Performance Evaluation of FIR Low-Pass and High-Pass Filtering for Alpha–Beta EEG Signal Preprocessing in Stroke Patients

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ABSTRACT

Electroencephalography (EEG) signals are inherently non-stationary and highly susceptible to various noise sources, such as baseline drift, muscle artifacts, and electrical interference. These disturbances can significantly degrade EEG signal quality, particularly in clinical stroke analysis, thereby affecting the reliability of neurological interpretation. This study aims to evaluate the effectiveness of Finite Impulse Response (FIR) Low-Pass Filter (LPF) and High-Pass Filter (HPF) as preprocessing techniques for improving EEG signal quality in the Alpha–Beta frequency bands (8–30 Hz). The dataset used in this study consists of private clinical EEG recordings obtained from ischemic stroke patients. The preprocessing pipeline includes signal normalization, FIR filter design, and signal filtering. Quantitative evaluation is performed using Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE), supported by frequency-domain analysis using Power Spectral Density (PSD). The results indicate that FIR LPF with a cutoff frequency of 40 Hz achieves higher SNR and lower RMSE compared to FIR HPF at 1 Hz, demonstrating superior performance in suppressing high-frequency noise while preserving relevant Alpha–Beta EEG information. These findings suggest that FIR-based filtering is effective for enhancing EEG signal quality within the scope of this study. However, the results are limited to the investigated dataset and filter configurations, and further validation using larger datasets and alternative preprocessing methods is recommended.

I. INTRODUCTION

Stroke is a cerebrovascular disease that affects the blood vessels supplying blood to the brain. A stroke occurs when the blood supply to the brain is disrupted, causing brain cells to be deprived of oxygen and nutrients, which can result in permanent damage. This disruption of blood flow may be caused by vessel blockage (ischemic stroke) or blood vessel rupture (hemorrhagic stroke). Stroke is a medical emergency, and delayed treatment can lead to permanent disability or even death [1].

Understanding and managing stroke patients can be conducted through several approaches, including consultation with neurologists, examinations using CT scans and MRI, and the use of electroencephalography (EEG). Among these methods, clinical assessment by physicians is commonly performed through visual observation and documentation using the National Institutes of Health Stroke Scale (NIHSS), which is a standardized instrument for measuring stroke severity [2]. However, this method has limitations, particularly when patients are unable to communicate, and assessment results may vary between clinicians. MRI and CT scan examinations also have drawbacks, as exposure to radiation may potentially damage body cells, making repeated examinations less desirable [3]. In contrast, EEG is considered a more effective alternative because it measures brain activity through electrodes placed on the scalp, is relatively low-cost, non-invasive, poses no risk during examination, provides accurate results, and is highly beneficial for monitoring and evaluating stroke patients during rehabilitation [4].

Electroencephalography (EEG) is a technique used to record brain wave activity by measuring the brain's bioelectrical signals. EEG recordings are obtained using highly sensitive electrodes attached to the scalp according to established standards [5]. During the recording process, EEG signals are highly susceptible to noise and interference, such as muscle artifacts, eye movements, and electrical interference. These disturbances arise because EEG signals are inherently non-stationary, non-linear, and time-varying, making signal processing challenging. To transform these signals into a more stationary, linear, and analyzable form, signal processing techniques are required, particularly signal cleaning or filtering methods. Signal cleaning must be performed according to specific frequency bands, as it is crucial when analyzing particular EEG rhythms such as alpha (8–13 Hz) and beta (13–30 Hz) waves. These frequency bands are widely used in applications such as cognitive load detection, relaxation analysis, and Brain–Computer Interface (BCI) systems [6].

