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# CLASSIFICATION AND PREDICTION OF ECG MORPHOLOGY AND INTERVALS FEATURES

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**Abstract-** For the identification and diagnosis of numerous heart-related disorders, ECG signals are frequently employed. A recent application that is expanding quickly at the moment is feature extraction using ECG. A multitude of factors, including baseline wander interference, motion artefact, equipment noise, electrode contact noise, EMG noise, and others can contaminate the ECG signal as it is being acquired. Kaiser, Rectangle, Hamming, Hanning, and Welch windows were used. MSE, SNR, Positive Peak, and THD performance measures for power line interference, muscle noise, and EMG noise were used to analyse and compare the output. This study provides an ideal ECG noise elimination windowing system that determines which window should be used for a specific noise type.

**Abbreviations:** ECG: Electro cardio graphy; MSE: Mean Square Error; SNR: Signal to Noise Ratio; THD: Total Harmonic Distortion.

## I. INTRODUCTION

The vast majority of systems nowadays undertake signal processing for ECG analysis and interpretation. ECG signal processing aims to extract information from the signal that isn't immediately visible through visual analysis, as well as to increase measurement accuracy and reproducibility (as compared to manual measurements). The ECG is frequently taken while the patient is moving around or exerting themselves to the point that the signal is distorted by various sorts of noise, sometimes coming from another physiological activity of the body.

As a result, noise reduction is a key goal of ECG signal processing. In certain cases, noise masks the waveforms of interest so completely that their presence cannot be detected until the right signal processing has been used. For the objective of finding sporadic disruptions in the heart rhythm, electrocardiographic data may be captured over an extended period of time (i.e., many days). The resulting ECG recording has enormous data volumes as a result, quickly using up storage space [1–5].

## II. HEART

The cardiovascular system's main organ, the heart, is situated in the mediastinum. It is shielded by the rib cage, the spinal column, and the bone elements of the sternum in that order. The main cardiac pacemaker, known as the Sinoatrial (SA) node, is situated in the upper part of the right atrium. Its intrinsic rate ranges from 60 to 100 bpm. The AV node is a component of the AV junctional tissue. Conduction is slowed, and this causes a little delay before impulses reach the ventricles. Its intrinsic rate ranges from 40 to 60 bpm [6-9].

The heart is a muscular organ that circulates oxygenated blood throughout the body. It draws in the dirty, anaemic blood from the veins and pushes it to the lungs where it is cleaned up. The heart is located posterior to the sternum and medial to the lungs in the thoracic cavity. The heart is divided into four chambers: the right atrium, left atrium, right ventricle, and left ventricle. The heart also contains several atrioventricular and sinoatrial nodes.

The human heart's blood flow is shown in Fig. 1.1. Whereas the left and right ventricles are located in the lower chamber of the heart, the left and right atria are located in the upper chamber. The fibrous, non-conductive tissue that connects the ventricles to the atria keeps the ventricles and atria electrically separated from one another. Large veins like the superior and inferior vena cava take in deoxygenated blood, which then enters the right atrium. Blood is forced into the right ventricle as a result of the right atrium contracting. The ventricle is stretched at this point, maximising the effectiveness of its contraction (pump).

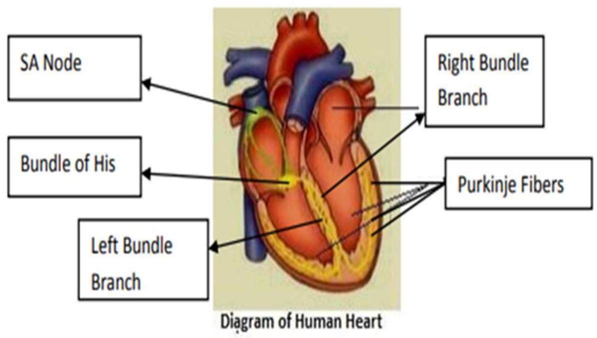



Fig.1. Conduction System structure [10].

The Phases of the Heart The cardiac cycle contains two stages [10].

Systole: The blood-filled ventricles start to contract. The tricuspid and mitral valves shut (between atria and ventricles). Via the pulmonic and aortic valves, blood is expelled.

