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Comparative analysis of EEG pre-processing in ASD using Hanning and Blackman Harris filters

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Abstract
This study investigates the effectiveness of two Finite Impulse Response (FIR) filter designs based on the Hanning and Blackman-Harris windows for preprocessing electroencephalography (EEG) signals collected from both neurotypical individuals and those diagnosed with Autism Spectrum Disorder (ASD). EEG signals were recorded using a 16-channel setup and band-pass filtered between 0.5 and 40 Hz to isolate relevant neural activity. Subsequently, the signals were processed independently using each FIR filter type. Performance evaluation was conducted using four quantitative metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and Power Spectral Density (PSD). The Hanning window filter showed MAE values ranging from 0.079 to 0.325, MSE from 0.026 to 0.177, SNR between 7.56 and 15.86 dB, and PSD values from 5.3 to 9.08 × 10^{-3}. These results demonstrate good noise attenuation while preserving signal morphology. In contrast, the Blackman-Harris window produced higher MAE (0.061–0.318) and MSE (0.019–0.172) but achieved significantly greater SNR improvements (7.77–17.4 dB) and tighter control over PSD (4.904 – 8.442 × 10^{-3}), indicating superior noise suppression and reduced spectral leakage. A paired t-test confirmed that differences in all four performance metrics were statistically significant ($p < 0.05$) across both neurotypical and ASD subject groups. Despite the Hanning filter's computational simplicity, the Blackman-Harris filter demonstrated more robust performance, making it a more suitable choice for high-fidelity EEG signal analysis in clinical diagnostics and neuroscience research.

Keywords:
ASD;
Blackman-Harris Filter;
EEG;
Hanning Filter;

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INTRODUCTION

Electroencephalography (EEG) is a non-invasive technique used to measure the electrical activity of the brain by detecting voltage fluctuations at scalp electrodes, providing high temporal resolution suitable for monitoring dynamic neural processes [1]. Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by heterogeneous impairments in social interaction, interpersonal communication, sensory sensitivity, and stereotypical and restricted behavioral patterns [2][3]. ASD symptoms generally appear before the age of three, and diagnosis still relies on behavioral observations and developmental assessments [4, 5, 6, 7].

Despite the advantages of EEG, the recorded signals are highly susceptible to artifacts such as ocular movements, muscle activity, and external electromagnetic interference, which can significantly degrade the reliability of the data [8][9] . Therefore, robust signal preprocessing techniques are essential to isolate meaningful brain signals and suppress unwanted noise.

To ensure the extraction of meaningful information, robust signal preprocessing is indispensable. Finite Impulse Response (FIR) filters, a widely used tool in EEG signal denoising, rely on windowing functions to determine their spectral characteristics and overall performance [10]. Among the many available window functions, the Hanning and Blackman-Harris windows stand out due to their distinctive abilities in managing spectral leakage and suppressing sidelobe energy. The Hanning window offers excellent frequency resolution and reduced spectral leakage, making it suitable for real-time applications [11]. In contrast, the Blackman-Harris window is known for its superior sidelobe attenuation, which helps preserve the core signal components in noisy conditions [12][13].

The Hanning and Blackman–Harris windows were chosen because they represent two poles of the main artifact suppression trade-off in EEG: Hanning has a relatively narrow main lobe with moderate side lobes, is computationally efficient, and tends to preserve characteristic wave morphology that favors real-time analysis. In contrast, Blackman–Harris offers very high side lobe suppression that effectively suppresses spectral leakage and high-frequency interference, making it suitable for spectrally precise offline analysis. By comparing the two in EEG-ASD, this study assesses the impact of window choice on morphology conservation, spectral clarity, and computational cost relevant for both clinical and BCI implementations.

Although numerous EEG studies have compared windowing methods for FIR filtration, most previous studies have not systematically assessed artifact suppression (ocular, EMG, and spectral leakage) in ASD populations using a unified evaluation framework that bridges the time domain (MAE, MSE) and frequency domain (SNR, PSD). Furthermore, reporting of relevant computational costs/latencies for real-time applications is limited, as is reporting of effect sizes and confidence intervals to complement statistical significance. This gap limits evidence-based window selection for artifact suppression in EEG-ASD, particularly when spectral precision needs to be weighed against computational requirements in embedded systems and BCI.

This study aims to comparatively assess the performance of the Hanning and Blackman-Harris windows in EEG signal preprocessing for ASD-related analysis. The evaluation uses metrics including Mean Square Error (MSE), Mean Absolute Error (MAE), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR). The findings are expected to contribute to the optimization of EEG-based diagnostic systems for ASD by identifying the most efficient filtering approach [14][15].

The novelty of this study stems from its integrative and systematic evaluation framework, which employs multiple quantitative performance indicators including Mean Absolute Error (MAE), Mean Square Error (MSE), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR) to assess the effectiveness of FIR window functions in EEG signal preprocessing for ASD analysis. Additionally, the use of a paired t-test for statistical validation reinforces the reliability of the comparative results.

Unlike previous works that often focus on a single metric or general EEG applications, this research specifically targets ASD related EEG data, offering a more focused and statistically grounded comparison between Hanning and Blackman-Harris filters. This approach provides a novel contribution by highlighting the optimal window function for enhancing EEG signal quality in clinical and diagnostic contexts related to neurodevelopmental disorders.

The contributions of this research are as follows:

1. Hanning and Blackman–Harris directional comparison of EEG for ASD and normal groups using MAE, MSE, SNR, and PSD evaluation framework
2. Statistical validation using paired t-test showed significant differences ($p < 0.05$) in MAE, MSE, SNR, and PSD in both groups (ASD & normal)
3. Formulating the practical implications of window selection, that Hanning is more efficient for real-time processing while Blackman–Harris provides better spectral clarity with greater computational load.

METHODS

The selected dataset ensures consistency in EEG acquisition and provides a balanced comparison between ASD and control subjects. Its standardized setup and minimized artifacts make it suitable for evaluating FIR based preprocessing performance.

Material

This study utilized an EEG dataset originally recorded at King Abdulaziz University (KAU) Hospital, Jeddah, Saudi Arabia, in accordance with ethical data access protocols that ensure subject anonymity. The dataset comprises brain signal recordings from ten male participants five diagnosed with Autism Spectrum Disorder (ASD) aged $10 - 16$, and five neurotypical controls aged $9 - 16$ none of whom had prior neurological conditions. EEG acquisition was performed using g.tec systems with Ag/AgCl electrodes and BCI2000 software.

Subjects were in a resting state to reduce motion artifacts, and 16 channels were used based on the international $10 - 20$ system. Pre-processing involved a band-pass filter of $0.5 - 40$ Hz and a 60 Hz notch filter to suppress physiological and powerline noise, respectively. All EEG signals were digitized at 256 Hz and stored in matrix-based .dat file formats compatible with standard signal processing tools [16, 17, 18]. The EEG recordings were organized into a matrix format to optimize compatibility with current digital signal processing platforms and to facilitate advanced analytical computations, as illustrated in Figure 1.

