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ECG SIGNAL DENOISING USING DISCRETE WAVELET TRANSFORM

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ABSTRACT

The electrocardiogram (ECG) is crucial and widely used diagnostic tool for heart diseases; however, the presence of various noise components can distort the ECG waveform, leading to inaccurate interpretations. This research focuses on the utilization of Discrete Wavelet Transform (DWT) for denoising ECG signals. In this paper, we introduce an innovative DWT-based architecture for ECG denoising, designed to effectively eliminate reference line wander, power line interference, white noise, muscle artifacts, and impulsive noise through a single comprehensive process that incorporates signal decomposition and thresholding. Experimental assessments were performed on the MIT-BIH database, utilizing a 360 Hz sampling frequency over a 15-second duration. Denoising performance was calculated by measuring improvements in Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR) under various noise power levels. Our proposed DWT-based algorithm consistently outperformed traditional filter-based techniques, demonstrating superior MSE and SNR enhancements. Notably, the average enhancements in Signal-to-Noise Ratio (SNR) ranged up to 10% for baseline wander, a reduction of -15 dB for power-line interference, and an increase of 50% for white noise when compared to conventional low-pass filter, notch filter, and moving average filter approaches, respectively. These improvements were consistently experimental across different noise power levels, highlighting substantial gains in signal clarity. Additionally, significant reductions in MSE, with improvements of 0.003, further underscored the effectiveness of proposed architecture. These quantitative results affirm the accuracy and efficiency of our method, offering substantial enhancements in ECG signal quality and clarity. This improvement contributes to more precise subsequent analyses, ultimately benefiting the diagnosis and treatment of heart diseases.

KEYWORDS: Denoising; electrocardiogram; Packet Wavelet Transform; Thresholding;

1. INTRODUCTION

The electrocardiogram (ECG) is a crucial diagnostic tool widely used in clinical practice to assess the electrical activity of the heart. However, ECG signals are often contaminated by various types of noise, which can significantly compromise the accuracy and reliability of diagnostic information. ECG denoising is, therefore, a critical step to enhance the quality of ECG signals and improve the precision of cardiac analysis. Discrete Wavelet Transform (DWT) has emerged as a great technique for ECG denoising due to its ability to capture both time and frequency information simultaneously. Many studies emphasis on using DWT to denoise ECG noisy data. Poornachandra has proposed a sub-band level-dependent DWT-based technique to eliminate additive white Gaussian noise contaminated in ECG signals. His approach is being tested to see if the noise-free signal can be reconstructed using the universal threshold property (Poornachandra, 2008). Karthikeyan et al. investigated a DWT-based denoising algorithm by incorporating different thresholding techniques to remove three major sources of noise from acquired ECG signals: power line interference, baseline wandering, and high frequency noises. Therefore, three well-known mother wavelet methods (Symlet 8, Coiflets 6, and Duabiches 4) and four different approaches of thresholding were used to denoise ECG signals. The results of the experiments showed that all of these methods were able to significantly reduce noise while preserving the shape of the ECG signal (Karthikeyan, Murugappan, & Yaacob, 2012). Lin et al. suggested a discrete wavelet based with (Symlet 5) as the mother function to decomposing noisy ECG signals to remove power-line interference, baseline wander and Muscle Artefacts noises. Then, feature detection is carried out using the soft-thresholding approach. At SNR 5 dB, the SNR improvement is at least 10 dB, and the