Diastole: Blood enters the atria and travels via the ventricles' open mitral and tricuspid valves.

## III. CONTRIBUTION IN THE PAPER

The study of the ECG signal for the categorization of heartbeats is the subject of this thesis. The thesis' main contributions may be summed up as follows:

• A novel feature extraction method based on the Stock well transform is proposed (S-transform). Since it can characterise temporal frequency information, the wavelet transform is typically utilised as a feature extraction approach for ECG beat categorization. For the study of ECG signal, the wavelet interpretation might occasionally be counterintuitive. It can only probe the power or amplitude spectrum in the immediate area.

One will still be required to search for the effects of a local event even if it just affects the low frequency portion of the ECG signal. It will be challenging to interpret an ECG signal using a wavelet-based technique. The non-adaptive nature of wavelet analysis presents another challenge. Once the fundamental wavelet has been chosen, all the ECG data must be examined using it. In order to address the aforementioned shortcomings of the wavelet transform, the S-transform based feature extraction approach is developed in this study.

The frequency invariant amplitude response, the progressive resolution, and the absolutely referenced phase data Moreover, ST displays the signal in the time-frequency domain as opposed to WT's time-scale axis. As a result, it is simpler to analyse the frequency information in the ST than it is in the WT.

## IV. SPECTRUM ANALYSIS

## SIGNAL PROCESSING AND TIME–FREQUENCY ANALYSIS

Time-frequency analysis in signal processing refers to methods that analyse a signal concurrently in the time and frequency domains utilising a variety of time-frequency representations. Time-frequency analysis examines a two-dimensional signal, a function whose domain is the two-dimensional real plane, obtained from the signal via a time-frequency transform, as opposed to viewing a 1-dimensional signal (a function, real or complex-valued, whose domain is the real line) and some transform (another function whose domain is the real line, obtained from the original via some transform). [11] [12]

The mathematical justification for this research is that since functions and the representation of their transforms are closely related, it is easier to understand them when they are studied together as a two-dimensional entity. Consider the Fourier transform as a 90° rotation in the associated time-frequency plane. Four such rotations yield the identity, and two such rotations simply reverse direction. This illustrates the 4-fold periodicity of the Fourier transform and the fact that the two-fold Fourier transform reverses direction (reflection through the origin).

While every slowly increasing locally integrable signal may have its frequency spectrum obtained using the Fourier transform technique, this method necessitates a detailed description of the signal's behaviour across time. In fact, one may consider points in the (spectral) frequency domain as combining data from all over the time domain. Even though it is mathematically beautiful, this method is not suitable for studying signals with uncertain future behaviour. For instance, to achieve non-zero entropy in any communication system, one must assume some level of uncertain future behaviour (if one already knows what the other person will say one cannot learn anything).

## FORMULATIONS

The formulation of a valid time-frequency distribution function can take a variety of forms, giving rise to a number of well-known time-frequency distributions, including:

- Short-time Fourier transform (including the Gabor transform),
- Wavelet transform,
- Bilinear time–frequency distribution function (Wigner distribution function, or WDF),
- Modified Wigner distribution function, Gabor–Wigner distribution function, and so on (see Gabor–Wigner transform).
- Hilbert–Huang transform

## PRE-PROCESSING

For the construction of digital filters like the Finite Duration Unit Pulse Response (FIR) filter, window approaches are frequently utilised. One method effectively used to treat ECG data for measurement and noise reduction is the FIR filter[6]. The influence of a system on the input signal may be represented in both the time domain and the frequency domain. They are used to change the biosignal by reducing noise. It is not always possible to investigate all the properties of ECG signals using the time domain approach of signal analysis. As a result, a signal's frequency representation is necessary. Filters are therefore created in the frequency domain [13].

For the ECG signal in this case, we are utilising Kaiser Window and a rectangle window.

One or more types of noise or artefacts, such as power-line interference, baseline drift, electrode motion artefact, data-collection device noise, and electromyogram (EMG) noise caused by motion artefacts and muscle contraction, frequently interfere with the ECG signal during recording [14],[15]. The ECG signal's value is most significantly impacted by EMG noise.

