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EEG Performance Signal Analysis for Diagnosing Autism Spectrum Disorder Using Butterworth and Empirical Mode Decomposition

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Abstract **Electroencephalography (EEG) is a technique used to measure electrical activity in the brain by placing electrodes on the scalp. EEG plays an essential role in analyzing a variety of neurological conditions, including autism spectrum disorder (ASD). However, in the recording process, EEG signals are often contaminated by noise, hindering further analysis. Therefore, an effective signal processing method is needed to improve the data quality before feature extraction is performed. This study applied the Butterworth Band-Pass Filter (BPF) as a preprocessing method to reduce noise in EEG signals and then used the Empirical Mode Decomposition (EMD) method to extract relevant features. The performance of this method was evaluated using three main parameters, namely Mean Square Error (MSE), Mean Absolute Error (MAE), and Signal-to-Noise Ratio (SNR). The results showed that EMD was able to retain important information in EEG signals better than signals that only passed through the BPF filtration stage. EMD produces lower MAE and MSE values than Butterworth, suggesting that this method is more accurate in maintaining the original shape of the signal. In subject 3, EMD recorded the lowest MAE of 0.622 compared to Butterworth, which reached 20.0, and the MSE value of 0.655 compared to 771.5 for Butterworth. In addition, EMD also produced a higher SNR, with the highest value of 23,208 in subject 5, compared to Butterworth, which reached only 1,568. These results prove that the combination of BPF as a preprocessing method and EMD as a feature extraction method is more effective in maintaining EEG signal quality and improving analysis accuracy compared to the use of the Butterworth Band-Pass Filter alone.**

Keywords Autism Spectrum Disorder; Electroencephalography; Empirical Mode Decomposition; Butterworth Band-Pass Filter.

I. Introduction

Autism is a comprehensive developmental disorder that results in obstacles in socialization, communication, and behavior. The disorder ranges from mild to severe. This autistic symptom generally appears before the child reaches the age of 3 years old [1]. Autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by impairment of sensory modulation. This sensory modulation deficit will eventually cause them to have difficulties in adaptive behavior and intellectual functioning. They also often show a tendency to perform consistent rituals or routines, as well as resistance to changes in their routines [2]. The disorder in people with ASD is related to functional changes in the frontal lobe and temporal lobe, generally showing increased activity in brain waves at the delta (δ) – theta (γ) frequency in the frontal area of the brain, which is associated with poor cognitive ability [3]. People with autism generally show lower brain wave activity at the Alpha (α) frequency, which is usually associated with a state of relaxation. Instead, they tend to have higher brainwave activity at the Beta (β) frequency, which is related to focus and concentration conditions. This indicates that patterns of brainwave activity may play a role in ASD's developmental disorder [4].

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Brain activity can be studied through research media in the form of functional images produced by measuring brain signals with EEG (electroencephalography). EEG is a technique used to measure the brain's spontaneous electrical activity, resulted from the transmission of electrical signals between neurons. The process of recording EEG signals is carried out over a short period of time, usually between 20 to 40 minutes. This data is obtained by placing electrodes at various points on the scalp [5]. This noise can come from various sources, both internal and external, that cause interference with the brain signals being measured. In this case, noise reduction (denoising) is an important and fundamental part of EEG signal processing, one method that can be used is the Butterworth band-pass filter (BPF) [6].

EEG signals require an advanced processing process so that relevant data can be found and analyzed correctly by using the feature extraction method. The feature extraction method transforms the raw signal into a collection of highly important informative features. These features can be classified and analyzed in various applications, such as emotion recognition, brain-computer interface (BCI), seizure detection, and ASD detection. The feature extraction process typically involves several steps, including signal preprocessing, decomposition, and extraction of relevant features from the processed signal. A variety of techniques can be used for feature extraction, including statistical measurement, frequency-time analysis, and advanced signal decomposition methods such as Empirical Mode Decomposition (EMD) [7],[8].

Empirical Mode Decomposition (EMD) is a data-driven method that breaks down complex signals into a limited number of intrinsic mode functions (IMFs). Each IMF represents a simple oscillation mode that reflects the underlying characteristics of the original signal. EMDs are particularly effective for analyzing non-stationary and nonlinear signals, such as EEGs, as they can adapt to data without requiring pre-defined basic functions [8].

Previous research with a different object i.e. on ERP signals, IMF from EMD was able to analyze non-stationary ERP signals, with IMF1 providing the best classification results [9]. Other studies have suggested that EMD decomposition on EEG signals improves the accuracy, sensitivity, and specificity of the model by about 5%, 6%, and 5% respectively [10].

In this study, the main focus of the researcher was to measure the performance of feature extraction methods using EMD to determine how effective this method is for extracting important information from EEG signals. The measurement of the performance of the method was carried out with three calculation parameters, namely Mean Square Errors (MSE), Mean Absolute Errors (MAE), Signal to Noise Ratio (SNR) and Power Spectral Density (PSD).

The main contributions of this study include: 1) assessing the extent to which EMD can extract important information from EEG signals in order to improve classification accuracy, 2) evaluating the impact of using Butterworth band-pass filter (BPF) in improving signal quality before feature extraction, 3) measuring EMD performance with 3 evaluation parameters, namely Mean Square Errors (MSE), Mean Absolute Errors (MAE), Signal to Noise Ratio (SNR), and Power Spectral Density (PSD), to assess its effectiveness in EEG analysis for ASD studies, and 4) comparing the performance of EMD methods with other methods.

To achieve this goal, the collected EEG signals went through a pre-processing stage with BPF to reduce noise before being extracted using the EMD method. Furthermore, the resulting features were analyzed based on predetermined performance parameters. The study was further structured as follows: part II discusses the EEG datasets used as well as the methods of preprocessing and extraction of features; part III displays the results of BPF preprocessing and the results of the EMD method performance analysis based on the selected evaluation parameters; and part IV discusses the interpretation of the results, presenting conclusions that summarize the research objectives, key findings, and possible future developments.

II. Research Method

In this section, Fig. 1 illustrates the methodology applied in this study, starting from the pre-processing stage, which uses a Butterworth Band Pass Filter to filter out unwanted frequencies so that the processed EEG signal becomes cleaner and more ready to be analyzed in the next stage. After going through the pre-processing stage, the EEG signal was then processed at the feature extraction stage, where the Empirical Mode Decomposition (EMD) method was used to decompose the signal into its intrinsic components. This process aims to extract the main characteristics of the EEG signal so that the information obtained becomes more representative and easier to analyze at a later stage.