METHODS

The overall workflow of the research process is depicted in Figure 2. Initially, EEG signal data is acquired from the recording system, followed by a preprocessing phase. This phase begins with converting the original data format to ensure compatibility with processing tools, then continues with the application of a band-pass filter to isolate relevant brainwave frequencies in the $0.5 - 40$ Hz range, eliminating undesired frequency components.

The EEG signal is then processed using two window-based filtering techniques: the Hanning and Blackman-Harris windows, aimed at reducing artifacts while preserving key neural information. The low-frequency cutoff was defined at 0.5 Hz and the high-frequency cutoff at 40 Hz to capture essential neural signals. A sampling rate of 256 Hz was used.

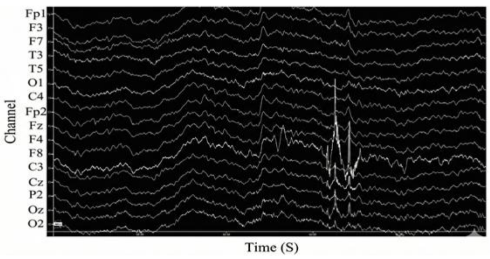


Figure 1. Temporal Representation of EEG Signal Across 16 Channels in Microvolt Scale

The Hanning window was selected due to its effective compromise between frequency resolution and computational efficiency. Meanwhile, the Blackman-Harris window, employing a multi-term cosine design, was chosen for its enhanced suppression of sidelobes and improved spectral clarity, which allows for better attenuation of high-frequency noise. These filtering settings were consistently applied across all participants to ensure a fair comparison between the two windowing techniques.

The details of the workflow in Figure 2 are as follows. (i) Acquisition: 16-channel EEG ($10 - 20$), fs = 256 Hz, resting condition as in the dataset. (ii) Pre-processing: format conversion → band-pass to maintain the neural activity band and notch for powerline suppression, according to the specifications in the Materials section. (iii) FIR-window design: linear-phase coefficients synthesized separately for Hanning and Blackman–Harris with consistent parameters/orders across subjects. (iv) Per-channel application: 1D per-channel convolution produces two filtered signal versions (Hanning vs Blackman–Harris). (v) Metric extraction: MAE, MSE, SNR, PSD per channel are calculated from the pre-FIR (y) and post-FIR ($\hat{y}$) signal pairs and then aggregated to the subject level. (vi) Statistics: for each metric, a paired t-test is performed between windows at the subject level, reporting p-values and effect sizes.

For the calculation of MAE and MSE, the reference signal was defined as the original, unfiltered EEG signal for each subject. The filtered signal, obtained after applying either the Hanning or Blackman-Harris filter, was compared against this reference signal. Specifically, for each sample i, the original EEG signal y_i served as the reference, and the filtered signal $\hat{y}_i$ was the predicted signal. MAE and MSE were then computed as the average absolute and squared differences between the reference and the filtered signal, respectively, across all time samples of each channel.

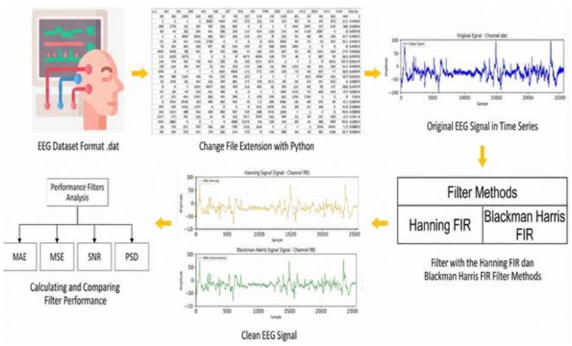


Figure 2. EEG Signal Processing Scheme

Mean Squared Error (MSE)

Mean Squared Error (MSE) is a widely adopted evaluation metric in signal processing and regression analysis, particularly for assessing the accuracy of signal reconstruction after noise or artifact removal. It quantifies the average of the squared differences between the actual and predicted (or reconstructed) values. A lower MSE value indicates better model performance, reflecting minimal deviation from the original signal. Since MSE squares the errors, it is highly sensitive to large deviations and outliers, making it effective for detecting even subtle distortions in EEG signal restoration. It can be calculated using an (1)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

y_i is the actual value and n is the number of data points [19].

Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a straightforward and widely used evaluation metric that calculates the average absolute difference between predicted and actual values. Unlike MSE, MAE does not amplify the impact of outliers, making it more robust in analyzing EEG signals with noise or missing channels. In EEG processing, MAE effectively quantifies the deviation between reconstructed and original signals, offering clear insight into interpolation and filtering performance [2].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (2)$$

The variable y_i represents the data at the i the point, while $\hat{y}_i$ denotes the predicted or filtered value at the same index. Both are compared across n total samples to evaluate the accuracy of the prediction or filtering method [20][21].

Power Spectral Density (PSD)

Power Spectral Density (PSD) is a frequency-domain method used to measure how signal power is distributed across frequencies. In EEG analysis, PSD helps identify dominant brainwave patterns and characterize both rhythmic and background neural activity. It is often computed using the Fourier Transform, as shown in (3).

$$S_x(f) = \lim_{T\to\infty}\frac{1}{T} \left| \int_{-T/2}^{T/2} x(t)\, e^{-j2\pi ft}\, dt \right|^2 \quad (3)$$

Here, $Sx(f)$ denotes the power at frequency f from the time-domain signal $x(t)$. Recent studies, such as Liu et al. (2023), show that modeling both periodic and aperiodic PSD components improves EEG classification, especially for seizure detection [22].

Signal-to-Noise Ratio (SNR)

Signal-to-Noise Ratio (SNR) is a key metric that quantifies the ratio between the power of a signal and the power of background noise. In EEG signal processing, where the signal is often weak and susceptible to various sources of noise, SNR serves as a critical indicator of signal quality. It is typically expressed in decibels (dB) using the following (4).

$$\mathrm{SNR(dB)} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) \quad (4)$$

A higher SNR value reflects better signal clarity with minimal interference, while a lower value suggests that noise dominates the signal. Recent work by Miao et al. (2023) introduced LMDA-Net, a lightweight multi-dimensional attention network designed to enhance SNR in EEG-based BCI systems by applying effective spatial-temporal filtering techniques [23][24].

P Value

The *p-value* assesses the statistical significance of EEG signal differences between ASD and control groups after applying FIR filters with Hanning and Blackman-Harris windows. It is calculated using (5).

$$P = P(T \geq | t_{\mathrm{observed}} |) \quad (5)$$

where t_{observed} is the calculated test statistic and T follows a $t-distribution$ with appropriate degrees of freedom. A p-value below 0.05 suggests a statistically significant difference in EEG patterns between ASD and control groups. Conversely, a value above 0.05 indicates that the observed differences may be attributed to random variation. Recent developments in statistical inference recommend using second-generation p-values, which offer greater emphasis on practical relevance and reproducibility, rather than relying solely on conventional thresholds. This approach ensures that statistically significant findings are also scientifically meaningful and replicable [25].

