Jurnal Teknokes
Homepage: teknokes.org; Vol. 18, No. 1, pp. 67-73, March 2025;
e-ISSN: 2407-8964
p-ISSN: 1907-7904

RESEARCH PAPER

OPEN ACCES

Reducing Motion Artifacts in Holter Monitors Using Digital Butterworth Filters to Improve the Quality of ECG Signal Recordings and Utilize IoT Technology

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ABSTRACT
Electrocardiogram (ECG) signals are often affected by various types of noise, such as motion artifacts, baseline wander, and white noise, which can reduce the accuracy of heart health monitoring, especially in conditions of body activity involving movement. This study aims to reduce noise in ECG signals, particularly motion artifacts, using a Butterworth digital filter integrated in an Internet of Things (IoT)-based system to monitor ECG signal quality in real-time via a web platform. The method used involves applying Butterworth filters to ECG signals of various orders (2, 4, and 6) to evaluate their effect on Signal-to-Noise Ratio (SNR) under five body activity conditions: sitting, lying down, sitting-standing, walking, and upward hand movement. The results show that the use of higher-order filters generally increases the SNR value, with 4th order providing the optimal SNR improvement. In the sitting condition, the SNR value increased from 5.2317 dB (RAW) to 10.1382 dB (4th order), while the lying condition showed an increase from 5.32087 dB (RAW) to 10.8574 dB (4th order). The walking condition shows an increase in SNR from 3.85886 dB (RAW) to 9.02449 dB (4th order), but a decrease in SNR occurs at 6th order. The upward hand movement condition also shows an increase in SNR from 4.6565 dB (RAW) to 10.3855 dB (4th order). In conclusion, the Butterworth filter can be effective in improving ECG signal quality, especially for stable body conditions, but attention needs to be paid to the possibility of over-filtering at higher filter orders. This research opens up opportunities for further development in the use of adaptive or machine learning-based filters to handle different types of noise in IoT-based health monitoring applications. The implication is that this research shows the importance of selecting the right filter order in ECG signal processing for heart monitoring applications under varying body activity conditions. In addition, the results of this study can be used to develop a more accurate IoT-based ECG monitoring system that can reduce noise in ECG signals, support faster diagnosis, and improve the quality of real-time heart health monitoring.

PAPER HISTORY
Received Jan 02, 2025
Revised Feb 12, 2025
Accepted March 7, 2025
Published March 30,2025

KEYWORDS
Motion Artifact;
Holter ECG;
Digital butterworth filter;
Quality signal;
Internet of Thing.

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1. INTRODUCTION

Cardiovascular diseases, particularly heart disease, are the leading cause of death in the United States, with about 1 in 3 deaths related to heart problems. More than 655,000 people die each year from this disease in the United States. Globally, cardiovascular diseases also pose a serious threat, ranking as the leading cause of death. Data from the WHO in 2015 showed that more than 17 million deaths were caused by cardiovascular diseases, with 8.7 million of those specifically due to heart disease, accounting for about 31% of total global deaths. This figure is predicted to rise to 36% of total deaths by 2020, making it twice as deadly as cancer.

To address this issue, several approaches have been proposed in recent years. In 2020, the use of digital filters such as Low-Pass, High-Pass, and Band-Pass Filters (LPF, HPF, BPF) at frequencies of 0.8–3.5 mV was able to reduce noise in ECG signals. This technology was combined with a real-time display on an LCD for heart rate (BPM) and signal graphs using Delphy software, although data transmission was still done manually by transferring the SD Card. In 2020, N. Sasirekh et al. conducted research to remove noise in ECG signals using digital filters. The research showed that the Neural Network-

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DOI: https://doi.org/10.35882/teknokes.v18i1.18

e-ISSN: 2407-8964
p-ISSN: 1907-7904

based filtering concept provides better results in removing baseline wander and white noise than other traditional methods. In addition, this technique has the potential to be further applied in dealing with motion artifact noise, which often occurs during the ECG acquisition process. However, the drawback of this study is that its focus is limited only to the removal of white noise and baseline wander, without considering other noise such as motion artifact, which is also significant in real-world ECG applications. Another more advanced approach involves the use of Neural Networks for signal filtering, which has proven to be more effective in eliminating noise such as base wander and white noise compared to conventional methods. This paves the way for the application of similar techniques in reducing powerline noise and motion artifacts in ECG signals. In 2020, methods based on Recurrent Neural Networks (RNN) and Deep Neural Networks (DNN) were used to reduce motion artifacts, demonstrating better performance with improved SNR and reduced RRMSE compared to previous approaches.