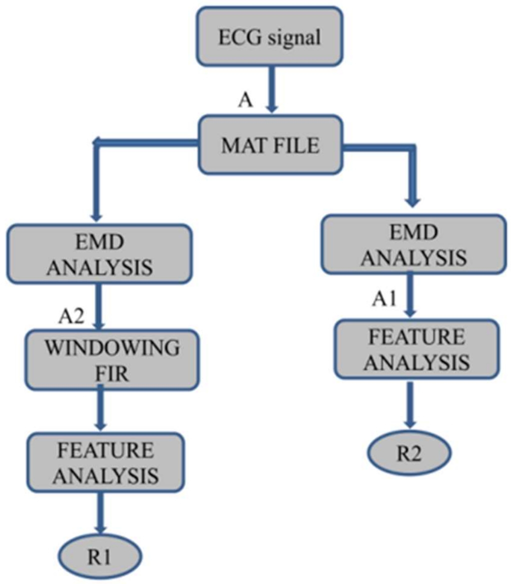



Fig. 2. Flow chart of proposed algorithm.

**Basic Steps to Solve Sliding Window Problem**

With this technique, we can quickly calculate things with defined computation windows and obtain the results more efficiently than with nested loops (naive approach). This algorithm's primary objective is to utilise the result from one window to calculate the result from the following window.

Suppose there is a group of friends of 12 people and they decided to party together but the major concern is who is going to throw that treat. After a lot of discussion among them, they concluded that they are sitting at a round table and the group of three who is sitting adjacent to each other and had the sum of age of every member of that group is maximum among other groups of the same size will pay the bill.

## V. PROPOSED METHODOLOGY/ ALGORITHM- SIDING WINDOW

Number your figures in the following order: Controlling transmitted data and spotting anomalies in discrete signals are two applications of the sliding window approach in discrete time signal processing. Let's have a look at a discrete time signal with length N, where x(n) = x(1), x(2),... x(N) [13]. A group of sub signals of length q, with the maximum amount of unexpected morphological changes in terms of the anomaly score, are what the sliding window aims to produce. A sliding window of length q passes through the time signal to produce a series of sub signals for this purpose. M sub signals as a result of this take the form of

X1= {x11, x12, x13,……………………..x1q}
X2= {x21, x22, x23,……………………..x2q}
..
..
..
XM= {xM1, xM2, xM3,…………………xMq}

Consider a window with a length of n and a pane that is fixed in it with a length of k to better understand the sliding window approach. Take into account that the pane is originally at the very left, or 0 units from the left. Now, tie the window to the n-element array arr[] and the pane to the k-element current sum. If we now exert force on the window, it will move a unit of distance forward. The following k components will be covered by the pane.

**Applying sliding window technique:**

1. Using a linear loop, we sum the first k terms out of n terms and store the result in the variable window sum.
2. After that, we shall linearly scan the array to the end while monitoring the largest sum.
3. Subtract the first element from the previous block and add the final element of the current block to obtain the current total of a block of k items.

Classification

A supervised machine learning approach called "Support Vector Machine" (SVM) may be applied to classification or regression problems. Yet, categorization issues are where it is most frequently utilised. While using the SVM algorithm, each data point is represented as a point in n-dimensional space (where n is the number of features you have), with each feature's value being the value of a certain coordinate. Then, we do classification by identifying the hyper-plane that effectively distinguishes the two classes.

## VII. RESULT AND SIMULATION

The dataset utilised in this investigation was compiled by CSE and the online MIT-BIH Arrhythmia Database[12]. The nearly 4000 long-term Holter recordings that were acquired by the Arrhythmia Laboratory are the source of the ECGs included in the MIT-BIH Arrhythmia Database. Sixty percent of these recordings came from patients who were admitted [12].

