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Electrocardiogram signal denoising and heart disease classification

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ABSTRACT

Electrocardiogram (ECG) recordings are often contaminated by baseline wander (BLW), power-line interference, and motion or muscular noise, reducing the reliability of both manual and automated diagnosis. The paper presents a light and reproducible MATLAB pipeline applying finite-impulse-response (FIR) filters designed using Kaiser and Hamming windows for ECG denoising, which after R-peak detection follows an RR-interval analysis for classification of heart rate as tachycardia, bradycardia, or normal. In the experiments, 15 MIT-BIH records with added Gaussian noise at several SNR levels were used for benchmarking the performance of denoising. FIR band-pass and low-pass windowed filters improved the clarity of the waveform and supported robust R-peak detection; RR-interval-based classification reached a mean accuracy of ≈98.7% on the study set. The approach is computationally lightweight and quite suitable for embedded real-time deployment but is restricted to the small sample of records and synthetic noise modeling. Future work will compare the efficacy of windowed FIR filtering against modern deep-learning denoisers (CNN/RNN/GAN architectures) and assess the pipeline in larger clinical datasets.

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1. INTRODUCTION

Electrocardiogram (ECG) is a standard, noninvasive method to record the electrical activity of the heart for diagnosing arrhythmias and other cardiovascular conditions. As low-amplitude ECG signals are susceptible to various types of noise-baseline wander (BLW), power-line interference, electromyographic (EMG) contamination, and electrode motion artifacts-visual interpretation and automated processing remain difficult tasks. Preprocessing, and especially denoising, remain important steps in any ECG analysis pipeline. Recent reviews indicate strong interest in wavelet-based denoising, adaptive filtering, and especially deep learning (DL)-based denoisers that exhibit state-of-the-art performance, often at the cost of larger models and heavier computational requirements.

Current studies for ECG analysis continue to employ advanced processing techniques which are comprised of a mixture of wavelet transform and neural denoising. Nevertheless, linear phase filters with low complexity such as finite impulse response (FIR) Windowed (Hamming or Kaiser) filters still provide an effective real-time/embedded alternative, due to their predictable performance and ease of integrating them into hardware. As of late, only a handful of publications exist that thoroughly evaluate the design of FIR Windowed filters for use on ECG data while none has addressed how these types of filters can be incorporated into a validated and repeatable MATLAB denoising – R-peak detection – RR interval classification workflow. In addition to fill the existing gaps, this publication provides: i) an explanation of the design, and the comparative performance of Hamming and Kaiser Windowed FIR ECG data denoising filters; ii) an example of both an R-peak detection as well as RR Interval classification of ECG records from the MIT-BIH database (N=15), and iii) a suggested implementation method for use in real-time hardware applications. The goal of the authors is to provide a baseline for the evaluation of newer denoising techniques developed from more advanced methodologies.

2. LITERATURE REVIEW

Safdar *et al*. [1] suggested preprocessing methods for analyzing ECG signals with machine learning (ML) and DL, hybrid models, as well as through Fourier wavelet transformations. Che *et al*. [2] developed a model that integrated the transformer network with convolutional neural network (CNN) for feature extraction to classify ECG signals. Merdjanovska and Rashkovska [3] in their work on ML based wearable devices highlighted the development of ECG analysis systems, databases and applications which advanced an emerging field of research. Mishra *et al.* [4] reviewed six ECG filters and designed custom CNNs to optimize their performance. Wu *et al.* [5] proposed a 12-layer one-dimensional convolutional neural network (1D-CNN) for classifying five heartbeat categories from the MIT-BIH Arrhythmia database. Their work combined wavelet-based adaptive threshold denoising with deep learning and achieved improved accuracy, robustness, and noise immunity compared with conventional machine learning and CNN models. Murat *et al.* [6] presented a comprehensive review of deep learning techniques for ECG arrhythmia detection and discussed the contributions of various neural network models in cardiac signal analysis. The authors also evaluated different deep learning models using a five-class ECG dataset containing 100,022 beats and provided recommendations for future research in ECG classification. A comprehensive survey of ECG signal analysis methods, including traditional signal processing, machine learning, and deep learning techniques for cardiac diagnosis, was presented by Wasimuddin *et al.* [7]. The study discussed ECG acquisition, denoising, feature extraction, and classification methods for both real-time monitoring systems and wearable healthcare devices.