In addition, in 2012, a type II Chebyshev digital filter was used to eliminate high-frequency noise from ECG signals in real-time, with a design tailored to the characteristics of the obtained signals. Building on previous research, the author intends to develop a different approach by utilizing Butterworth digital filters.

This research aims to reduce motion artifacts in Holter ECG recordings while utilizing IoT technology to facilitate data transmission without the need to remove the SD Card. By simply pressing a button, the recorded data will be automatically sent via an IoT connection. this study is expected to enhance heart monitoring quality and assist in faster and more accurate diagnoses in the future.

2. MATERIALS AND METHOD

In this study, data were collected by recording ECG signals using a holter monitor on patients performing various activities, namely moving the upper body, sitting then standing, sitting still, lying down, and walking.

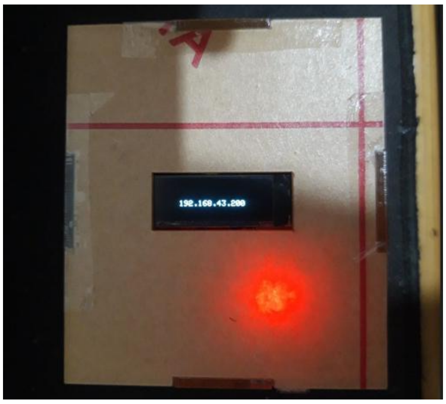

Figure 1. Module and Circuit Design

FIGURE 1 shows the holter monitor module used during the recording process.

The recording results produced four types of data: raw data as well as data that had gone through filtering with 2nd, 4th, and 6th order filters. The recording data was saved in CSV format for further analysis using MATLAB software. The analysis included evaluation of the signals before and after filtering, fast Fourier transform (FFT) to identify signal differences, and calculation of signal to noise ratio (SNR).

A. The Diagram Block

Based on FIGURE 2, the process begins with the patient performing specific activities such as sitting, lying down, transitioning from sitting to standing, and walking. The AD8232 module then processes the ECG signal using its built-in high-pass filter (HPF) at 0.5 Hz and low-pass filter (LPF) at 100 Hz to minimize interference from frequencies below 0.5 Hz and above 100 Hz, ensuring a clean ECG signal. The microcontroller receives the analog signal from the AD8232 and converts it into a digital format using analog-to-digital conversion (ADC). It then applies additional filtering with a cutoff HPF at 0.5 Hz and an LPF at 45 Hz.

The filtered data can be stored using an SD card module, which waits for a command from the website to save the data onto the SD card. The website wirelessly displays the ECG signal in real-time, plotting it dynamically while offering functionality to select filter orders for evaluating their effectiveness. Additionally, the website can send commands to the microcontroller to initiate data storage on the SD card.