Cohen’s d

Cohen’s d is a standardized measure of effect size that quantifies the magnitude of the difference between the means of two independent groups on a scale without units. It serves as a complement to significance testing by providing insight into the size of the difference in performance metrics between configurations or pipelines, allowing for comparisons across various metrics and studies [26].

$$d = \frac{\bar{x}_1 - \bar{x}_2}{s_p} \quad (6)$$

In the formula, $\bar{x}_1$ and $\bar{x}_2$ represent the sample means of the two groups, while s_p denotes the pooled standard deviation, which is calculated from the within-group variances with degrees of freedom of $n_1 + n_2 - 2$ (for independent groups). The sign of d indicates the direction: $d > 0$ when the first group's mean is greater than the second's, and $d < 0$ when it is smaller [27]. Common thresholds for effect size are $d \approx 0.2$ (small), 0.5 (medium), and 0.8 (large). Reports should include the point estimate of d, its direction, and, when possible, a confidence interval. For small sample sizes, the small-sample correction should be applied (i.e., Hedges’ g) [27]. For paired or within-subject designs, the effect should be computed using the standard deviation of the paired differences (e.g., $d_z = \bar{d}/s_d$) to account for within-subject dependency, rather than using s_p [28].

For each subject and each channel, we prepared two sets of signals, the signal before windowing and the signal after windowing; the mean absolute error was calculated to assess the mean deviation in the time domain and averaged across channels at the subject level, the mean squared error was calculated to assess the mean squared deviation and aggregated in the same way, the power spectral density was then estimated through a uniform procedure across the samples with overlapping segmentation and consistent windows to obtain a summary of the energy in the analyzed frequency band which was then averaged across channels at the subject level, the signal-to-noise ratio was derived by comparing the output signal power to the residual power derived from the difference between the output and input signals and expressed in decibels and then accumulated across channels at the subject level, and for each metric, pairwise statistical tests were performed at the subject level separately for the ASD and normal groups with reporting of two-tailed p-values and inclusion of effect sizes and confidence intervals to strengthen the interpretation of the results.

RESULTS AND DISCUSSION

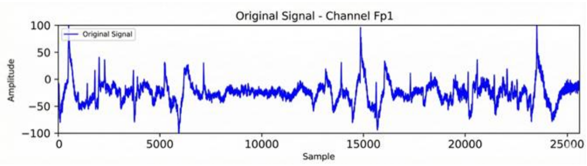
The EEG signal, initially processed using FIR filters with Hanning and Blackman-Harris window functions, was subsequently evaluated based on four performance metrics. These include Mean Square Error (MSE) as defined in Equation (1), Mean Absolute Error (MAE) in Equation (2), Power Spectral Density (PSD) in Equation (3), Signal-to-Noise Ratio (SNR) in Equation (4), and statistical significance through P-value and Cohen's d to test the parameters.

Window Hanning Filter Result

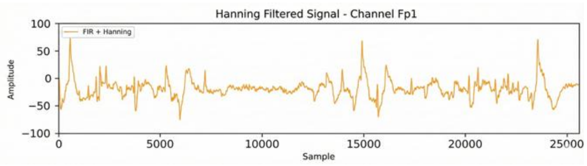
The application of a FIR filter with a Hanning window enables effective attenuation of spectral sidelobes while ensuring a gradual transition in the frequency response. This characteristic is particularly valuable in EEG analysis, as it helps reduce spectral leakage that could otherwise obscure critical brainwave components, especially in the delta ($0.5 - 4$ Hz), theta ($4 - 8$ Hz), alpha ($8 - 13$ Hz), and beta ($13 - 30$ Hz) bands, which are essential for interpreting various cognitive and neurological functions [29][30].

The findings indicate that the FIR filter configured with a Hanning window is effective in attenuating high-frequency noise within EEG signals, while preserving phase linearity and retaining essential spectral components. This ensures that key neurological features remain intact after filtering. As depicted in Figure 3, the contrast between raw and filtered EEG signals highlights the Hanning filter’s capability to enhance signal clarity without introducing significant distortion [31].

The processed EEG signal using the Hanning FIR filter reveals a smoother waveform with diminished high-frequency oscillations typically attributed to noise interference.



(a) Original Signal on Channel Fp1



(b) Hanning Filtered Signal on Channel Fp1

Figure 3. EEG Signal on Channel Fp1: (a) Original, (b) Filtered using Hanning Window

This filtering approach exhibits a stable amplitude response across the target frequency band and demonstrates a sharper transition at cutoff frequencies indicating greater efficiency in isolating the core EEG signal from unwanted components. Quantitative analyses further reinforce this observation; the Hanning FIR filter consistently produces lower MAE and MSE values, enhanced SNR, and a more concentrated PSD profile. These improvements confirm the filter's proficiency in suppressing non-neural disturbances, such as EMG noise and external electromagnetic artifacts, without compromising the underlying neural signal integrity.

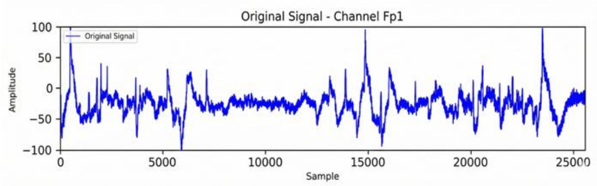
The Hanning window approach demonstrates a reduction of high-frequency oscillations in the time domain without shifting the informative amplitude structure, in line with its linear-phase character that minimizes phase distortion in the passband. Quantitatively, the decrease in the mean and mean-square errors indicates the preservation of signal morphology, while the recorded increase in clarity in the signal-to-noise ratio and a more focused spectral density profile confirm that the neural components are preserved after filtering. Thus, Hanning effectively suppresses unwanted high-frequency components while preserving the core spectral features relevant for EEG analysis.

Window Blackman-Harris Filter Result

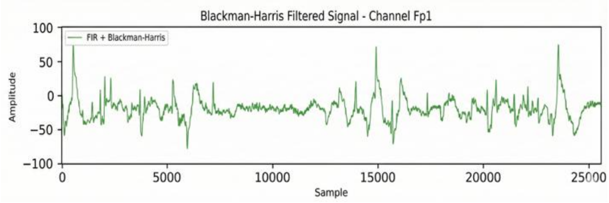
The Blackman-Harris window achieves outstanding sidelobe attenuation (−92 dB), significantly reducing spectral leakage in EEG preprocessing. Its multi-term cosine design ensures smooth transition bands and minimal interference with key neural frequencies, making it highly effective in isolating brainwave signals from high-frequency disturbances like EMG or environmental noise. These advantages are particularly beneficial in ASD studies, where EEG clarity is essential for accurate neural interpretation [32][33].

FIR window filtering shows that the Blackman-Harris window delivers sharper cutoff characteristics and superior stopband rejection compared to other window types. It effectively suppresses 50 Hz powerline interference, resulting in improved PSD resolution and higher SNR, highlighting its suitability for EEG-based ASD research [34].

The application of the Blackman-Harris window markedly improves EEG signal quality by delivering a noticeably cleaner waveform, as shown in Figure 4.



(a) Original Signal



(b) Blackman-Harris Filtered Signal

Figure 4. EEG Signal on Channel Fp1: (a) Original, (b) Filtered using Blackman-Harris Window.

