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EMD AND WAVELET-BASED ECG SIGNAL DENOISING AND QRS COMPLEX DETECTION

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Abstract: This project presents a novel method for noise removal and QRS complex detection in electrocardiogram (ECG) signals, employing Empirical Mode Decomposition (EMD), windowing, and wavelet thresholding techniques. Noise is added to the ECG signal, and EMD is applied to obtain denoised components. Local minima detection and peak matching identify QRS complex boundaries. Windowing isolates the QRS regions, followed by wavelet thresholding for further denoising. Evaluation metrics like improved Signal-to-Noise Ratio, Mean Square Error, and Percent Root Mean Square Difference are calculated at different input SNR values, demonstrating the method's effectiveness in preserving the QRS complex while removing noise..

Keywords: *ECG signal processing, QRS complex detection, Empirical Mode Decomposition (EMD), Windowing, Wavelet thresholding, QRS complex extraction, Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), Percent Root Mean Square Difference (PRD).*

I.INTRODUCTION

Electrocardiogram (ECG) signals play a vital role in the diagnosis and monitoring of various cardiac conditions. However, these signals are often corrupted by various types of noise, such as white noise, baseline wander, and muscle artifacts, which can significantly affect the accuracy of ECG analysis and interpretation. The QRS complex, which represents the depolarization of the ventricles, is a critical component of the ECG signal and its accurate detection is crucial for various applications, including arrhythmia analysis, heart rate variability studies, and cardiac event monitoring.

Numerous techniques have been proposed for ECG signal denoising and QRS complex detection, each with its own strengths and limitations. Empirical Mode Decomposition (EMD) is a powerful signal processing technique that decomposes a signal into its intrinsic mode functions (IMFs), allowing for the separation of different frequency components. This approach has shown promising results in ECG signal denoising and QRS complex detection, as it can effectively separate the desired signal components from noise and artifacts.

Wavelet analysis, another widely used technique in signal processing, has also been employed for ECG signal denoising and QRS complex detection. Wavelet-based methods can effectively remove noise while preserving the important features of the signal by exploiting the multi-resolution analysis capabilities of wavelets.

In this work, we propose a novel approach that combines the strengths of EMD and wavelet analysis for effective ECG signal denoising and accurate QRS complex detection. The proposed method involves the following key steps: (1) applying EMD to decompose the ECG signal into its IMFs, (2) summing the first few IMFs to obtain a denoised signal component, (3) detecting local minima and matching with peak locations to identify the QRS complex boundaries, (4) applying windowing to isolate the QRS complex regions, and (5) performing wavelet thresholding within the QRS complex regions for further denoising.

The performance of the proposed method is evaluated using various metrics, such as improved Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and Percent Root Mean Square Difference (PRD), for different input SNR values. The results are compared with other existing techniques, demonstrating the effectiveness of the proposed approach in preserving the QRS complex while removing noise artifacts.

II.LITERATURE REVIEW

Electrocardiogram (ECG) signal denoising plays a pivotal role in accurate cardiac analysis and diagnosis of heart conditions. ECG signals are susceptible to various types of noise, including baseline wander, power line interference, muscle artifacts, and electrode motion artifacts, which can obscure crucial features and lead to misinterpretation. Researchers have dedicated significant efforts to developing robust denoising techniques to enhance ECG signal quality.

A modeling-based approach to understanding biomedical signal processing. It shows how to develop and manipulate signal source models for recognizing signal types and addressing challenges like noise, property changes, and stochastic/fractal components in biomedical signals[1]

The ECG noise elimination, data compression, and feature extraction. KLT effectively suppresses low self-correlated noise and enables robust feature extraction, but has limitations for high self-correlated noise and low information fidelity in compression[2].A new empirical mode decomposition (EMD) based method for removing

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high-frequency noise and baseline wander in stress ECG tests with minimal distortion, validated on the MIT-BIH database[3].