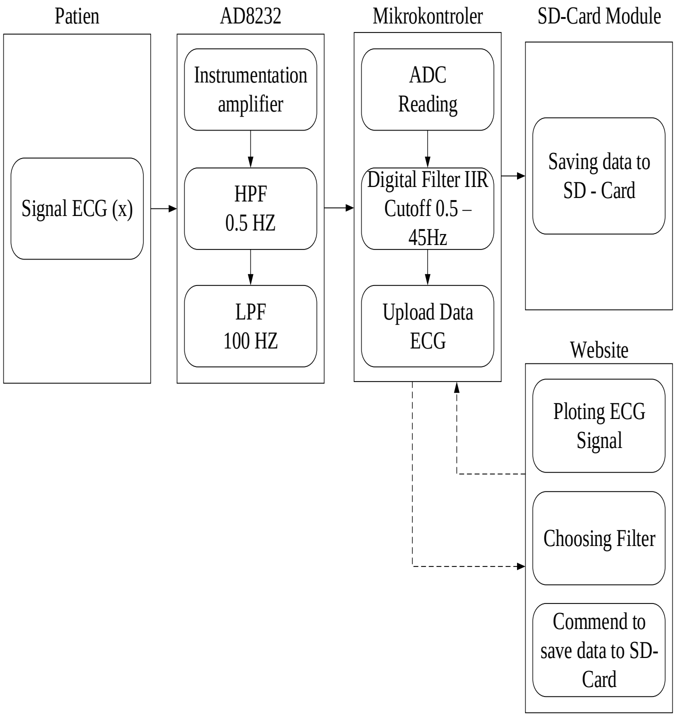

Figure 2. System Block Diagram

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

B. The Flowchart

FIGURE 3 shows the system flow diagram, starting with the program initialization process. At this stage, the microcontroller initializes the required libraries and other essential programs. The system then checks whether an SD card has been inserted. If no SD card is detected, it continuously prompts the user to insert one. Once the SD card is detected, the system proceeds to initialize it to prepare for data storage. Next, the module attempts to establish a WiFi connection. If the connection fails, it keeps retrying until a successful connection is made. Once connected to WiFi, the AD8232 module begins reading the ECG signal. This analog signal is then converted into digital data. Afterward, the system checks for a connection to the designated website. If not connected, it repeatedly attempts until the connection is successful. Once the connection is established, the user is prompted to select a filter order. If no selection is made, the system continues prompting until a filter order is chosen.Once the filter order is selected, the ECG signal is plotted on the website. Finally, the system asks the user whether they would like to save the data to the SD card. If the user agrees, the data is stored. If not, the system returns to repeat the previous process.

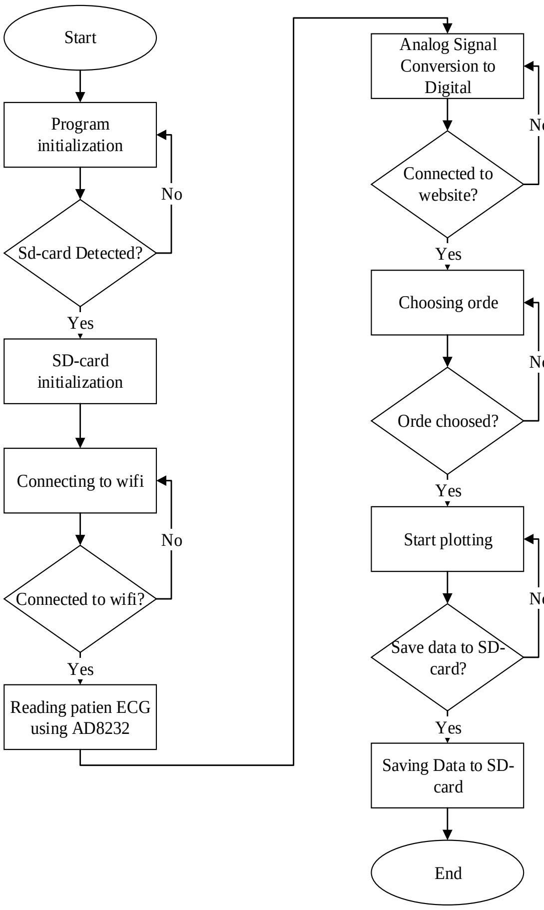

Figure 3. Flow chart system

3. RESULTS

In this study explains the testing mechanism of the devices reading results on ECG signals before and after the filtering process, as shown in FIGURE 2.

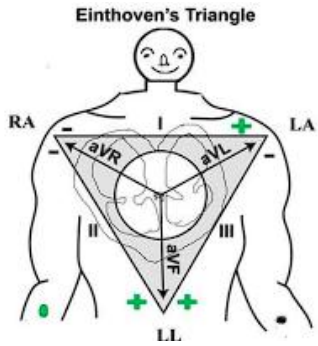

Figure 4. ECG Lead Placement [26]

In FIGURE 4, there is a guide for ECG lead placement used to capture ECG signals from the body, where the lead II configuration is used for electrode placement. The data collection process uses a custom-made ECG module, and signals are captured from human subjects to gather noise, which will be used to test the digital filter created. To evaluate the filter's effectiveness, frequency analysis is conducted on the ECG signal using an FFT (Fast Fourier Transform) plot in MATLAB. ECG signals from the Arduino are saved in CSV format and then exported to MATLAB for further analysis. In MATLAB, the frequencies present in the extracted ECG signal are analyzed to determine which frequencies have been attenuated by the filter.
In FIGURE 5, the unfiltered ECG signal is shown, which has undergone the FFT process in MATLAB to reveal the frequencies present in the ECG signal. FIGURE 3 displays both the ECG signal and the FFT results. The FFT plot illustrates the frequencies extracted from the ECG signal.

