff_frequency)
Sampling Rate (sampling_rate)
Output: Filtered Signal (filtered_signal)

1. **N** = length(x)
2. **frequencies** = create_fft_frequencies (N, sampling_rate)
3. **spectrum** = calculate_fft(x, N)
4. **for** k from 0 to N - 1 **do**
5. **frequency** = **frequencies**[k]
6. **if** abs(**frequency**) > **cutoff_frequency** then
7. spectrum[k] = 0
8. end if
9. end for
10. filtered_signal = calculate_ifft (spectrum, N)
11. return real_part(filtered_signal)
12. Configure size with row=2, col=1, size (15, 10) using matplotlib

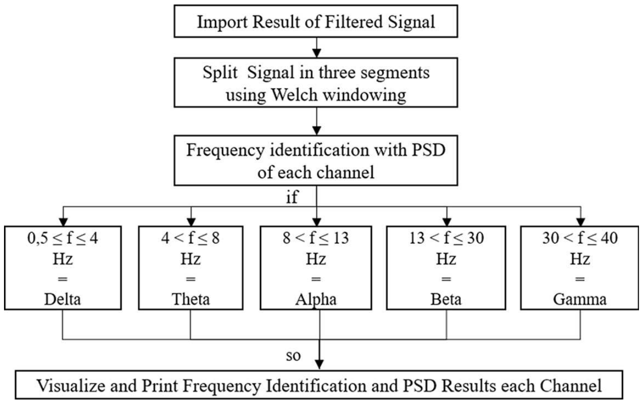
3.4. Power spectrum density (PSD)

In Welch's approach, the PSD is estimated by partitioning the signal into multiple overlapping segments and computing the modified periodogram for each segment, which are then averaged to obtain a more stable spectral estimate [49]. The Welch method calculates the periodogram of 50% overlapping segments. The method computes spectral estimates by segmenting the input signal into smaller portions of equal length derived from the original sample set. Equation (2) represents the Welch periodogram formulation, which is used to determine the PSD of the FFT-processed signal [50]:

$$S(k) = \frac{1}{L} \sum_{l=1}^{L} \Phi_l(k) \tag{2}$$

where $S(k)$ is a PSD with the Welch periodogram method, L is the L-th signal segment, and $\Phi_l(k)$ is the periodogram function. In this study, Equations (1) and (2) are described in a Python library with a backup of these equations to make it easier for researchers to analyze the input EEG signals. Figure 3 presents the block diagram of the PSD identification and the frequency of each channel per loop.

Figure 3
Block diagram of frequency identification and PSD system



3.5. Analysis of variance (ANOVA)

ANOVA is a statistical technique employed to assess whether differences among group means are statistically significant [51, 52]. In EEG, ANOVA is widely applied to evaluate variations in spectral power across channels, conditions, or time segments [20, 53]. It helps confirm whether changes in frequency bands are meaningful rather than random fluctuations [54, 55]. In this study, one-way repeated-measures ANOVA was conducted to assess the consistency of EEG frequency characteristics identified through the combined FFT–PSD analysis. The ANOVA analysis is used only as an exploratory statistical indicator rather than a definitive inferential statistical test.

3.6. Internet of Things (IoT)

IoT is a concept of an object embedded with technology such as sensors and software to communicate, control, connect, and exchange data while connected to the internet [56–58]. Technology is the key to creating an IoT healthcare system that makes device access more effective in observing, recording, monitoring, and managing all interactions between various things online [59–61]. Blynk is an IoT platform for remote device control, displaying sensor data, storing data, and creating project dashboards with buttons, sliders, graphs, and other widgets [62, 63]. In this study, Blynk was configured with a Raspberry Pi 4B for data processing and obtaining notifications of five frequency classifications of detected EEG signals [64].

3.7. System design

The Raspberry Pi is attached to an LCD monitor, which is equipped with touchscreen characteristics, in this case, to make it simpler to reach the Raspberry Pi 4B if an error happens in the system, and is powered by a 5V power supply adapter, and the LCD is linked by an HDMI-to-micro-HDMI connection and a micro-USB cable as a power source. Figure 4 presents the prototype design built in this study.

Figure 4
Prototype design

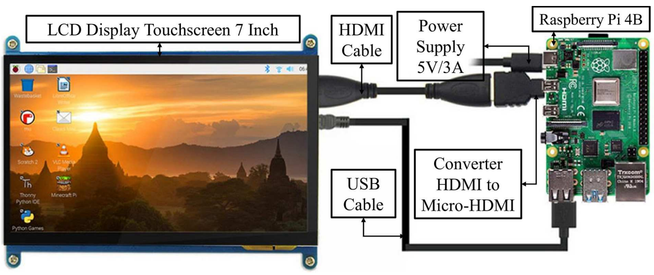


Table 2 shows several supporting components used in creating this system.

To safeguard the prototype's electronic components, a protective enclosure was constructed, ensuring that all modules remain securely housed. The finalized casing design is presented in Figure 5. The prototype case is divided into two compartments: one for the LCD and the other for housing the remaining electronic components. To reduce the increase in temperature of the Raspberry Pi when used, holes are designed on the edge of the case as air cavities. Figure 5 presents the system architecture built in this study with a Raspberry Pi configured against the Blynk application.

Based on Figure 5, the prototype integrated with the Blynk library has been connected to the internet and is ready to transmit analysis results using the Blynk server to display them to the Blynk App in message notifications. Figure 6 presents a flow diagram of the process of calculating the average PSD and frequency per channel for each loop and sending the calculation results to the Blynk App in the form of a notification.