After the features were extracted, this research continued with the next step of evaluating and analyzing the performance of the methods used by measuring the quality of the processed signal using three main parameters, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and Signal-to-Noise Ratio (SNR).

In this research, Python version 3.13 was used to implement the signal processing circuit. The SciPy

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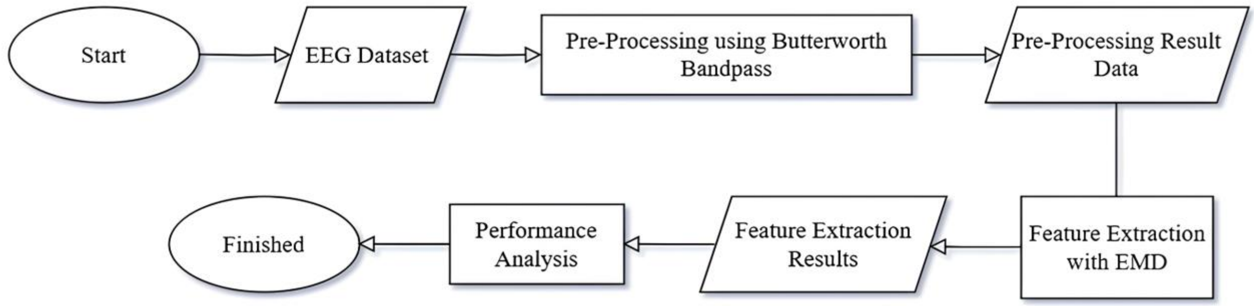

Fig. 1. Flowchart of EEG Signal Processing Using Butterworth Bandpass and EMD Feature Extraction

library was utilized specifically for the scipy signal.butter function to design a 4th-order band-pass Butterworth filter, as well as scipy.signal.filtfilt to apply zero-phase filtering to avoid phase changes in the EEG signal. For the Empirical Mode Decomposition (EMD) process, the PyEMD library was used by implementing the original EMD algorithm. All preprocessing steps, including filtering and EMD, were performed using custom Python scripts developed in-house for this study. The scripts can be shared upon request to support transparency and reproducibility. All processing was performed on a standard workstation with 16 GB of RAM and an Intel i7 processor. The code structure is modular for easy reuse and adaptation to other EEG datasets.

A. Material

This study used the EEG dataset obtained from King Abdul-Aziz University (KAU), Jeddah, Saudi Arabia [11]. This dataset has also been used for previous research [12],[13]. This dataset is publicly available and can be obtained by sending a formal request via email to Dr. Mohammed Jaffer Alhaddad, as described [14]. In this study, we followed the same procedure to obtain the dataset, while ensuring participant confidentiality by not disclosing personally identifiable information. The data were recorded while the subjects were in a relaxed state to minimize artifacts, using a g.tec EEG cap equipped with Ag/AgCl electrodes, G.tec USB amplifiers, and BCI2000 software. During recording, the data was filtered online with a band-pass (0.1–60 Hz) and notch (60 Hz) filter and digitized at 256 Hz. The recordings are 16-channel data sampled at 256 Hz. It includes recordings from eight autistic children, all boys aged between 10 and 16 years old, with a total signal duration of 4104.2 seconds. The control group consisted of eight boys aged 9 to 16 years old with no history of neurological disorders, contributing to a total signal duration of 4534.9 seconds. All EEG recordings were conducted following the international 10–20 electrode placement system. [15], [16].

These datasets were stored in file format with .dat extension, which generally contain binary or text data and are often automatically generated by the associated software. The original format may be difficult to read because it contains a large amount of data that supports various program functions. Therefore, in this study, the dataset was converted to a .xlsx format to make it easier to process. The following is an example of the display of EEG signals generated by the BCI2000Viewer (Fig. 2). This view generally shows a standard 10-20 electrode placement system, in which electrodes are placed at specific points on the scalp [17].

In this system, several main electrodes were used to record brain activity. On the front or front of the head, the electrodes used include Fp1, Fp2, F3, and F4. In the central or middle part of the head, there are electrodes C3, C4, and Cz. Meanwhile, the electrodes in the temporal side of the head include T3, T4, T5, and T6. In the parietal or upper back of the head, the electrodes used are P3, P4, and Pz. Finally, in the occipital or lower back of the head, there are O1 and O2 electrodes [18], [19], [20]. Each electrode records electrical activity in different areas of the brain, providing a comprehensive picture for analysis, especially in understanding conditions such as autism.

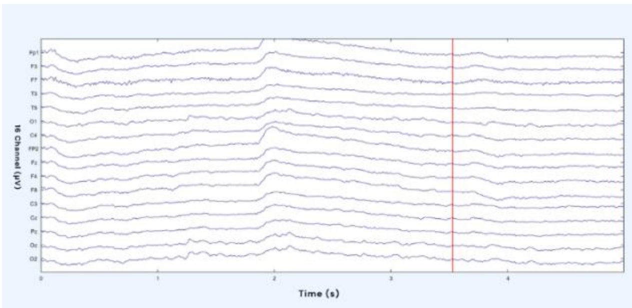

Fig. 2. Visualization of EEG Dataset with 16 Channels Over Time in Microvolts

B. Butterworth Band-Pass Filter

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Butterworth band-pass filters are a type of signal processing filter designed to have a flat frequency response on the band-pass. It is also referred to as the maximum flat magnitude filter. The frequency response of the Butterworth filter is very flat at the bandpass and gradually decreases to zero at the band stop. Generally, a band-pass filter consists of a high-pass filter (HPF) followed by a low-pass filter (LPF). High-pass filters (HPF) miss high-frequency signals but attenuate frequencies lower than cut-off frequencies. Low-pass filters (LPF) miss low-frequency signals but attenuate frequencies higher than cut-off frequencies [21].

The two filters were then multiplied to form a band-pass filter. This aims to allow the signal that has a frequency between the two cut-offs to pass through without experiencing a significant decrease in amplitude, while signals outside this range will be muffled [22]. The characteristic of the Butterworth band-pass filter is that it has a very even amplitude response within the permissible frequency range (band-pass). However, the phase response of these filters is non-linear, which means that the phase changes in the signal passing through these filters vary depending on the frequency of the signal [17].