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majority of the improvements were achieved even with varying SNR (H.-Y. Lin, Liang, Ho, Lin, & Ma, 2014). Singh et al. described a novel ECG denoising method that combines the strengths of Non-Local Means (NLM) and Discrete Wavelet Transform (DWT) techniques. Their approach utilises a two-level decomposition of the ECG signal to obtain detail and approximation coefficients. High-frequency noise is removed through DWT-based thresholding of the detail coefficients, while low-frequency noise is eliminated by applying NLM to the Level 2 approximation coefficients. The method reduces computational time for both NLM and DWT, resulting in a lower overall computational load (O. Singh & Sunkaria, 2017). An effective ECG denoising technique employing a combined discrete wavelet and Savitzky-Golay (S-G) filter was proposed by (Fars Samann & Schanze, 2019). The consideration of wavelet order and the type of mother wavelet was undertaken during the study of the performance of the suggested design. To achieve optimal results, we placed significant emphasis on selecting the appropriate frame size, determining the order of the S-G filter, choosing the right type of wavelet, and specifying the wavelet order. It's important to note that selecting the best parameters for the new filter involves striking a balance between noise reduction and distortion, which is also applicable to our proposed algorithm. During the initial phases of signal processing, it is essential to eliminate noise from the raw ECG signal before embarking on Feature Extraction. A highly effective method for noise reduction involves employing the Discrete Wavelet Transform (DWT). This technique effectively deals with prevalent problems like baseline drifting and diminishes undesired noise by attenuating high-frequency components within the ECG signals. The objective here is to eliminate less critical information from the original signal, as discussed by (Patel, Sandhya, Raja, & S, 2021). (Liu & Du, 2021) developed an enhanced ECG denoising algorithm based on Wavelet-scale Correlation Coefficients to remove White Gaussian noise. The experiments were carried out using ECG signals sourced from the MIT-BIH database, and the findings indicated that the enhanced denoising algorithm led to a notable 6.67% improvement in the mean Signal-to-Noise Ratio (SNR), a marginal 0.01% reduction in the mean Root Mean Squared (RMS) error, and the generation of a smoother ECG signal. By comparing with traditional wavelet coefficient correlation denoising method, the improved wavelet coefficient correlation denoising method proposed in this paper has a better denoising effect.

In this manuscript, one architecture is suggested for denoising ECG using DWT which presents a complete plan for cleaning up ECG signals using a method using DWT. We specifically deal with four common noises in ECG signals: wandering noise, power line issues, white noise, and muscle movement interference. The contribution of our suggested approach that makes a difference is that we don't handle each problem separately. Instead, we tackle them all together, which seems to work better. To prove this, we conducted careful tests using real ECG data from the MIT-BIH database. Our tests show that our method is really good at reducing the effects of wandering, noise from power lines, random noise, and muscle interference. This makes the ECG signals more accurate and trustworthy.

The main contents of the manuscript are as follows: second section for introducing denoising using Discrete Wavelet Transform and Thresholding rules. In the third section, proposed designs are suggested for denoising ECG. In the fourth section, the results of experiments are presented and then evaluated for performance, we discuss the experiment and summarise the advantages of the wavelet design. Lastly, the fifth section gives the conclusion.

2. METHODOLOGY

The Discrete Wavelet Transform (DWT) is a potent signal processing tool that facilitates analysis in both the time and frequency domains. It accomplishes this by breaking down a signal into multiple frequency components at different scales, making it possible to extract crucial signal characteristics and isolate noise components (Srivastava & Prasad, 2013). Figure 1 provides an illustration of the DWT process applied to a discrete digital signal x[n]. The signal undergoes a series of high-pass (HPF) and low-pass (LPF) filtering stages, resulting in approximation (a1) components from *H(w)* and detail (d1) components from *G(w)*. Subsequent stages continue this process through down-sampling, maintaining the signal's length. DWT provides excellent time resolution at high frequencies (HF) and frequency resolution at low frequencies (LF), making it suitable for ECG signal analysis (Chatterjee, Thakur, Yadav, Gupta, & Raghuvanshi, 2020). The filter coefficients, denoted as *H(w)* and *G(w)*, are determined using the scaling function and wavelet function, respectively. In signal reconstruction, an inversely symmetrical approach is employed along with up-sampling. By combining the forward and reverse DWT theory with the concept of thresholding, noisy ECG signals can be effectively denoised. The accurate estimation of the signal x depends on the proper selection of the mother wavelet (Donoho & Johnstone, 1995). Different mother wavelets enable a suitable representation of the signal in the wavelet domain. Considering an L-sample observed data x[k], where k = 0, 1, 2, 3, ..., L - 1, the denoising process is carried out by the following equation:

$$x_i[k] = \sum_{k=0}^{L} x[\mathrm{k}] + w[k] \tag{1}$$

$x[k]$ is the original data which was corrupted by any type of noise $w[k]$ with variance σ^2 and making a noisy signal $x_i[k]$.

