Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics
e-ISSN: 2656-8624
Homepage: https://ijeeemi.org/; Vol. 7, No. 3, pp. 461-474, August 2025

RESEARCH PAPER

OPEN ACCES

Performance Comparison of Variational Mode Decomposition and Butterworth Filtering in Processing EEG Signals of Autism Patients

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Abstract

Electroencephalography (EEG) is a non-invasive technique for monitoring and recording the brain's electrical activity with electrodes applied to the scalp. The method is important in neurological studies, like that of Autism Spectrum Disorder (ASD), because it measures patterns of brain waves that can identify developmental abnormalities. However, EEG signals are often contaminated by multiple noise sources, including eye movements, muscle activity, and extraneous interference. This interference can significantly reduce the quality and intelligibility of signals. Therefore, preprocessing is required to enhance the reliability and precision of the data obtained. In this study, a Butterworth Band-Pass Filter (BPF) was used during preprocessing to filter out undesirable frequency components and to mitigate noise. After filtering, EEG signals were handled using the Variational Mode Decomposition (VMD) technique. VMD is an adaptive method for decomposing multidimensional signals into intrinsic mode functions while preserving critical details of the original data. For performance comparison, four quantitative metrics were used: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Signal-to-Noise Ratio (SNR). Results showed that VMD performed better than BPF alone. As an example, for Subject 1, VMD achieved an MAE of 0.26 and MSE of 0.42, which was far superior to the MAE of 13.72 and MSE of 674.96 of BPF. Subject 3 had the least RMSE (0.40) when using VMD, whereas BPF scored 25.90. VMD also reported a highest SNR of 28.56, compared to BPF's 2.43. Overall, integrating VMD with BPF significantly improves EEG signal quality and enables more accurate analysis, particularly in ASD-related studies.

Paper History
Received April 02, 2025
Revised July 10, 2025
Accepted August 5, 2025
Published August 10, 2025

Keywords
ASD;
EEG;
VMD;
Butterworth;

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I. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by repetitive behaviors, difficulties in social interaction, and barriers in communication [1]. The disorder can be detected as early as 14 months of age and has a broad spectrum of symptoms and functional limitations [2]. ASD generally appears in early childhood and significantly impacts cognitive development, socio-emotional abilities, sensori-motor functions, and the individual's ability to interact and adapt to the surrounding environment [3].

Electroencephalography (EEG) is a non-invasive method widely used in neurological research, including the development of more objective diagnostic procedures for ASD [4][5]. EEG captures the brain's electrical activity by utilizing electrodes placed at specific locations on the scalp, providing insight into cognitive functions such as perception, attention, and memory [6][7]. The EEG recording process usually takes around 30 minutes to obtain sufficient data. However, signal quality is often disturbed by artifacts and noise from internal and external sources, which can reduce the accuracy of the analysis [8][9]. Therefore, the preprocessing stage becomes crucial, including using a Butterworth Bandpass Filter (BPF) to remove frequency components outside the physiological range [10].

The BPF is one of the methods used in EEG signal processing to improve data quality by focusing on the relevant frequency range of brainwaves. In principle, the designer configures this filter to preserve signals within a specific frequency range while damping components outside that range. This stage plays a critical role in EEG analysis because external noise and physiological artifacts often contaminate the recorded signals, interfering with accurate data interpretation [11]. One of the primary advantages of Butterworth filters is their smooth frequency response characteristics in the bandpass region, making them capable of preserving the original signal shape without introducing additional

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Digital Object Identifier (**DOI**): https://doi.org/10.35882/ijeeemi.v7i3.105

distortion, thus making them an ideal choice for EEG applications [12].

Feature extraction is an important stage in EEG signal analysis for isolating the main characteristics of complex and nonlinear data. This process converts the raw signal into numerical parameters that represent brain activity patterns in a structured manner. Various applications, including emotion classification, BCI development, early epilepsy detection, and identification of neurodevelopmental disorders such as ASD, employ the resulting features extracted by researchers. In general, these stages include pre-processing, signal decomposition, and feature selection, with approaches that include statistical methods, time-frequency domain transformations, and nonlinear decompositions such as Variational Mode Decomposition (VMD) [13][14].

Variational Mode Decomposition (VMD) is an adaptive method that decomposes complex signals into narrow-band modes with specific frequency characteristics [15]. Unlike traditional approaches, VMD formulates the process as an optimization problem that iteratively minimizes the total bandwidth using the Hilbert transform and spectral shifting, resulting in well-separated Intrinsic Mode Functions (IMF) [16]. In EEG signal analysis, each IMF represents a specific frequency range, allowing more detailed identification and analysis of brainwave activities, such as delta, theta, alpha, beta, and gamma waves. Several previous studies have evaluated the effectiveness of decomposition methods, particularly VMD, in analyzing non-stationary brain signals. VMD serves to decompose ERP signals into several subbands (modes) representing different frequency components, so that important features of the signal can be isolated more effectively than other decomposition methods, such as Empirical Mode Decomposition (EMD) [17]. Another study showed that the VMD method can achieve a sensitivity and specificity of 99.32% and 99.31%, respectively [18].

This research focuses on evaluating the performance of the feature extraction method using VMD to assess its effectiveness in extracting important information from EEG signals. The performance of this method is evaluated using four main parameters, namely Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Signal-to-Noise Ratio (SNR). These four parameters provide an overall picture of the quality of feature extraction produced by the VMD method in the context of EEG signal processing.

Figure 1 illustrates the methodological flow used in this study. The process begins with a preprocessing stage, wherein the EEG signal is filtered using a Butterworth band-pass filter to remove irrelevant frequency components, resulting in a cleaner signal for analysis. Next, in the feature extraction stage, the VMD method decomposes the EEG signal into several IMFs, each representing a distinct frequency characteristic. The final stage involves evaluating the method's performance using the MSE, MAE, RMSE, and SNR indicators.

The main contributions of this study include: 1) evaluating the ability of the VMD method to extract relevant information from EEG signals to improve analysis accuracy; 2) assessing the role of the Butterworth BPF filter in improving data quality at the preprocessing stage; 3) measuring the effectiveness of VMD through four evaluation parameters (MSE, MAE, RMSE and SNR); and 4) comparing the performance of VMD with other feature extraction techniques to assess the relative advantages of VMD in EEG analysis.