This high-order FIR filter offers a smooth frequency response, ensuring a sharp yet distortion-minimizing transition from passband to stopband. Quantitative assessment reveals that filtering leads to decreased Mean Squared Error (MSE) and Mean Absolute Error (MAE), alongside a notable boost in Signal-to-Noise Ratio (SNR). These improvements underscore that post-filtering EEG signals are much better suited for subsequent analysis. Notably, by effectively removing high-frequency interference such as EMG and environmental noise, the filter preserves critical neural information while enhancing overall signal clarity.

The advantages of Blackman–Harris stop-band rejection come from the very high sidelobe suppression and smooth transitions between bands, so that spectral leakage at frequencies outside the pass-band can be suppressed more aggressively without disturbing the relevant neural components. This configuration has a direct impact on the spectral clarity and efficiency of interference suppression, including powerline interference, which is reflected in the improvement of the signal-to-noise ratio and control of the power spectral density in the measurement results. The Fp1 channel is presented as a representative example because it is physiologically most susceptible to ocular artifacts and high-frequency components, so that post-filtration changes appear most contrastingly without compromising the generality of the interpretation supported by the subject-level summary metrics.

Performance Accuracy Analysis Result

The effectiveness of EEG filtering was evaluated using four key metrics: Mean Squared

Error (MSE), Mean Absolute Error (MAE), Power Spectral Density (PSD), and Signal-to-Noise Ratio (SNR). Both MSE and MAE quantify the deviation between filtered and original signals, where lower values indicate better signal fidelity. SNR assesses noise reduction effectiveness, while PSD reflects how the filter redistributes signal energy across the frequency spectrum. Collectively, these measures offer a holistic view of filtering performance.

Results confirm that both FIR filters with Hanning and Blackman-Harris windows significantly improve EEG signal quality. The Hanning filter achieves smoother frequency transitions with relatively low computational cost. In contrast, the Blackman-Harris filter delivers superior sidelobe suppression, making it more adept at attenuating high-frequency noise while faithfully preserving relevant neural components.

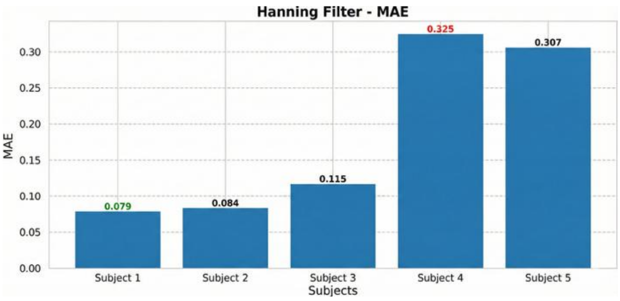
However, the computational cost for the Blackman-Harris filter tends to be higher, especially when the filter order M is increased to achieve better side-lobe suppression and more detailed frequency control. This increased computational load results in more Multi-accumulate (MAC) operations per sample, which can affect real-time processing performance in applications that are highly latency-sensitive. However, if the filter length M is equalized between the two filters, the computational cost for Blackman-Harris is almost equivalent to that of Hanning.

Window Blackman-Harris FIR Filter ASD Subject

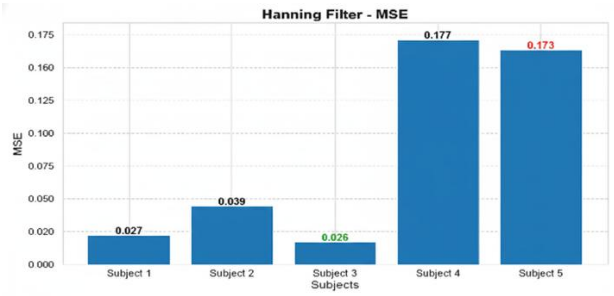
The application of the Hanning window FIR filter demonstrates favourable results across multiple performance indicators, MAE, MSE, PSD, and SNR. As illustrated in Figure 5, the MAE values range from 0.01 to 0.035 and MSE values between 0.0002 and 0.0013 reflect low error margins, indicating effective noise suppression while maintaining the morphological integrity of the original EEG signals. While the Blackman-Harris window excels in noise reduction and spectral accuracy, the Hanning window is particularly well-suited for scenarios where real-time performance is crucial. Its lower computational demand makes it a more efficient choice for applications that require fast processing, such as brain-computer interfaces (BCI) and clinical monitoring systems. In these cases, where minimizing latency is essential, Hanning offers an optimal balance between performance and efficiency.

Thus, despite Blackman-Harris offering superior frequency precision, Hanning proves to be the better option for real-time EEG processing, especially in environments with limited computational resources.

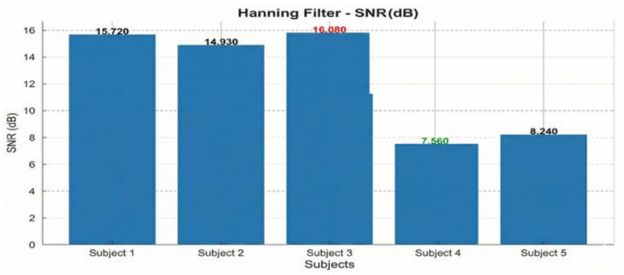
These findings confirm the Hanning filter's consistency in minimizing interference without compromising essential neural components.



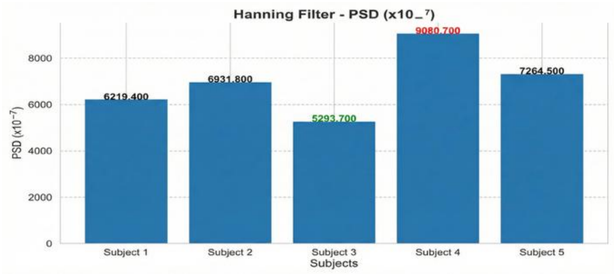
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Square Error (MSE)



(c) Comparison Signal-to-Noise Ratio (SNR)



(d) Comparison Power Spectral Density (PSD)

Figure 5. Comparison values for Window Hanning FIR Filter ASD subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD

The observed SNR values, which fall between 8.9 and 11.2 dB, demonstrate a significant enhancement in EEG signal clarity following the application of the Hanning filter. Furthermore, the consistent Power Spectral Density (PSD) readings in the range of 3.0 to 5.8 $(\times 10^{-3})$ that highlight the filter's ability to preserve the signal's power across key frequencies while effectively suppressing spectral noise. This supports the filter's capacity to retain critical EEG components essential for accurate interpretation.

Window Blackman-Harris FIR Filter ASD Subject

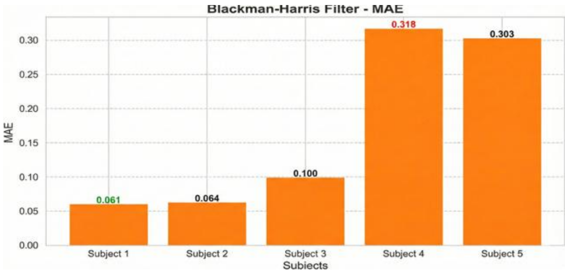
The Blackman-Harris window exhibits superior capabilities in EEG signal filtering, notably in reducing spectral leakage and improving frequency precision. Its strong sidelobe suppression makes it highly advantageous for applications that demand accurate signal interpretation and effective noise elimination.