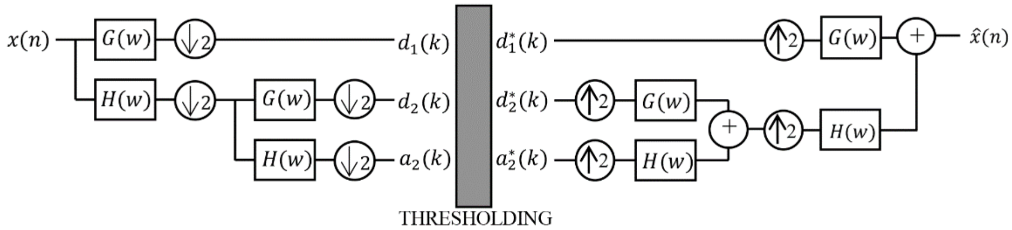

Fig.(1):- The denoising structure described in (Chatterjee et al., 2020) involves a Two-Level Discrete Wavelet Transform.

According to (Abdulbaqi & Al-din, 2020) , researchers are interested in removing noise from ECG signals, which can be classified into different types based on their frequency bands. These types of noise include:

- **Baseline wander:** A low-frequency noise that can be caused by respiration, movement, or electrical interference.
- **Power line interference:** A medium-frequency noise caused by the electrical power grid.
- **Electromyographic (EMG) noise:** A high-frequency noise caused by muscle activity.
- **Electrode motion artifacts:** Noise caused by the electrodes moving on the skin.

Each type of noise has its own unique frequency characteristics, which can be used to develop algorithms to remove it from the ECG signal. The wavelet transform can be used to decompose an ECG signal into its different frequency components. The coefficients corresponding to the noisy parts of the ECG signal are then set to zero, or “thresholded”. This removes the noise from the signal. The signal is then reconstructed from the thresholded coefficients. This process can be used to remove a variety of noise from ECG signals, including baseline wander, muscle artifacts, and power line interference (Xu, Luo, Li, & Song, 2017).

To denoise ECG signals where are corrupted by these noises, the DWT is applied in the following steps:

Step 1: Decomposition (DWT)
Using the Discrete Wavelet Transform (DWT), the ECG signal undergoes a decomposition process, breaking it down into its frequency components at various scales. This decomposition effectively separates the noise components from the core ECG signal.

Step 2: Thresholding
The wavelet coefficients obtained through the decomposition are subsequently subjected to a thresholding process. Thresholding entails either removing or reducing coefficients that fall below a specified threshold, treating them as noise components. Various thresholding techniques can be employed, including hard thresholding (setting coefficients below the threshold to zero) or soft thresholding (reducing coefficients toward zero through shrinkage).

Step 3: Reconstruction (IDWT)
Following the thresholding step, the altered wavelet coefficients are employed to reconstruct the denoised ECG signal. This reconstruction procedure entails the application of the inverse Discrete Wavelet Transform (DWT), resulting in the retrieval of a clean ECG signal with reduced noise.

Researchers have looked at many different wavelet families, such as Duabiches, Symlet, and Coiflets, each with its own strengths and weaknesses that affect how well it can reduce noise. The choice of mother wavelet and thresholding method is very important for the denoising process. Thresholding is a key factor in achieving optimal denoising results. It determines how much noise to remove without losing important information (Tan & Du, 2009). The DWPT is a better way to analyse signals than the uniform frequency band because it can break down the signal into smaller pieces at different levels of detail. This makes it easier to find and remove noise, and to identify important features in the signal (Alves, Costa, de Araujo Ribeiro, de Sousa Neto, & Rocha, 2016).

2.1 Universal Threshold Technique

The universal thresholding approach estimates the standard deviation of background noise in a signal using a noise level estimator module based on the detail coefficient level. Hard and soft thresholding are the conventional thresholding methods introduced by (Donoho & Johnstone, 1994). In other words, the universal thresholding approach is a method for determining the standard deviation of background noise in a signal without knowing the underlying distribution of the noise. It does this by using a noise level estimator module based on the detail coefficient level. The detail coefficient level is a measure of the amount of high-frequency information in a signal. Hard and soft thresholding are two conventional thresholding methods that can be used to remove noise from a signal.

$$Thr = SD\sqrt{2\ ln\ N} \tag{2}$$

Given the number of coefficient samples (N) and the estimated noise level (SD), the noise level estimation can be calculated using the following equation:

$$SD = \frac{MAD(w[k]_{d,j})}{0.6745} \tag{3}$$

where $w[k]_{d,j}$ represent the values of the wavelet transform of a signal at the jth level of decomposition, for the dth detail sub-band. These coefficients measure the high-frequency information in the signal at that level.