Previous studies have generally focused on quantitatively evaluating the performance of high-pass and low-pass filters; however, comprehensive quantitative evaluations using standardized performance metrics remain limited [7]. Without proper evaluation, the effectiveness of high-pass and low-pass filters in suppressing non-stationary, non-linear, and time-varying signal characteristics cannot be quantitatively determined. Other studies have proposed standard clinical datasets with controlled noise conditions to facilitate EEG signal filtering [8]. Such controlled-noise standards aim to manage the inherent non-stationary, non-linear, and time-varying characteristics of EEG signals. Nevertheless, a major limitation of these studies is the reliance on public datasets rather than private or real clinical data collected directly from stroke patients [9]. When public datasets are used, quantitative noise reduction assessments may not accurately reflect real clinical conditions [10]. Insufficient noise reduction can lead to prolonged processing times and results that do not accurately represent the physiological condition of actual stroke patients.

This study focuses on analyzing high-pass and low-pass filters by leveraging EEG waveforms and stimulus-based evaluations. This approach is essential because combining waveform analysis with stimulus-based analysis enables a comprehensive quantitative evaluation framework. Based on the identified research gaps, this study investigates EEG signal processing using Finite Impulse Response (FIR) Low-Pass Filters (LPF) and High-Pass Filters (HPF) as standard procedures for quantitative evaluation of signal quality, particularly in the alpha–beta frequency bands. Alpha–beta rhythms are directly associated with sensory and motor functions, which are critically affected in stroke patients. In addition, this study conducts a comprehensive analysis of signal distribution changes across EEG frequency bands after filtering using band-pass filtering analysis.

The contributions of this study include providing a quantitative performance evaluation of FIR LPF and FIR HPF for EEG signal cleaning, offering recommendations for optimal filter parameters, and developing an automated pipeline for signal analysis and visualization. This research strengthens the methodological foundation of EEG preprocessing in neurological studies and clinical applications.

II. METHOD

This study employs a methodological framework consisting of five main stages: dataset acquisition, signal normalization, FIR LPF and HPF design, signal filtering, and evaluation.

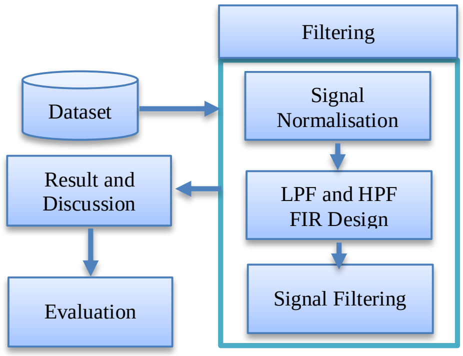

Figure 1. Research Stages

A. Dataset

The dataset used in this study is private data collected directly from the research subjects through collaboration with a physiotherapy clinic in Mojokerto, East Java, Indonesia. The data were obtained from patients who had experienced an acute stroke affecting either the right or left side of the body [11]. Data collection from stroke patients was conducted only after obtaining informed consent from the patients and their families, as well as approval from the attending physicians and the clinic or hospital where the data were collected [12]. This procedure was required because all data collection involving human subjects must comply with ethical committee regulations issued by the clinic or hospital.

A total of four participants were involved in the EEG recording process, consisting of two male and two female participants aged between 57 and 75 years. During data acquisition, EEG signals were recorded from two channels, C3 and C4, while participants performed a hand-grasp movement stimulus. The total recording duration was 60 seconds, following the signal acquisition protocol outlined below:

- Seconds 1–5: Baseline
- Seconds 5–10: Relax
- Seconds 10–55: Recording
- Seconds 55–60: Relax

The demographic and clinical information of the participants involved in the EEG recording process is presented in Table I.

TABLE I
PARTICIPANT DATA

No.	Participant	Age	Gender	Diagnosis
1	P01	75	Wanita	Ischemia
2	P02	65	Pria	Ischemia
3	P03	57	Pria	Ischemia
4	P04	69	Wanita	Ischemia

B. Filtering

1. Signal Normalization

Signal normalization is the process of transforming signal values into a specific range (e.g., 0–1 or −1 to 1) to maintain computational stability, prevent dominance by large values, and ensure that all features are on a comparable scale. The normalization equations for the 0–1 scale and −1 to 1 scale are defined as follows [13]:

Equation (1): Normalization to 0–1 scale

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Equation (2): Normalization to −1 to 1 scale

$$x_{norm} = 2.\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \quad (2)$$

where x represents the signal data.