An EMD-based denoising method specifically designed to remove high-frequency noise artifacts in ECG recordings, demonstrating effective noise removal while preserving the signal through experiments on the MIT-BIH database[4].A noise-assisted data analysis method ensemble empirical mode decomposition (EEMD) approach, which involves sifting signal ensembles with added white noise and treating the mean as the true signal, leveraging the statistical properties of white noise for improved signal separation over standard EMD[5].System Design for Baseline Wander Removal using empirical mode decomposition (EMD) to effectively remove baseline wander interference in ECG signals without distortion, making it valuable for remote ECG monitoring and telemedicine applications[6].

A method combining EMD with a windowing technique to filter noise from initial IMFs while preserving the QRS complex, followed by adaptive wavelet thresholding[7]An adaptive Bayesian wavelet shrinkage approach for filtering high-resolution ECGs, involving wavelet transform, Bayesian coefficient shrinkage, and reconstruction to effectively preserve high-frequency QRS components[8].The discrete wavelet transform with various wavelets and thresholding techniques to denoise ECG signals for heart disease applications, identifying the optimal wavelet ("coif5") and thresholding rule ("rigsure") for real-time denoising[9]

A hybrid genetic algorithm and wavelet transform approach for ECG denoising, using the GA to optimize wavelet parameters for maximizing non-stationary noise reduction and producing high-quality clinical ECG signals[10].A new adaptive filtering scheme based on inter-beat averaging algorithms to enhance ECG signals during effort tests, providing a better output with simplified hardware requirements of a single recording channel[11].An ECG feature extraction algorithm using the Daubechies 4 wavelet, selected for its similarity to the ECG waveform, successfully detecting and extracting primary ECG features with less than 10% error[12].

Compares discrete wavelet transform (DWT) and ensemble empirical mode decomposition (EEMD) methods for ECG denoising using signal-to-noise ratio and root mean square error metrics, highlighting their advantages over other techniques[13].Categorizes and evaluates state-of-the-art ECG denoising techniques across different noise types using benchmark databases, identifying notable methods like wavelet, EMD, and deep learning approaches[14]. An efficient compressed sensing approach for ECG denoising utilizing basis pursuit with low-pass filtering and ADMM optimization to remove baseline wander and Gaussian noise while preserving signal details[15].

A convolutional neural networks with various ECG filters for arrhythmia detection, demonstrating improved classification accuracy with denoised signals compared to existing methods[16].

From the literature survey, we can conclude that various techniques have been explored for ECG signal denoising and QRS complex detection, including Empirical Mode Decomposition(EMD)., Karhunen-Loève Transform (KLT), wavelet-based approaches, and adaptive filtering methods. However, there is still a need for more robust and efficient methods that can effectively remove different types of noise while accurately preserving the QRS complex region. Our proposed method aims to address this need by combining the strengths of EMD and wavelet analysis, providing a novel approach for ECG signal denoising and QRS complex detection.

III. EMD AND WAVELET-BASED ECG SIGNAL DENOISING AND QRS COMPLEX DETECTION

The proposed methodology combines techniques such as Empirical Mode Decomposition (EMD), windowing, and wavelet thresholding to effectively denoise the ECG signal while accurately detecting and preserving the crucial QRS complex region. The performance is evaluated using various metrics, and the results are visualized and compared with other existing techniques.