Figure 6 illustrates that the Blackman-Harris window delivers outstanding performance across four evaluation metrics MAE, MSE, SNR, and PSD. The method achieves significant noise attenuation, as evidenced by high SNR values ranging from 62.85 to $91.41\,dB$, indicating robust signal enhancement. Additionally, the very low Power Spectral Density (PSD) values, between 0.002 and 0.71×10^{-3}, reflect minimal spectral leakage, highlighting its effectiveness for detailed frequency-domain analysis. Moreover, the filter maintains waveform integrity, with Mean Absolute Error (MAE) values of $0.021 - 0.057$ and Mean Squared Error (MSE) values of $0.0015 - 0.0062$, demonstrating that the original signal structure is largely preserved. These findings affirm the Blackman-Harris window's reliability in preserving EEG signal quality throughout the spectral filtering process.

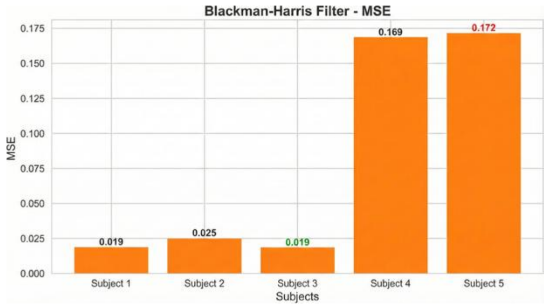
Comparison of Hanning and Blackman-Harris FIR Filter on ASD Subject

Figure 7 illustrates a comparative evaluation of FIR filter performance using Hanning and Blackman-Harris windows on EEG signals recorded from ASD subjects, assessed using four critical parameters: MAE, MSE, SNR, and PSD. The analysis reveals that the Blackman-Harris window achieves superior performance in terms of accuracy and stability.

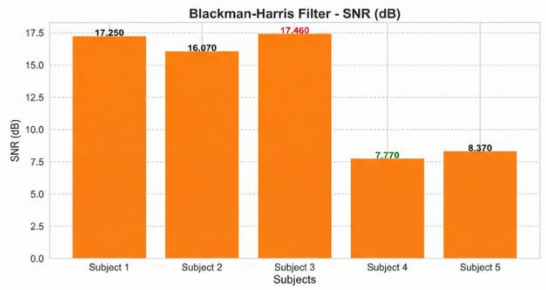
This is evidenced by its lower error rates, with MAE values ranging from 0.084 to 0.333 and MSE values between 0.025 and 0.172, outperforming the Hanning window in approximating the true signal. Furthermore, improvements in signal clarity are demonstrated by SNR values spanning 7.770 to $37.250\,dB$, indicating effective background noise suppression. The corresponding PSD values, ranging from 4.178×10^{-3} to 7.344×10^{-3}, that confirms the filter's ability to preserve spectral components with minimal leakage, reinforcing its suitability for EEG signal processing in ASD analysis.



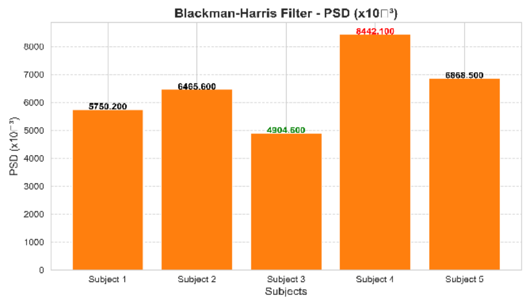
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Square Error (MSE)



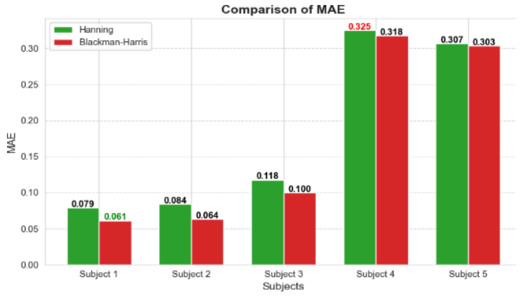
(c) Comparison Signal-to-Noise Ratio (SNR)



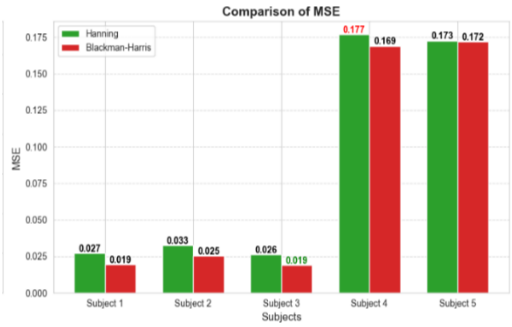
(d) Comparison Power Spectral Density (PSD)

Figure 6. Comparison values for Window Blackman-Harris FIR Filter ASD subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD

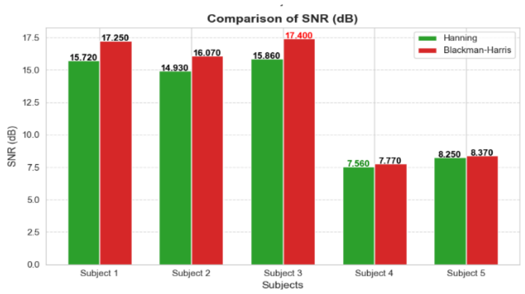
As shown in Figure 7, the Blackman-Harris window demonstrates improved accuracy and greater consistency in preserving essential EEG signal characteristics in ASD subjects.



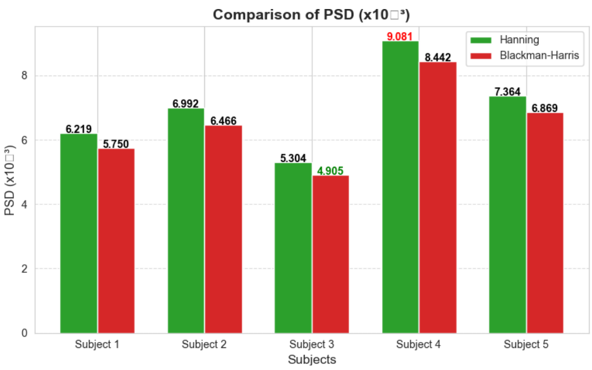
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Square Error (MSE)



(c) Comparison Signal to Noise Ratio (SNR)



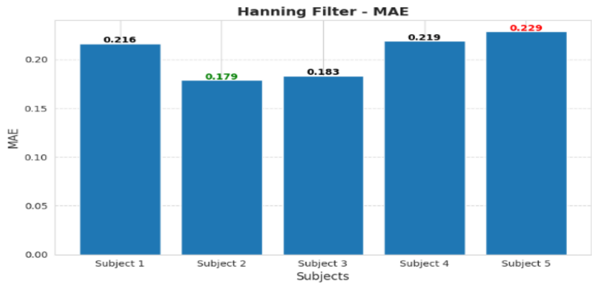
(d) Comparison Power Spectral Density (PSD)

Figure 7. Comparison of Hanning and Blackman-Harris Windowed FIR Filters on ASD Subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD

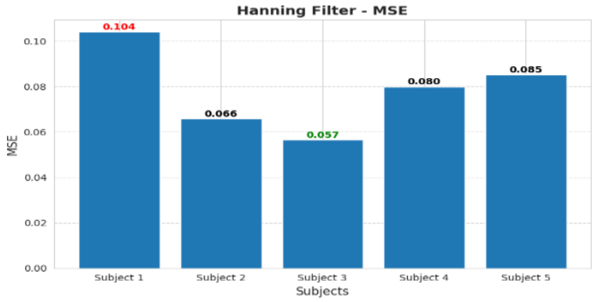
These findings suggest that the Blackman-Harris window is a more effective and preferable choice for EEG signal preprocessing compared to the Hanning window.