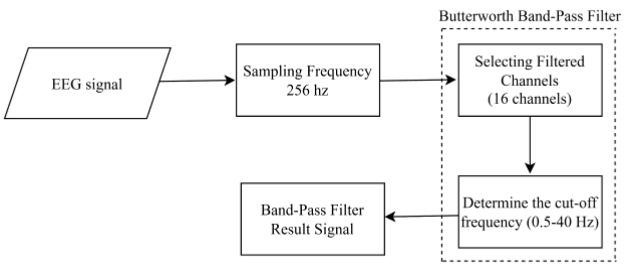

Fig. 3. Diagram of EEG Signal Processing Using Butterworth Band-Pass Filter with 0.5–40 Hz Cutoff Frequency

The EEG signals used in this study were sampled with a frequency of 256 Hz to ensure coverage of the relevant spectrum of brain activity. As many as 16 channels (all channels) were selected for analysis. Next, the EEG signals were filtered using a Butterworth band-pass filter with a cut-off frequency of 0.5-40 Hz in the preprocessing stage. The EEG signals were recorded with a sampling frequency of 256 Hz were first filtered using a Butterworth Band-Pass Filter (BPF) as illustrated in Fig. 3. This particular filter was selected because it had a flat frequency response to the passband, and was capable of preserving the original signal shape with minimal distortion. The filtering was applied to 16 EEG channels; the chosen frequency range was 0.5-40 Hz, covering all main EEG bands (delta, theta, alpha, beta, and a few low gamma bands). The resulted time series were filtered using a bandpass filter of cutoff 0.5 Hz and 40 Hz to eliminate very low-frequency artifacts arising due to signal drift, slow body movements, and noise from muscle activity and environmental interference, respectively. We used a 4th order filter, which balances between sharp frequency selection and stability of the filter system. The selection of these parameters was adjusted to the characteristics of the EEG signal so that the process of feature extraction and further analysis can run optimally.

C. Empirical Mode Decomposition

The main concept of EMD is to find the right timescale to show the physical properties of the signal [23]. Then, using functions, the signal was converted to an intrinsic mode, known as Intrinsic Mode Functions (IMF) [9]. The IMF must meet two conditions with the first condition, the maximum value of the signal amplitude is equal to the number of zero crossings across the signal time domain, or the maximum difference is 1, and the average value of the envelope formed by the maximum and minimum

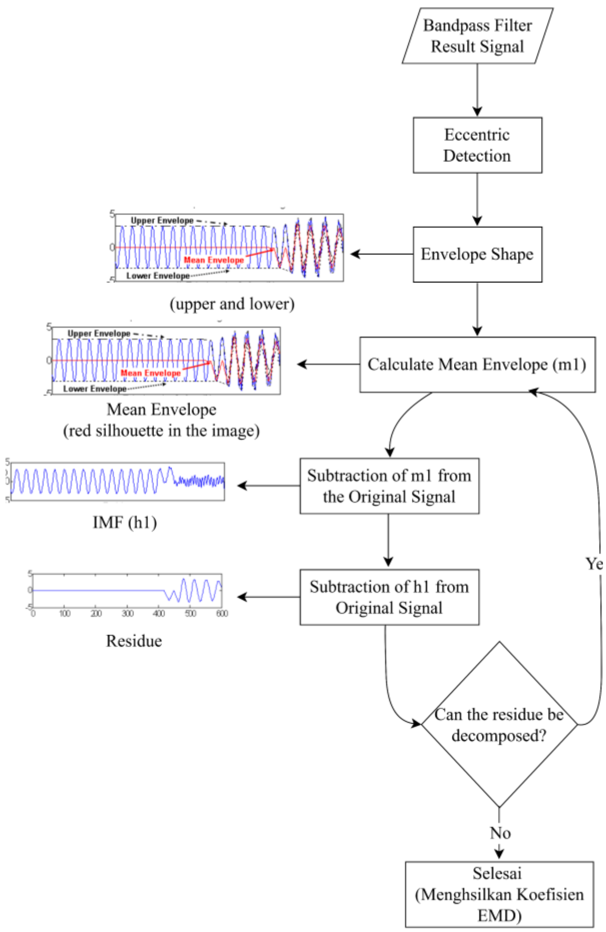

Fig. 4. Flowchart of Empirical Mode Decomposition (EMD) Process for Signal Decomposition

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amplitude of the signal is zero [10]. The specific steps of EMD are as follows in Fig. 4:

a. Identifying the maximum and minimum values of the $x(t)$ signal, namely the upper envelope and lower envelope values.
b. Calculating the mean value between the value of the upper envelope and the lower envelope which is defined as m_1 as explained in Eq. (1) [24]. The difference between the data (initial signal) and m1 results in the h_1 component, which is also known as the first IMF

$$h_1 = x(t) - m_1 \quad (1)$$

The first IMF from the data can also be defined as Eq. (2) [24]:

$$c_1 = h_{1r} \quad (2)$$

c. Removing *c1* from the residue can be done using the Eq. (3) [24]:

$$r_1 = x(t) - c_1 \quad (3)$$

So that the equation is obtained Eq. (4) [24]:

$$x(t) = \sum_{i=1}^{n} c_i + r_i \quad (4)$$

The signal was broken down into n-empirical modes and residues (rn), which, if all the results of decomposition and residues are recombined, it will form the original signal.

d. By repeating the process in the second step, several stable IMFs were formed, and eventually, a constant or convergent residue was obtained [24].

EMD is preferred in EEG signal analysis due to its ability to adaptively extract intrinsic mode functions (IMF) without relying on predefined basis functions, unlike traditional methods such as Fourier Transform (FT) or Discrete Wavelet Transform (DWT). This approach is particularly effective for non-stationary and nonlinear signals, as it preserves local signal characteristics and excels in noise reduction. These advantages make EMD more accurate and flexible compared to conventional decomposition techniques [25], [26].

D. Selection of IMF

In the Empirical Mode Decomposition (EMD) process, the EEG signal is split into a number of Intrinsic Mode Functions (IMFs) representing different frequency components. However, not all IMFs are relevant for further analysis, so an IMF selection stage is required to ensure that only significant components of the original signal are used. In this study, five relevant IMFs were used based on their level of relevance to the original signal. This IMF selection was done using the energy-based, correlation-based, and PSD distance-based selection methods.