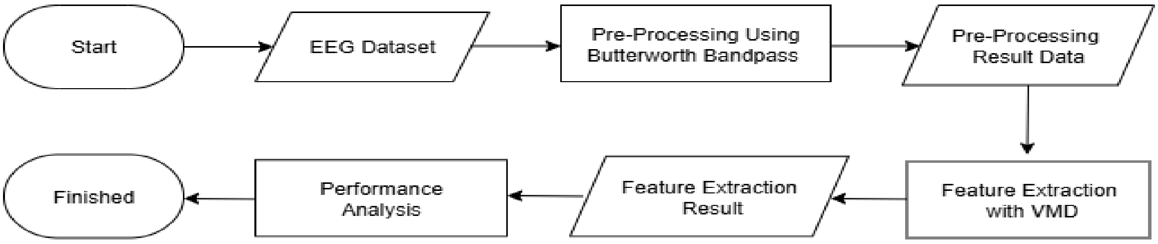

Fig. 1. Flowchart of EEG Signal Processing with Butterworth Bandpass Filtering and VMD for Feature Extraction

The obtained EEG signals were initially processed through a preprocessing stage using a BPF filter to minimize noise interference and achieve the research objectives. Furthermore, feature extraction was carried out by applying the VMD method. The resulting features were analyzed using predetermined performance parameters: MSE, MAE, RMSE, and SNR. The structure of this journal is as follows: Section I discusses the background, research objectives, primary contributions, and general article structure. Section II describes the EEG data, preprocessing procedures, and feature extraction techniques. Section III discusses the preprocessing results using BPF and evaluates of VMD performance. Section IV contains the interpretation of the results, conclusions, and suggestions for further research.

II. Materials and Methods

A. Dataset

The EEG signal dataset used in this study was obtained from King Abdul-Aziz University (KAU), Jeddah, Saudi Arabia [19] and has been widely referenced in previous studies [20][21]. This dataset is publicly accessible upon official request to Dr. Mohammed Jaffer Alhaddad [22]. This study followed the same request procedure while maintaining the confidentiality of the participants. EEG data were recorded while the subjects were relaxed to minimize artifacts, using an EEG cap device from g.tec with Ag/AgCl electrodes, a USB signal amplifier, and BCI2000 acquisition software. Signal filtering was performed online with a 0.5 - 40 Hz band-pass filter. Data were recorded in digital form with a sampling frequency of

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256 Hz and included 16 EEG channels. The subjects were divided into two groups: eight boys with ASD (aged 10-16 years, total duration 4104.2 seconds) and eight boys in a control group (aged 9-16 years, without a history of neurological disorders, total duration 4534.9 seconds). All EEG recordings followed the international 10-20 electrode placement system [23][24].

The dataset is stored in a .dat file format, which generally contains data in binary or text-based data generated automatically by acquisition software, such as BCI2000. This format cannot be read directly because it contains complex data structures. This study processed EEG data in .dat format using the Python environment in Google Colab. The data reading process was carried out using the BCI2kReader module, which is specifically designed to read BCI2000 output. This module enables the systematic extraction of signal data from each EEG channel, thereby facilitating the analysis and visualization stages. Figure 2 shows an example of EEG signal visualization from reading .dat files based on the international standard electrode placement system 10-20.

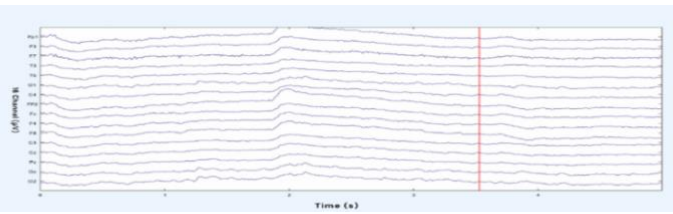

Fig.2 EEG Signal Representation Across 16 Channels Over Time in Mikrovolts

Brain activity is recorded in this system using several main electrodes placed according to the international 10-20 system. In the frontal area (front of the head), electrodes Fp1, Fp2, F3, and F4 are used. In the central area (middle of the head), electrodes C3, C4, and Cz are used. The temporal area (side of the head) is recorded by electrodes T3, T4, T5, and T6, while the parietal area (top of the back of the head) is covered by electrodes P3, P4, and Pz. The occipital area (bottom of the back of the head) is covered by electrodes O1 and O2 [25][26]. Each electrode records electrical signals from different brain areas, allowing for a comprehensive spatial analysis of brain activity, especially in identifying patterns related to conditions such as autism [27].

Before the main transmission, the EEG signal underwent a pre-processing stage that included the selection of 16 channels and a cut duration of up to 100 seconds (25.600 samples) to maintain consistency in the amount of data between channels and stability in the analysis process. The selection of this duration was chosen to balance between adequate representation of brain activity with processing efficiency. All channels are then normalized to the range of −100 to 100 μV to equalize the amplitude scale and enhance numerical stability during the filtering and decomposition stages. Although detrending was not explicitly applied, the DC component is mitigated by setting the DC=0 parameter in the VMD method, ensuring that the decomposition results are free from non-oscillatory components that can interfere with the analysis.

B. EEG Data Processing Pipeline

In this study, signal processing was implemented using Python version 3.11.12. The SciPy library was utilized, especially the scipy.signal uses the butter function to design a 4th-order band-pass Butterworth filter and the scipy.signal module. The filtfilt function is used to implement the zero-phase filtering process, which avoids phase distortion in the EEG signal. The VMD process was implemented using the vmdpy library, a Python library that provides an efficient implementation of the VMD algorithm. All pre-processing stages, including VMD filtration and decomposition, were implemented using Python scripts explicitly developed for this study. All processing was performed on a standard workstation with 16 GB of RAM and an Intel Core i7 processor.

C. Butterworth Band-Pass Filter

The Butterworth bandpass filter is a type of signal processing filter designed to pass frequencies within a specified range while maintaining a smooth and flat frequency response in the passband. Its gradual attenuation of frequencies outside this band minimizes distortion of the desired signal. This characteristic makes the Butterworth filter particularly effective for applications requiring signal integrity, such as biological signals like EEG [28].This study applied the Butterworth filter to EEG signals to isolate frequency components relevant to brain activity, effectively reducing interference from environmental noise and biological artifacts such as muscle and eye movements. The band-pass filter is constructed by combining high-pass and low-pass filters, allowing frequencies within the target range to pass with minimal distortion while attenuating frequencies outside this range [29].

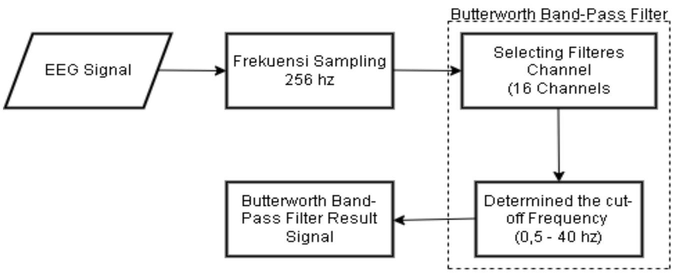

Fig. 3 Diagram of EEG Signal Processing Using Butterworth Band-Pass Filter with 0.5–40 Hz Cut-off Frequency

The EEG data utilized in this study were acquired at a sampling frequency of 256 Hz across 16 electrode channels. During the preprocessing phase, a 4th-order band-pass Butterworth filter with cutoff frequencies between 0.5 Hz and 40 Hz was applied to eliminate noise outside the physiological EEG range, as noted in prior studies [30]. This filter was chosen because it has a flat frequency response in the passband, thus preserving the original waveform. To avoid phase distortion that could

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affect temporal analysis, filtering was performed bidirectionally using the zero-phase filtering method via the SciPy library's filtfilt function. This technique filters the signal both forward and backward to cancel out phase shifts, thereby preserving the accuracy of the timing of necessary signals, such as wave peaks or responses to stimuli.