3.8. Test method

This study used a secondary EEG dataset from patients with ASD provided by KAU, consisting of recordings from 16 channels [16]. All segments of EEG data were selected and processed through a custom Python program developed on a Raspberry Pi 4B platform. Several Python libraries were utilized, including BCI2kReader for dataset import, NumPy and SciPy for numerical processing, and Matplotlib for data visualization. The FFT was utilized to suppress high-frequency noise artifacts, after which PSD estimation based on Welch's periodogram was performed to identify the dominant frequency band in each 30-s segment.

The mean PSD and centroid frequency for each segment were calculated to identify the dominant brainwave component representing the subject's neural state. Based on the identified frequency, the system automatically generated therapy recommendations corresponding to the associated frequency band, which were subsequently delivered in real time to the Blynk IoT platform as automated notifications. To statistically validate the consistency and significance of frequency variations between

Table 2
Supporting components

Items	Sum (pcs)	Specifications	Justification
LCD display	1	7.0-inch, touchscreen	Shows information and access Raspberry Pi
Adapter	1	Power Supply: 5V	Enable Raspberry Pi
HDMI cable	1	1 m	Show desktop from Raspberry Pi
Micro USBc	1	30 cm	Enable LCD Display
Casing box	1	Cardboard	Protect electronic components
Smartphone	1	OS: Android 12, RAM: 8 GB, ROM: 128 GB	Install the Blynk App and get notifications on smartphones

Figure 5
IoT system architecture

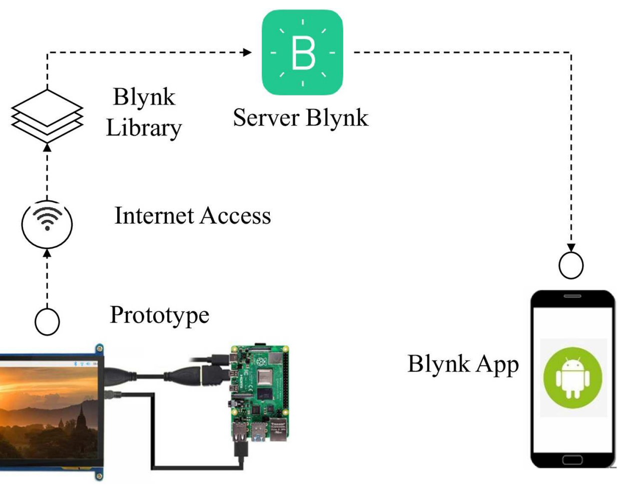
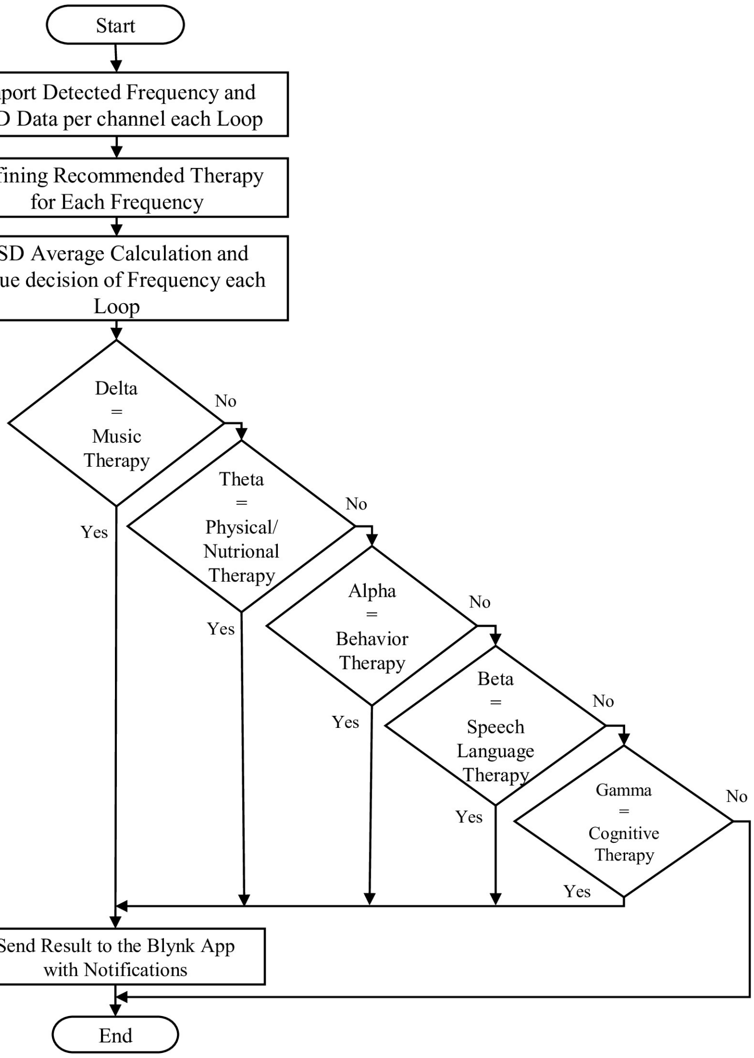


Figure 6
Flowchart of calculation of average PSD and frequency, definition of therapy, and notification to the Blynk app



consecutive segments, a one-way repeated-measures ANOVA was conducted to evaluate the mean band power across the various EEG channels. Table 3 presents the description of the dataset used.