Hard thresholding is a technique that sets all coefficients below a certain threshold value (the threshold) to zero, while leaving all coefficients above the threshold unchanged. The threshold value can be chosen manually or automatically. In other words, hard thresholding is a way of simplifying a signal or image by keeping only the most important information. It is often used in signal processing and image processing to remove noise or to compress data. The Hard Threshold values can be computed by:

$$w'[k]_{d,j} = \begin{cases} w[k]_{d,j}, & |w[k]_{d,j}| > Thr. \\ 0, & |w[k]_{d,j}| < Thr. \end{cases} \tag{4}$$

Soft thresholding is a more effective denoising technique than hard thresholding, which simply sets all coefficients below the threshold to zero. This is because soft thresholding preserves some information from the small coefficients, which can help to reduce noise without introducing too much distortion, soft thresholding can be achieved as shown by:

$$w'[k]_{d,j} = \begin{cases} w[k]_{d,j} - Thr., & w[k]_{d,j} > Thr. \\ w[k]_{d,j} + Thr., & w[k]_{d,j} < Thr. \\ 0, & |w[k]_{d,j}| < Thr. \end{cases} \tag{5}$$

2.2 Evaluation of the performance for signal denoising methods

The effectiveness of the proposed denoising architecture is evaluated quantitatively using the following performance metrics: mean squared error (MSE), signal-to-noise ratio (SNR), and improvement in the SNR ($SNR_{improvement}$):

$$SNRinput = 10\ \times\ log(\frac{Power_{Signal}}{Power_{Noise}}) \tag{6}$$

$$MSE = \frac{\sum_{n=1}^{N}(x[n] - \bar{x}[n])^2}{N} \tag{7}$$

$$SNRoutput = 10 \times log10\ \frac{\sum_{n=1}^{N} x^2[n]}{\sum_{n=1}^{N}(x[n]-\bar{x}[n])^2} \tag{8}$$

$$SNR_{improvement} = SNR_{output} - SNR_{input} \tag{9}$$

3. THE PROPOSED ARCHITECTURE FOR ECG DENOISING

In this study, noisy ECG signals are subjected to decomposition into eight levels using the Discrete Wavelet Transform (DWT). The source of these noisy ECG signals is the MIT-BIH database. Decomposition in terms of frequencies of the input ECG signals, as illustrated in Figure 2 and summarized in Table 1, is performed to describe the frequency passband of the ECG Signal for the given sampling frequency of Fs = 360 Hz over a 15-second duration, resulting in a total of 5640 data point samples in this work. In this paper, we present a single architecture designed for the purpose of reducing noise in ECG signals through the utilization of the Discrete Wavelet Transform (DWT). The schematic representation of this architecture can be observed in Figure 3. Typically, ECG signal recordings containing frequencies exceeding 120 Hz do not contain significant information of relevance (Mbachu, Victor, Emmanuel, & Nsionu, 2011). Consequently, we make adjustments to zero out the wavelet coefficients associated with cD1.