2. LPF and HPF FIR Design

A Finite Impulse Response (FIR) filter is a digital filter with a finite impulse response, meaning that the output depends only on a finite number of previous input samples. The general FIR filter equation is given as follows [14] : Equation (3): FIR Filter

$$y[n] = \sum_{k=0}^{M-1} h[k]\, x[n-k] \quad (3)$$

Where y[n] is the output signal, x[n] is the input signal, h[k] epresents the filter coefficients, and M denotes the filter length.

3. Signal Filtering

In digital signal processing, filtering is fundamentally a convolution operation between the input signal x[n] and the filter impulse response h[n]. The Low-Pass Filter (LPF) is designed to pass low-frequency components while attenuating high-frequency components such as noise, whereas the High-Pass Filter (HPF) is used to remove very low-frequency components, such as electrode movement artifacts. The signal filtering equation is expressed as follows [15]: Equation (4): Signal Filtering

$$y[n] = x[n] * h[n] = \sum_{k=0}^{M-1} h[k]\, x[n-k] \quad (4)$$

Where y[n] is the output signal, x[n] is the input signal, h[k] represents the filter coefficients, M is the filter length, and h[n] denotes the FIR filter impulse response [16].

C. FIR Filter Design and Justification

The design of the Finite Impulse Response (FIR) Low-Pass Filter (LPF) and High-Pass Filter (HPF) in this study was conducted by considering the spectral characteristics of EEG signals within the alpha–beta frequency band (8–30 Hz) and the requirement to preserve linear-phase properties [17]. FIR filters were selected due to their ability to produce a stable linear-phase response, thereby minimizing phase distortion and preserving the waveform shape of EEG signals, which is essential for biological signal analysis.

The FIR HPF was designed with a cutoff frequency of 1 Hz to remove very low-frequency components, such as baseline drift and electrode movement artifacts, without affecting the main physiological components of EEG signals. Meanwhile, the FIR LPF employed a cutoff frequency of 40 Hz to suppress high-frequency noise, including muscle artifacts and environmental interference, while preserving EEG signal information within the alpha–beta frequency band. The selection of this cutoff range is consistent with EEG literature indicating that most clinically relevant EEG physiological information is contained below 40 Hz [18].

The FIR filter order was set to 301 taps (numtaps = 301) to achieve a balance between frequency transition sharpness and filter response stability. This order was chosen to ensure sufficient attenuation in the stopband without introducing excessive computational complexity. In addition, a Hamming window was applied in the filter design due to its low sidelobe characteristics, which effectively reduce spectral leakage commonly observed in non-stationary EEG signals [19].

Overall, the combination of design parameters—including cutoff frequencies, filter order, and window type—was selected to accommodate the non-stationary characteristics of alpha–beta EEG signals and to ensure that the filtering process functions as a stable and controlled preprocessing stage. However, this filter design is not intended to serve as a universal optimal configuration, but rather as an approach tailored to the dataset and research objectives of this study. Further evaluations involving parameter variations and comparisons with other filtering methods may be conducted in future studies to obtain more generalizable configurations.

D. Evaluation

The evaluation in this study employs the Signal-to-Noise Ratio (SNR) method, where SNR represents the ratio between the energy of the desired signal and the energy of noise. A higher SNR value indicates better signal quality. The SNR formulation used in this study is expressed as follows [20]:

$$SNR = 10\, log_{10}\left(\frac{\sum_{t=1}^{N} x(t)^2}{\sum_{t=1}^{N}(x(t) - \hat{x}(t))^2}\right) \quad (5)$$

Where $x(t)$ denotes the original signal, $\hat{x}(t)$ represents the filtered signal, and N is the number of samples.