1. Energy-based selection method

The energy of each IMF is calculated according to Eq. (5) [23]. Since higher energy IMF is considered the best representation of the original signal, they are arranged in descending order of energy [27].

$$E\ \mathrm{IMF}i = \sum_{n=}^{p-1} |\mathrm{IMF}i[n]|^2 \quad (5)$$

Eq. (5) [23] calculates the energy of the i th IMF as the sum of squares of the absolute values of that IMF at each point in time. Where $\mathrm{IMF}i[n]$ is the value of the i th IMF at index n, and p is the total number of samples. This energy, $E\ \mathrm{IMF}i$, reflects the contribution of the IMF to the original signal-the higher the energy, the more significant the IMF.

2. The correlation-based selection method

The correlation coefficient for each MFI was calculated according to Eq. (6) [23]. The IMF which has a high correlation coefficient is considered a good representation of the original signal [28]. Therefore, the IMF is ranked from the one with the highest correlation coefficient to the lowest [23],[29].

$$p_{x,\mathrm{IMF}i} = \frac{Cx, \mathrm{IMF}i}{\sigma_x \sigma \mathrm{IMF}i} \quad (6)$$

Eq. (6) [23] calculates the correlation coefficient between the original signal x and the i IMF. Where $Cx, \mathrm{IMF}i$ is the covariance of the two σ_x and $\sigma\mathrm{IMF}i$ are their standard deviations. A high coefficient value indicates that the IMF is most similar to the original signal.

3. The PSD distance-based selection method

Other IMF selection methods, based on power spectrum density (PSD), were also used using the power spectrum density of the original signal and the IMF [30]. The distances between the estimated PSDs were calculated using the Kullback Liebler (KLD) distance method, as shown in Eq. (7) [23]. An IMF was deemed the most representative of the original signal when its PSD closely matches that of the original, minimizing the difference between the two. Therefore, the IMF was ranked from the lowest to the highest IMF PSD range [23],[31].

$$dis_{kLD}(x, IMF_i) = \sum_{n=0}^{N-1} log_{\frac{S_x(\omega_k)}{S_{IM\,Fi}}}\ \omega_k\,, = \frac{2\pi}{N} k \quad (7)$$

Eq. (7) [23] calculates the Kullback-Leibler distance (KLD) between the PSD of the original signal x and the i -th IMF, using the respective PSD values at

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frequency $\omega_k = \frac{2\pi}{N}k$, with N as the number of points. Here, $S_x(\omega_k)$ and $S_{IM\,Fi(\omega_k)}$ are the PSD of the original signal and the IMF. The smaller the KLD value, the more similar the IMF is to the original signal.

E. Performance Analysis

The results of EEG signal processing that has gone through the decomposition stage using the Empirical Mode Decomposition (EMD) method was then calculated, analyzed, and compared based on three evaluation parameters, namely mean squared error (MSE), mean absolute error (MAE), and signal-to-noise ratio (SNR).

1. Mean Squared Errors (MSE)

MSE is used to evaluate measurement models, such as regression models or other forecasting methods [32]. The equations of MSE in mathematics are as follows:

$$MSE = \frac{\sum_{i=1}^{N}[(x_i) - (y_i)]^2}{N} \tag{8}$$

Eq. (8) [32], (x_i) is the original value of the experiment result or the recorded value of the EEG signal, while (y_i) is the predictive value or signal created after the filtration process and N is the amount of data or samples used for analysis. This is important in the context of ASD because the brains of individuals with ASD exhibit distinctive and complex activity patterns, so preservation of the original signal dynamics is essential to accurately detect such patterns [33].

2. Mean Absolute Errors (MAE)

Mean Absolute Error (MAE) is an evaluation metric that is widely used to measure the average magnitude of errors in a series of predictions, regardless of direction. It is defined as the average of the absolute difference between the predicted and actual values. [34]. The MAE equations in mathematics are as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \tag{9}$$

In Eq. (9) [34], (x_i) represents true value, (y_i) is the predictive value, and N is the number of observations. This metric provides a clear indication of the average error in the predictions made by a model [35]. A small MAE value indicates high reliability in preserving the important characteristics of the signal, which in turn increases the accuracy in identifying typical ASD indicators or biomarkers [36].

3. Signal To Noise Ratio (SNR)

This metric is particularly useful in clinical settings and studies involving EEG, as it allows for an assessment of the model's performance in predicting outcomes associated with brain activity [37]. The SNR equation in mathematics is as follows

$$SNR = 10\log_{10}\left\{\frac{\sum_{n=1}^{N}[x(n)]^2}{\sum_{n=1}^{N}[x(n) - \hat{x}(n)]^2}\right\} \tag{10}$$

In Eq. (10) [37], $x(n)$ represents true value, $\hat{x}(n)$ is the predicted value, and N is the amount of data or sample used for analysis. In the context of EEG signals, higher SNR indicate clearer and more interpretable EEG signals, which are critical for accurate analysis and interpretation in a wide range of applications, including brain-computer interfaces (BCIs) and clinical diagnostics [38]. EEG signals with high SNR allow for more precise identification of neural patterns specific to ASD, thus supporting the diagnosis process and development of more effective interventions [39].

4. Test Statistics

In the performance evaluation of EEG signal denoising methods, inferential statistical analysis often utilizes paired t-test to determine whether the performance difference between two methods is statistically significant. Theoretically, this test considers the difference in metric values (such as MAE, MSE, or SNR) of each pair of observations derived from two different methods. The formula for the paired t-test can be expressed as follows Eq. (11) [40]:

$$t = \frac{\bar{d}}{s_d \,/\, \sqrt{n}} \tag{11}$$

where $\bar{d}$, is the mean of the differences between pairs, s_d is the standard deviation of the differences, and n denotes the number of sample pairs as in Eq. (11) [40]. The obtained t value was compared with the critical value of the t distribution ($df = n$ - 1) to calculate the p value, which is the probability that the observed difference occurred by chance. Mathematically as in Eq. (12) [40]:

$$p = 2(1 - T(|t|, df)) \tag{12}$$

with T as the cumulative distribution function of t, representing cumulative probability under t distribution [40].