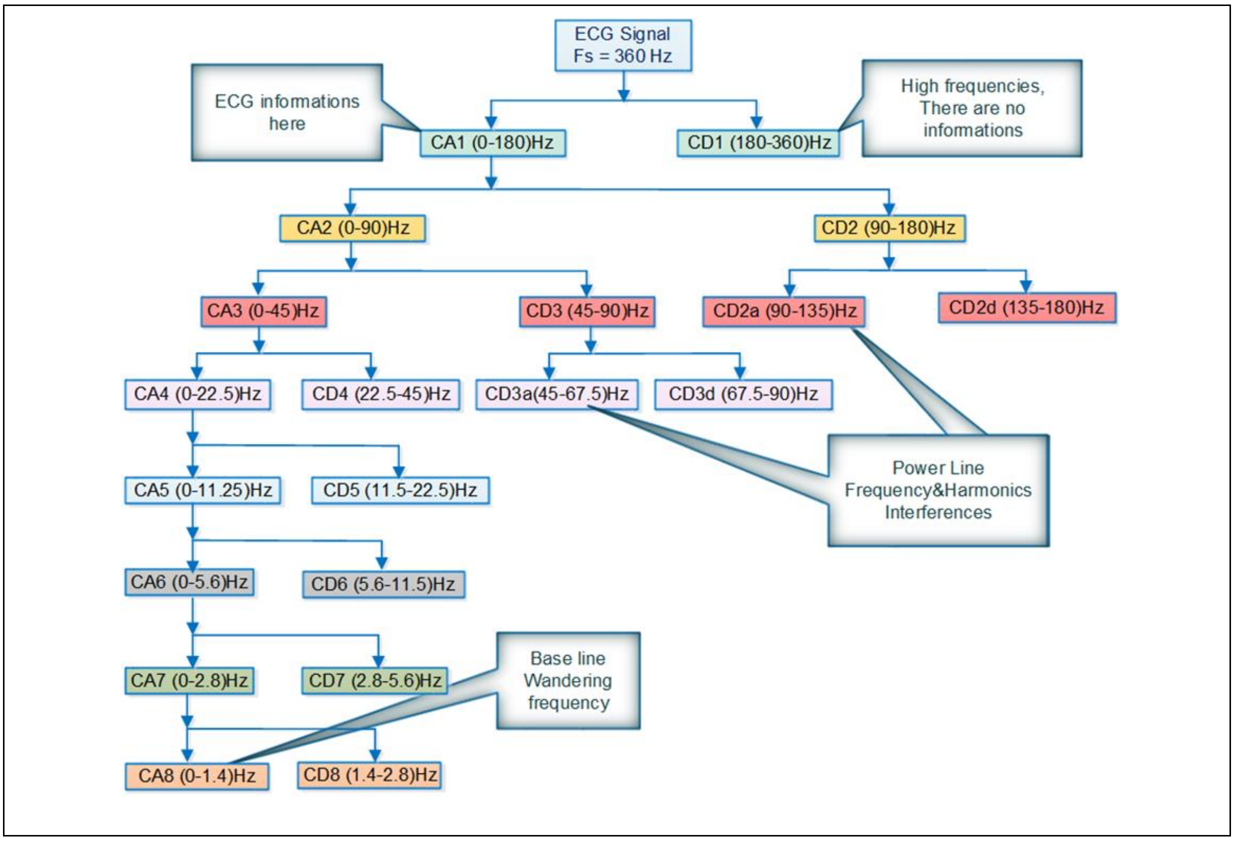

Fig.(2):- Displays an 8-level decomposition using the Discrete Wavelet Transform (DWT) in terms of frequencies applied to the input ECG signal (sampled at Fs=360 Hz).

In this work, each type of the following noises was denoised by the suggested method independently. Real-world ECG signals vary greatly from patient to patient and are often corrupted by noise, which makes it necessary to conduct denoising in order to develop a reliable recognition model. In other words, we need to remove the noise from ECG signals before we can use them to train a machine learning model to recognize different heart conditions accurately. This is because the noise can interfere with the model's ability to learn the underlying patterns in the data.

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Table (1): -frequency passband characteristics of the ECG signals when the sampling frequency is set to 360 Hz

Level	Frequency of Approximation Coefficients (Hz)	Frequency of Detail Coefficients (Hz)
L1	cA1 band: 0 – 180	cD1 band: 180 – 360
L2	cA2 band: 0 – 90	cD2 band: 90 – 180
L3	cA3 band: 0 – 45	cD3 band: 45 – 90
L4	cA4 band: 0 – 22.5	cD4 band: 22.5 – 45
L5	cA5 band: 0 – 11.25	cD5 band: 11.25 – 22.5
L6	cA6 band: 0 – 5.625	cD6 band: 5.625 – 11.25
L7	cA7 band: 0 – 2.8125	cD7 band: 2.8125 – 5.625
L8	cA8 band: 0 – 1.4063	cD8 band: 1.4063 – 2.8125