III. Result and Discussion

A. Characteristics of the EEG Dataset

The dataset used in this study consists of clinical EEG data (private dataset) obtained directly from stroke patients through collaboration with a physiotherapy clinic. The raw EEG signals exhibit typical characteristics of biological signals, namely non-stationary and non-linear behavior, and are contaminated by various types of noise, including electrode movement artifacts, eye activity, muscle activity, and electrical interference. These conditions emphasize the necessity of applying signal preprocessing stages prior to further analysis.

TABLE II
DATASET CHARACTERISTICS

Index Sempel	Channel	
	C3	C4
0	-97801797	-269730742
1	-98720682	-269572500
2	-99329092	-271050605
3	-98649375	-271788438
4	-97562188	-270803184

Variations in values across sample indices reflect the non-stationary and time-varying nature of EEG signals. These fluctuations are inherent to brain electrical activity and are influenced by the patient's physiological condition as well as the presence of noise.

B. Signal Normalization Result

The signal normalization stage aims to equalize the amplitude scale of EEG signals to prevent dominance by extreme values during the filtering process. The normalization results indicate that the signal amplitude range becomes more controlled and stable. This process enhances numerical stability during the design and application of FIR filters and ensures consistent comparison of signal characteristics across segments.

TABLE III
SIGNAL NORMALIZATION

Sempel	C3
1	-0.083140
2	-0.106663
3	-0.080383
…	…
1599	0.093971
1600	0.091404

Signal normalization range: 0 to −0.047612

The data presented represent normalized EEG signals from channel C3 with a total of 1600 samples that have been transformed into a standardized numerical scale. The normalization process ensures that amplitude differences do not influence subsequent filtering and evaluation stages.

Based on the normalized values, the signal amplitudes are distributed within a range close to zero, with relatively small maximum and minimum values. This condition indicates that the original signal values have been successfully compressed into a limited range, thereby reducing the influence of extreme values (outliers) and improving numerical stability during computational processing.

C. FIR Low-Pass and High-Pass Filter Design

The design of the FIR Low-Pass Filter (LPF) and High-Pass Filter (HPF) was conducted to separate frequency components relevant to neurophysiological activity. The FIR HPF was designed to remove very low-frequency components associated with baseline drift and motion artifacts, whereas the FIR LPF was designed to reduce high-frequency components typically originating from muscle noise and environmental interference.

The selection of FIR filters provides the advantage of a linear-phase response, thereby avoiding temporal distortion in EEG signals. This property is crucial for preserving waveform morphology and physiological information within the alpha and beta frequency bands.

```
numtaps = 301  # cukup halus untuk EEG
# Low-pass 40 Hz
lpf = firwin(numtaps, cutoff=40, fs=fs,
pass_zero=True)

# High-pass 1 Hz
hpf = firwin(numtaps, cutoff=1, fs=fs,
pass_zero=False)
```

The output of this code consists of two FIR coefficient vectors:

- lpf: FIR Low-Pass Filter coefficients with a 40 Hz cutoff frequency,
- hpf: FIR High-Pass Filter coefficients with a 1 Hz cutoff frequency.

These coefficients are subsequently used in the convolution (filtering) process between the EEG signal and the FIR filters to generate EEG signals that have been cleaned from low- and high-frequency noise. Conceptually, the application of these two filters results in EEG signals that:

- are free from DC components and very low-frequency artifacts,
- exhibit reduced high-frequency noise above 40 Hz,
- preserve essential information within the clinically relevant alpha and beta frequency bands.

D. EEG Signal Filtering Results

The filtering results demonstrate an improvement in EEG signal quality, both visually and analytically. After the application of the FIR High-Pass Filter (HPF), the EEG signals no longer exhibit significant baseline drift. Subsequently, the application of the FIR Low-Pass Filter

(LPF) produces smoother signals with reduced high-frequency noise, without removing essential information within the Alpha (8–13 Hz) and Beta (13–30 Hz) frequency bands.