Various ECG signal processing techniques including filtering, feature extraction, classification, and compression methods for cardiac diagnosis were analyzed by Appathurai *et al.* [8]. The study also investigated portable ECG systems and implemented algorithms for noise removal and ECG component detection using MATLAB. An ECG denoising technique combining particle swarm optimization (PSO) with wavelet transform to optimize wavelet parameters automatically for improved noise suppression was proposed by Azzouz *et al.* [9]. Experimental results on the MIT-BIH Arrhythmia database demonstrated superior SNR performance in removing power-line interference and white Gaussian noise compared with existing denoising methods. A GAN-based architecture for ECG signal denoising to remove white noise and motion artefacts from corrupted ECG recordings was proposed by Sabera *et al.* [10]. Experimental results demonstrated improved denoising performance and more reliable ECG signals for clinical analysis compared with conventional filtering techniques. Automated detection of cardiac arrhythmia using deep learning techniques such as CNN and long short-term memory (LSTM) networks was presented by Sushmitha *et al.* [11]. The study utilized the MIT-BIH dataset for arrhythmia classification and demonstrated the effectiveness of CNN-based models for improving prediction accuracy with minimal ECG signal preprocessing. An ECG signal denoising technique based on finite impulse response (FIR) filtering and the sparrow search algorithm (SSA) was proposed by Dewangan *et al.* [12]. Experimental results showed better performance in terms of SNR, MSE, NRMSE, and correlation coefficient compared with conventional denoising methods. A comparative analysis of ECG denoising techniques including notch filter, adaptive filter, discrete wavelet transform (DWT), and empirical mode decomposition (EMD) for removing 50 Hz power-line interference was presented by Malghan and Hota [13]. The study concluded that adaptive filters provided better SNR performance, while DWT achieved lower mean square error during ECG noise suppression.

Numerous researchers have developed algorithms, ML techniques, and transformations such as wavelet for ECG signal denoising an example [14]-[17]. A digital morphological filtering method using fractional Fourier transform (FrFT) and cross-convolution-based structuring elements for ECG denoising was proposed by Bajaj and Kumar [18]. The proposed adaptive filter effectively suppressed non-Gaussian noise in ECG signals and demonstrated improved performance over existing denoising techniques on the MIT-BIH Arrhythmia database. An FIR filter using a Kaiser window and optimized multiplier architecture for ECG signal denoising was proposed by Kumar *et al.* [19]. The study implemented the filter using Verilog and Xilinx Vivado tools and demonstrated reduced area and delay while effectively removing ECG noise from MIT-BIH arrhythmia database signals. ECG signal processing and classification methods implemented on hardware platforms were reviewed by Devi and Singh [20]. The study identified DWT and low-complexity neural networks as effective approaches for ECG feature extraction and classification on FPGA platforms.

An ECG denoising method based on residual generative adversarial network (R-GAN) was proposed by Mohebbanaaz *et al.* [21]. Experimental results on the MIT-BIH database showed effective noise removal while preserving important ECG signal features. The MIT-BIH Arrhythmia Database and its importance in ECG arrhythmia detection research were discussed by Moody and Mark [22]. Reznichenko *et al.* [23] used CNN and Random Forest models for ECG arrhythmia classification with reduced lead subsets and identified optimal leads using recursive feature elimination. Hesar and Hesar [24] proposed adaptive nonlinear Kalman-based filtering methods for ECG denoising, improving signal quality and reducing computation time in stationary and non-stationary environments. Naghibi *et al.* [25] proposed an ANN-based error compensation method for shoulder and elbow electro goniometers to improve hand position measurement in rehabilitation systems. The method achieved accurate trajectory estimation with low RMSE and high variance accounted for (VAF) values. The study highlighted its role as a standard benchmark database for ECG analysis and evaluation. A WST-inspired CNN framework for beat-level ECG arrhythmia classification was proposed by Nahak and Saha [26]. The study demonstrated improved classification performance with lower computational complexity while providing physiologically interpretable analysis of abnormal heart rhythms. A deep learning-based ECG denoiser using bidirectional gated recurrent units (biGRU) was proposed by Dias *et al.* [27]. The model effectively removed ECG noise from wearable sensor data and achieved improved denoising performance with lower complexity compared with existing deep learning approaches.