The chosen frequency range of 0.5-40 Hz corresponds to standard EEG bands commonly used in the literature, including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and low gamma (30-40 Hz). Frequency filtering below 0.5 Hz helps eliminate low-frequency artifacts, such as baseline shifts and slow body movements. Filtering above 40 Hz aims to reduce muscle artifacts and environmental noise. Although it may cause information loss in the high gamma band (>40 Hz) and slow oscillations (<0.5 Hz), it was deemed appropriate for this study's focus on feature extraction from the principal EEG bands widely used in previous studies [6].

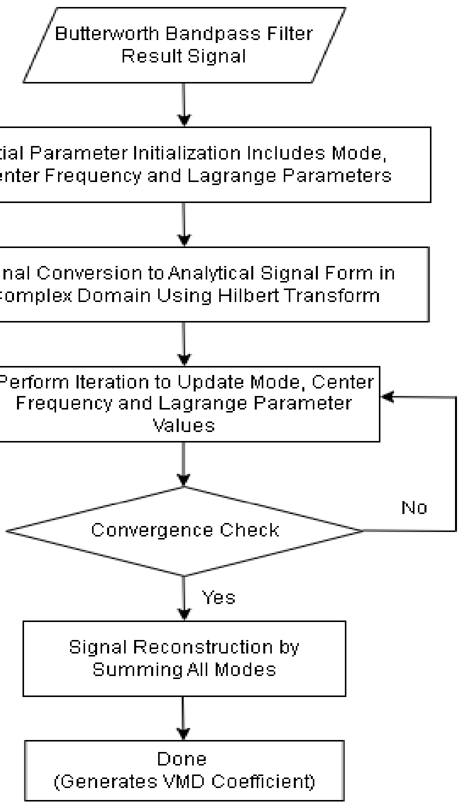

Fig. 4 Flowchart of Variational Mode Decomposition (VMD) Process for Signal Decomposition

D. Variational Mode Decomposition

VMD is a signal processing algorithm designed to separate a complex signal into several discrete oscillatory modes. Each mode has a center frequency, amplitude, and phase determined through an iterative optimization process [31]. The main goal of this approach is to minimize the spectral overlap (mode mixing) that often occurs in conventional decomposition methods, while maintaining the integrity of the spectral characteristics of each mode [32].

In this study, VMD was applied following the initial filtering process using a Butterworth bandpass filter (0.5 - 40 Hz). Filtering acts as an initial stage to remove noise outside the physiological range of the EEG, while VMD functions as a decomposition-based denoising technique to further enhance signal quality. The integration between the Butterworth bandpass filter and VMD is carried out sequentially, where the filter acts as an initial stage to filter out frequency components outside the physiological range of the EEG. The results of this process are then used as input for VMD, which functions as a decomposition-based denoising technique. This processing ensures that the VMD method operates effectively on signals that have been cleaned of neurologically irrelevant low- and high-frequency artifacts. The specific steps of VMD process are outlined in Figure 4 and described as follows:

a) Parameter Initialization
The initial stage of VMD includes the initialization of parameters such as the number of modes (K), penalty parameter (α), convergence tolerance (τ), initial center frequency (ω_k), and Lagrange multiplier (λ). Proper initialization is important to ensure the stability and accuracy of the decomposition during the iterative process.

b) Variational Optimization Formulation
VMD is formulated as a variational optimization problem to find the mode $u_k(t)$and center frequency ω_k that minimizes the total bandwidth of all modes (Eq. (1)):

$$\min_{\{u_k\}\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega k t} \right\|_2^2 \right\} \tag{1}$$

$$So\ that \sum_{k=1}^{K} u_k(t) = f(t)$$

The Hilbert transform forms the analytical signal, which is then transformed to the frequency domain with centering at frequency ω_k via the exponential $e^{-j\omega kt}$.

c) Lagrangian Function and Augmented Optimization
To solve the constrained optimization problem in Eq. (1), an augmented Lagrangian function is formed as follows (Eq. (2)):

$$\mathcal{L}(u_k, \omega_k, \lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega k t} \right\|_2^2 + \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k(t) \rangle \tag{2}$$

The α parameter penalizes the bandwidth of each mode, while λ(t) maintains the signal reconstruction.

d) Iterative Update of Modes and Frequencies
After the Lagrangian function is formed, iterative updates of the mode $\hat{u}_k^{n+1}$, center frequency $\hat{\omega}_k^{n+1}$ and Lagrange multiplier $\hat{\lambda}_k^{n+1}(\omega)$are performed in the frequency domain.

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1. Mode Update Eq. (3):

$$\hat{u}_k^{n+1} = \frac{\hat{f}(\omega) - \sum_{i=1,i<k}^{K} \hat{u}_i^{n+1}(\omega) - \sum_{i=1,i<k}^{K} \hat{u}_i^{n}(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{3}$$

2. Center frequency update (Eq. (4)):

$$\hat{\omega}_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u}_i^{n+1}(\omega)| d\omega}{\int_0^\infty |\hat{u}_i^{n+1}(\omega)| d\omega}, k \in \{1,2,\dots,K\} \tag{4}$$

3. Lagrange multiplier update (Eq. (5)):

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^{n}(\omega) + \tau \left[\hat{f}(\omega) - \sum_{k}^{K} \hat{u}^{n+1}(\omega) \right] \tag{5}$$

e) Convergence Check (Eq. (6)):
Iteration will be stopped if the relative change between modes of the last two iterations is smaller than a threshold of ϵ

$$\sum_{k}^{K} \|\hat{u}_k^1 - \hat{u}_k^n\| / \|\hat{u}_k^1\|_2^2 < \varepsilon \tag{6}$$

f) Signal Reconstruction:
After the iterative process reaches convergence, the decomposed signal is obtained by summing up all the calculated modes (Eq. (7)):

$$\hat{x}(t) \sum_{k=1}^{K} u_k(t) \tag{7}$$

VMD was applied to EEG signals for denoising purposes, with the main parameters being: number of modes $K = 5$, penalty parameter $\alpha = 2000$, and convergence tolerance of 10^{-4}. The value of K was selected based on an empirical approach, drawing on previous studies, which found that five modes are sufficient to represent the main components of the EEG signal without causing over-decomposition [33]. The decomposition modes were then analyzed based on their frequency spectrum and energy distribution. Modes with dominant frequencies that are within the typical range of EEG waves, such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-40 Hz), and have significant energy distribution, are considered to represent the main components of the signal. In contrast, modes with very high frequencies and low energy, which typically indicate the presence of noise or artifacts, are ignored during the reconstruction of the denoised signal. The penalty parameter value $\alpha = 2000$ was chosen based on previous studies, which showed that this value provides an optimal balance between frequency selectivity and decomposition stability in non-stationary signals, such as EEG. In a study by Gundala et al. [34], the value of $\alpha = 2000$ is proven to produce effective mode separation without causing significant spectral leakage, making it suitable for use in EEG signal denoising applications. A convergence tolerance of 10^{-4} was set to ensure that the iterative process reaches a stable condition with reproducible results [34].