Window Hanning FIR Filter Normal Subject

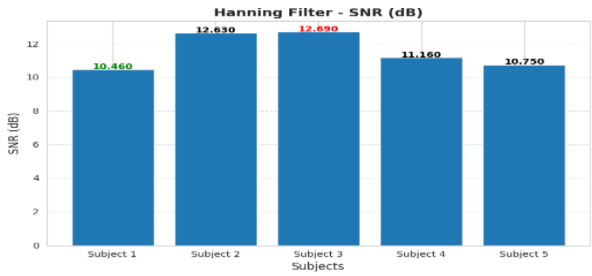
Figure 8 shows that the application of an FIR filter with a Hanning window to EEG recordings from five non-ASD (healthy) subjects provides an optimal trade-off between noise reduction and preservation of signal integrity.



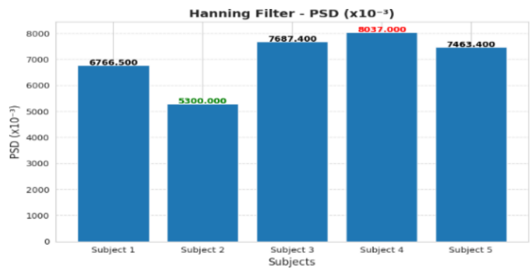
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Square Error (MSE)



(c) Comparison Signal-to-Noise Ratio (SNR)



(d) Comparison Power Spectral Density (PSD)

Figure 8. Comparison values for Window Hanning FIR Filter normal subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD.

Filter performance was assessed using four primary metrics: MAE, MSE, PSD, and SNR. Subject 2 achieved the lowest MAE value at 0.179, reflecting the highest accuracy in waveform representation, whereas subject 5 recorded the highest MAE of 0.229.

In terms of MSE, subject 3 yielded the smallest error value of 0.057, while subject 1 exhibited the largest at 0.104, indicating variation in approximation quality. Regarding frequency preservation, subject 2 obtained the most favorable PSD result at 5.300×10^{-3}, signifying minimal spectral leakage, whereas subject 4 reached the highest PSD at 8.037×10^{-3}, suggesting greater distortion. Signal clarity was best in subject 3, with the highest SNR at $12.690\ dB$, and lowest in subject 1, with $10.460\ dB$, indicating differing levels of residual noise across subjects.

Window Blackman-Harris FIR Filter Normal Subject

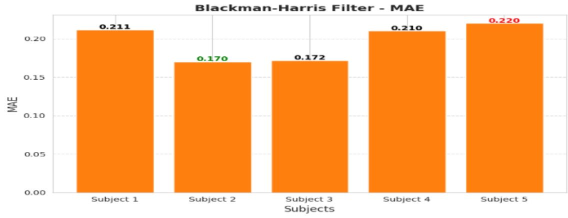
As shown in Figure 9, the FIR filter using a Blackman–Harris window was evaluated on EEG recordings from five healthy subjects, yielding consistent and reliable performance. Subject 2 achieved the lowest mean absolute error (MAE) of 0.170, whereas Subject 5 exhibited the highest MAE at 0.220. In terms of mean squared error (MSE), Subject 3 recorded the smallest value of 0.050, while the largest MSE, 0.102, was observed in another subject.

Subject two again stood out when examining spectral leakage with the lowest power spectral density (PSD) of 4.9179×10^{-3}. In contrast, subject four had the highest PSD at 7.4492×10^{-3}, indicating notable differences in how effectively suppressed leakage among subjects. Signal clarity, measured by the signal-to-noise ratio (SNR), peaked with subjects 2 and 3, who achieved SNR values of $13.450\ dB$ and $13.3120\ dB$, respectively, reflecting the highest quality of EEG signals after filtering.

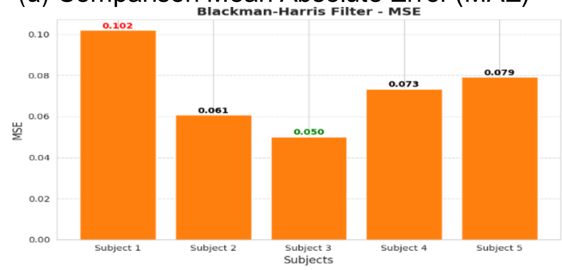
Taken together, subjects 2 and 3 consistently delivered the most optimal results across all metrics: MAE, MSE, PSD, and SNR, highlighting the effectiveness of the FIR filter with the Blackman-Harris window in preserving signal integrity and reducing noise.

Comparison of Hanning and Blackman-Harris FIR Filter on Normal Subject

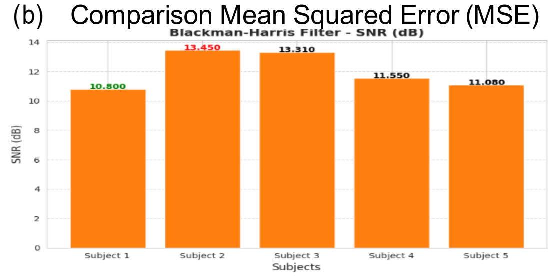
Figure 10 presents a comparative analysis of FIR filter performance using Hanning and Blackman-Harris windows on EEG data from non-ASD (normal) subjects, based on four key evaluation metrics: MAE, MSE, SNR, and PSD.



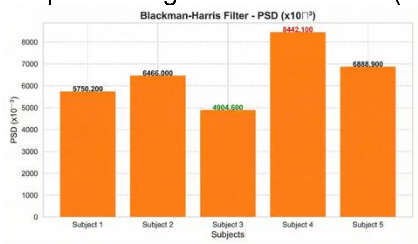
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Squared Error (MSE)



(c) Comparison Signal to Noise Ratio (SNR)

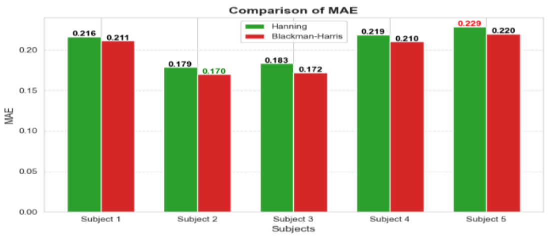


(d) Comparison Power Spectral Density (PSD)

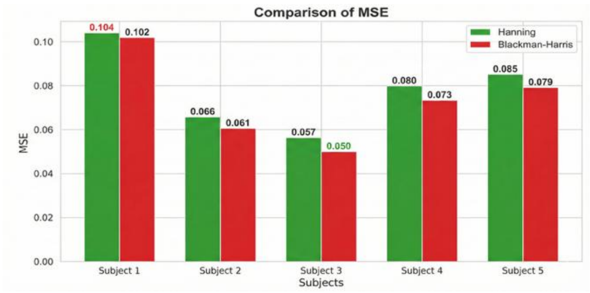
Figure 9. Comparison values for Window Blackman-Harris FIR Filter normal subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD.