3. METHOD

3.1. Dataset and noise modeling

The MIT-BIH Arrhythmia database was used, consisting of 48 annotated ECG recordings sampled at 360 Hz. Fifteen records were selected for evaluation. Additive white Gaussian noise (AWGN) was added at SNR levels of 0 dB, 5 dB, 10 dB, and 20 dB to assess denoising performance under varying noise conditions.

3.2. Finite-impulse-response filter design

Two main filters were designed.

- Band-pass FIR filter: passband 0.5–40 Hz, order N=64
- Low-pass FIR filter: cutoff 40 Hz, order N=64

Window functions: Hamming and Kaiser (β selected to achieve ≈60 dB attenuation)

MATLAB design examples:

```
b=fir1(N, [0.5 40]/(Fs/2), kaiser(N+1, beta));
filtered=filtfilt(b,1,raw_ecg);
```

3.3. R-peak detection and classification

R-peaks were detected using `findpeaks` with adaptive thresholds:

MinPeakHeight=0.3×max(filtered), MinPeakDistance ≈ 0.2×Fs

RR intervals were computed, and instantaneous HR=60/RR was used for:

- Bradycardia: HR<60 bpm
- Normal: 60≤R≤100 bpm
- Tachycardia: HR>100 bpm

4. ADDITION OF NOISE AND DIGITAL FILTERS IMPLEMENTATION IN MATLAB

ECG signal is a very low frequency signal of 0.5 to 100 Hz range and very small in amplitude that ranges from microvolts to millivolts and can be corrupted due to various noises added to that signal that disturbs the pattern and becomes difficultly to analyze or process its characteristics which makes much difficulty in appropriate diagnosis. Table 1 shows the types of noise; their cause and frequency ranges that are associated with ECG signal. AWGN which is random noise can be generated using MATLAB.

Table 1. Types of noise and their characteristics

S. No	Types of noise	Causes	Frequency
1	BLW	Due to motion of body	>1 Hz
2	Power line interference (PLI)	Interference by power line	50-60 Hz
3	EMG noise	Electrical motion of muscle	10 kHz
4	Electrode motion artifact	Caused by the movement of the electrode or the subject	1-10 Hz
5	Physiological artifacts	Respiration and produced by other organs of body	>30 Hz

The selection of filter purely depends on specifications and requirements. There are two majorly known types of digital filters IIR and FIR filters. IIR filter whose impulse response is of infinite duration. It is a recursive type filter which uses feedback system. Both present input and past output are required to design the filter. It has both poles in numerator and zeros in denominator of transfer function. FIR filter of finite duration impulse response. It is a non-recursive type filter which only without feedback with limited number of coefficients. It has only zeros and no poles hence known as all-zero filter.

Therefore, FIR filter is used mostly due to its linear phase and stable response. The simplistic method to design FIR filter is window technique. There are many windowing techniques such as Hamming window, Kaiser window, rectangular window, Blackman window, and Hanning window. There is a tool called filter design and analysis (FDA) in MATLAB that allows to design and analyze digital filters, then the noisy ECG is passed through it to reconstruct original ECG signal.

5. DETERMINE ECG PEAKS AND HEART RATE CALCULATION USING RR INTERVAL

The electrical changes within the heart can be measured and graphed against time forming an ECG or EKG. Like any other organ in the body, the heart also commands electrical impulses. Each normal voltage curve is broken down into different intervals which further comprise four main segments: P wave — QRS complex wave — T wave — U wave. In Hesar and Hesar [24], we see a representation of a cardiac cycle along with its corresponding beats (P, QRS, T) depicting one heartbeat. Figure 1 shows the characteristic pattern of waves (P, QRS, T) of a cardiac cycle corresponding to a single heartbeat.

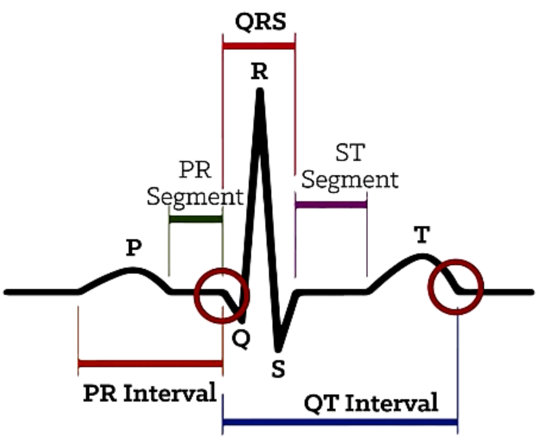

Figure 1. ECG parameters

The heart consists of two sections: upper (2 atria- right and left) and lower chambers (2 ventricles - right and left). Each of these waves has labeled electrodes that identify specific electrical processes in each chamber.