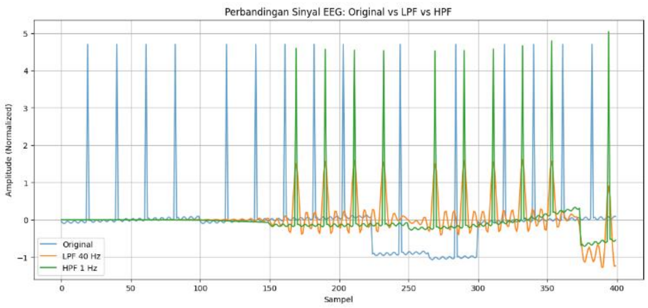

Figure 2. EEG Signal Filtering Results per Sample

As shown in Figure 2, the original EEG signal exhibits sharp and unstable amplitude fluctuations, indicating the presence of artifacts and noise at both low and high frequencies. The high-amplitude spikes observed in the signal reflect the influence of artifacts such as muscle activity and environmental interference, which are commonly found in raw EEG recordings.

After applying the 40 Hz FIR Low-Pass Filter (LPF), the EEG signal appears smoother with a significant reduction in high-frequency components. The LPF effectively suppresses high-frequency noise without eliminating the main EEG signal patterns. This is evidenced by the reduction of extreme amplitude spikes while preserving the temporal structure of the signal.

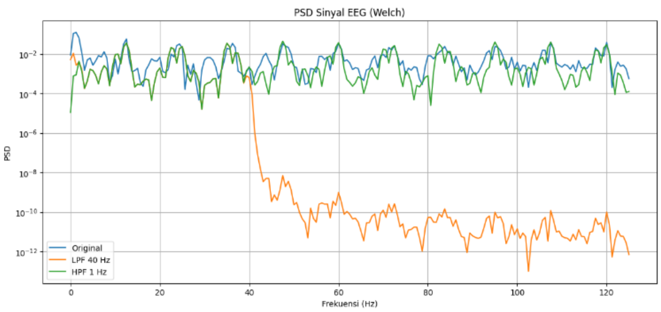

Figure 3. EEG Signal Filtering Results in the Frequency Domain

Meanwhile, as shown in Figure 3, the application of the 1 Hz FIR High-Pass Filter (HPF) results in signals with a more stable baseline. The HPF effectively removes very low-frequency components and DC shifts (baseline drift), causing the signal to oscillate around zero. However, the amplitude of the HPF-filtered signal still exhibits high-frequency variations, as this filter is not designed to suppress high-frequency components.

E. Signal Quality Evaluation

Signal quality evaluation was conducted using the Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) to assess the effectiveness of the filtering process. The evaluation results indicate improvements in both metrics after the signals underwent normalization and filtering stages. These improvements suggest that the energy of informative signal components becomes more dominant relative to noise energy.

TABLE IV
SIGNAL QUALITY EVALUATION

Sempel	**Filter**	**SNR (dB)**	**RMSE**
0	LPF 40 Hz	-1.090056	1.133712
1	HPF 1 Hz	-2.089068	1.271901

Table IV presents the comparative performance evaluation of the FIR Low-Pass Filter (LPF) at 40 Hz and the FIR High-Pass Filter (HPF) at 1 Hz in improving EEG signal quality, evaluated using the SNR and RMSE metrics. Based on the SNR values, the FIR LPF at 40 Hz yields an SNR of −1.09 dB, whereas the FIR HPF at 1 Hz produces an SNR of −2.09 dB. Although both SNR values remain within the negative range, the FIR LPF demonstrates a higher SNR than the FIR HPF. This indicates that the 40 Hz LPF is more effective in increasing the dominance of informative signal components, particularly by reducing high-frequency noise that is prevalent in raw EEG signals.

In terms of RMSE, the FIR LPF at 40 Hz results in an error value of 1.13, which is lower than that of the FIR HPF at 1 Hz with an RMSE of 1.27. The lower RMSE value indicates that LPF-filtered signals exhibit smaller amplitude deviations relative to the reference signal compared to HPF-filtered signals.