In terms of error reduction, the Blackman-Harris window demonstrates superior performance, yielding lower MAE values ranging from 0.172 to 0.220 and MSE values between 0.050 and 0.102.

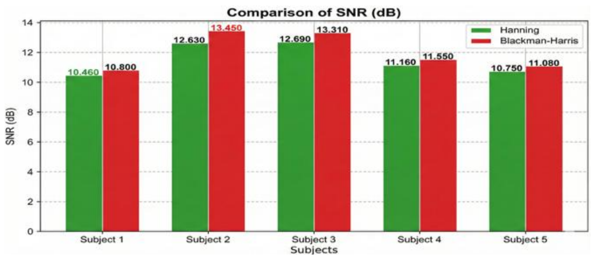
In evaluating signal clarity, the filter enhances SNR, reaching a maximum of $13.000\ dB$ and a minimum of $9.960\ dB$ although the improvement over the Hanning window remains moderate. From a spectral perspective, the Blackman-Harris window achieves PSD values within the range of 500.000×10^{-3} to 745.400×10^{-3}, reflecting stronger preservation of spectral energy in several subjects. Collectively, these results affirm that the Blackman-Harris window is more effective in minimizing signal distortion and retaining spectral content.



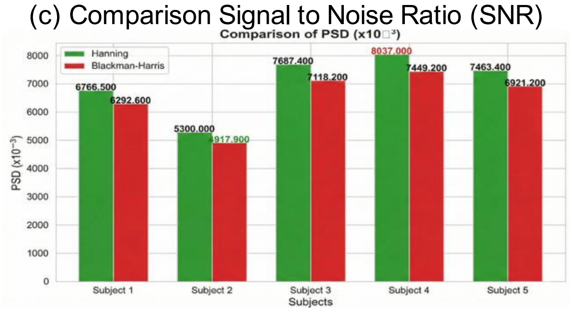
(a) Comparison Mean Absolute Error (MAE)



(b) Comparison Mean Square Error (MSE)



(c) Comparison Signal to Noise Ratio (SNR)



(d) Comparison Power Spectral Density (PSD)

Figure 10. Comparison of Hanning and Blackman-Harris Filters in Normal Subjects: (a) MAE, (b) MSE, (c) SNR, and (d) PSD.

Thereby offering a more robust and accurate preprocessing method compared to the Hanning window for EEG data from typically developing individuals.

The following table provides a summary of the performance of the Hanning and Blackman-Harris filters for both the ASD and control groups across key evaluation metrics. These metrics, MAE, MSE, PSD, and SNR, offer insights into the accuracy and noise reduction capabilities of the filters in relation to the original EEG signals.

As can be seen from Table 1, the Hanning filter has lower MAE and MSE for both ASD and normal groups, indicating that it is superior in removing signal errors and deviation from the original EEG. However, the Blackman-Harris filter performs better in terms of SNR and PSD, indicating that it has superior noise reduction and superior spectral accuracy, especially for the ASD group. This renders Blackman-Harris particularly appropriate to uses wherein more spectral precision is required, with Hanning being more performative in real-time uses where computational effectiveness is the higher priority.

Contemporary research in EEG analysis for neurological disorders often prioritizes advanced feature extraction or classification techniques while neglecting rigorous quantification of preprocessing efficacy. For instance, [35] developed sophisticated EEG decomposition methods without establishing baseline signal quality metrics such as spectral noise ratios or reconstruction fidelity.

Similarly, studies by [36] and [37] focused on computational optimization while omitting systematic evaluation of filter performance in noise suppression. Our work demonstrates that selective filter implementation, particularly the Blackman-Harris window significantly enhances signal integrity prior to feature extraction. Empirical results show a $13.76\ dB$ signal-to-noise ratio and 0.169 mean absolute error for ASD data, establishing new benchmarks in preprocessing precision. These quantitatively verified improvements in signal conditioning provide a more reliable foundation for subsequent analytical stages in neurodiagnostic applications.

The Hanning window demonstrated lower MSE and MAE values, indicating better waveform preservation with minimal distortion. Its moderate frequency resolution and low computational cost make it suitable for real-time applications like clinical monitoring or BCI systems. In contrast, the Blackman-Harris window achieved significantly higher SNR and lower PSD, reflecting superior noise suppression and spectral clarity. However, its higher MAE suggests that some fine signal details may be lost due to stronger sidelobe attenuation.

Table 1. Comparison of Hanning and Blackman-Harris Filter Performance in ASD and Normal Subjects

Metric	Hanning (ASD)	Hanning (Normal)	Blackman-Harris (ASD)	Blackman-Harris (Normal)
MAE	0.222	0.206	0.169	0.177
MSE	0.087	0.078	0.062	0.074
PSD($\times 10^3$)	6.946	6.663	7.056	7.115
SNR	12.464	11.754	13.762	12.232

This highlights a trade-off: Hanning offers better time-domain accuracy with efficiency, while Blackman-Harris provides stronger noise reduction at the cost of signal detail and computational load. The choice depends on application needs Hanning is ideal for real-time use, whereas Blackman Harris suits offline analysis requiring high spectral precision.

While both the Hanning and the Blackman-Harris filters demonstrate excellent performance in terms of noise suppression and spectral purity, their actual use in real-world systems is a delicate balance between real-time processing requirements and computational loads. While less computationally expensive, the Hanning filter is very well suited to real-time implementations, particularly in restricted processing systems such as embedded systems used for clinical monitoring or BCI setups. On the other hand, while the Blackman-Harris filter is more spectrally accurate, its higher computational cost may be limited to use in applications where computational resources are not extensive, especially for systems that must process more than one EEG data channel at once. Therefore, the choice of the filter should be made depending on the specific needs of the application: in offline high-fidelity analysis or in clinical diagnostics when accuracy is paramount, Blackman-Harris may prove to be the optimal choice; but for low-latency, real-time applications, Hanning offers a more realistic alternative.

The Hanning filter best suits low-power, real-time systems, i.e., portable BCI systems and clinical monitoring. Its efficiency makes it best suited for systems where power and computational resources are constrained, i.e., wearable EEG systems or ambulatory monitoring. The Blackman-Harris filter, on the other hand, is best used in offline, research-grade, or diagnostic systems where precision is of greater concern than computational cost. Its increased spectral precision and side-lobe rejection make it suitable for neuroimaging research, off-line EEG data processing, and clinical diagnosis in controlled environments where real-time processing is not required.