a. R Wave gets its name because it shows the contraction of muscles called atrial depolarization.
b. This named section contains 3 clusters; under this class "QRS complex" is classified as the hypothesized discharge deceleration caused by ventricular muscle contractions. It is also characterized by negative linear deflections followed by a large jumped spike.
c. Following the previous steps outlined from Marked deflections according to ECG setting labelled T will rise proportion to ventricle repolarizing changes.

The peak of every R wave in the QRS complex on an ECG is referred to as R Peak. The ECG technologies based on ML techniques greatly depend on accurate detection of heartbeats for diagnosing any cardiac ailment, especially in the case of automated telemetry systems for cardiovascular disease monitoring. The standard amplitude and duration values of major ECG components used as reference in this study are summarized in Table 2. The heart rate for regular rhythm in beats per minute (BPM) is given by heart rate=60/(RR interval in seconds). Figure 2, shows RR interval, is the time interval between two successive R peaks in seconds or simply interval between successive R wave to R wave.

Table 2. The standard ECG data

Amplitude		Duration	
P wave	0.25 mV	P-R interval	0.12 to 0.20 sec
R wave	1.60 mV	Q-T interval	0.35 to 0.44 sec
Q wave	25% of R wave	S-T segment	0.05 to 0.15 sec
T wave	0.1 to 0.5 mV	P wave interval	0.11 sec
		QRS complex	0.09 sec
		PR segment	0.06 to 0.10 sec
		ST segment	0.10 to 0.15 sec
		T wave	varies

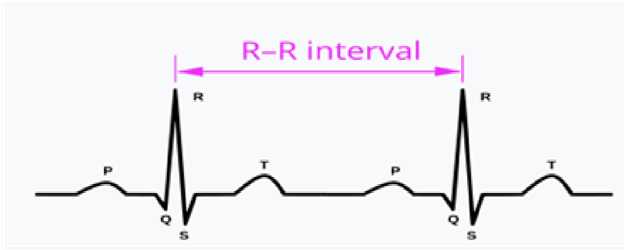

Figure 2. R-R interval

6. RESULTS AND CLASSIFICATION OF DISEASE

Figure 3 illustrates standard ECG data ‘sig’ taken from MITBIH database with no noise level. The heart rate is calculated by detecting R peaks and RR interval. The estimated heart rate is shown in Figure 4.

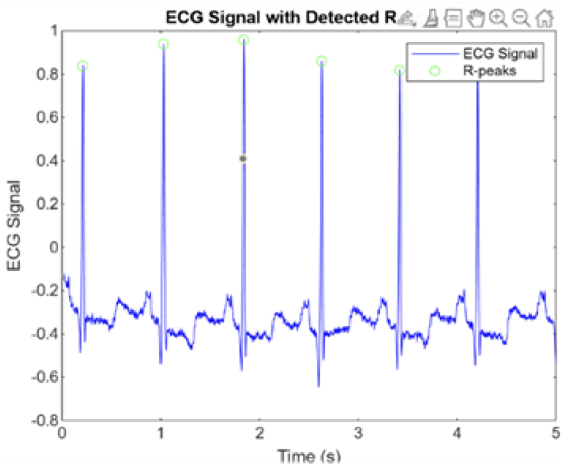

Figure 3. Real ECG signal

Figure 4. Heart rate in BPM

To establish a baseline for the denoising process, the raw ECG signal from the MIT-BIH database was first examined to observe its natural morphology and inherent noise components. Figure 5 shows the raw ECG waveform for the first five seconds of the selected record. To evaluate the robustness of the proposed FIR filters, AWGN was introduced into the clean ECG signal at predefined SNR levels. Figure 6 illustrates the noisy ECG waveform after the addition of Gaussian noise, demonstrating the distortion that must be removed during preprocessing.