Figure 4. Signal Evaluation Results Based on SNR and RMSE Comparison

Overall, the evaluation results presented in Table IV and Figure 4 indicate that the FIR LPF at 40 Hz outperforms the FIR HPF at 1 Hz in terms of both SNR improvement and amplitude error reduction (RMSE). This finding is consistent with the characteristics of EEG signals, which are generally more contaminated by high-frequency noise; therefore, the application of an LPF has a more pronounced impact on improving signal quality.

However, the persistently negative SNR values indicate that noise remains relatively dominant in the EEG signals. Consequently, the sequential combination of FIR HPF and FIR LPF (band-pass filtering) or integration with more advanced signal-cleaning methods is recommended to achieve more optimal EEG signal quality.

F. Comparative Analysis of FIR LPF and FIR HPF on EEG Signal Quality

The analysis focuses on a quantitative comparison of the performance of the Finite Impulse Response (FIR) Low-Pass Filter (LPF) and High-Pass Filter (HPF) in improving EEG signal quality within the alpha–beta frequency bands. The evaluation was conducted using the Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) metrics, which represent the dominance of informative signal energy over noise and the degree of amplitude deviation in the filtered signals, respectively.

Based on the evaluation results, the FIR LPF with a cutoff frequency of 40 Hz produced higher SNR values than the FIR HPF with a cutoff frequency of 1 Hz. The increase in SNR achieved by the FIR LPF indicates that high-frequency noise reduction contributes significantly to improving the energy ratio of relevant EEG signals, particularly within the alpha–beta bands. In contrast, the FIR HPF primarily functions to remove very low-frequency components such as baseline drift but does not directly suppress high-frequency noise that remains dominant in raw EEG signals.

In terms of RMSE, the FIR LPF also demonstrated lower error values compared to the FIR HPF. Lower RMSE values indicate that LPF-based filtering better preserves the amplitude characteristics of the normalized EEG signals without introducing significant distortion. Conversely, the FIR HPF tends to produce greater amplitude variability, as high-frequency components with fluctuating characteristics are still retained.

Given the non-stationary nature of EEG signals and the absence of an ideal reference signal, the interpretation of evaluation metrics must be conducted with caution. In this study, SNR is not intended to represent absolute signal quality but is instead used as a relative indicator to compare the effectiveness of the filtering methods. Higher SNR values following LPF application indicate increased dominance of physiological signal components over noise, although the SNR values remain within a negative range due to the intrinsic characteristics of clinical EEG signals. RMSE is employed as a complementary metric to ensure that improvements in SNR are not achieved at the expense of signal amplitude stability.

Overall, the comparative analysis indicates that the FIR LPF is more effective than the FIR HPF in improving EEG signal quality within the alpha–beta frequency bands, particularly in reducing high-frequency noise. Nevertheless, the FIR HPF remains essential for eliminating low-frequency artifacts and baseline shifts. Therefore, the findings suggest the potential use of a combined FIR HPF and FIR LPF approach as a complementary preprocessing strategy. These findings are limited to the specific filter parameters and dataset used in this study and are not intended to serve as a universal standard procedure, but rather as an exploratory evaluation to support FIR-based preprocessing in clinical EEG analysis.

G. Evaluation of EEG Signal Quality After FIR Filtering

This subsection presents a comprehensive performance evaluation of EEG signal preprocessing using Finite Impulse Response (FIR) Low-Pass Filter (LPF) and High-Pass Filter (HPF) in the alpha–beta frequency bands for stroke patients. The evaluation integrates quantitative metrics and visual analysis to assess the effectiveness of each filtering approach in suppressing noise while preserving physiologically meaningful EEG components.

Quantitative evaluation is conducted using Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE). SNR is used to quantify the relative dominance of informative EEG signal components over noise, whereas RMSE measures the amplitude deviation of filtered signals with respect to normalized reference signals. These metrics are particularly appropriate for EEG analysis due to the inherently non-stationary nature of EEG signals and the absence of an ideal noise-free reference.