E. Performance Analysis

EEG signals decomposed using the VMD method were evaluated using four performance parameters: MSE, MAE, RMSE, SNR, and p-value. These four metrics are used to quantitatively calculate, analyze, and compare the quality of the signal decomposition results.

1. Mean Square Error (MSE)

MSE is one of the evaluation metrics used to calculate the average of the squares and the difference between the actual and predicted values. MSE is widely used in statistical model evaluation because it provides a quantitative assessment of the degree of deviation of the prediction from the actual data. A lower MSE value reflects better model accuracy and a stronger resemblance to the actual signal. The MSE calculation formula is written as follows (Eq. (8)):

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

where x_i represents the original value of the EEG signal, y_i the value after processing, and N the total number of samples. MSE gives more weight to significant errors due to its quadratic nature, making it a sensitive indicator of outliers. Therefore, MSE is effectively used to analyze EEG signals with complex signal variations [35].

2. Mean Absolute Error (MAE)

MAE measures the average absolute difference between the original and predicted values. In the context of EEG signal processing, MAE is used to assess the extent to which the processed signal is close to the original recorded signal. The calculation formula is as follows (Eq. (9)):

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |x_i - y_i|^2 \tag{9}$$

where $x_i$is the original value of the EEG signal, $y_i$is the predicted or processed signal, and N is the total number of samples. MAE gives a direct idea of the average error without considering the direction of deviation. A smaller MAE value indicates that the difference between the original signal and the processed signal is smaller, which means that the performance of the signal processing method is better [36].

3. Root Mean Square Error (RMSE)

RMSE quantifies the square root of the average squared differences between the original and predicted values. In the context of EEG signal processing, RMSE is used to evaluate the accuracy of signal processing methods by giving greater weight to errors with large values. The calculation formula is expressed as follows (Eq. (10)):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2} \tag{10}$$

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where x_i is the original value of the EEG signal, y_i is the predicted or processed signal, and N represents the total number of samples. This formula gives a direct idea of the average error size without considering the direction of deviation. A smaller value indicates that the difference between the original signal and the processed signal is smaller, which means that the performance of the signal processing method is better [37].

4. Signal To Noise Ratio (SNR)

SNR is an evaluation metric that measures the ratio between the desired signal power and the unwanted noise power. SNR is an important indicator for assessing signal quality and clarity in signal processing, including EEG signals. A high SNR value indicates that the signal is dominant over noise, making the analysis and interpretation process easier. SNR is generally expressed in decibels (dB) and is calculated using the following Eq. (11):

$$SNR = 10\, log_{10} \left\{ \frac{\sum_{n=1}^{N} [x(n)]^2}{\sum_{n=1}^{N} [x(n) - \hat{x}(n)]^2} \right\} \quad (11)$$

where $x(n)$ denotes the original signal, $\hat{x}(n)$ is the processed or predicted signal, and N is the number of samples. In the context of this research, the SNR value is used to evaluate how well the applied method is able to maintain the original information of the EEG signal after going through the decomposition and filtration stages [38].

5. Test Statistics

In the performance evaluation of EEG signal denoising methods, inferential statistical analysis is often performed using a paired t-test to determine whether the performance difference between two methods is statistically significant. This test is based on the difference in the values of evaluation metrics (such as MAE, MSE, RMSE, or SNR) of pairs of data obtained from two different methods. Mathematically, this test is formulated as follows (Eq. 12):

$$t = \frac{\bar{d}}{s_d \,/\, \sqrt{n}'} \quad (12)$$

where $\bar{d}$ is the mean difference between pairs, s_d is the standard deviation of the difference, and n is the number of sample pairs. The *t*-value obtained is then compared to a *t*-distribution with degrees of freedom $df = n - 1$ to calculate the p-value, which indicates the probability that the difference is random. The calculation of the p-value is shown in Eq. (13):

$$p = 2(1 - T(|t|, df)) \quad (13)$$

with T being the cumulative distribution function of the t distribution [39].

6. Cohen's D

Effect size analysis, using Cohen's d, is employed to strengthen the results of the performance evaluation of the compared methods. This analysis provides quantitative information on the magnitude of the difference between two groups, regardless of sample size, thus enriching the interpretation of inferential statistical results such as t-tests. Cohen's d is calculated using the following formula:

$$d \frac{\overline{X_1} - \overline{X_2}}{s_{pooled}} \quad (14)$$

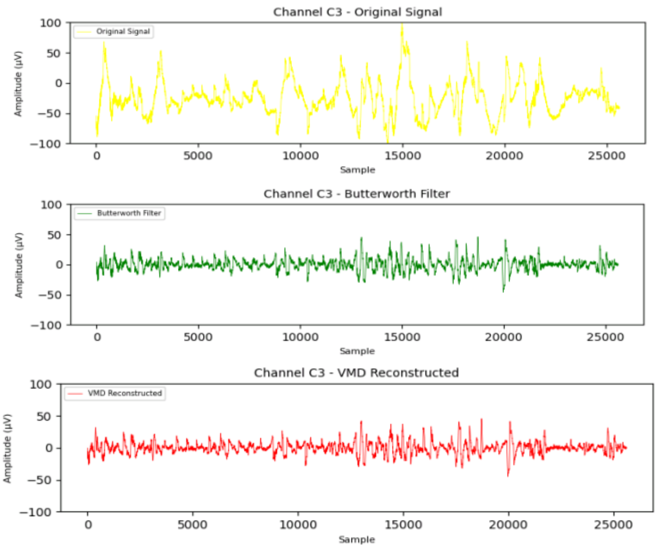
where $\overline{X_1}$ and $\overline{X_2}$ are the means of each group, and s_{pooled} is the combined standard deviation obtained from the variances of both groups. This calculation assumes that the variances of both groups are relatively similar [2].

III. RESULTS

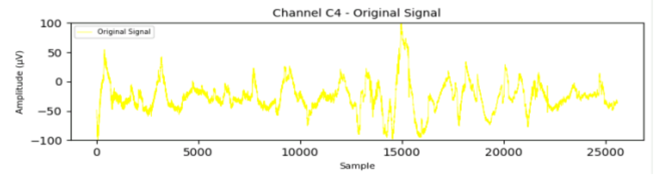
In the initial stage of EEG signal transmission, a Butterworth Band-Pass Filter was applied to to remove irrelevant frequency components. The filtered signal was then analyzed using the VMD method, which separated the complex signal into several intrinsic modes with specific frequency characteristics. These modes were reconstructed into a signal representing the original signal's primary information. The quality of the decomposition and reconstruction process was evaluated using four parameters, namely MSE (Eq. 8), MAE (Eq. 9), RMSE (Eq. 10), and SNR (Eq. 11).