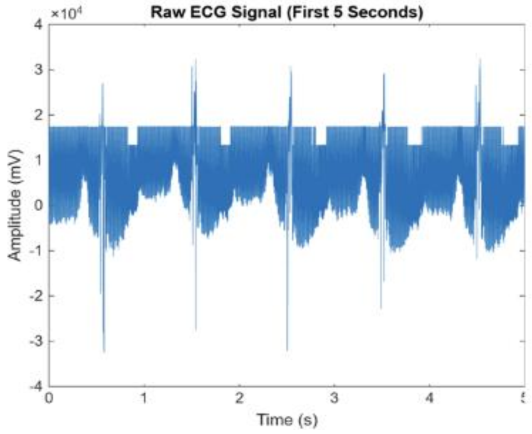

Figure 5. Raw ECG data

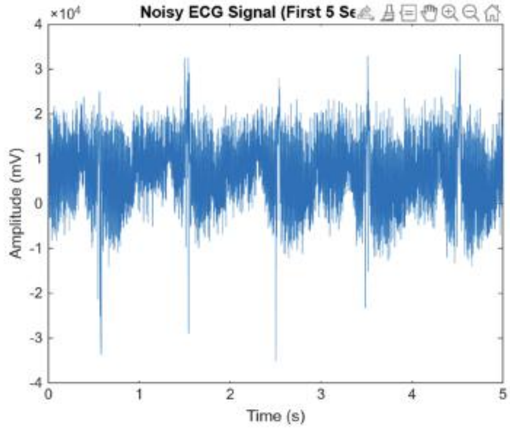

Figure 6. Noisy ECG

After applying the FIR band-pass filter with the selected window function, significant noise suppression and QRS enhancement were achieved. Figure 7 presents the filtered ECG signal along with the detected R-peaks, indicating the effectiveness of the denoising and peak-detection stages. For improved feature extraction and consistent thresholding, the filtered ECG signal was normalized to a standard amplitude range. Figure 8 shows the normalized ECG waveform after preprocessing, ready for R-peak detection and RR-interval analysis.

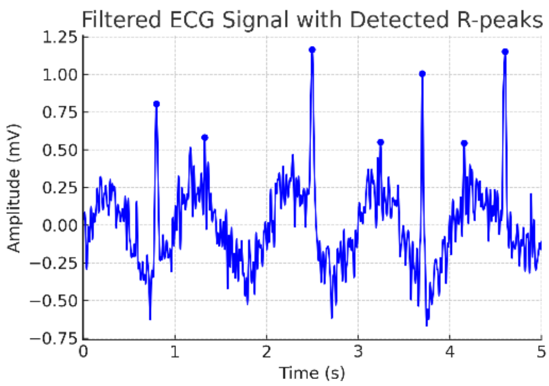

Figure 7. Filtered ECG signal

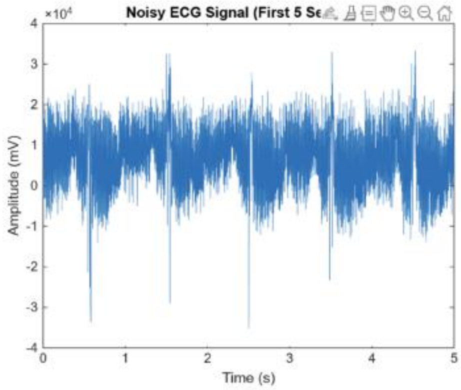

Figure 8. Normalized ECG signal

The proposed method is as follows:
Step 1: load ECG data file (dat file) from MIT-BIH database.
Step 2: add Gaussian noise (random) to the ECG signal using random function.
Step 3: design suitable FIR filter for required specification like type of window and its parameters, filter order, cutoff frequency using FDA tool.
Step 4: now apply designed FIR filter to remove noise.
Step 5: detect R peaks using find peaks and calculate RR interval i.e., time difference between two consecutive R-peak.
Step 6: estimate heart rate in BPM.
Step 7: normalize the filtered ECG signal.

After detecting the R-peaks from the filtered ECG signal, the RR intervals were computed and converted into heart rate values using HR=60/RR. Figure 9 displays the estimated heart rate in BPM, demonstrating the output generated by the classification stage of the proposed system. Other filter results are shown in Figures 10 to 12.