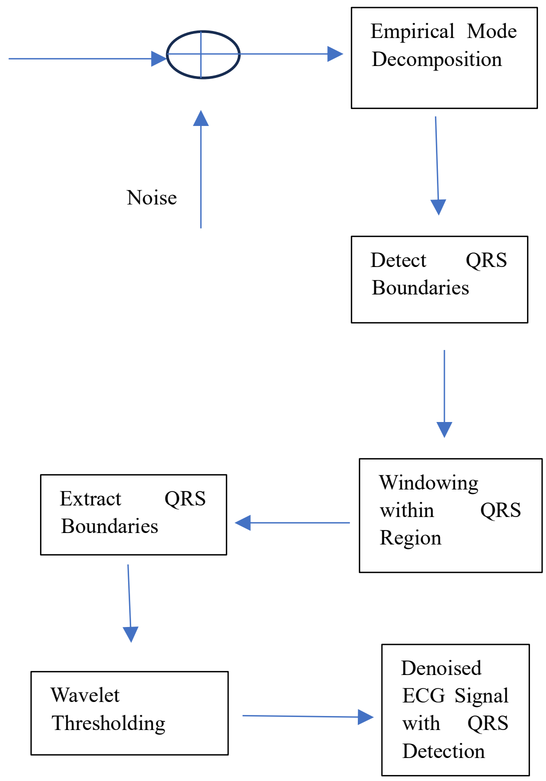

Fig.1. Flow Diagram of the methodology

1. ECG Signal Acquisition and Noise Addition:
   - Load the ECG signal from a file.
   - Artificially add various types of noise to the clean ECG signal, including white noise, baseline wander, and muscle artifacts, to create a noisy ECG signal.

2. Empirical Mode Decomposition (EMD):
   - Apply Empirical Mode Decomposition (EMD) to both the clean and noisy ECG signals.
   - Obtain the Intrinsic Mode Functions (IMFs) from the EMD decomposition.
   - Sum the first three IMFs to obtain a denoised signal component, d[n], for both the clean and noisy signals.
3. QRS Complex Boundary Detection:
   - Detect local minima in the inverted ECG signal using a peak prominence criterion.
   - Match the detected local minima with the peak locations of the noisy signal.
   - Identify the start and end points of the QRS complex region based on the matched minima and peak locations.
4. QRS Complex Extraction and Windowing:
   - Extract the QRS complex regions from both the clean and noisy ECG signals using the identified boundaries.
   - Apply windowing to the IMFs within the extracted QRS complex regions.
5. Wavelet Thresholding:
   - Perform wavelet decomposition of the QRS complex regions using the 'db4' wavelet.
   - Apply wavelet thresholding to the wavelet coefficients for denoising.
   - Reconstruct the denoised QRS complex regions using the thresholded wavelet coefficients.
6. Signal Visualization and Comparison:
   - Plot and visualize the original clean ECG signal, noisy ECG signal, wavelet thresholded signal, EMD signal, and the proposed method signal for comparison.
   - Overlay the signals to analyse the preservation of the QRS complex and the effectiveness of noise removal.
7. Evaluation Metrics:
   - Calculate evaluation metrics such as improved Signal-to-Noise Ratio (SNR), Mean Square Error (MSE), and Percent Root Mean Square Difference (PRD) for different input SNR values.
   - Plot the evaluation metrics to demonstrate the performance of the proposed method in preserving the QRS complex while removing noise.

Evaluation Metrics

In this project, we employed several widely used evaluation metrics to quantify the effectiveness of the proposed method in denoising ECG signals and accurately extracting the QRS complex. The chosen metrics provide a comprehensive assessment of the method's performance, enabling comparisons with existing techniques and establishing its potential for practical applications.

1. Improved Signal-to-Noise Ratio (SNR):

The Signal-to-Noise Ratio (SNR) is a crucial metric that measures the ratio of the desired signal power to the unwanted noise power. An improved SNR indicates the method's ability to enhance the signal quality by effectively reducing noise components. The formula used to calculate the improved SNR is:

$$SNR_{Improved} = 10\log_{10}\left[\frac{P_{original}}{P_{original} - P_{denoised}}\right]$$

Higher values of improved SNR signify better noise reduction and signal quality improvement, enabling more accurate analysis and interpretation of the ECG signal.