This study utilized a single-subject case analysis approach to demonstrate the technical feasibility and computational workflow of the proposed EEG-IoT system. One participant was selected from the available KAU dataset containing 11 subjects with confirmed ASD diagnoses. The selection criterion prioritized signal quality and recording completeness to ensure reliable frequency analysis and system validation. The EEG data consisted of two consecutive 30-s segments (loops) recorded from 16 channels at a 256 Hz sampling rate, providing sufficient temporal resolution for spectral decomposition and statistical comparison.

While single-subject analysis limits generalizability, it serves the primary objective of this research: establishing proof of concept for an integrated signal-processing pipeline combining FFT filtering, PSD estimation, ANOVA validation, and IoT-based notification delivery. This methodological choice enables detailed examination of signal characteristics and system responsiveness without the confounding variables introduced by inter-subject variability. Future studies will expand to multi-subject validation

Table 3
Dataset description

Attributes	Description
Dataset source	King Abdul Aziz University (KAU), EEG signals for ASD
File format	.dat (BCI2000 format)
Total subjects	1 subject used for sample analysis from a total of 11 available subjects
Recording duration	30 s per loop (two consecutive loops; 60 s total analyzed duration)
Electrodes	16 channels
Sampling rate	256 Hz

to assess system performance across diverse neurophysiological profiles within the ASD population.

4. Results

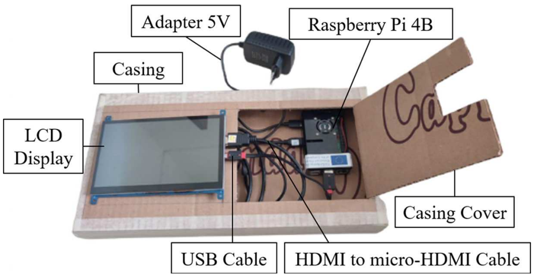
4.1. Prototype design result

After constructing the system model based on the Python program, all hardware components listed in Table 2 were integrated into a unified module and enclosed within a protective casing to ensure their operational safety and physical security. The prototype was built conceptually according to needs and maintained durability and comfort. Figure 7 presents the result of the prototype design that has been developed in this study.

4.2. Preprocessing dataset result

The EEG dataset in ".dat" format was imported using the BCI2kReader library. Figure 8(a) illustrates the unprocessed EEG recordings obtained from all 16 channels, whereas Figure 8(b) provides a magnified view of the 0–100 ms interval to emphasize the waveform morphology. The raw signals exhibit noticeable artifacts and fluctuations caused by involuntary movements during the recording session, such as eye blinks, hand motions, or discomfort from the ASD participants. Additional interference may also arise from environmental electrical noise or electrode contact instability. To obtain a cleaner signal suitable for frequency-domain analysis, a filtering process was applied to preserve the relevant neural activity components.

Figure 7
Prototype design result



4.3. Noise filtering using FFT result

By applying the FFT using Python's scientific computing libraries, the EEG recordings were denoised to attenuate unwanted signal components and improve the clarity of the resulting waveforms. Figures 9(a) and (b) present the filtered EEG data for the 16 channels over the analyzed 60-s duration, comprising two consecutive 30-s loops, and a zoomed view of the first 100 ms, respectively. After filtering, the waveforms appear smoother and more stable, with reduced high-frequency fluctuations.

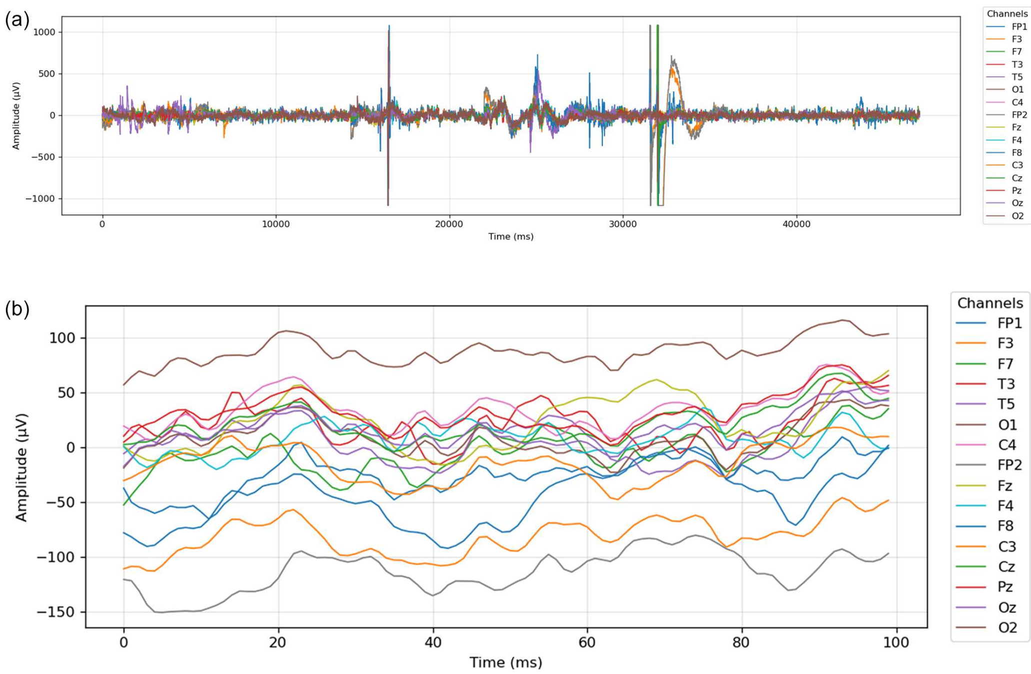
The signal morphology in Figure 9(b) demonstrates improved continuity and reduced amplitude spikes, indicating effective attenuation of motion and environmental artifacts. Once the filtering process was completed, the clean EEG signals were subjected to PSD analysis to determine the predominant Delta, Theta, Alpha, Beta, and Gamma frequency components across all EEG channels within each 30-s interval.