A. Butterworth Band-Pass Filter Result

Applying a Butterworth band-pass filter to EEG signals aims to retain the relevant frequency components within the range of 0.5 Hz to 40 Hz, while reducing interference from frequencies outside this range. The filter is characterized by a smooth frequency response in the passband area without ripples, which makes it effective in maintaining the integrity of the primary signal without causing significant distortion.



a) Channel C3



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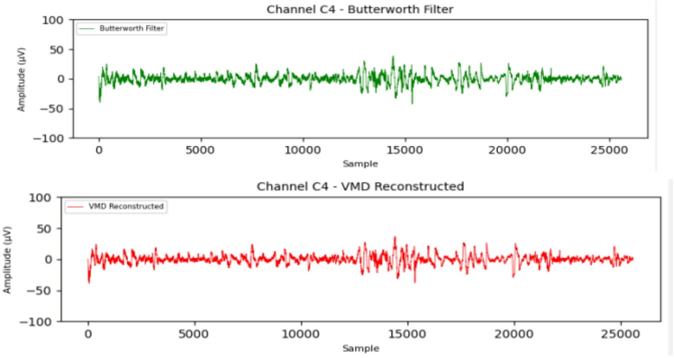


b) Channel C4

Fig. 5 Result of Butterworth Bandpass Filter and VMD Method of Autism EEG Signal

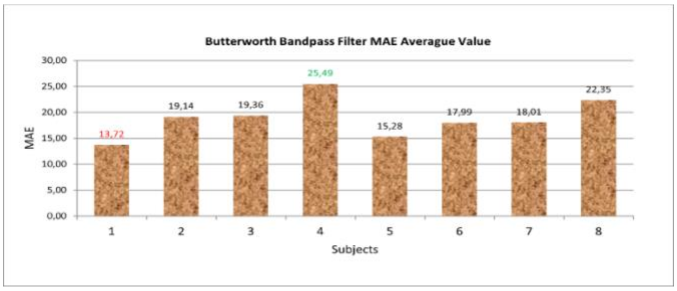
As shown in Fig. 5, the filtering process was applied to a 16 channel EEG signal from an individual with autism. Before filtering, the raw signal (yellow) contained large fluctuations due to artifacts, which affected the signal's stability. After going through the Butterworth bandpass filtering process (green), the signal became cleaner, with more regular frequency and amplitude. This process effectively preserved important information within the 0.5-40 Hz band while suppressing irrelevant out-of-band components.

B. Variational Mode Decomposition (VMD) Method Results

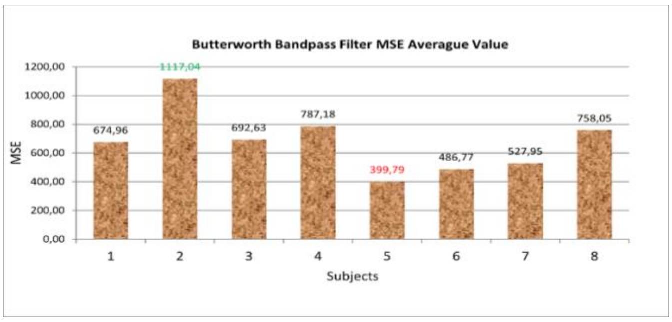
Following the pre-processing stage, the VMD method further analyzes the EEG signal. Based on the analysis results in Figure 5, the application of VMD (red) improved the quality of EEG signals in subjects with autism spectrum disorder. This method effectively filters and extracts more relevant intrinsic components on each channel, thus improving the signal representation. Implementing VMD after the pre-processing stage can reduce residual noise and small fluctuations in the signal, resulting in a cleaner EEG signal that reflects brain activity more accurately. The visualization of the EEG signal processing results in this study explicitly demonstrates the improvement in signal quality achieved through the combined application of a Butterworth Bandpass Filter and VMD. Thus, the inclusion of visual analysis plays a crucial role in confirming the effectiveness of the proposed method, as well as providing a practical representation of the advantages of VMD in enhancing the reliability of EEG data, particularly in populations with autism spectrum disorders.

C. Method Performance Accuracy Analysis Results

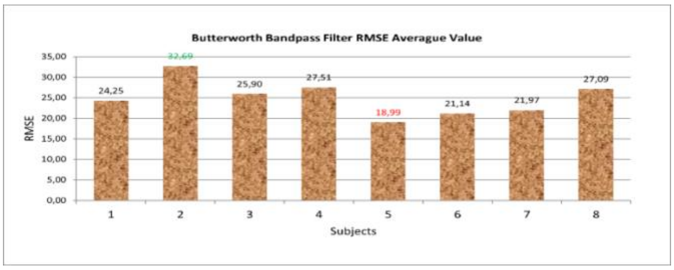
To evaluate the performance of the filtering process on EEG signals, this study uses four main evaluation parameters, namely MSE, MAE, RMSE, and SNR. These four metrics are used to measure the effectiveness of the filtration method in improving signal quality through interference reduction and preservation of relevant information. Based on the analysis, the combination of a Butterworth bandpass filter and the VMD method shows optimal performance in improving EEG signal quality. The Butterworth bandpass filter effectively preserves the frequency components corresponding to the EEG signal range. At the same time, VMD contributes to the decomposition of the signal into more informative intrinsic modes, thereby reducing interference and preserving important features of the original signal.



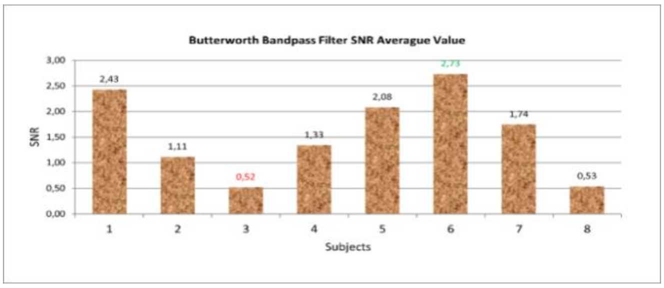
a) Comparison of Mean Absolute Errors (MAE)



b) Comparison of Mean Square Errors (MSE)



c) Root Mean Squared Errors (RMSE)



d) Comparison of Signal to Noise Rasio (SNR)

Fig. 6 Comparison of MAE, MSE, RMSE and SNR values for the Butterworth bandpass filter across different subjects

1. Butterworth Band Pass Filter

Fig. 6 presents the performance analysis of the Butterworth bandpass filter based on four main evaluation parameters: MAE, MSE, RMSE, and SNR. The MAE plot illustrates the inter-subject variability in error values, with the highest error recorded at 25.49 (green) and the lowest at 13.72 (red). This variation indicates different EEG