TABLE V
SIGNAL-TO-NOISE RATIO (SNR) OF EEG SIGNALS BEFORE AND AFTER FIR HIGH-PASS AND LOW-PASS FILTERING

Channel	SNR	
	After FIR LPF (db)	**After FIR HPF (db)**
C3	-5.85 dB	-32.14 dB
C4	-5.58 dB	-20.66 dB

Table V presents the SNR values of EEG signals after FIR LPF and FIR HPF for channels C3 and C4. The results indicate that FIR LPF achieves substantially higher SNR values compared to FIR HPF for both channels. This improvement suggests that suppressing high-frequency noise using LPF contributes more effectively to enhancing the signal-to-noise characteristics of alpha–beta EEG signals than removing low-frequency components alone. In contrast, the lower SNR values observed after HPF indicate that baseline drift removal does not sufficiently mitigate high-frequency noise that remains dominant in the raw EEG signals.

TABLE VI
ROOT MEAN SQUARE ERROR (RMSE) OF EEG SIGNALS AFTER FIR HIGH-PASS AND LOW-PASS FILTERING

Channel	RSME	
	After FIR LPF (db)	**After FIR HPF (db)**
C3	14704.74	15599.41
C4	1020.55	790.73

Table VI summarizes the RMSE values obtained after FIR LPF and FIR HPF. For channel C3, FIR LPF yields a lower RMSE than FIR HPF, indicating improved amplitude stability after low-pass filtering. For channel C4, FIR HPF results in a lower RMSE, suggesting that baseline correction plays a more significant role for this channel. These findings highlight the channel-dependent characteristics of EEG signals and emphasize that different filtering strategies may influence amplitude stability differently across channels.

TABLE VII
COMPARATIVE PERFORMANCE OF FIR HPF AND FIR LPF

Channel	SNR FIR LPF (dB)	RMSE FIR LPF	SNR FIR HPF (dB)	RMSE FIR HPF
C3	-5.85	14704.74	-32.14	15599.41
C4	-5.58	1020.55	-20.66	790.73

To facilitate direct comparison, Table VII provides a consolidated overview of the performance of FIR LPF and FIR HPF based on both SNR and RMSE metrics. Overall, FIR LPF demonstrates superior performance in terms of SNR improvement, whereas FIR HPF shows selective advantages in amplitude stabilization for specific channels. This comparative analysis confirms that LPF and HPF address different noise characteristics and should be interpreted as complementary rather than competing preprocessing techniques.

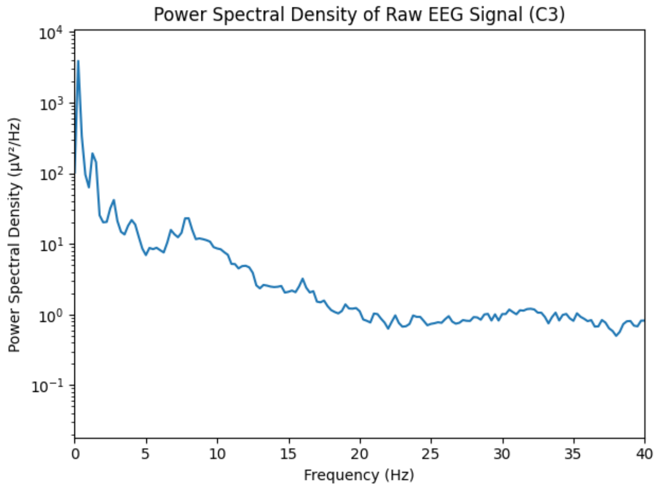

Figure 5. Power Spectral Density of Raw EEG Signal

Figure 5. Power Spectral Density (PSD) of the raw EEG signal for channel C3 computed using the Welch method. The spectrum shows a broad distribution of power across low and high frequencies, indicating the presence of baseline drift and high-frequency noise prior to filtering.