III. Result

There are several results obtained from the raw processing of EEG signals, the first result is the result of the signal from the butterworth band pass filter. The signal of the butterworth band pass filter results then becomes an input for the empirical method of decomposition mode, the results obtained are in the form of an IMF which is then reconstructed into one IMF. The IMF was analyzed for performance using three parameters, namely Mean Square Errors (MSE) using Eq. (8) [32], Mean Absolute Errors (MAE) using

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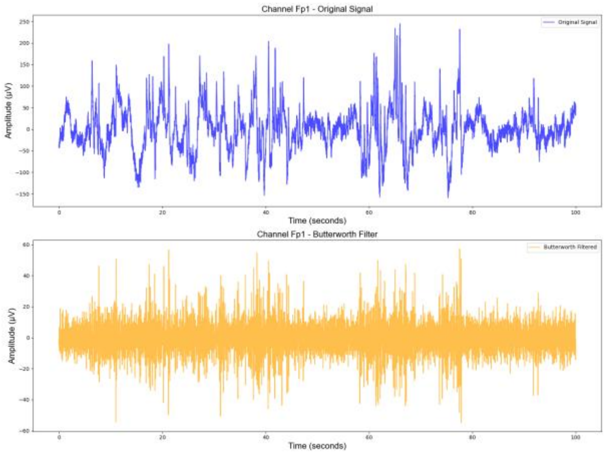
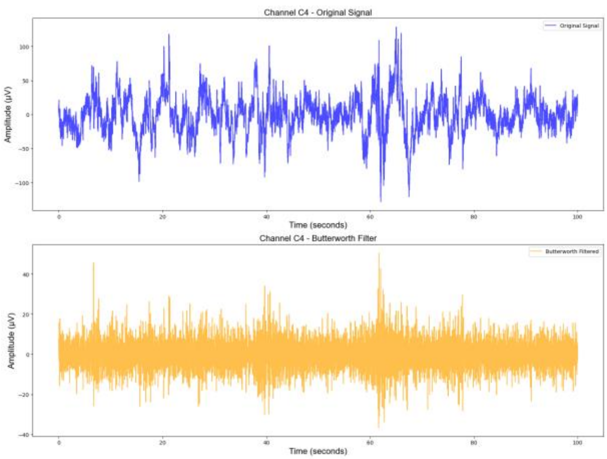
Eq. (9) [34] and Signal to Noise Ratio (SNR) using Eq. (10) [37].

A. Butterworth Band-Pass Filter Result

The butterworth bandpass filter was used to maintain the EEG signal within a certain frequency range, which is between 0.5 Hz to 40 Hz, with the main purpose of filtering and removing frequency components that are outside these limits. The working principle of this filter is based on the characteristics of the Butterworth frequency response, which is known to have a smooth frequency response without ripples in the passband band, resulting in optimal filtering without excessive distortion of the desired signal.



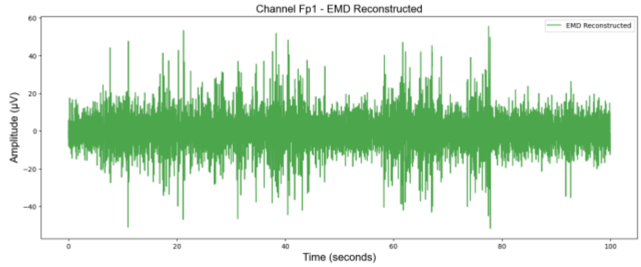
(a) Channel Fp1



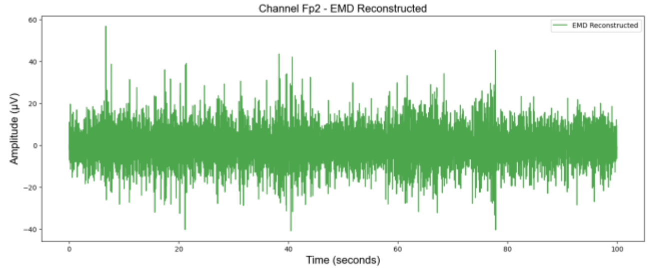
(b) Channel Fp2

Fig. 5. Result of butterworth band-pass filter of autism EEG signal

Fig. 5 shows the application of the Butterworth bandpass filter to the 16-channel EEG signal of individuals with autism. Before filtering, the raw EEG signal (blue) shows large fluctuations due to artifacts, which cause instability. After the filtering process using butterworth band pass (yellow), the signal quality improves, with a more stable frequency and amplitude. This filter maintains a signal in the range 0.5 - 40 Hz while reducing amplitudes outside of that limit.



(a) Channel Fp1



(b) Channel Fp2

Fig. 6. Result of empirical mode decomposition method of autism EEG signal

B. Empirical Mode Decomposition (EMD) Method Results

After going through the initial filtering process, the EEG signal was then further processed using Empirical Mode Decomposition (EMD). The results of the analysis shown in Fig. 6 reveal that the application of EMD can effectively improve the quality of EEG signals in individuals with autism. This method significantly refines the signal on each channel by extracting more relevant intrinsic components. By applying EMD after the initial screening stage, any disturbances or small fluctuations that remain in the EEG signal can be further reduced, resulting in a cleaner and more representative signal of actual brain activity.

C. Method Performance Accuracy Analysis Results

To assess the performance of filters on EEG signals, this study used three main evaluation parameters, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and Signal-to-Noise Ratio (SNR). These three parameters were used to measure the extent to which the filtering method applied can improve signal quality by reducing interference and retaining relevant information.

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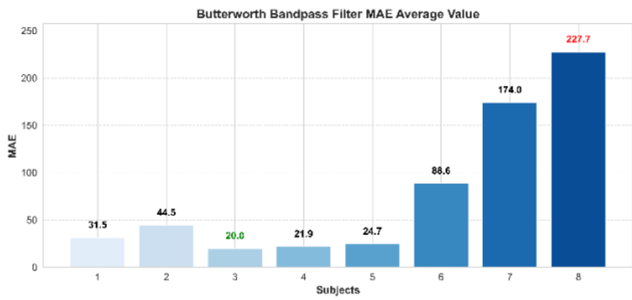
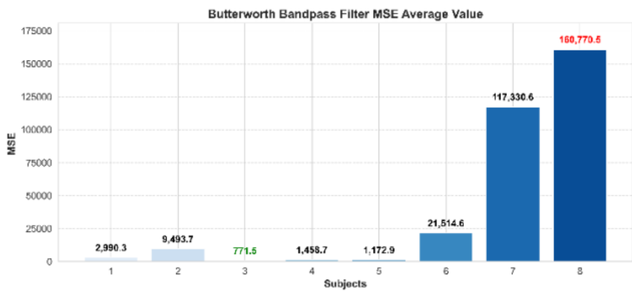
Based on the results of the analysis, the methods used, namely the Butterworth bandpass filter and Empirical Mode Decomposition (EMD), proved to be effective in improving the quality of EEG signals. Butterworth's bandpass filters help maintain the required frequency components, while EMDs play a role in separating the signal components so that interference can be reduced and important information in the EEG signal is maintained.