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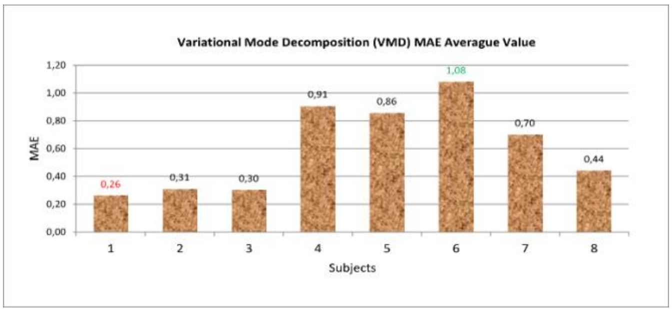
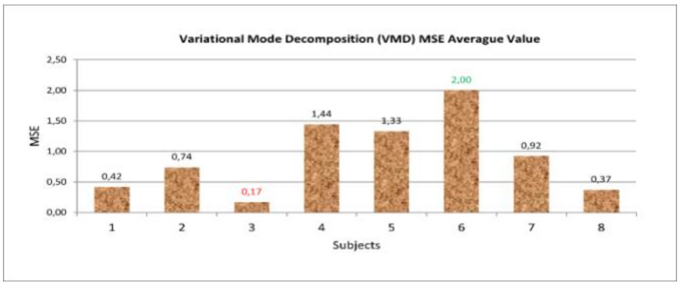
signal responses to the filtering process among individuals. Thus, the MSE values support this finding, showing a substantial error range between the filtered and original signals, from 399.79 to 1117.04. The RMSE values follow a similar pattern, ranging from a minimum of 18.99 to a maximum of 32.69, reflecting differences in reconstruction error.

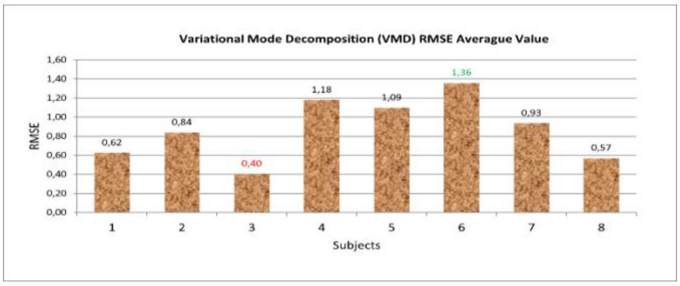
The SNR results demonstrate the filter's effectiveness in terms of noise reduction, with values ranging from 0.52 dB to 2.73 dB. While the Butterworth bandpass filter generally enhances EEG signal clarity, its performance is influenced by the unique characteristics of each recording. As such, its effectiveness may vary between subjects.



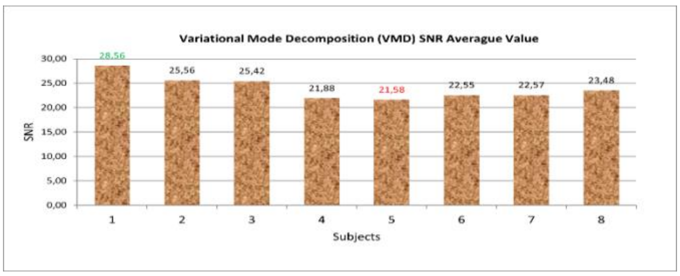
a) Comparison of Mean Absolute Errors (MAE)



b) Comparison of Mean Square Errors (MSE)



c) Comparison of Root Mean Squared Errors (RMSE)



d) Comparison of Signal to Noise Ratio (SNR)

Fig. 7 Comparison of MAE, MSE, RMSE, and SNR values for VMD across different subjects

2. Variational Mode Decomposition

Fig. 7 presents a quantitative analysis of the performance of the VMD method in processing EEG signals based on four evaluation parameters: MAE, MSE, RMSE, and SNR. In Fig. 7(a), the distribution of MAE values shows the variation in decomposition accuracy among subjects. The highest MAE was recorded in subject six at 1.08, while the lowest was observed in subject one at 0.26. A lower MAE value indicates greater effectiveness of the VMD preserving the original signal structure. Fig. 7(b) illustrates the variation in MSE, which reflects the squared deviation between the decomposed and original signals. Subject 6 showed the highest MSE at 2.00, while Subject 3 had the lowest at 0.17. These results indicate that the effectiveness of VMD denoising varies depending on the characteristics of each EEG signal. Furthermore, Fig. 7(c) displays the RMSE values, ranging from 0.40 in Subject 3 to 1.36 in Subject 6. A lower RMSE indicates a smaller reconstruction error, reinforcing the consistency of VMD in maintaining signal fidelity for a given subject.

Meanwhile, Fig. 7(d) displays the SNR value after VMD processing, representing the signal quality ratio to noise ratio. Subject 1 obtained the highest SNR value, 28.56 dB, while subject 5 recorded the lowest value, 21.58 dB. The high SNR reflects the improved clarity of the decomposed signal. These results indicate that VMD has significant potential in improving EEG signal quality.

3. Comparison results of Butterworth Band-Pass Filter method with VMD method

Fig. 8 presents a performance comparison between the Butterworth Band-Pass Filter and VMD on EEG signals, based on four main evaluation parameters: MAE, MSE, RMSE, and SNR. In Fig. 8(a), VMD consistently shows lower MAE values compared to the Butterworth filter in most subjects. This indicates that VMD can better maintain the original characteristics of the post-processed EEG signal. The highest MAE value in the Butterworth method was recorded at 25.49 (Subject 4), while the highest value in VMD was only 0.91. The lowest MAE value was achieved by VMD in Subject 1 at 0.26, much lower than the lowest Butterworth value of 13.72. Fig. 8(b) compares the MSE values. VMD shows significantly smaller deviation between the processed and original signals. The highest MSE value in VMD was only 2.00 (subject 6), while in Butterworth it reached 1117.04. The lowest MSE value for VMD was 0.17 (subject 3), which is still much lower than the lowest value of Butterworth of 692.63. These findings indicate that VMD is more accurate in reducing interference without eliminating important information from the EEG signal.

Fig. 8(c) shows similar trends in the RMSE parameter. VMD produces the highest RMSE value of 1.09 and the lowest of 0.40, while the Butterworth filter produces the highest value of 32.69 (Subject 2) and the lowest of 18.99 (Subject 5). This difference indicates that the VMD method produces a smaller reconstruction error, making it more reliable in maintaining the signal shape. Fig. 8(d) shows the results of the SNR value comparison. VMD produces a significant increase in signal quality, with the highest SNR value of 28.56 dB (subject 1) and the lowest

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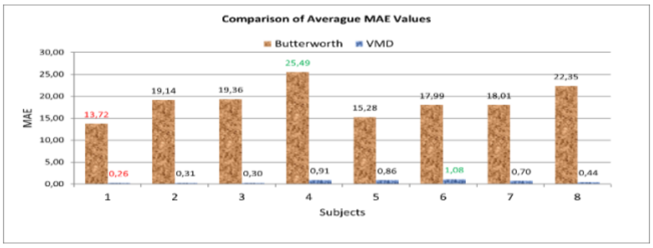
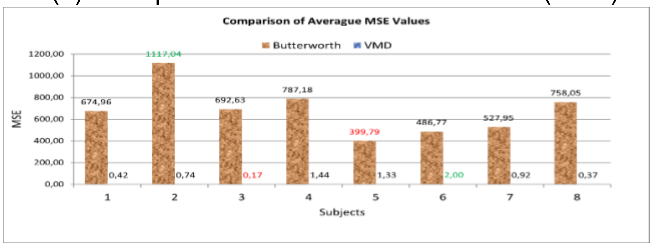
of 21.58 dB (subject 5). In contrast, Butterworth only produces a maximum SNR value of 2.43 dB and a minimum of 2.08 dB. This shows that VMD is effective in suppressing noise and can substantially improve the clarity of the EEG signal.