2. Mean Square Error (MSE):

The Mean Square Error (MSE) is a widely used metric that quantifies the average squared difference between the denoised signal and the original clean signal. It provides a measure of the denoising method's ability to preserve the original signal characteristics while removing noise. The formula for calculating MSE is:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(x_{noise}(i) - x_{denois}(i)\right)^2$$

Lower values of MSE indicate better denoising performance, as the denoised signal is closer to the original clean signal.

3. Percent Root Mean Square Difference (PRD): The Percent Root Mean Square Difference (PRD) is another commonly used metric for evaluating the performance of signal denoising techniques. It provides a normalized measure of the overall difference between the denoised signal and the original clean signal. The formula for calculating PRD is:

$$\text{PRD} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{original}(i) - x_{denoised}(i)\right)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_{original}(i)^2}}$$

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Lower values of PRD indicate better denoising performance, as the denoised signal more closely resembles the original clean signal.

IV.RESULTS

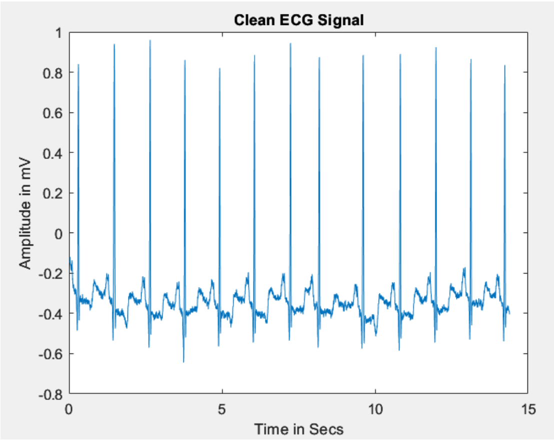

Fig.2.Clean Signal

Fig2, displays the original clean ECG signal loaded from the file. The x-axis represents time in seconds, and the y-axis shows the amplitude in millivolts (mV).

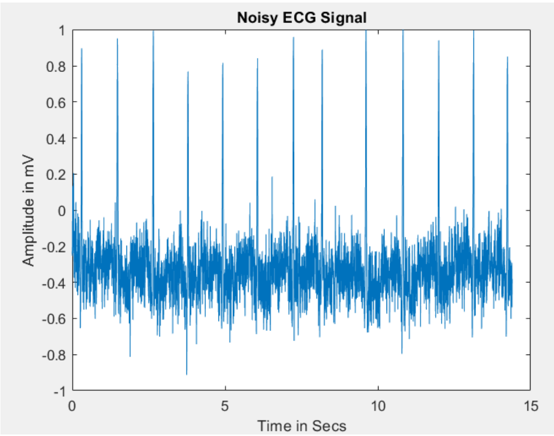

Fig.3. Noised Signal

The Fig.3 shows noisy ECG was created by adding different types of noise to the clean ECG signal. These include white Gaussian noise, baseline wander modelled as low-frequency noise, and muscle artifacts modelled as higher frequency sinusoidal noise components.