1. Butterworth Band Pass Filter

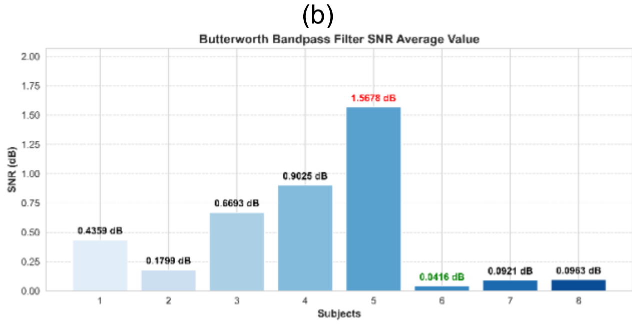
Fig. 7 presents an analysis of the Butterworth band-pass filter's performance based on three key parameters: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Signal-to-Noise Ratio (SNR). The MAE graph highlights differences in error values across subjects, where the highest MAE (227.7) is marked in



(a)

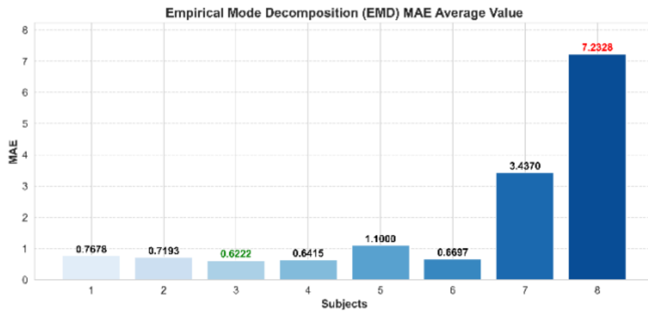


(b)

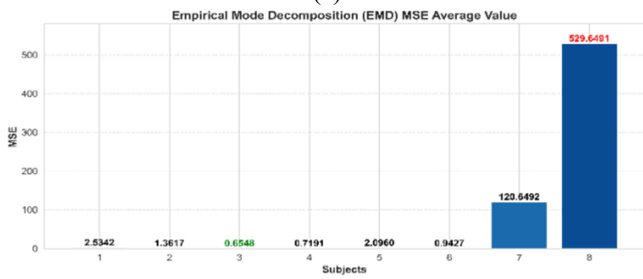


(c)

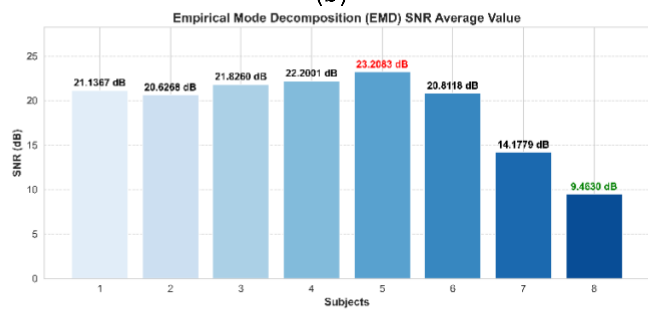
Fig. 7. Comparison of (a) MAE, (b) MSE, and (c) SNR values for the Butterworth bandpass filter across different subjects



(a)



(b)



(c)

Fig. 8. Comparison of (a) MAE, (b) MSE and (c) SNR values for EMD across different subjects

red, while the lowest (20.0) is shown in green. This indicates notable variations in the filter's impact on EEG signals across different subjects.

Furthermore, the MSE values reveal a significant disparity between the filtered signal and the original signal, with the maximum error reaching 160,770.5 and the minimum at 771.5, reflecting different levels of deviation caused by the filtering process. The SNR results also demonstrate the filter's noise reduction effectiveness, with values ranging from a maximum of 1.6578 dB to a minimum of 0.0416 dB. These variations indicate that while the Butterworth band-pass filter enhances signal clarity, its performance may vary depending on the characteristics of individual EEG recordings.

2. Empirical Mode Decomposition

Fig. 8 part shows the comparison of Mean Absolute Error (MAE), Mean Square Error (MSE), and Signal-to-Noise Ratio (SNR) values in the performance analysis of the Empirical Mode Decomposition (EMD) method on

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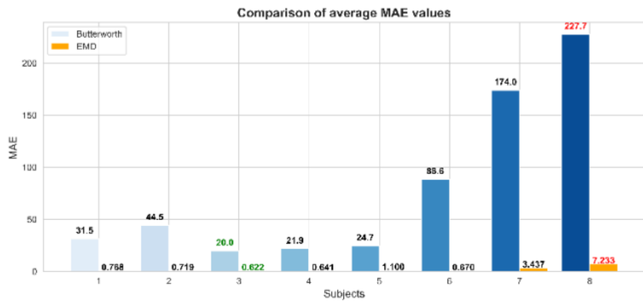
EEG signals. In Fig. 8 part (a), a variety of MAE values are shown with red, indicating the highest value (7.2328 in subject 8), and green signifying the lowest value (0.6222 in subject 3). Lower MAE values indicate the effectiveness of the filter in maintaining the characteristics of the original signal. Fig. 8 part (b) illustrates the difference in MSE values, which indicates the extent to which the filtered signal deviates from the original signal. The highest MSE value was found in subject 8 (529.6491), while the lowest value was found in subject 3 (0.6548). This significant difference confirms that the effectiveness of the EMD method in filtering out noise may vary between subjects. Fig. 8 part (c) displays the SNR, which indicates the quality of the signal after applying the EMD method. The highest SNR value was recorded in subject 5 (23.2083 dB), while the lowest SNR was found in subject 8 (9.4630 dB), which is marked in green. The higher the SNR value, the better the quality of the signal produced after processing.