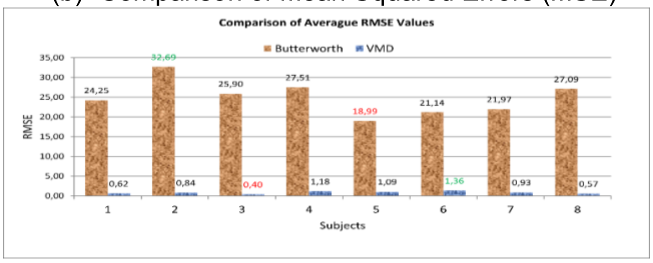
While VMD demonstrated consistently superior overall performance across all evaluation parameters, some inter-subject variability was observed. This variation is attributed to inherent differences in EEG signal characteristics, such as muscle and eye artifact levels, recording quality, and dominant frequency spectral distribution. The SNR values of VMD, ranging from a minimum of 21.58 dB to a maximum of 28.56 dB, confirmed that although this method is effective, its performance still depends on individual signal conditions. Therefore, the general application of VMD needs to consider the characteristics of each subject, and individualized parameter adjustments may be required to achieve optimal and consistent denoising results.



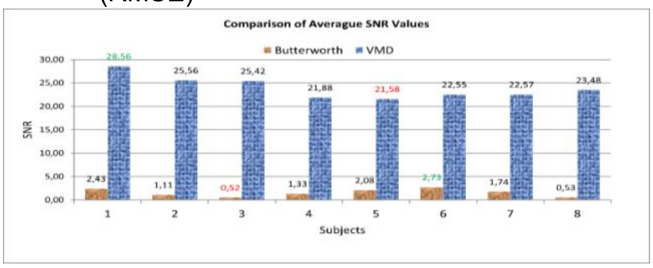
(a) Comparison of Mean Absolute Errors (MAE)



(b) Comparison of Mean Squared Errors (MSE)



(c) Comparison of Root Mean Squared Errors (RMSE)



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

Fig. 8 Comparison of MAE, MSE, RMSE, and SNR values between the Butterworth bandpass filter and VMD in EEG signal processing.

IV. Discussion

A. Performance of Butterworth Filters and VMD

This study aims to evaluate the performance of the Butterworth Band-Pass Filter and the VMD methods in denoising EEG signals, based on four main evaluation parameters: MAE, MSE, RMSE, and SNR. The test results show that the Butterworth filter produces high-performance variations between subjects. The MAE values range from 13.72 to 25.49, reflecting inconsistent accuracy in reducing noise without changing the basic shape of the signal. The highest MSE value reaches 1117.04, indicating a significant deviation between the filtered and reference signals. This is reinforced by the high RMSE values (18.99-32.69) and low SNR values (0.52-2.73 dB), which overall indicate the limitations of this method in improving the EEG signals' clarity.

In contrast, the application of the VMD method showed superior and stable denoising performance. The resulting MAE values ranged from 0.26 to 1.08, indicating consistency in maintaining the original characteristics of the signal. The low MSE value (0.17-2.00) indicates that the signal reconstruction results by VMD are very close to the original signal, also supported by the RMSE value (0.40-1.36). The improvement in post-process quality with VMD is reflected in the high SNR value, ranging from 21.58 dB and 28.56 dB. These results affirm VMD's effectiveness in significantly increasing the signal-to-noise ratio. The quality of the denoising method significantly affects the accuracy of EEG signal analysis, especially in cases of ASD that depend on brain rhythm and connectivity patterns. The presence of noise can disguise important features, making the diagnosis process less accurate. Therefore, VMD is more feasible for clinical EEG signal analysis and EEG-based diagnostic systems.

The results show that the VMD method is superior to the Butterworth Band-Pass Filter in maintaining the original shape of the EEG signal. In Subject 1, VMD produced low MAE and MSE values, reflecting a clean signal with minimal distortion. In contrast, Butterworth showed a significant deviation in Subject 2 (MAE = 19.14; MSE = 1117.14), which risks interfering with identifying typical ASD patterns. The RMSE and SNR values further strengthen the finding that VMD produces a signal closer to the original shape with higher clarity. In Subject 6, the RMSE obtained by VMD was 1.36, much lower than the value of 21.14 produced by Butterworth. Likewise, the SNR value of VMD indicates better signal quality. Therefore, the MAE, MSE, RMSE, and SNR parameters not only reflect technical performance but also contribute significantly to the accuracy of EEG diagnosis for individuals with ASD.

Improvements in EEG signal performance after the denoising process using VMD has been validated through quantitative metric evaluation such as MAE, MSE, RMSE, and SNR. To assess the extent to which the denoised signal represents the actual brain activity, Power Spectral Density (PSD) analysis was performed on the signal before and after the VMD process. The analysis results showed that the power distribution across the primary EEG frequency bands remains largely undistorted. For

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example, in channel C3, the PSD values in the delta and theta bands before denoising were recorded at 43.52 μV²/Hz and 3.63 μV²/Hz, respectively. After the VMD process, the values remained unchanged at 43.55 μV²/Hz and 3.63 μV²/Hz. A similar pattern was also observed in channel 7, where the delta band had a PSD value of 34.42 μV²/Hz (before) and 34.44 μV²/Hz (after).

These findings indicate that VMD not only improves the numerical quality of the signal but also preserves important features relevant for clinical interpretation. By maintaining the proportion of power in the physiological frequency band, this method allows the preservation of authentic neurological signals while reducing artifact interference. Although this study did not include clinical annotation-based validation or detection of specific neurophysiological events (e.g., epileptiform spikes, event-related potentials, or responses to stimuli), these results provide a strong basis for considering the VMD method for further clinical applications.

B. VMD vs Butterworth Performance Comparison

The Butterworth Band-Pass Filter and VMD comparison results show that VMD consistently performs better in every evaluation parameter tested. In all subjects, VMD produces lower MAE and MSE values and higher SNR values, reflecting the ability of this method to maintain the integrity of the EEG signal. For example, in Subject 5, VMD recorded an MAE of 1.08, MSE of 2.00, and RMSE of 1.36, while Butterworth showed much higher values with an MAE of 17.99, MSE of 486.77, and RMSE of 21.14. Additionally, in Subject 1, VMD produced the best signal quality with an SNR reaching 28.56 dB, starkly contrasting with Butterworth's results, which only reached 2.43 dB.

This paper also conducted statistical tests to evaluate the significance of the improvement in EEG signal quality using the combined approach of the Butterworth Bandpass Filter and VMD. The paired sample t-test of the Butterworth method confirmed that the differences in evaluation metrics values were statistically significant. As presented in Eq. (12), the following p-values were obtained: MAE ($p = 0.00000216$), MSE ($p = 0.00005665$), RMSE ($p = 0.00000126$), and SNR ($p = 0.00000004$). These values are far below the significance threshold of 0.05, indicating that the performance improvement of the BPF–VMD combination is not random but is supported by strong statistical evidence.