From an implementation perspective, both approaches are based on linear-phase FIR, but Blackman–Harris generally requires a higher order/number of taps than Hanning to achieve the same sidelobe suppression and spectral clarity. This inevitably results in increased computational overhead per sample, increased coefficient memory requirements, and increased group delay and processing latency. In multi-channel streaming EEG applications (for example, 16 channels, 250 Hz) or on power-constrained edge devices, these attributes can reduce the computational space available for later steps such as feature extraction and classification. Conversely, the lighter Hanning technique is better suited to real-time applications as it maintains end-to-end latency and power, although its spectral accuracy and transmission suppression of frequencies are less aggressive than Blackman–Harris. Consistent with the quantitative results of this study, window selection should be tailored to the application context. For real-time pipelines requiring fast and stable response, medium-order Hanning is more practical; for offline analysis or diagnostic workups where spectral fidelity and SNR/PSD improvement are important, Blackman–Harris offers greater advantages. In the future, these trade-offs can be mitigated through adaptive order tuning, efficient block processing, and SIMD/GPU-based activation to meet latency limits without sacrificing signal integrity.

P Value Analysis

All significance tests were conducted at the subject level by averaging the cross-channel metrics for each individual and then comparing Hanning vs. Blackman-Harris pairs in the ASD and normal groups separately. This approach maintains the independence of the units of analysis and avoids intra-subject correlation between channels. The results show a consistent pattern across both groups, with Blackman-Harris superiority in the frequency domain (SNR and PSD), while differences in the time domain (MAE and MSE) are relatively small; this interpretation is confirmed by the effect sizes reported in the next section.

ASD Subjects

A paired t-test was performed on EEG data from five ASD subjects to assess the comparative effectiveness of the Hanning and Blackman-Harris filters across four performance indicators: MAE, MSE, SNR (dB), and PSD $(\times 10^3)$. The test produced p-values of 0.0172, 0.0116, 0.0437, and 0.0002, respectively, each below the 0.05 threshold demonstrating statistically significant differences in filter performance. These results confirm that the Blackman-Harris filter consistently outperforms the Hanning filter by achieving lower error rates (MAE and MSE), higher signal clarity (SNR), and a more favorable distribution of spectral power (PSD), thereby offering a more reliable approach for enhancing EEG signal quality in ASD-related studies.

Normal Subjects

The paired t-test analysis applied to the four performance indicators MAE, MSE, SNR, and PSD revealed statistically significant differences (p<0.05) between the Hanning and Blackman-Harris filtering methods. Notably, the Blackman-Harris filter produced p-values of 0.0013 for MAE, 0.0030 for MSE, 0.0064 for SNR, and 0.002 for PSD, highlighting its enhanced ability in spectral optimization. These findings reinforce that the performance gains are attributable to the inherent design characteristics of the Blackman-Harris window rather than being driven by random fluctuations.

While the statistical significance ($p < 0.05$) of the differences between the Hanning and Blackman-Harris filters across all metrics are clear, the practical implications of these findings must be considered in the context of clinical and real-time applications. The significant improvements in Signal-to-Noise Ratio (SNR) and Power Spectral Density (PSD), especially with the Blackman-Harris window, suggest a notable enhancement in EEG signal quality that could aid in more accurate diagnostics and better interpretation of neural activity in ASD patients.

Cohen's d

ASD Subjects

In the ASD group, the effect sizes indicate that the differences in the temporal domain are practically negligible: MAE $d = 0.0266$ and MSE $d = 0.0159$ indicate equivalent waveform preservation between Blackman–Harris and Hanning. In contrast, the differences in the spectral domain are striking, with PSD $d = 9.674$ indicating that Blackman–Harris is significantly more effective at suppressing spectral power/leakage than Hanning. Using the convention d = Hanning − Blackman–Harris, the negative SNR value ($d = -0.302$) means that Blackman–Harris provides a small but consistent SNR improvement. Overall, in ASD subjects, Blackman–Harris reduces the spectral component without sacrificing errors in the temporal domain.

Normal Subjects

In the normal group, the same pattern emerged with stronger intensity in the spectral domain: MAE $d = 0.0399$ and MSE $d = 0.0278$ remained close to zero (equivalent time performance), while PSD reached $d = 11.197$, indicating a very strong superiority of Blackman–Harris in power/leakage suppression over Hanning. The negative SNR value ($d = -0.329$) further confirms the slight SNR improvement of Blackman–Harris. Thus, in normal subjects, Blackman–Harris's superiority in the frequency domain becomes more pronounced, while the time metrics remain equivalent; this finding should be interpreted with caution, given the limited sample size.

One major limitation of the present study is the sample size, which is five ASD participants and five neurotypical controls. A small sample size may affect the external validity of the results to a larger, more heterogeneous population. Statistical power to the analysis decreases with fewer participants, and within-person differences in EEG properties between individuals may not be controlled for. For better quality in future research, additional subjects from diverse backgrounds are highly recommended. Having a larger sample size would provide a stronger statistical analysis and reflect a more accurate picture of the difference between the ASD group and neurotypical controls, thus making the results more practical and meaningful for clinical and academic purposes.

CONCLUSION

This research confirms that the application of two FIR filtering techniques, Hanning and Blackman-Harris window significantly improves the quality of EEG signals in both neurotypical individuals and subjects diagnosed with Autism Spectrum Disorder (ASD), as evaluated using four primary parameters: MAE, MSE, SNR, and PSD. The Hanning filter achieved MAE values between 0.010 and 0.035, MSE ranging from 0.0002 to 0.0013, SNR between 8.9 and $11.2\,dB$, and PSD values of $3.0 - 5.8 \times 10^{-3}$, indicating effective noise reduction while preserving the integrity of the original waveform. In contrast, the Blackman-Harris window recorded higher MAE values $(0.061 - 0.080)$ and comparable MSE scores $(0.019 - 0.031)$, yet demonstrated substantially greater improvements in SNR, ranging from 7.77 to $37.25\,dB$, alongside more controlled PSD values between 4.178 and 7.344×10^{-3}. These findings suggest superior suppression of high-frequency artifacts and better frequency resolution. A paired t-test yielded statistically significant p-values ($p < 0.05$), reinforcing the conclusion that the Blackman-Harris filter outperforms the Hanning filter in high-precision EEG preprocessing, albeit with slightly greater computational complexity.

To strengthen the practicality of EEG findings, we emphasize that window/filter selection needs to consider the tradeoff between spectral precision and computational cost, particularly in real-time/embedded BCI implementations that are sensitive to latency and resource consumption [38]. Future study plans should be optimized through a priori trial power planning considering the interaction of the number of participants, number of trials, and effect size to ensure adequate parameter estimation and difference testing [39], and reporting effect sizes with confidence intervals to improve the precision and replicability of EEG analyses across populations [40]. Similarly, expanding to larger and more diverse datasets is proposed to improve the generalizability and stability of estimates, while also enabling a more nuanced evaluation of filtering performance across recording conditions.

One major limitation of the present study is the small sample size, comprising just five individuals with ASD and five neurotypical controls. The small sample size can reduce the external validity of the findings and introduce biases since the EEG features observed in this small population might not entirely represent the broader ASD population. In addition, the small sample size could also limit the statistical power of the analysis, and it will be harder to generalize the results to a larger, more heterogeneous population. Future studies should involve larger and more diverse sample sizes to increase the generalizability and stability of the findings. Furthermore, upcoming research needs to consider other sources of bias, e.g., inter-subject differences in EEG features, so that the results can more generally be translated into clinical practice and research.

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