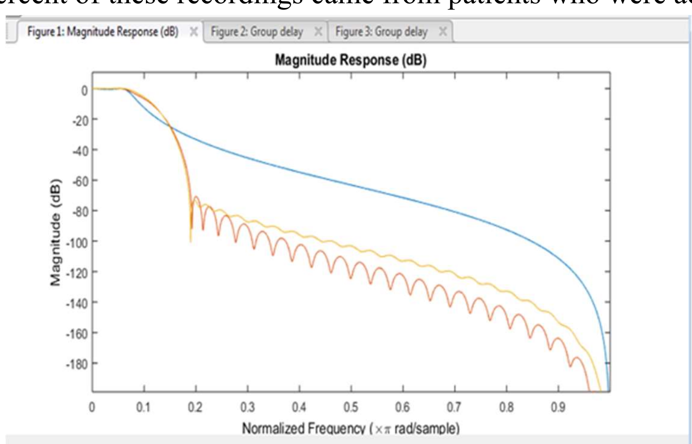



Fig. 3. Magnitude and Frequency curve.

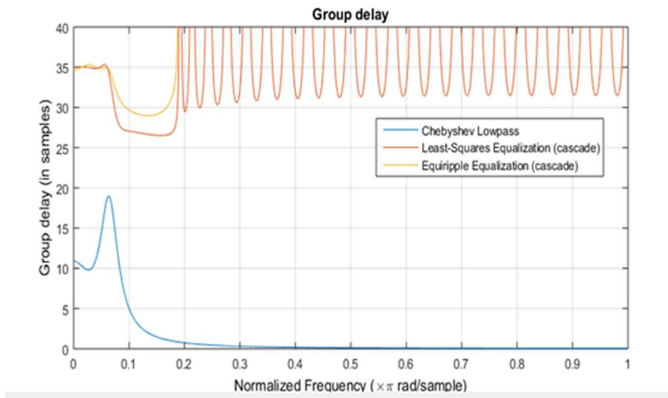



Fig. 4. Group Delay and Frequency Curve.

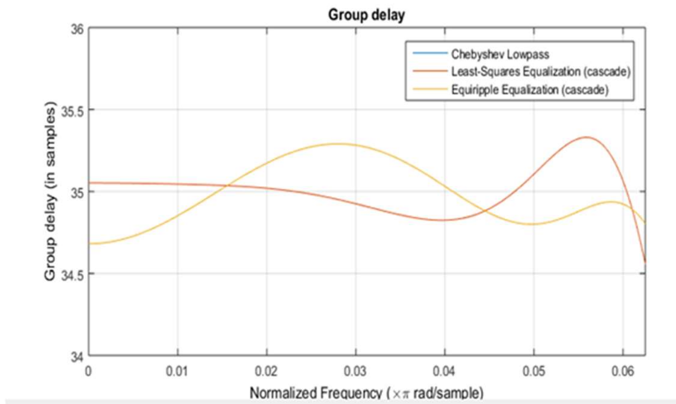
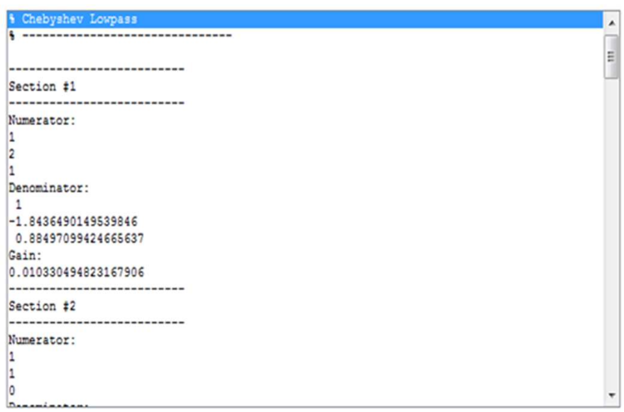



Fig. 5. Group Delay and  Normalized Frequency Curve.



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% Chebyshev Lowpass
% ------------------------------

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Section #1
-------------------------
Numerator:
1
2
1
Denominator:
 1
-1.8436490149539846
 0.8849709942466563 7
Gain:
0.01033049482316790 6
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Section #2
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Numerator:
1
1
0
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Fig. 6.Properties.