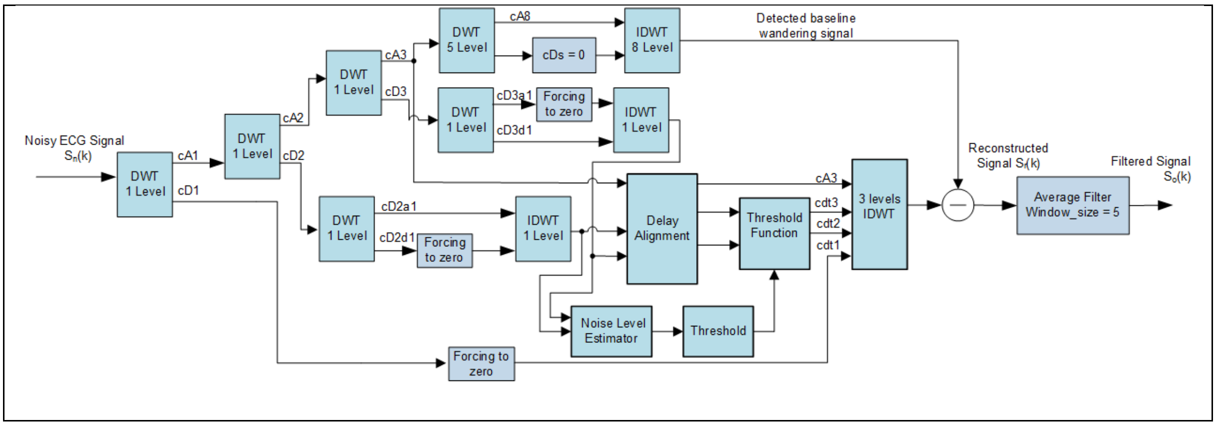

Fig.(3):- The schematic diagram illustrating the proposed architecture to denoise ECG signals utilising the Discrete Wavelet Transform (DWT).

3.1 Wander Noise Modelling

Baseline wandering refers to a specific type of noise that affects the ECG signal, introducing a low-frequency artefact. This noise occurs due to variations in the impedance between the electrode and the patient's skin. The typical frequency range for baseline wandering is generally below 1 Hz as described by (Kher, 2019). This class of interferences can be represented by relating a sine wave formed to the ECG signal $s_i[\mathrm{k}]$.

$$s_n[k] = s_i[\mathrm{k}] + w_i[\mathrm{k}] \qquad (10)$$

where $s_n[\mathrm{k}]$ is the noisy ECG signal. The $w_i[\mathrm{k}]$ is the wander noise and modelled as the following formula:

$$w_i[\mathrm{k}] = A\,sin(2\pi\, f_w\, k) \qquad (11)$$

Where A and f_w are the wander amplitude and frequency respectively. The last level in decomposing operation includes wander noise and this approach has been successfully implemented to effectively eliminate the low-frequency noises from the ECG signals as demonstrated in Figure 3.

3.2 Power Line Interference (PLI) Modelling

Power line interference (PLI) is a consequence of the presence of the power supply frequency, typically at 50 Hz, along with its harmonics. The electromagnetic fields generated by power lines and nearby equipment result in significant interference. This interference can degrade signal quality, obscuring important details that are critical for clinical monitoring and diagnosis (Y.-D. Lin & Hu, 2008). The frequency spectrum of power line interferences is relatively narrow and cantered around the power supply frequency. In this study, we modelled PLI by adding a sinusoidal signal with a frequency of 50 Hz which is a pure, sine wave signal that oscillates back and forth at a rate of 50 times per second. This type of signal is often used to represent power line interference, as it is the frequency of the alternating current (AC) power that is used in many countries, as described by the following formula:

$$w_{PLI}[k] = A\,sin(2\pi\, 50\, k) \qquad (12)$$

$w_{PLI}[\mathrm{k}]$ represents the amount of power line interference at time step k. now, the ECG signal is contaminated with PLI (power line interference).

$$s_n[k] = s_i[k] + w_{PLI}[k] \qquad (13)$$

The concept of determination of the PLI frequency band as shown in Figure 3 is to identify the range of frequencies in which the PLI noise is most dominant. This can be done by plotting the magnitude spectrum of the ECG signal, which shows the amplitude of each frequency component in the signal. In this case, the frequency band of the PLI noise can be estimated to be between 45 Hz and 55 Hz. The PLI noise will typically appear as a peak in the spectrum, and the frequency band of the PLI noise can be determined by finding the range of frequencies around the peak. A Semi-Packet wavelet transform based method is proposed by clearing coefficients of frequency range of the PLI frequency band then remove out the PLI noise.