3. Comparison results of butterworth band pass filter method with empirical mode decomposition (EMD) method Comparison results of butterworth band pass filter method with empirical mode decomposition (EMD) method

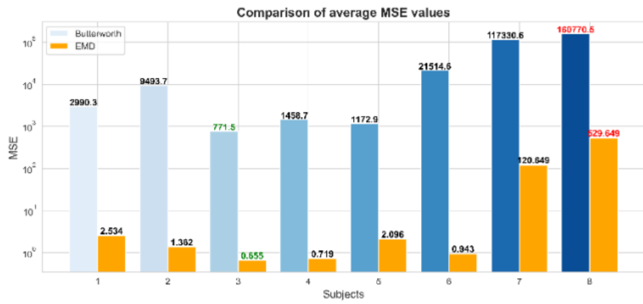
Fig. 9 shows the comparison of Mean Absolute Error (MAE), Mean Square Error (MSE), and Signal-to-Noise Ratio (SNR) values in the performance analysis of Butterworth Band-Pass Filter and Empirical Mode Decomposition (EMD) on EEG signals. Fig. 9 part (a) illustrates that EMD maintains a lower MAE value compared to Butterworth Band-Pass Filter in most subjects, indicating that this method is more effective in maintaining the original shape of the EEG signal after processing. The highest MAE value for Butterworth was found in subject 8 (227.7), while the highest value for EMD was only 7.233. The lowest MAE value was achieved by EMD in subject 3 with a value of 0.622, which is lower compared to the lowest value of Butterworth (20.0).

Fig. 9 part (b) shows a comparison of the MSE values, which measures the extent to which the filter result deviates from the original signal. EMD has a lower MSE value compared to the Butterworth Band-Pass Filter, especially in subject 3 (0.655 for EMD versus 771.5 for Butterworth). However, in subject 8, EMD has an MSE of 529.649, which is still much smaller than the Butterworth value (160770.5). This shows that EMD is more stable in maintaining the accuracy of the signal compared to Butterworth.

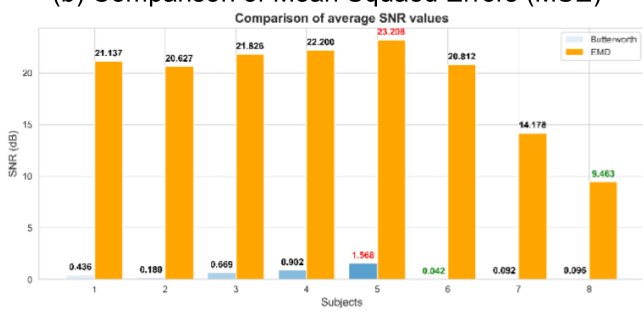
Fig. 9 part (c) displays the SNR value, which indicates the signal quality after filtration. EMD produced higher SNR values than Butterworth, especially in subject 5, where EMD recorded the highest SNR value of 23.208, while Butterworth only produced 1.568. However, in subject 8, EMD recorded



(a) Comparison of Mean Absolute Errors (MAE)



(b) Comparison of Mean Squaed Errors (MSE)



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

Fig. 9 Comparison of MAE, MSE and SNR values between Butterworth band-pass filter and EMD in eeg signal processing

an SNR of 9.463, which although lower compared to other subjects, was still much higher than Butterworth (0.096). Overall, the Empirical Mode Decomposition (EMD) method showed better performance compared to the Butterworth Band-Pass Filter in maintaining cleaner and more accurate EEG signals. With lower MAE and MSE values and higher SNR, EMD proved superior in removing noise without deforming the original signal too much, making it a more effective method for EEG signal processing.

IV. Discussion

This study aims to evaluate the effectiveness of the Butterworth Band Pass Filter and Empirical Mode Decomposition (EMD) methods in the EEG signal denoising process, based on three main parameters namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and Signal-to-Noise Ratio (SNR).

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The analysis showed that the Butterworth Band Pass Filter method produced considerable variation in MAE values between subjects, with the highest value of 227.7 and the lowest value of 20.0. This shows that how well this filter works, it relies a lot on the special traits of each EEG signal, and that the noise is not always fully removed for all people. Also, the big MSE number (biggest 160770.5) points out a large difference between the filtered signal and the real signal, hinting that this way might lead to big signal errors sometimes. The small SNR numbers (highest 1.6578 dB and lowest 0 0416 dB) support the idea that a filter's skill to make signal better is small.

In contrast, the EMD method shows a more stable and superior performance compared to Butterworth. The highest MAE value produced by EMD is only 7.2328 (in subject 8), while the lowest value is 0.6222 (in subject 3), which is much lower than that of Butterworth. The MSE values obtained are also much smaller, ranging from 0.6548 to 529.6491, indicating that the EMD-generated signal is closer to the original signal. The highest SNR value of 23.2083 dB (in subject 5) shows a significant improvement in signal quality compared to the Butterworth.

The technical performance of denoising methods greatly affects the accuracy of diagnosis, especially in the case of Autism Spectrum Disorder (ASD) which depends on EEG signal details such as spectral power, brain connectivity, and rhythm patterns. If the signal is still contaminated with noise, important features can be hidden. The EMD method proved to be better at preserving signal quality, as seen in subject 3 with low MAE and MSE values, indicating the signal is clean and still resembles its original shape. In contrast, the Butterworth filter on subject 8 produced large distortions (MAE = 227.7; MSE = 160770.5), risking obscuring the typical EEG patterns that are important in detecting important ASDs. High SNR values on EMD also indicate the signal is clearer and easier to analyze. Therefore, metrics such as MAE, MSE and SNR not only assess technical performance, but also support more accurate and reliable EEG diagnosis in ASD.

Direct comparison between the two methods shows a significant advantage of EMD over Butterworth in all evaluation parameters. In almost all subjects, EMD was able to produce lower MAE and MSE, as well as higher SNR. For example, in subject 3, EMD produced MAE = 0.622 and MSE = 0.655, while Butterworth produced MAE = 20.0 and MSE = 771.5. Meanwhile, in subject 5, EMD showed the highest performance with an SNR of 23.208 dB, far ahead of Butterworth which only produced an SNR of 1.568 dB.

To find out if the performance gaps between Butterworth Band-Pass Filter and Empirical Mode Decomposition (EMD) are essential, a statistical test using a matched t-test (using Eq. (11) [40] was done on MAE, MSE, and SNR values. The results showed a big important difference in MAE ($p = 0.0257$, where $p < 0.05$), showing that EMD keeps the EEG signal form better. For MSE the difference was not big important ($p = 0.\ 1195$, where p is more than 0. 05), hinting that the difference might be caused by luck. This p value was calculated using Eq. (12) [40].

On the other hand, the SNR change was very important ($p = 0.\ 00000725$, where p is less than 0. 001), proving that EMD makes much clearer signals trust ranges backed these findings, the ranges for MAE and SNR did not have zero, strengthening the importance of the difference, while the MSE range did have zero, in agreement with its not important p-value. On the whole, these results show that EMD gives solid boosts in signal quality and clearness for EEG denoising.