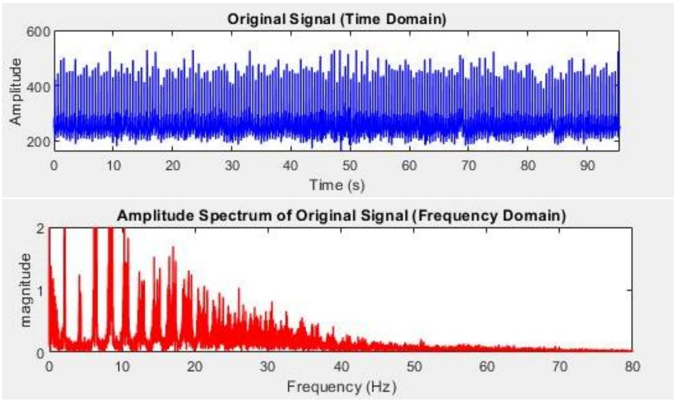

Figure 5. ECG Acquisition During Movement Before Filtering and Processing in MATLAB

In FIGURE 6, the ECG signal after applying a second-order filter is shown, which has undergone the FFT process in

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

MATLAB to identify the frequencies present in the ECG signal. The results of the ECG signal and FFT can be seen in FIGURE 4. The FFT plot displays the frequencies extracted from the ECG signal. Many frequencies outside the ECG range, which is typically between 0.5 and 40 Hz, have begun to be attenuated and are gradually decreasing.

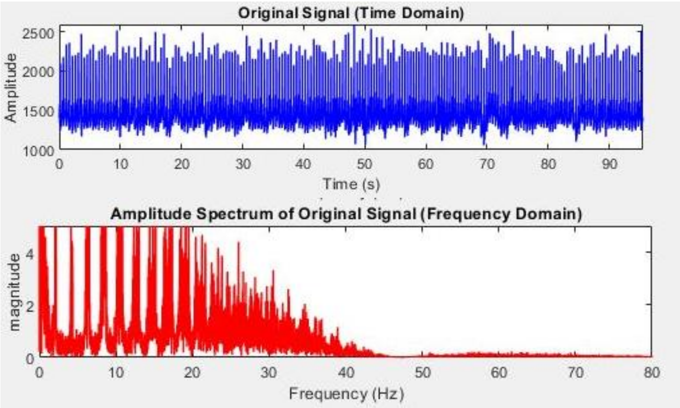


Figure 6. ECG Acquisition During Movement After Second-Order Filtering and Processing in MATLAB

In FIGURE 7, the ECG signal from the first data acquisition, which has been processed using a fourth-order filter, is shown. Below it is the FFT plot. The FFT plot displays the frequencies that have been attenuated by the filter. The red graph indicates where the second-order filter has applied frequency suppression.

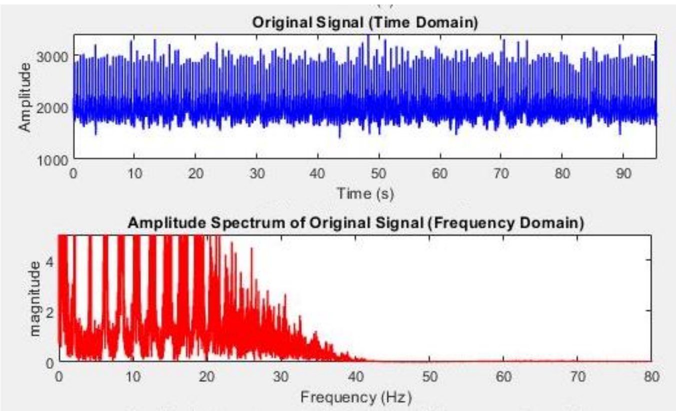
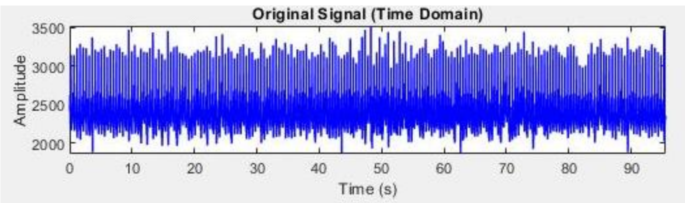


Figure 7. ECG Acquisition During Movement After Fourth-Order Filtering and Processing in MATLAB