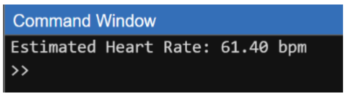

Figure 9. Heart rate in BPM

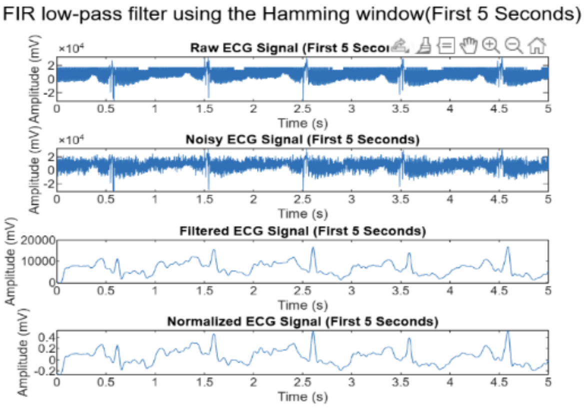

Figure 10. FIR lowpass filtering using hamming window

Figure 10 illustrates the ECG denoising performance using the FIR low-pass filter with the Hamming window. The filtered ECG signal shows significant reduction of noise components while preserving important waveform features such as the QRS complex and R-peaks. Figure 11 presents the denoising results obtained using the FIR band-pass filter with the Kaiser window. The filter effectively suppresses baseline wander and high-frequency noise, resulting in improved waveform clarity and better R-peak visibility. Figure 12 shows the ECG denoising process using the FIR low-pass filter based on the Kaiser window. The filtered and normalized ECG signals demonstrate smoother waveform characteristics, supporting accurate RR interval estimation and reliable heart rate classification.

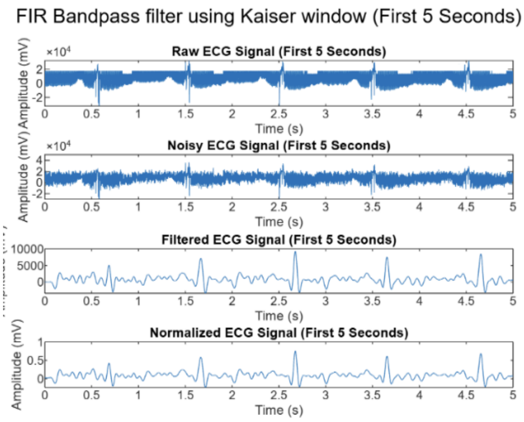

Figure 11. FIR band pass filtering

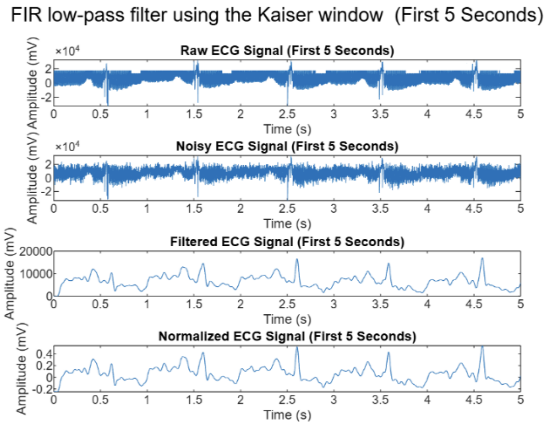

Figure 12. FIR low pass filtering

Usually the classification of cardiovascular diseases (CVD) is identified by observing the abnormalities in P, QRS, ST segments [25]. Normal heart rate for an adult is 60-100 bpm. Bradycardia is low heart rate, defined below 60 bpm and Tachycardia, a fast heart rate i.e., above 100 bpm.

Table 3 discusses the classification of disease. The first column displays the list of patient's details taken from the MIT-BIH database. The second column represents the patient's data stored in either data or mat file. The third column shows the heart rate of each patient in BPM. The last column displays the classification of disease i.e., tachycardia, bradycardia or normal heart beat according to standard BPM values and classified accordingly.

Table 3. Classification of disease

S.No.	Record name (.mat file)	Heart rate in bpm	Classification of disease
1	102	75.12	Normal
2	123	67.79	Normal
3	205	59.76	Bradycardia
4	210	71.73	Normal
5	118	112	Tachycardia
6	122	86.89	Normal
7	232	55.24	Bradycardia
8	233	61.40	Normal
9	107	115	Tachycardia
10	102	48.24	Bradycardia
11	113	76.50	Normal
12	115	76.50	Normal