The higher SNR in the EMD method means that the EEG signal is cleaner and easier to distinguish from noise. In autism diagnosis, this is important as it helps capture brain activity patterns that are typical in individuals with ASD, such as alpha or gamma waves. With a clearer signal, the analysis results become more accurate, and the risk of misinterpretation is reduced. This finding is in line with previous studies on EEG applications [41]. So, the higher the SNR, the better the data quality to support proper diagnosis.

These results indicate that the EMD method is more consistent in maintaining the original shape of the EEG signal and more effective in removing noise. This is also supported by the results of previous studies in EEG signal processing, one of which is research for Depth of Anesthesia (DOA) estimation using the Multivariate Empirical Mode Decomposition (MEMD) + Sample Entropy method resulted in a Mean Square Error (MSE) of 142.31 ± 85.52 and Mean Absolute Error (MAE) of 8.44 ± 2.37, where the Empirical Mode Decomposition (EMD) method shows much better performance in the EEG signal denoising process. The lowest MSE value obtained using EMD is 0.655, and the lowest MAE value of EMD is 0.622 [42].

In another similar study, the Kalman Filter method was used as a denoising technique on EEG signals. Kalman Filter has advantages in dynamic system estimation, but its performance is limited for non-linear and non-stationary signals such as EEG. The research using Kalman Filter resulted in an SNR of 4.34 dB. In contrast, in this study, the Empirical Mode Decomposition (EMD) method produces the highest SNR of 23.208 dB, which is significantly higher than the Kalman Filter [43].

Previous studies have evaluated two methods for reducing EOG artifacts in EEG signals, namely Discrete Wavelet Transform–Least Mean Square (DWT-LMS) and Discrete Wavelet Transform–Minimum Error Entropy (DWT-MEE). Both approaches

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utilize the Discrete Wavelet Transform (DWT) to isolate the signal components containing artifacts, which were then processed using Adaptive Noise Cancellation techniques with the Least Mean Square (LMS) and Minimum Error Entropy (MEE) algorithms. Based on the test results, the DWT-LMS method produced an average Signal-to-Noise Ratio (SNR) of 3.32 dB, while DWT-MEE provided an improvement in signal quality with an SNR value of 4.72 dB.On the other hand, this study uses the Empirical Mode Decomposition (EMD) approach and achieves superior results, with an SNR value of 23.208 dB, far exceeding the achievements of the previous two methods [44].

In another study, the Variational Mode Decomposition (VMD) method was used to improve EEG signal quality by decomposing the signal into band-limited intrinsic mode functions and utilizing a zero-crossing threshold to detect muscle artefacts. This method successfully increased the SNR value by up to 9.0 dB in simulated data. Although effective and computationally efficient, VMD still depends on the careful selection of decomposition parameters such as the number of modes and penalty factor. Meanwhile, in this study, the Empirical Mode Decomposition (EMD) method produced an SNR of 23.208 dB, much higher than VMD, demonstrating its effectiveness in handling non-linear and non-stationary EEG signals [45].

In another study, a hybrid denoising method combining Empirical Mode Decomposition (EMD), Detrended Fluctuation Analysis (DFA), and Wavelet Packet Decomposition (WPD) was applied to EEG signals and produced an SNR of 20.24 dB and an MAE of 12.24. In contrast, in this study, the Empirical Mode Decomposition (EMD) method achieved a higher SNR of 23.208 dB and a lower MAE of 0.622, demonstrating more effective denoising performance in preserving the quality of EEG signals [46].

Although the results show that the Empirical Mode Decomposition (EMD) method performs better than the Butterworth Band-Pass Filter based on MAE, MSE, and SNR values, there are some important limitations to note. Technically, Butterworth has the potential to cause signal distortion, especially at low frequencies important for EEG analysis, such as delta and theta waves. Meanwhile, EMD faces challenges in the Intrinsic Mode Function (IMF) extraction process, including the risk of generating artifactual components if the number of IMFs is not optimally determined. In addition, performance differences between subjects-for example, the high MAE and MSE values in subject 8-indicate that the effectiveness of the method is strongly influenced by individual signal characteristics. With a limited sample size, the generalizability of these findings to a wider population still needs to be tested. Therefore, further studies with a larger number of subjects and more diverse characteristics, as well as exploration of adaptive or hybrid filtration methods, are urgently needed to improve the consistency and validity of the results.

The Empirical Mode Decomposition (EMD) method was shown to produce cleaner EEG signals-with lower MAE and MSE and higher SNR than Butterworth. This improved signal quality is very important in a clinical context, particularly for autism spectrum disorders (ASD), as it enables more accurate identification of brain activity patterns and supports the application of machine learning in ASD classification. In addition to improving the accuracy of early diagnosis, EMD also helps evaluate therapy response more precisely. The superiority of EMD in reducing noise without changing the original shape of the signal makes it a highly recommended denoising method, both for neurophysiology research, spectrum analysis, and system development such as Brain-Computer Interface (BCI).

V. Conclusion

This study aims to compare the effectiveness of Butterworth Band-Pass Filter and Empirical Mode Decomposition (EMD) in EEG signal processing. The analysis results show that EMD consistently provides superior performance in maintaining the original shape of the signal and reducing noise interference. On the Mean Absolute Error (MAE) metric, EMD produces the lowest value of 0.6222 and the highest of 7.2328, while Butterworth records the lowest MAE value of 20.0 and the highest of 227.7. For Mean Square Error (MSE), EMD has a range of values between 0.6548 and 529.6491, much smaller than Butterworth, which shows the lowest value at 771.5 and the highest at 160,770.5. In terms of Signal-to-Noise Ratio (SNR), EMD managed to improve the signal quality with the highest value of 23.2083 dB and the lowest of 9.4630 dB, much better than Butterworth, which only reaches the highest value of 1.6578 dB and the lowest of 0.0416 dB. Complementing the analysis, a paired t-test showed a significant difference in MAE ($p = 0.0257$) and highly significant in SNR ($p = 0.00000725$), confirming the superiority of EMD. The difference in MSE was not significant ($p = 0.1195$) and was supported by confidence intervals that included zero. Thus, EMD is proven to be more effective in minimizing distortion and maintaining the clarity of EEG signals. For further development, research can be directed towards optimizing the selection of Intrinsic Mode Functions (IMF) or integration with other filtration methods to improve the accuracy of EEG signal analysis in clinical applications and neuroscience research.

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