4.4. Frequency identification using PSD result

The analysis involved processing EEG data from all 16 channels, which were partitioned into two temporal segments to facilitate frequency-domain assessment through PSD estimation. The PSD analysis was performed for each segment to determine the dominant brainwave activity and its corresponding frequency band. The output of the analysis was visualized as a spectrum graph representing the distribution of signal power across frequencies.

For display purposes, the FP1 channel was chosen as the representative example because it demonstrated stable signal quality

Figure 8
Raw data EEG signal: (a) full view and (b) index [0:100]



and holds clinical significance for examining frontal-lobe neural activity. The frequency peaks indicate the dominant neural oscillations used for further ANOVA-based validation.

4.4.1. FP1 channel of Loop 1

Figure 10(a) presents PSD analysis of the FP1 channel during the first 30 s of EEG recording. The graph shows that PSD amplitudes range approximately up to 1400 $\mu V^2/Hz$, followed by a gradual decline in power as frequency increases toward the higher bands. This pattern reflects slow-wave activity typically associated with low arousal or relaxed states. Figure 10(b), plotted on a semi-logarithmic scale, provides clearer visualization of the spectral decay, confirming that power values diminish progressively across frequency bands up to the Gamma range (30–40 Hz).

Figure 9
Noise-filtering results using FFT: (a) full view and (b) index [0:100]

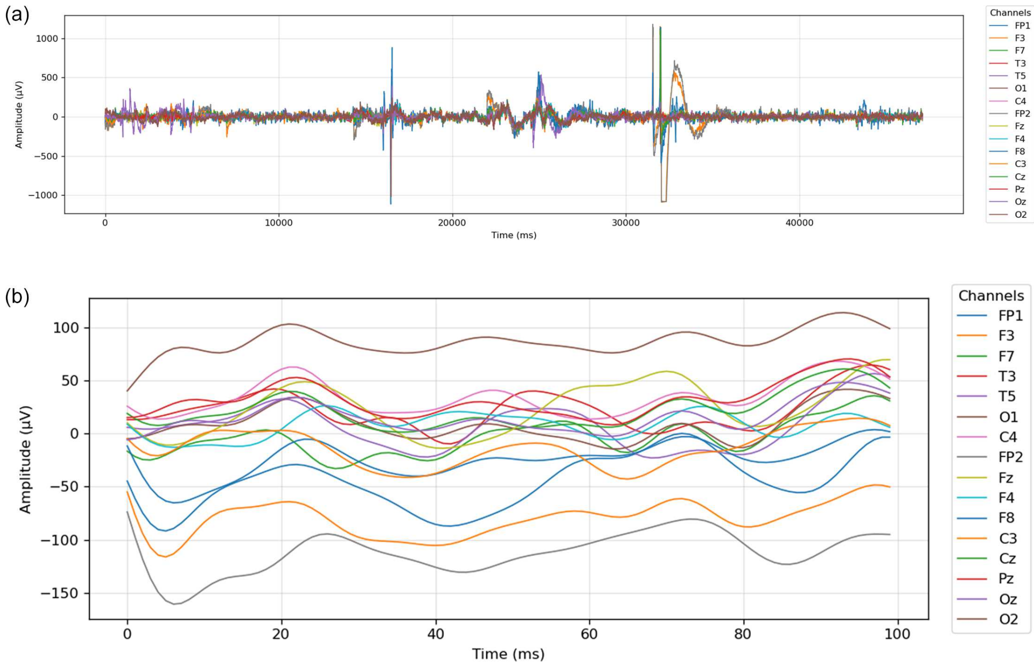


Figure 10
Frequency and PSD channel FP1 Loop 1: (a) linear scale and (b) semi-logarithmic scale