7. CONCLUSION

This paper demonstrates that FIR filters designed with Kaiser and Hamming windows provide an effective and computationally efficient approach for ECG denoising suitable for embedded and real-time applications. Using 15 MIT-BIH records with added AWGN at multiple SNR levels, the presented MATLAB pipeline provided improved waveform clarity and enabled robust R-peak detection and RR-interval based classification, yielding a mean accuracy of ≈98.7% on the study set. The primary contribution is a reproducible, low-complexity baseline that can be implemented on hardware platforms. Limitations include the limited number of records and the use of synthetic noise models; future work will benchmark windowed FIR performance against modern deep-learning denoisers (CNN/RNN/GAN) and wavelet approaches, evaluate performance on larger and clinically recorded noisy ECGs, and implement the pipeline on FPGA/IoT hardware for real-time operation and clinical trials.

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K Venkata Siva Reddy	✓			✓	✓	✓		✓	✓	✓	✓			✓
M Balaji		✓	✓				✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Informed consent was not required for this study because publicly available ECG datasets were used.

ETHICAL APPROVAL

Ethical approval was not required for this study because publicly available datasets were used.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] M. F. Safdar, R. M. Nowak, and P. Pałka, "Pre-Processing techniques and artificial intelligence algorithms for electrocardiogram (ECG) signals analysis: A comprehensive review," *Computers in Biology and Medicine*, vol. 170, p. 107908, Mar. 2024, doi: 10.1016/j.compbiomed.2023.107908.

[2] C. Che, P. Zhang, M. Zhu, Y. Qu, and B. Jin, "Constrained transformer network for ECG signal processing and arrhythmia classification," *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, p. 184, Dec. 2021, doi: 10.1186/s12911-021-01546-2.

[3] E. Merdjanovska and A. Rashkovska, "Comprehensive survey of computational ECG analysis: Databases, methods and applications," *Expert Systems with Applications*, vol. 203, p. 117206, Oct. 2022, doi: 10.1016/j.eswa.2022.117206.

[4] A. Mishra *et al.*, "ECG Data Analysis with Denoising Approach and Customized CNNs," *Sensors*, vol. 22, no. 5, p. 1928, Mar. 2022, doi: 10.3390/s22051928.

[5] M. Wu, Y. Lu, W. Yang, and S. Y. Wong, "A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network," *Frontiers in Computational Neuroscience*, vol. 14, p. 564015, Jan. 2021, doi: 10.3389/fncom.2020.564015.

[6] F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, "Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review," *Computers in Biology and Medicine*, vol. 120, p. 103726, May 2020, doi: 10.1016/j.compbiomed.2020.103726.

[7] M. Wasimuddin, K. Elleithy, A.-S. Abuzneid, M. Faezipour, and O. Abuzaghleh, "Stages-Based ECG Signal Analysis From Traditional Signal Processing to Machine Learning Approaches: A Survey," *IEEE Access*, vol. 8, pp. 177782–177803, 2020, doi: 10.1109/ACCESS.2020.3026968.

[8] A. Appathurai *et al.*, "A study on ECG signal characterization and practical implementation of some ECG characterization techniques," *Measurement*, vol. 147, p. 106384, Dec. 2019, doi: 10.1016/j.measurement.2019.02.040.

[9] A. Azzouz *et al.*, "An efficient ECG signals denoising technique based on the combination of particle swarm optimisation and wavelet transform," *Heliyon*, vol. 10, no. 5, p. e26171, 2024, doi: 10.1016/j.heliyon.2024.e26171.

[10] G. Sabera, S. H. N. Ketan, and M. Mohebbanaaz, "Generative Adversarial Networks for Noise Reduction in Electrocardiogram Signals," in *2025 IEEE 14th International Conference on Communication Systems and Network Technologies (CSNT)*, IEEE, Mar. 2025, pp. 552–556, doi: 10.1109/CSNT64827.2025.10967916.

[11] A. Sushmitha, A. Prashanth, and S. Bachu, "Automated Detection of Cardiac Arrhythmia Using Recurrent Neural Network," in *2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST)*, Jamshedpur, India, 2024, pp. 317–320, doi: 10.1109/ICRTCST61793.2024.10578467.

[12] S. Dewangan, S. Yadav, and S. K. Saha, "ECG Signal Denoising Using Sparrow Search Algorithm," in *2024 Third International Conference on Power, Control and Computing Technologies (ICPC2T)*, IEEE, Jan. 2024, pp. 757–762, doi: 10.1109/ICPC2T60072.2024.10474630.