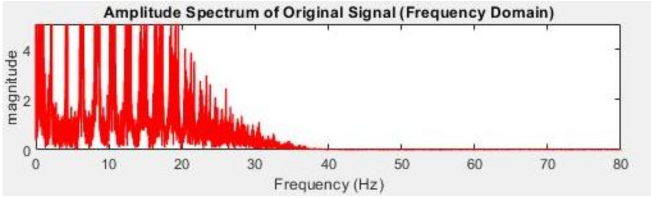


Figure 8. ECG Acquisition During Movement After Sixth-Order Filtering and Processing in MATLAB

FIGURE 8 shows the ECG signal from the first data acquisition, which has been processed using a sixth-order filter, is shown. Below it is the corresponding FFT plot. The FFT plot reveals the frequencies that have been attenuated by the filter, with the red graph indicating where the sixth-order filter has applied frequency suppression.

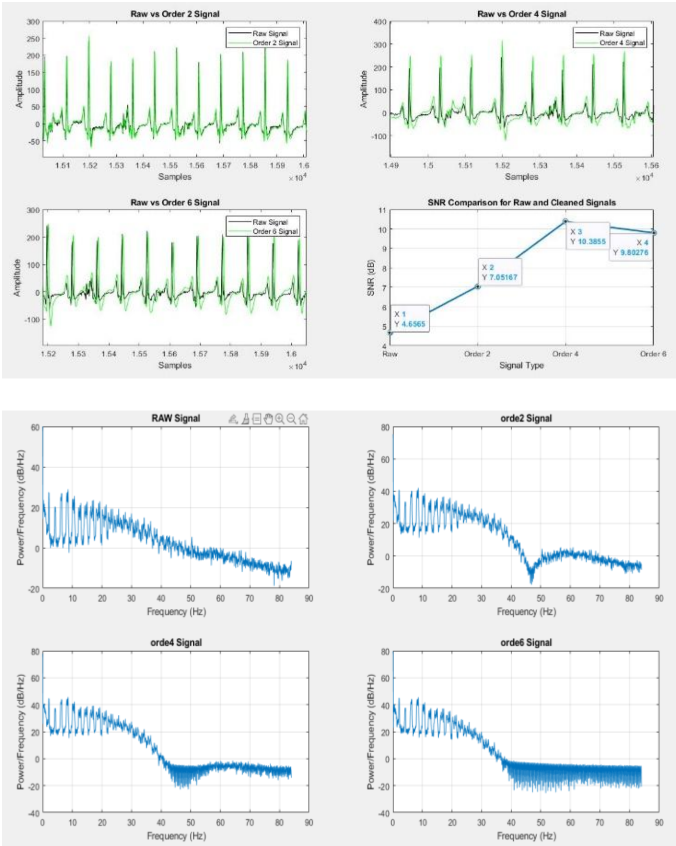


Figure 9. Testing The Filter Effectiveness Using Signal to Noise Ratio

In FIGURE 9, the ECG signal from the first data acquisition, which has been processed using second, fourth and sixth-order filter and has been processed on the Matlab using signal to noise ratio. And the result is on the raw signal we got 4.6565, on the second-order filter we got 7.05167, on the fourth-order we got 10.3855 and on the sixth-order we got 9.80276.

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e-ISSN: 2407-8964
p-ISSN: 1907-7904

TABLE 1 shows the SNR (Signal-to-Noise Ratio) values in dB (decibels) of the ECG signals for five body activity conditions: sitting, lying down, sitting-standing, walking, and upward hand movement. The SNR values were calculated from the raw signal (RAW) as well as after the filtering process with 2nd order, 4th order, and 6th order. In general, the SNR values increased as the filter order increased up to 4th order, then slightly decreased at 6th order. The lying condition resulted in the highest SNR values, while the walking condition had the lowest SNR values at all filter levels. For example, in the lying condition, the SNR value increases from 5.32087 dB (RAW) to 10.8574 dB (4th order) before slightly decreasing to 10.409 dB (6th order), while in the walking condition, the SNR value from 3.85886 dB (RAW) increases to 9.02449 dB (4th order) before decreasing to 8.43422 dB (6th order).

Table 1. dB Value in the SNR Calculation Result.

Condition	RAW (dB)	Orde2 (dB)	Orde4 (dB)	Orde6 (dB)
Sit	5.2317	6.73281	10.1382	9.67221
Lie down	5.32087	7.44444	10.8574	10.409
Sit then stand	4.8467	6.46023	9.7763	9.18835
Walk	3.85886	5.66855	9.02449	8.43422
Upper motion	4.6565	7.05167	10.3855	9.80276

In the Excel graph visualization in FIGURE 10, the ECG signal results before the filtering process are displayed on the website.