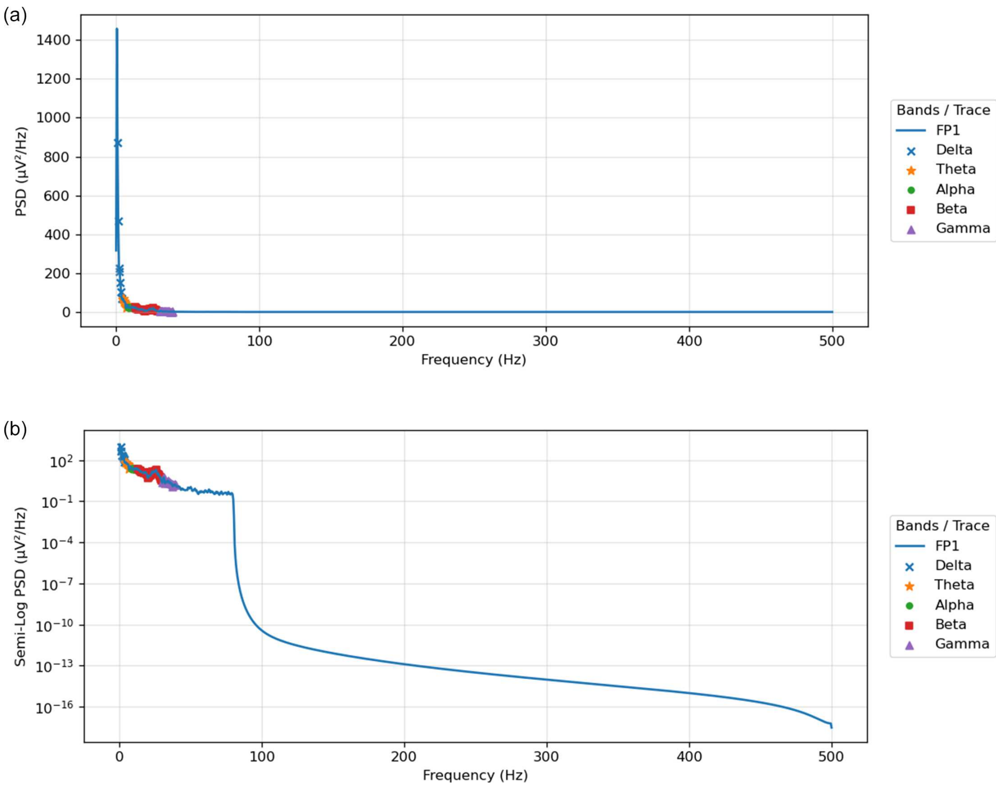


Table 4 presents the identification of the highest frequency and PSD values for each frequency band in the FP1 channel during Loop 1.

Table 4
Identify the highest frequency and PSD of FP1 Loop 1

No.	PSD ($\mu V^2/Hz$)	Frequencies (Hz)	Status
1	824.41	1.68	Delta
2	182.22	5.10	Theta
3	115.90	11.76	Alpha
4	137.61	19.80	Beta
5	26.46	32.50	Gamma

Based on the data in Table 4, the Delta frequency on channel FP1 shows the highest PSD data of 824.41 $\mu V^2/Hz$ at a frequency of 1.68 Hz. The Theta frequency on channel FP1 obtained the highest PSD data of 182.22 $\mu V^2/Hz$ at a frequency of 5.10 Hz. The Alpha frequency on channel FP1 recorded the highest PSD data of 115.90 $\mu V^2/Hz$ at 11.76 Hz. The Beta frequency on channel FP1 obtained the highest PSD data of 137.61 $\mu V^2/Hz$ at a frequency of 19.80 Hz, and the Gamma frequency on channel FP1 showed the highest PSD data of 26.46 $\mu V^2/Hz$ at a frequency of 32.50 Hz.

4.4.2. FP1 channel of Loop 2

Based on Figure 11(a), the Delta frequency remains dominant in Loop 2, with a peak PSD value of approximately 1280.31 $\mu V^2/Hz$, occurring at a centroid frequency of 1.75 Hz. This amplitude is slightly higher than that of Loop 1 (824.41 $\mu V^2/Hz$ at 1.68 Hz), indicating stronger low-frequency activity during the subsequent segment. The similar dominance of the Delta band across both loops may be attributed to the short temporal interval between analyses, which captures relatively stable resting-state conditions.

The detailed PSD distribution across frequency bands is presented in Table 5.

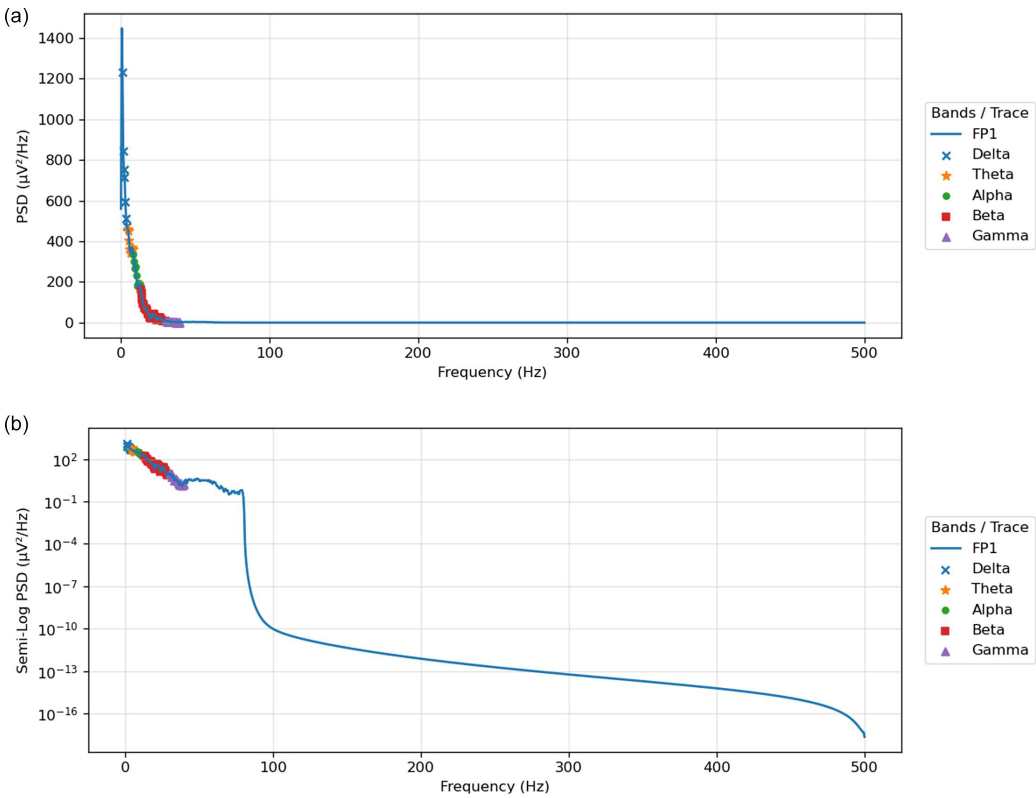
Table 5
Identify the highest frequency and PSD of FP1 Loop 2