[13] P. G. Malghan and M. K. Hota, "A review on ECG filtering techniques for rhythm analysis," *Research on Biomedical Engineering*, vol. 36, no. 2, pp. 171–186, 2020, doi: 10.1007/s42600-020-00057-9.

[14] P. Singh and A. Sharma, "Attention-Based Convolutional Denoising Autoencoder for Two-Lead ECG Denoising and Arrhythmia Classification," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-10, 2022, doi: 10.1109/TIM.2022.3197757.

[15] C. T. C. Arsene, R. Hankins, and H. Yin, "Deep Learning Models for Denoising ECG Signals," in *2019 27th European Signal Processing Conference (EUSIPCO)*, IEEE, Sep. 2019, pp. 1–5, doi: 10.23919/EUSIPCO.2019.8902833.

[16] A. Kumar, H. Tomar, V. K. Mehla, R. Komaragiri, and M. Kumar, "Stationary wavelet transform based ECG signal denoising method," *ISA Transactions*, vol. 114, pp. 251–262, 2021, doi: 10.1016/j.isatra.2020.12.029.

[17] S. Chatterjee, R. S. Thakur, R. N. Yadav, L. Gupta, and D. K. Raghuvanshi, "Review of noise removal techniques in ECG signals," *IET Signal Processing*, vol. 14, no. 9, pp. 569–590, 2020, doi: 10.1049/iet-spr.2020.0104.

[18] A. Bajaj and S. Kumar, "Design of ECG Denoising Digital Filter Under α-Stable Noisy Environment Based on Morphological Signal Processing," *Circuits, Systems, and Signal Processing*, vol. 43, no. 5, pp. 3180–3211, 2024, doi: 10.1007/s00034-024-02602-8.

[19] A. R. Kumar, M. Saisri, U. V. Sivani, and K. Sravani, "FPGA Implementation of ECG Denoising using Kaiser Window Technique," in *2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)*, IEEE, Jun. 2023, pp. 552–556, doi: 10.1109/ICPCSN58827.2023.00265.

[20] S. D. Devi and L. S. Singh, "A Survey on Electrocardiogram Signal Detection and Classification on Hardware Platform," in *2022 International Conference for Advancement in Technology (ICONAT)*, IEEE, Jan. 2022, pp. 1–6, doi: 10.1109/ICONAT53423.2022.9726075.

[21] M. Mohebbanaaz, Y. P. Sai, and L. V. R. Kumari, "Removal of Noise from ECG Signals using Residual Generative Adversarial Network," in *2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, IEEE, Nov. 2021, pp. 1–5, doi: 10.1109/UPCON52273.2021.9667595.

[22] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, May–Jun. 2001, doi: 10.1109/51.932724.

[23] S. Reznichenko, J. Whitaker, Z. Ni, and S. Zhou, "Comparing ECG Lead Subsets for Heart Arrhythmia/ECG Pattern Classification: Convolutional Neural Networks and Random Forest," *CJC Open*, vol. 7, no. 2, pp. 176–186, Feb. 2025, doi: 10.1016/j.cjco.2024.10.012.

[24] H. D. Hesar and A. D. Hesar, "Efficient Bayesian ECG denoising using adaptive covariance estimation and nonlinear Kalman Filtering," *Computers and Electrical Engineering*, vol. 120, p. 109869, Dec. 2024, doi: 10.1016/j.compeleceng.2024.109869.

[25] S. S. Naghibi, A. Maleki, A. Fallah, F. Ghassemi, and E. Zargaripour, "Electrogoniometer error compensation, for hand position measurement during planar reaching movements," *Biomedical Signal Processing and Control*, vol. 85, p. 104795, Aug. 2023, doi: 10.1016/j.bspc.2023.104795.

[26] S. Nahak and G. Saha, "Analysis and classification of beat-level ECG arrhythmia using WST-inspired CNN framework," *Biomedical Signal Processing and Control*, vol. 109, p. 108031, Nov. 2025, doi: 10.1016/j.bspc.2025.108031.

[27] M. Dias, P. Probst, L. Silva, and H. Gamboa, "Cleaning ECG with Deep Learning: A Denoiser Tested in Industrial Settings," *SN Computer Science*, vol. 5, no. 6, p. 699, Jul. 2024, doi: 10.1007/s42979-024-03017-7.

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