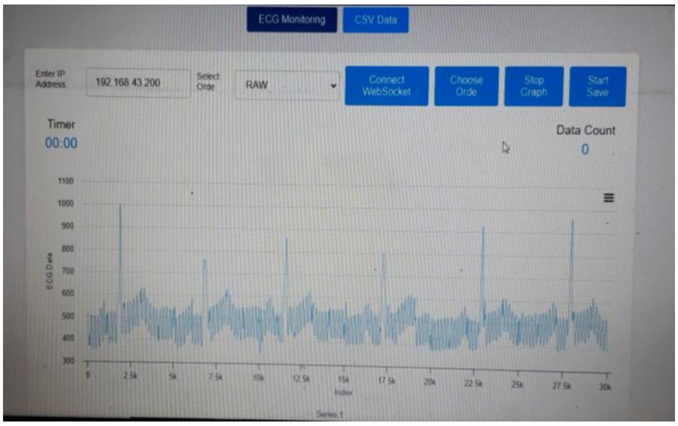

Figure 10. ECG Display on the Website Without Filtering Selection

In FIGURE 11, the graph visualization shows the ECG signal after being processed through a second-order filter, which can be selected using a filter order selector on the website.

Figure 11. ECG Display on the Website with Second-Order Filtering Selection

4. DISCUSSION

The Analysis of this study show that the use of higher order filters can generally increase the SNR value, which reflects the ability of the filter to reduce noise in the ECG signal. The increase in SNR value up to the 4th-order filter indicates that the filter at this order is able to optimally separate the signal from the noise without reducing the important information of the ECG signal. However, the decrease in SNR value at the 6th-order filter indicates the possibility of over-filtering, which may cause distortion or loss of important components in the signal. The lying condition produces the highest SNR value, indicating that body activities with little movement tend to provide a more stable ECG signal. In contrast, the walking condition had the lowest SNR value, reflecting the high level of noise due to motion artifacts.

When compared to the previous study by N. Sasirekh et al. in 2020, which focused on removing baseline wander and white noise using Neural Network-based filters, this study has the advantage of evaluating the effects of different types of body movements on ECG signals. The large number of motion types analyzed provides a more comprehensive picture of the impact of motion artifacts on ECG signal quality. However, the weakness of this study is that it focuses only on the effect of motion artifacts, without considering other types of noise such as baseline wander and white noise, which are also significant in the ECG signal acquisition process.

The implication of this study is the importance of selecting an appropriate filter order to improve ECG signal quality, especially in applications involving significant body motion, such as in holter monitoring or other portable devices. The results also suggest that the design of ECG signal processing systems should consider the type of user activity to minimize motion artifacts. In addition, this research opens up opportunities to develop adaptive or

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machine learning-based filters that are capable of handling different types of noise simultaneously, thereby improving the accuracy of ECG signal monitoring under real-world conditions.

5. CONCLUSION

This research aims to improve ECG signal quality by reducing noise, especially motion artifacts, using Butterworth digital filters integrated in an IoT-based system. The main focus of the research is to evaluate the effect of filter order on Signal-to-Noise Ratio (SNR) under various conditions of body activity, such as sitting, lying down, walking, and other movements, with the results directly displayed on a web platform.The results show that the use of higher order filters can increase the SNR value up to 4th order, which reflects optimization in separating signal from noise without losing important information. However, at the 6th order filter, there is a decrease in the SNR value which indicates the possibility of over-filtering, causing distortion or loss of important components of the signal. The lying condition provides the highest SNR value, indicating that body activity with little movement produces a more stable ECG signal. In contrast, the walking condition had the lowest SNR values, reflecting the significant impact of motion artifacts on signal quality.

There are several areas of further development in this research. For example, tests could be conducted to evaluate the effectiveness of different filter orders, or by combining IIR and FIR filters to achieve more optimal results. Future works include further development of this IoT-based system, such as the application of adaptive or machine learning-based filters to handle various types of noise simultaneously, including baseline wander, white noise, and motion artifacts. In addition, future research could extend the application of this system to wearable devices to improve user convenience, as well as enhance the real-time data analysis capabilities to support more accurate and rapid diagnosis via a web platform.

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p-ISSN: 1907-7904

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