No.	PSD ($\mu V^2/Hz$)	Frequencies (Hz)	Status
1	1280.31	1.75	Delta
2	598.59	6.24	Theta
3	321.94	11.76	Alpha
4	357.33	19.64	Beta
5	48.24	33.05	Gamma

The Theta band shows a peak PSD of 598.59 $\mu V^2/Hz$ at 6.24 Hz, followed by Alpha with 321.94 $\mu V^2/Hz$ at 11.76 Hz. The Beta band exhibits a PSD of 357.33 $\mu V^2/Hz$ at 19.64 Hz, while the Gamma band reaches 48.24 $\mu V^2/Hz$ at 33.05 Hz. The increase in Alpha and Beta activity compared to Loop 1 suggests a mild transition from deep relaxation toward moderate cognitive engagement, reflecting neural adaptation in the recorded segment.

At the end of each analysis loop, the program automatically computes the mean PSD values obtained across all 16 EEG channels. These average PSD results (in $\mu V^2/Hz$) are then converted into their corresponding dominant frequency values (in Hz), which represent the prevailing neural rhythm within that

Figure 11
Frequency and PSD channel FP1 Loop 2: (a) linear scale and (b) semi-logarithmic scale



segment. Based on the identified dominant frequency, the system generates an automated status message that is transmitted to the Blynk IoT application, providing real-time therapy recommendations aligned with the detected brainwave category. Table 6 presents the final results of each loop.

4.5. Statistical analysis using ANOVA

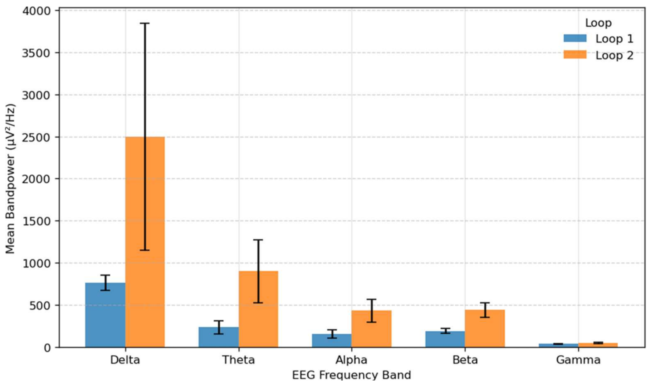
To evaluate the variation of EEG band power across recording segments, a repeated-measures ANOVA was applied to each EEG frequency band individually. For this study, the statistical assessment was carried out using data from one participant who contributed two recording loops out of the eleven subjects included in the overall dataset. This approach aimed to examine the temporal differences in neural frequency responses within the same individual, providing insight into how brain activity dynamics evolve across consecutive segments. The statistical outcomes further complement the real-time frequency-based therapy recommendations generated by the proposed IoT-integrated EEG system. Table 7 summarizes the repeated-measures ANOVA results across EEG frequency bands.

The F-statistic $F(1,15)$ indicates the between-loop and within-channel degrees of freedom, while the p-value and partial ηp^2 represent the statistical significance and effect size, respectively. The "sig." column denotes whether each band difference was significant, and the interpretation column outlines its physiological meaning.

Although the ANOVA results revealed slight increases in Theta and Beta band power, the Delta frequency remained the dominant component across both loops, with the highest mean PSD values. The statistical analysis indicated that the observed variation was not significant ($p = 0.2051$), confirming that the Delta band remained the dominant neural activity across the entire recording period. In the context of EEG-based therapy mapping, dominance of the Delta band indicates a deep relaxation or low-arousal neural state, which corresponds to music therapy in the system's recommendation framework. The observed increases in Theta and Beta power reflect only minor transitional responses: Theta being related to emotional stability and physical calmness and Beta suggesting brief cognitive engagement, but neither surpassed the Delta amplitude threshold.

Therefore, the system logically maintained the music therapy recommendation, as the overall EEG pattern remained Delta-dominant. This demonstrates that the algorithm prioritizes band dominance (absolute power hierarchy) rather than statistical significance alone when determining the most appropriate therapy. Figure 12 presents the comparison between Loop 1 and Loop 2 by mean band power.

Figure 12
Comparison of EEG band power across loops



4.6. Blynk App configuration result

Figure 13 illustrates an example of a notification displayed on the smartphone interface, showing the frequency status and corresponding therapy recommendation for each loop. The Blynk IoT configuration enables real-time transmission of EEG analysis results from the Raspberry Pi to a smartphone. Once a dominant frequency band is detected, the system automatically sends a notification showing the frequency status and corresponding therapy recommendation, allowing remote and continuous monitoring of the subject's condition.