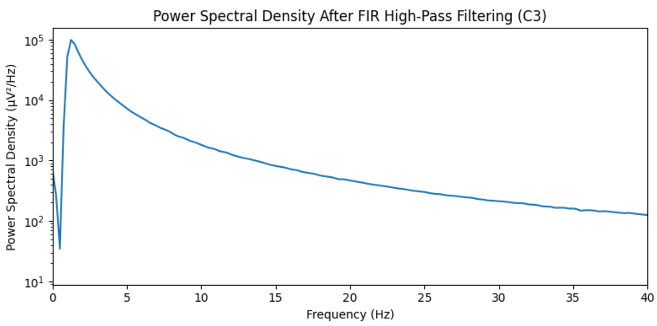

Figure 6. Power Spectral Density After FIR High-Pass Filtering

Figure 6. Power Spectral Density (PSD) of the EEG signal after FIR high-pass filtering for channel C3. The spectrum demonstrates effective attenuation of low-frequency components, indicating successful removal of baseline drift while preserving higher-frequency EEG activity.

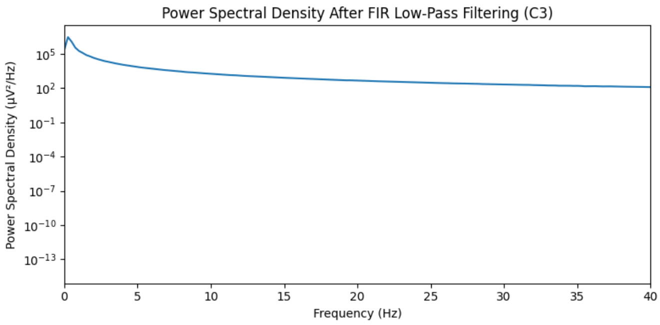

Figure 7. Power Spectral Density After FIR Low-Pass Filtering

Figure 7. Power Spectral Density (PSD) of the EEG signal after FIR low-pass filtering for channel C3. The spectrum shows effective attenuation of high-frequency noise while preserving dominant EEG activity within physiologically relevant frequency bands.

The combined use of quantitative metrics and spectral visualization provides a robust evaluation framework for FIR-based EEG preprocessing. The results indicate that FIR LPF is more effective in enhancing signal-to-noise characteristics within the alpha–beta bands, while FIR HPF plays an essential role in correcting baseline drift. Therefore, the findings support the use of FIR HPF and FIR LPF as complementary preprocessing steps rather than as standalone or universal solutions. These results are specific to the dataset and filter parameters used in this study and should be interpreted as an exploratory performance evaluation rather than a generalized clinical standard.

IV. CONCLUSION

This study demonstrates that, within the context of the dataset and experimental parameters used, the application of EEG signal preprocessing stages—including signal normalization, the design of Finite Impulse Response (FIR) Low-Pass Filters (LPF) and High-Pass Filters (HPF), and the filtering process—can measurably improve EEG signal quality. The FIR HPF was shown to be effective in removing low-frequency artifacts and baseline drift, whereas the FIR LPF was more optimal in reducing high-frequency noise without eliminating important information in the alpha–beta frequency band (8–30 Hz).

Signal quality evaluation using the Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) indicates that the FIR LPF produces higher SNR values than the FIR HPF, reflecting an increased dominance of physiological EEG signal components over noise. In addition, the relatively lower RMSE values obtained with the FIR LPF suggest that the filtering process does not introduce significant amplitude distortion into the normalized signals. Meanwhile, the FIR HPF continues to play an important role in improving EEG baseline stability.

Given the non-stationary nature of EEG signals and the absence of an ideal reference signal, SNR is employed as the primary indicator for evaluating relative improvements in signal quality, while RMSE serves as a complementary metric to ensure that such improvements are not achieved at the expense of signal amplitude fidelity. Therefore, the findings of this study are not intended to establish FIR-based preprocessing as a universal standard procedure, but rather as an exploratory evaluation limited to the experimental conditions, dataset, and filter parameters employed. Further studies using larger datasets and comparisons with other preprocessing methods are required to strengthen and generalize these findings.

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