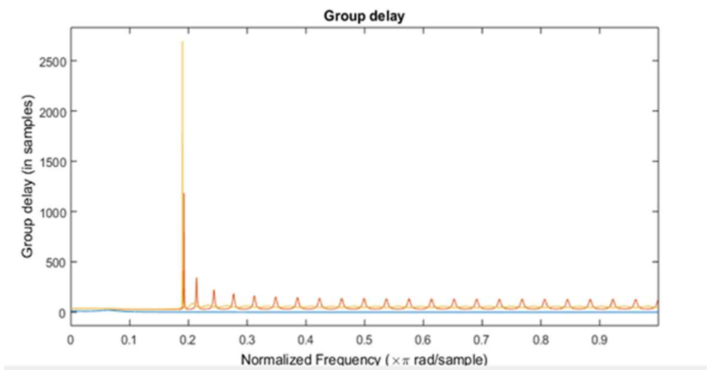


Fig. 7. Group Delay sample and Normalized Frequency Spectrum density.

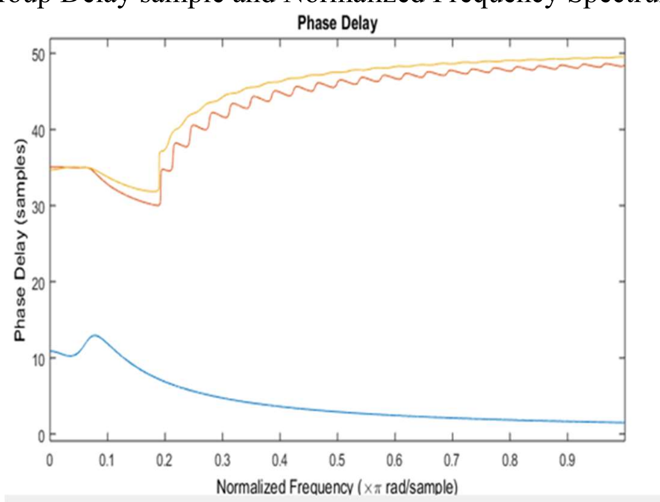


Fig. 8. Group Delay Sample rate.

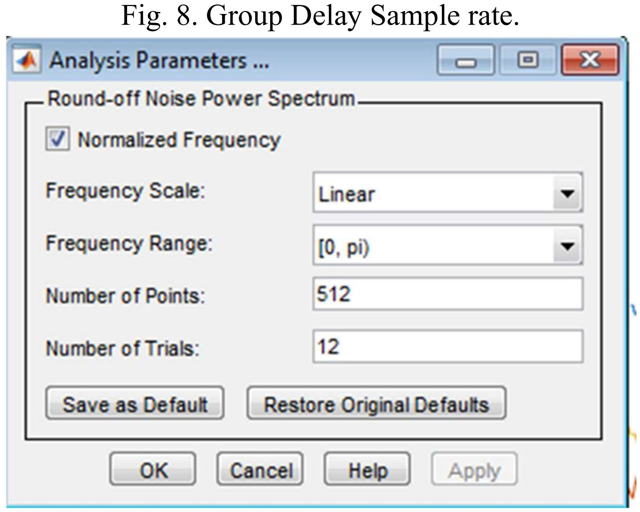


Fig. 9. Properties.

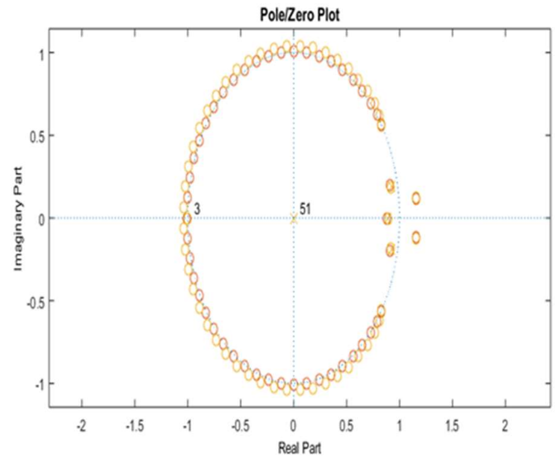


Fig. 10. Zero and Pole.