To evaluate the real-time capability of the proposed EEG–IoT system, several computational performance metrics were measured during system execution on the Raspberry Pi 4B platform. The evaluation focused on the processing time required for key signal analysis components, including FFT computation, PSD estimation, and the latency of IoT notification delivery to the Blynk application. The results presented in Table 8 indicate that the system can perform EEG signal processing efficiently within a short processing time, with FFT computation requiring 0.42 s

Table 6
Dominant frequency, average PSD, status, and therapy recommendation for each loop

No.	Avg. PSD ($\mu V^2/Hz$)	Freq. (Hz)	Status	Recommendation
1	764.41	1.68	Delta	Music therapy
2	2495.31	1.75	Delta	Music therapy

Table 7
Repeated-measures ANOVA results across EEG frequency bands

Bands	$F(1,15)$	p-val	ηp^2	Sig.	Interpretation
Delta	1.75	0.205	0.10	n.s	Stable low-frequency activity
Theta	3.28	0.090	0.18	n.s	Mild increase, not significant
Alpha	4.24	0.057	0.22	n.s	Slight rise in relaxed alertness
Beta	10.06	0.006	0.40	sig.	Significant increase (cognitive activation)
Gamma	2.21	0.158	0.13	n.s	No notable change

Figure 13
Notification on smartphone of final results each loop using Blynk

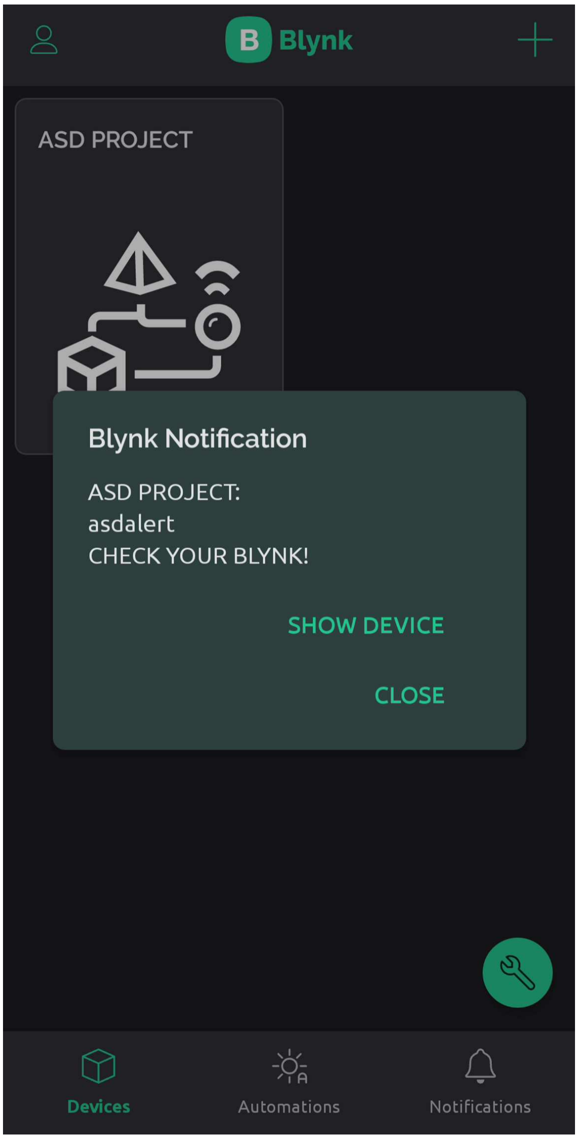


Table 8
System performance evaluation

Metric	Result (s)
FFT computation time	0.42
PSD computation time	0.31
Notification latency	1.2

and PSD computation requiring 0.31 s. Additionally, the average notification latency to the IoT interface was approximately 1.2 s. These results demonstrate that the proposed framework is capable of supporting near real-time monitoring and therapy recommendation in practical deployment environments.

5. Discussion

The findings of this investigation demonstrate that the proposed EEG-driven therapy recommendation framework functions effectively as a decision-support mechanism for clinicians and therapists managing interventions for children with ASD. The evaluation of the EEG recordings indicated that the Delta frequency band dominated both recording loops, with centroid frequencies of 1.68 Hz and 1.75 Hz, respectively. This low-frequency dominance indicates a deep relaxation state commonly observed during calm or resting conditions, which corresponds with the system's automated recommendation of music therapy. The outcome aligns with the established neurophysiological interpretation that Delta activity is associated with emotional regulation and sensory stabilization in ASD patients.

Although Delta remained dominant, a moderate increase in Beta band activity was detected across loops, reflecting a slight rise in cognitive engagement. The repeated-measures ANOVA supported this observation, revealing a statistically significant difference only in the Beta band ($F(1,15) = 10.06$, $p = 0.0063$, $\eta p^2 \approx 0.40$), while Delta ($p = 0.2051$), Theta ($p = 0.0904$), Alpha ($p = 0.0574$), and Gamma ($p = 0.1575$) bands did not differ significantly. These results indicate that while the subject maintained a stable relaxation baseline dominated by Delta activity, subtle variations in higher frequencies represented short-term neural responsiveness or environmental reactions.

The integration of FFT filtering, PSD analysis, and ANOVA validation into a Raspberry Pi 4B platform combined with Blynk IoT demonstrates the feasibility of implementing an affordable, compact, and real-time-capable EEG analysis platform. This configuration allows frequency monitoring and therapy recommendations to be sent instantly to the therapist's smartphone, enhancing accessibility and response time in therapeutic settings. Such features make the system suitable for use in home-based interventions or school environments where immediate feedback is valuable.

It is important to emphasize that this prototype serves as a supportive diagnostic and therapeutic aid, not a replacement for professional clinical judgment. The system automatically recommends therapy types based on the dominant EEG frequency, but the final therapy decisions remain under the therapist's discretion, taking into account the patient's behavioral, emotional, and environmental context. Therefore, the tool functions as an assistive framework to complement human expertise, promoting evidence-based and data-driven therapy planning for ASD.