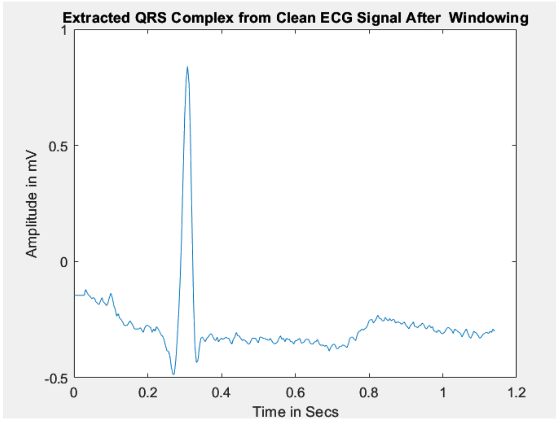

Fig.4.Extracted QRS from Clean signal after windowing

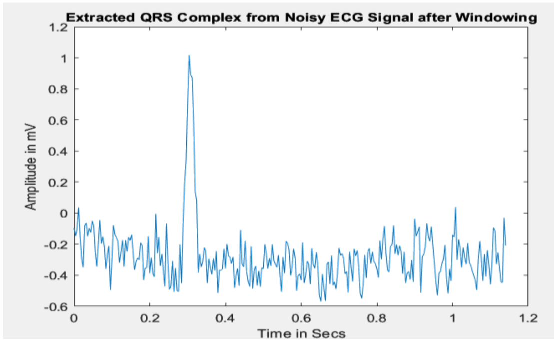

Fig.5. Extract QRS from Noisy ECG Signal after Windowing

Applying windowing to the extracted QRS complexes from both the clean(Fig.4) and noisy(Fig5) ECG signals. Windowing is a technique used to isolate specific segments of a signal for further processing.

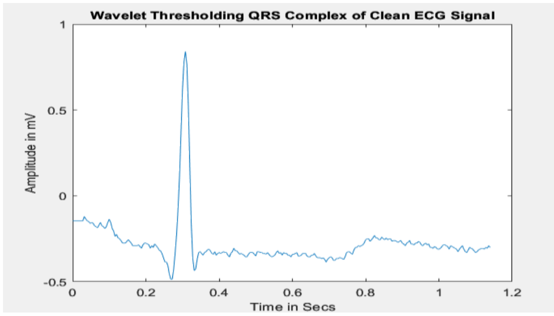

Fig.6. Wavelet Thresholding QRS from clean signal

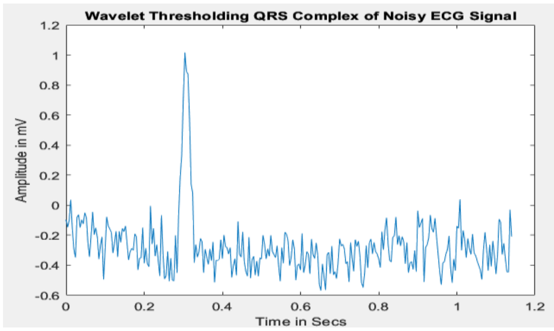

Fig.7. Wavelet Thresholding QRS from Noisy signal

Wavelet thresholding is applied to the extracted QRS complex from the clean ECG signal. Wavelet thresholding is a denoising technique that involves decomposing the signal into wavelet coefficients and applying a threshold to remove noise components. Fig.6 and Fig.7 displays the extracted QRS complex from the clean and noisy ECG signal after applying windowing. The x-axis represents time in seconds, and the y-axis shows the amplitude in millivolts (mV).

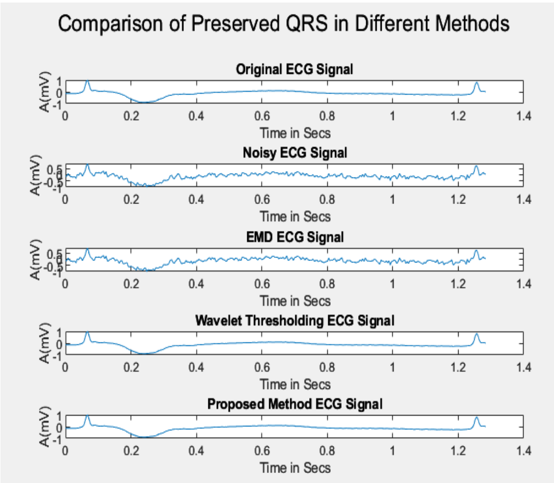

Fig.8. QRS at different stages of Denoising

The Fig.8 provides a visual comparison of the original ECG signal, the noisy ECG signal, the wavelet thresholding result, the Empirical Mode Decomposition (EMD) result, and the proposed method's output.