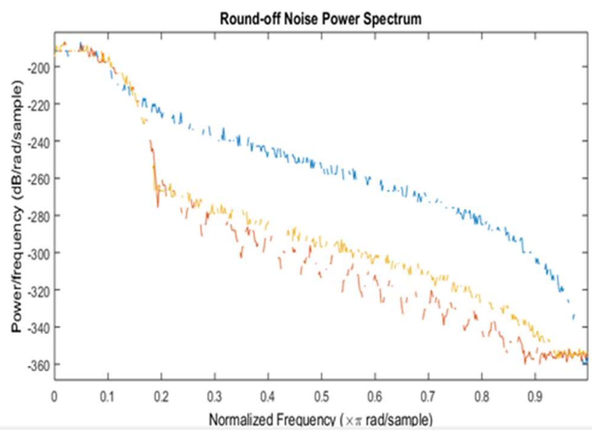


Fig. 11. Noise Power spectrum.

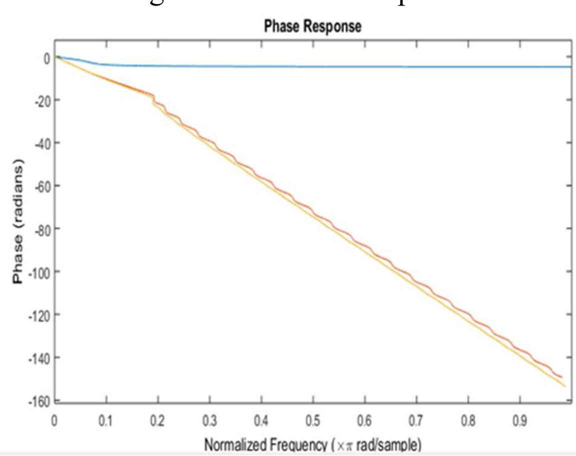


Fig. 12. Phase Response.


Fig. 13. Step Response.

## VIII. CONCLUSION

In order to reduce noise in the ECG signal, several windowing techniques are used in this research. Kaiser, Rectangle, Hamming, Hanning, and Welch windows were among the several windowing techniques utilised, while performance metrics including MSE, SNR, Positive Peak, and THD were used to assess output. It was discovered during the research of power line noise that Kaiser window performed the best out of all the selected performance characteristics. Closely following this came the Rectangle window, which similarly performed well across the board with the exception of SNR. Hence, in general, it can be claimed that the removal of power line noise from the ECG data was successfully accomplished by both Kaiser and Rectangle window.

Hanning window performance was good when THD was particularly taken into account. The analysis of muscle noise revealed that Kaiser and Rectangle window produced the best results for all the selected performance factors. Hamming window has striking similarities to both of these windows, particularly rectangular window. The three windows are effective in removing muscle noise from the ECG data, it might be said. Hence, any of these three windows can be taken into account depending on the application. Rectangle window and Kaiser window both produced adequate results while analysing an ECG signal that had been impacted by EMG noise. This suggests that, contrary to the pattern in the other two noises, Rectangle window is favoured over Kaiser window for reducing EMG noise from ECG data.

Further potential applications of this study include further system parameter optimization for each of these windows. Wavelet denoising technique can also be taken into consideration. The possibility exists for real-time systems.

## REFERENCE

[1] FatemehAfghah , ECG Language processing (ELP): A new technique to analyze ECG signals, Computer Methods and Programs in Biomedicine, Volume 202, April 2021, 105959, https://doi.org/10.1016/j.cmpb.2021.105959.

[2] Arun KumarSangaiah, An intelligent learning approach for improving ECG signal classification and arrhythmia analysis, Artificial Intelligence in Medicine, Volume 103, March 2020, 101788, DOI: 10.1016/j.artmed.2019.101788