In addition, the effect size analysis using Cohen's d (Eq. (14)) shows an enormous magnitude: MAE ($d = 6.93$), MSE ($d = 4.31$), RMSE ($d = 7.84$), and SNR ($d = –12.51$). The absolute value of Cohen's d far exceeding 0.8, which is generally categorized as a significant effect, indicates that the resulting difference is very practically significant. Although the d value for SNR is negative, this only reflects the direction of improvement (i.e., a higher SNR in the combined method) and does not imply that the effect is negligible. Thus, these results indicate that the integration of BPF and VMD substantially improves the quality of EEG signals compared to using Butterworth alone.

C. Research Limitation

Although VMD shows superior performance compared to the Butterworth Bandpass Filter based on MAE, MSE, RMSE, and SNR metrics, several limitations should be acknowledged. For example, the Butterworth can distort at low frequencies such as delta and theta. At the same time, VMD sometimes faces challenges in maintaining consistent mode separation, especially in complex and inter-individual varying signals. The differences in results between subjects indicate that the characteristics of each signal greatly influence the effectiveness of VMD. On the other hand, in terms of computational efficiency, VMD requires iterative processes and parameter adjustments, which can be challenging for real-time applications or systems with limited resources. Therefore, further research with a larger number and variety of subjects, as well as the exploration of adaptive or hybrid methods, is needed to improve the overall accuracy and efficiency of EEG signal processing.

In a study conducted by Prashant Singh et al., a hybrid denoising method combining Empirical Mode Decomposition (EMD), Detrended Fluctuation Analysis (DFA), and Wavelet Packet Decomposition (WPD) was applied to EEG signals. This approach yielded an SNR of 20.24 dB and an MAE of 12.24, indicating a moderate improvement in signal quality. In contrast, this study used the VMD method. It showed superior results, with an SNR of 28.56 dB and an MAE of 0.26, indicating more effective denoising performance in maintaining EEG signal integrity [36].

In a study conducted by Zhu Peibin et al., the DWT method was employed for EEG signal denoising due to its advantages in multi-resolution analysis, which enables effective signal decomposition across multiple frequency scales. Although this method is effective in handling non-stationary signals, its performance in improving signal clarity is still limited, as indicated by the SNR value of 14.45 dB. In contrast, this study employed the VMD approach and successfully achieved an SNR of up to 28.56 dB, indicating a significantly more substantial improvement. These findings indicate that while DWT provides solid frequency resolution, VMD is superior in minimizing distortion and preserving the original shape of EEG signals, making it more suitable for clinical analysis and neurodiagnostic applications [40].

One VMD-based denoising approach has been introduced by Manali Saini et al., which combines VMD with zero-crossing count-based artifact detection on single-channel EEG signals. This method shows an improvement in signal quality with an SNR value of up to 9.0 dB. In contrast to these approaches, this study applies VMD to multi-channel EEG data that has been previously filtered using a Butterworth bandpass filter, without a feature-based artifact detection stage. Instead, this method directly utilizes the spectral distribution of the decomposed modes to reconstruct the clean signal. The evaluation results demonstrate that this approach yields a more substantial performance improvement, with the highest SNR reaching 28.56 dB, indicating the effectiveness of VMD in preserving important information from brain signals, particularly in the context of ASD neurodiagnostics [41].

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A study conducted by Abdolahniya et al. evaluated two denoising approaches to reduce EOG artifacts in EEG signals, namely the Discrete Wavelet Transform–Least Mean Square (DWT-LMS) and the Discrete Wavelet Transform–Minimum Error Entropy (DWT-MEE) methods. Both methods rely on the Discrete Wavelet Transform (DWT) to extract signal components containing artifacts, followed by Adaptive Noise Cancellation using the LMS and MEE algorithms. Based on the evaluation results, DWT-LMS produced an average SNR of 3.32 dB, while DWT-MEE provided a slightly higher improvement with an SNR of 4.72 dB. In contrast to these approaches, this study directly applied the VMD method to multichannel EEG signals that had been filtered using a Butterworth Bandpass Filter, achieving the highest SNR of 28.56 dB. These results demonstrate the significant advantages of this approach in improving EEG signal clarity and retaining important neurophysiological information, particularly in the analysis of ASD cases [42].

The VMD method has been proven to produce cleaner EEG signals, indicated by lower MAE and MSE values, and higher SNR compared to the Butterworth method. This improvement in signal quality is crucial in clinical contexts, particularly in ASD cases, as it allows for more accurate identification of brain activity patterns and supports the performance of machine learning algorithms in ASD classification. In addition to improving the accuracy of early diagnosis, VMD also makes an important contribution in transmitting responses to therapy more precisely. The advantage of VMD lies in its ability to reduce noise without altering the original form of the EEG signal, making it a highly recommended denoising method in neurophysiological research, spectrum analysis, and development systems such as the Brain-Computer Interface (BCI).

D. Implications and Potential Use of VMD in Signal Denoising

VMD significantly improves the quality of EEG signals through a more precise denoising process. Compared to the Butterworth filter, VMD can simultaneously suppress error values (MAE, MSE, RMSE) and increase SNR, resulting in cleaner and more informative signals. In neurophysiological studies, especially those focused on ASD cases, signal clarity is crucial for recognizing typical brain activity patterns. Beyond its noise reduction capabilities, VMD also maintains the integrity of relevant signal components, thus supporting the development of machine learning-based classification algorithms and continuous patient monitoring.

V. Conclusion

This study aims to evaluate the effectiveness of the VMD method in improving EEG signal quality compared to the Butterworth Bandpass Filter. The results show that VMD provides consistently superior performance, with a MAE of 0.26 μV, MSE of 0.17 μV², RMSE of 0.40 μV, and the highest SNR of 28.56 dB. The paired t-test statistical test reveals a highly significant difference, with p-values of: MAE (2.16×10^{-6}), MSE (5.66×10^{-5}), RMSE (1.26×10^{-6}), and SNR (4.00×10^{-8}). Effectiveness analysis using Cohen's d yielded large values: MAE (d = 6.93), MSE (d = 4.31), RMSE (d = 7.84), and SNR (d = –12.51), indicating a powerful and significant improvement effect. In the future, it is recommended to combine VMD with optimization techniques such as Particle Swarm Optimization (PSO) or genetic algorithms, as well as integration with other methods such as ICA or DWT, to overcome mode mixing and improve the accuracy of EEG signal processing, especially in the context of clinical diagnosis of autism.

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Digital Object Identifier (**DOI**): https://doi.org/10.35882/ijeeemi.v7i3.105

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Indonesian Journal of Electronics, Electromedical Engineering, and Medical Informatics e-ISSN: 2656-8624
Homepage: https://ijeeemi.org/; Vol. 7, No. 3, pp. 461-474, August 2025

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