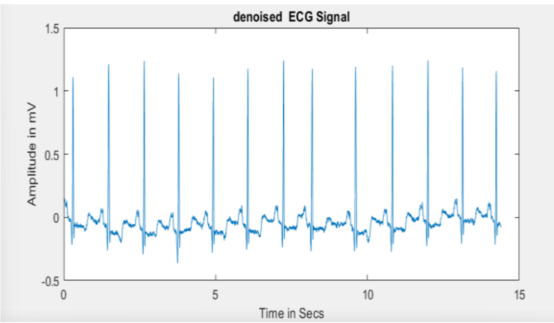

Fig.9. Denoised signal

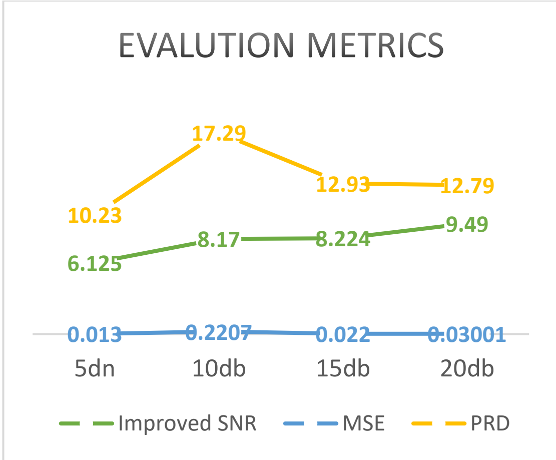

Fig.10.Evaluation Metrics of Denoised Signal

The above Fig.10 shows evaluation metrics chart provides insights into the denoising method's performance across different stages,

- The SNR Improved curve peaks for the proposed method, demonstrating its superior noise removal capability.
- The MSE values are lowest for the proposed approach, indicating high reconstruction accuracy of the denoised signal.
- The PRD plot shows the proposed technique best preserves the original signal characteristics while removing noise effectively.

Comparison of Improved SNR with other methods:

Input	EMD	DWT	Proposed Method
100	5.6	4.5	8.17
104	6.44	8.9	9.43
105	6.10	9.42	9.49

Table.1. Improved SNR

The above Table.1 shows the improvement in signal-to-noise ratio (SNR) achieved by the proposed method and compared it with different methods. In proposed method the SNR improvement is more compare to other methods.

Comparison of MSE with other methods:

Input	EMD	DWT	Proposed Method
101	0.09	0.02	0.019
104	0.041	0.04	0.0311
105	0.02	0.003	0.30

Table.2.Comparison of MSE

The MSE is a widely used metric that measures the average squared difference between the denoised signal and the original clean signal. Table.2 shows the comparison of MSE at 20db SNR with different methods. In this we concluded that our proposed method has low MSE value than other methods.