This study's advantages and disadvantages can be compared with other related research, as represented in Table 9. Future improvements may include expanding the dataset with multiple subjects, integrating multimodal behavioral data, and developing a more interactive visualization dashboard to display real-time EEG patterns.

Despite the promising results, several limitations should be acknowledged. The present study utilized EEG data from a single subject selected from an available dataset to demonstrate the technical feasibility of the proposed system architecture. While this approach enables detailed evaluation of the signal-processing pipeline and embedded implementation, it limits the generalizability of the findings across broader ASD populations. Future research will involve multi-subject datasets and longitudinal recordings to validate the robustness, stability, and clinical applicability of the proposed EEG–IoT framework.

It should be emphasized that the proposed EEG-frequency-to-therapy mapping functions as an assistive recommendation mechanism rather than a deterministic clinical prescription. The system is designed to support therapists by providing objective neurophysiological indicators, while the final therapeutic decisions remain under professional clinical judgment.

Compared with most EEG-based ASD systems that focus on diagnostic classification, the proposed system provides real-time therapy decision support using lightweight signal processing integrated with embedded IoT hardware.

Table 9
Comparison of methods, tools, and advantages with previous research

Ref.	Methods	Tools	Advantages	Drawbacks
[21]	DWT, FFT, PSD, SVM, LR, DT	– Wearable EEG – Sensor – Machine learning	– The use of wearable EEG devices enhances ASD detection by removing the requirement for complex wiring systems and enabling clinicians to observe neural activity in a more comfortable and non-intrusive setting – The experimental evaluation demonstrates that the model achieves an accuracy of 96%, attains perfect sensitivity at 100%, and yields an F1-score of approximately 95%	– This research just gives information on using tools of wearable sensors and machine learning for early detection of autism, but it doesn't provide solutions for therapy for autistic children
[45]	FFT, PSD	MATLAB	– The system is capable of analyzing EEG signals and brain wave frequencies – The system may be regarded as a dependable instrument for evaluating the effectiveness of dolphin-assisted therapy, offering utility not only for therapists but also for medical practitioners	– Signal analysis takes more time because it is still using a manual MATLAB system – Dolphin-assisted therapy is difficult for everyone to access and is not suggested for children
[50]	ICA, finite impulse response (FIR), PSD	MATLAB	– The application of FIR and ICA techniques effectively minimizes noise and artifact contamination in EEG recordings from both autistic and neurotypical subjects – PSD displays the power distribution between frequency components	– Utilizing both ICA and FIR necessitates additional steps in the MATLAB-based EEG signal analysis process, which consumes significant memory resources due to the software's demands
Proposed Method	FFT, PSD, ANOVA	– Raspberry Pi 4B – Python – Blynk	– The prototype can autonomously analyze EEG signals from autistic children and send the results of analysis to the Blynk App – Immediately analyze the input secondary dataset of EEG signals using BCI2KReader, along with FFT and PSD library in the Python program system – Integration of IoT into the system to allow for real-time and remote access to analytical results via smartphone	– Therapy recommendations are only a reference for therapy options and still require further consultation with a professional therapist – The overall results must be viewed manually in the program on the Raspberry Pi because the Blynk App only receives the final results of frequency identification and therapy recommendations

6. Conclusion

This study developed a real-time EEG-based therapy recommendation system using Python on a Raspberry Pi 4B integrated with the Blynk IoT platform. The system successfully filtered EEG signals, identified dominant frequency bands, and sent automatic therapy recommendations to a smartphone interface. Experimental results showed that the Delta band remained dominant in both loops (1.68–1.75 Hz), leading to music therapy recommendations. Meanwhile, ANOVA results indicated a significant change only in the Beta band ($p = 0.0063$), reflecting minor cortical activation while maintaining a relaxed neural baseline. Overall, the system functions as a decision-support tool to assist therapists in determining suitable therapies, not as a replacement for clinical judgment. Its integration of low-cost hardware and IoT connectivity demonstrates strong potential for accessible, data-driven ASD therapy applications.

Recommendations

Future improvements may include expanding the dataset with multiple subjects to enhance generalizability and conducting longitudinal studies to evaluate temporal consistency across extended periods. Integrating multimodal behavioral data, such as video analysis and physiological sensors, could provide a more comprehensive assessment of therapeutic responses. Developing a more interactive visualization dashboard to display real-time EEG patterns would improve user experience for therapists and caregivers. Additionally, implementing adaptive machine learning algorithms that can learn from individual patient profiles may further refine therapy recommendations. Field testing in clinical and home-based settings is recommended to validate the system's practical applicability and identify potential improvements in real-world therapeutic environments.

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Ethical Statement

The data used in this study were obtained from a publicly available and fully de-identified dataset, the KAU BCI dataset associated with the study "Diagnosis Autism by Fisher Linear Discriminant Analysis (FLDA) via EEG" [16]. Therefore, ethical approval and informed consent were not required.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The KAU BCI datasets that support the findings of this study are openly available at https://www.academia.edu/8920466/Diagnosis_Autism_by_Fisher_Linear_Discriminant_Analysis_FLDA_via_EEG, reference number [16].

Author Contribution Statement

Melinda Melinda: Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Nizam Albar:** Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Yuwaldi Away:** Methodology, Investigation. **Karlisa Priandana:** Validation, Writing – review & editing. **Prima Dewi Purnamasari:** Validation. **Muhammad Saifullah Nur:** Data curation. **Nurlida Basir:** Writing – review & editing. **Syahrul Gazali:** Validation, Resources.

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