[3] V.Gupta, A Comparison of ECG Signal Pre-processing Using FrFT, FrWT and IPCA for Improved Analysis, IRBM, Volume 40, Issue 3, June 2019, Pages 145-156, https://doi.org/10.1016/j.irbm.2019.04.003.
[4] Hemant Amhia, Stability and Phase Response Analysis of Optimum Reduced-Order IIR Filter Designs for ECG R-Peak Detection, Journal of Healthcare Engineering 2022(2):1-14, DOI:10.1155/2022/9899899.
[5] GeWang, ECG signal denoising based on deep factor analysis, Biomedical Signal Processing and Control, Volume 57, March 2020, 101824, https://doi.org/10.1016/j.bspc.2019.101824.
[6] DezhaoJiao, The chaotic characteristics detection based on multifractal detrended fluctuation analysis of the elderly 12-lead ECG signals, Physica A: Statistical Mechanics and its Applications, Volume 540, 15 February 2020, 123234, https://doi.org/10.1016/j.physa.2019.123234.
[7] PrashantKumar, Time-domain HRV Analysis of ECG Signal under Different Body Postures, Procedia Computer Science, Volume 167, 2020, Pages 1705-1710, https://doi.org/10.1016/j.procs.2020.03.435.
[8] HimaliSingh, Detection of sleep apnea from heart beat interval and ECG derived respiration signals using sliding mode singular spectrum analysis, Digital Signal Processing, Volume 104, September 2020, 102796, https://doi.org/10.1016/j.dsp.2020.102796.
[9] Y.S.Alshebly, Isolation of Fetal ECG Signals from Abdominal ECG Using Wavelet Analysis, IRBM, Volume 41, Issue 5, October 2020, Pages 252-260, https://doi.org/10.1016/j.irbm.2019.12.002.
[10] WeijieWang, Revisiting signal processing with spectrogram analysis on EEG, ECG and speech signals, Future Generation Computer Systems, Volume 98, September 2019, Pages 227-232, https://doi.org/10.1016/j.future.2018.12.060.
[11] MaheshChandra, Design and analysis of improved high-speed adaptive filter architectures for ECG signal denoising, Biomedical Signal Processing and Control Volume 63, January 2021, 102221, https://doi.org/10.1016/j.bspc.2020.102221.
[12] PéterKovác, Diagnostic quality assessment for low-dimensional ECG representations, Computers in Biology and Medicine Volume 150, November 2022, 106086, https://doi.org/10.1016/j.compbiomed.2022.106086.
[13] AmulyaAgrawal, ECG-iCOVIDNet: Interpretable AI model to identify changes in the ECG signals of post-COVID subjects, Computers in Biology and Medicine Volume 146, July 2022, 105540, https://doi.org/10.1016/j.compbiomed.2022.105540.
[14] A.S.A.Huque, HMM-based Supervised Machine Learning Framework for the Detection of fECG R-R Peak Locations, IRB Volume 40, Issue 3, June 2019, Pages 157-166, https://doi.org/10.1016/j.irbm.2019.04.004.
[15] Abel JD, Krupa D, Samiappan R, Kumar, Pravin Kumar S (2019) Multiple sub-filter adaptive noise canceller for fetal ECG extraction. Procedia Comput Sci 165:182–188. https://doi.org/10.1016/j.procs.2020.01.093.
[15] U.R. Acharya, S.L. Oh, Y. Hagiwara, J.H. Tan, M. Adam, A. Gertych, R. San Tan, A deep convolutional neural network model to classify heartbeats, Comput. Biol. Med. 89 (2017) 389–396.

[16] M. Kachuee, S. Fazeli, M. Sarrafzadeh, Ecg heartbeat classification: A deep transferable representation, in: 2018 IEEE International Conference on Health- care Informatics (ICHI), IEEE, 2018, pp. 443–444.
[17] S. Mousavi, A. Fotoohinasab, F. Afghah, Single-modal and multi-modal false ar-rhythmia alarm reduction using attention-based convolutional and recurrent neural networks, PLoS ONE 15 (1) (2020) e0226990.
[18] M. Zaeri-Amirani, F. Afghah, S. Mousavi, A feature selection method based on shapley value to false alarm reduction in icus a genetic-algorithm approach, in: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2018, pp. 319–323.
[19] P. Rajpurkar, A.Y. Hannun, M. Haghpanahi, C. Bourn, A.Y. Ng, Cardiologist-level arrhythmia detection with convolutional neural networks, arXiv preprint arXiv:1707.01836 (2017).
[20] Ö. Yıldırım, P. Pławiak, R.-S. Tan, U.R. Acharya, Arrhythmia detection using deep convolutional neural network with long duration ecg signals, Comput. Biol. Med. 102 (2018) 411–420.
[21] F. Murat, O. Yildirim, M. Talo, U.B. Baloglu, Y. Demir, U.R. Acharya, Application of deep learning techniques for heartbeats detection using ecg signals-analysis and review, Comput. Biol. Med. (2020) 103726.