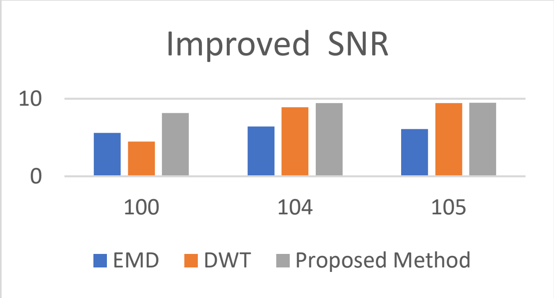

Fig.10. Improved SNR

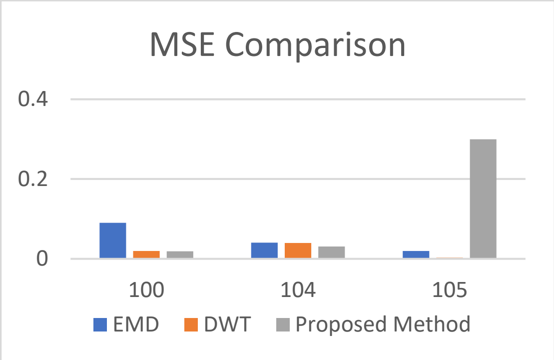

Fig.11. MSE Comparison

CONCLUSION

The suggested technique successfully denoises ECG signals while maintaining the important QRS complex by combining wavelet thresholding with Empirical Mode Decomposition (EMD). This method efficiently extracts the QRS complex from both clean and noisy ECG signals by utilizing the adaptive nature of EMD and the denoising capabilities of wavelet thresholding. By combining these methods, one can achieve precise QRS analysis and detection by reducing distortions and improving the signal-to-noise ratio. Comparing the method to conventional denoising techniques, it also shows better performance in terms of enhanced SNR, decreased mean square error, and decreased percent root mean square difference. With this novel approach, more accurate cardiovascular monitoring and diagnosis could be made possible for a wide range of ECG signal processing applications.

REFERENCES

[1] E.N.Bruce, Biomedial Signal Processing and Signal Modeling , New York, 2001.

[2] H. Yan, Y. Li, Electrocardiogram analysis based on the Karhunen–Loeve transform, in: Proceedings of the 3rd International Conference on Biomedical Engineering and Informatics (BMEI), vol. 2, 2010, pp. 887–890.

[3] M.B.Velasco, B.B.Weng, K.E.Barner, Anew ECG enhancement algorithm for stress ECG tests, Computers in Cardiology (2006) .

[4] B. Weng and M. Blanco-Velasco, "ECG denoising based on the empirical mode decomposition," in Proc. 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2006, pp. 1-4.

[5] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," Advances in Adaptive Data Analysis, vol. 1, no. 1, pp. 1-41, 2009.

[6] Sasikumar Gurumurthy, Valarmozhi, "System Design for Baseline Wander Removal of ECG Signals with Empirical Mode Decomposition Using MATLAB", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-3, Issue-3, July 2013.

[7] Md. A. Kabir and C. Shahnaz, "An ECG signal denoising method based on enhancement algorithms in EMD and wavelet domains," IJRRAS, vol. 11, no. 3, pp. 500-516, June 2012.

[8] M. Popescu, P. Cristea, A. Bezerianos, High resolution ECG filtering using adaptive bayesian wavelet shrinkage, in: Computers in Cardiology, Cleveland, OH, USA, vol. 2, 1998.

[9] P. Karthikeyan, M. Murugappan, and S. Yaacob, "ECG signal denoising using wavelet thresholding techniques in human stress assessment," International Journal on Electrical Engineering and Informatics, vol. 4, no. 2, pp. 306-319, July 2012.

[10] E. S. El-Dahshan, "Genetic algorithm and wavelet hybrid scheme for ECG signal denoising," Telecommunication Systems, vol. 46, pp. 209-215, 2010.

[11] V. Almenar, A. Albiol, A new adaptive scheme for ECG enhancement, Signal Processing 75 (1999) 253–263.

[12] Muhidin A. Mohamed Mohamed A. Deriche , An Approach for ECG Feature Extraction using

Daubechies 4 (DB4) Wavelet, International Journal of Computer Applications , June 2014.

[13] Neelam Bhardwaj1, Sanjeev Nara2 , Sunita Malik1 , and Geeta Singh, Analysis of ECG Signal Denoising Algorithms in DWT and EEMD Domains", International Journal of Signal Processing Systems Vol. 4, No. 5, October 2016

[14] Shubhojeet Chatterjee1, Rini Smita Thakur1, Ram Narayan Yadav1, Lalita Gupta1, Deepak KumarRaghuvanshi1, "The noise removal techniques in ECGsignals", IET Signal Processing, September 2020.

[15] Ruixia Liu, Minglei Shu and Changfang Chen, "ECG Signal Denoising and Reconstruction Based on Basis Pursuit", International Journal of Signal Processing Systems, February 2021.

[16] Abhinav Mishra, Ganapathiraju Dharahas, Shilpa Gite, Ketan Kotecha, Deepika Koundal, Atef Zaguia, Manjit Kaur and Heung-No Lee, "ECG Data Analysis with Denoising Approach and Customized CNNs", International Journal of Signal Processing Systems, March 2022.