3.3 White Noise Modelling

White noise is a common type of random noise that affects ECG signals. White noise in ECG signals refers to random, uncorrelated electrical disturbances that are superimposed on the original ECG waveform. This type of noise is characterised by its flat frequency spectrum, meaning it has an equal amount of energy across all frequencies (P. Singh, Pradhan, & Shahnawazuddin, 2017). The proposed ECG denoising architecture has 3 levels of decompositions. Then applying a threshold to the signal after estimation noise level, which has been applied to emphasise the signal and attenuate the noise (Fars Samann, Bamerni, Khorsheed, & Al-sulaifanie, 2021). For eliminating AWGN, an arrangement of the DWT and a moving average filter is proposed to develop more effective denoising techniques. Based on experimentation results, the moving average filter's window size is lowered to the smallest achievable value of three, and the decomposition of the DWT is limited to triple-layer denoising process.

3.4 Muscle Artefact Noise Modelling

Muscle artefact noise in ECG signals is a form of interference caused by the contraction or movement of muscles near the electrode placement sites. It represents one of the most prevalent sources of noise in ECG recordings and has a notable impact on the accuracy and dependability of ECG analysis. Muscle artefact noise can arise from muscle contractions, electrode movement, or Electromyographic (EMG) activity (Patel et al., 2021). In this study, the technique employed to filter muscle noise is analogous to dealing with white noise. The process involves utilising the Discrete Wavelet Transform (DWT) to decompose the noisy signal, followed by estimating the noise level and applying thresholding. Following this, all the modes that include signal elements are merged to reconstruct the filtered ECG signal, as outlined in (Appathurai et al., 2019).

4. EXPERIMENTATION RESULTS AND DISCUSSION

The denoised ECG signals are thoroughly compared to the original noisy signals using a variety of performance metrics, such as Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE), to assess the effectiveness of the denoising algorithm. In this analysis, we delve into the advantages and limitations of different thresholding methods and Discrete Wavelet Transform (DWT) wavelet families for handling each type of noise. To comprehensively assess the denoising methods introduced in section 3The same methods were used on five different ECG recordings for each noise source, one at a time. The results of these experiments are detailed in Table 2 through Table 5, offering insights into the effectiveness of the methods for various noise types. Furthermore, Table 6 provides a performance comparison of a number of mother wavelets when used to remove white noise from ECG signals using the Discrete Wavelet Transform (DWT). This comprehensive evaluation and comparison contribute to a better understanding of the suitability of different approaches and wavelets for ECG signal denoising.

Wander Noise Removing

Figure 4 demonstrates an ECG signal that has been intentionally contaminated with baseline wander noise. Subsequently, the signal undergoes DWT filtering, incorporating baseline correction as described in subsection 3.1 of the methodology. Table 2 provides a comprehensive overview of Different examples of baseline wander and the effects of removing the interference. It's crucial to highlight that the proposed DWT-based method outperforms the conventional Low Pass Filter in terms of both Mean Squared Error (MSE) reduction and Signal-to-Noise Ratio (SNR) improvement. This study designed a low-pass filter to have no more than 3 dB of ripple in the passband (0-0.25 Hz) and at least 60 dB of attenuation in the stopband. The filter order and cut-off frequency were determined using the method described by

(Wisana, Nugraha, & Rachman, 2021). In other words, the researchers in this study created a filter that allows low-frequency signals to pass through while blocking high-frequency signals. The filter is designed to have very little ripple in the passband, which means that the output signal is very similar to the input signal. The filter also has very high attenuation in the stopband, which means that high-frequency signals are blocked very effectively.

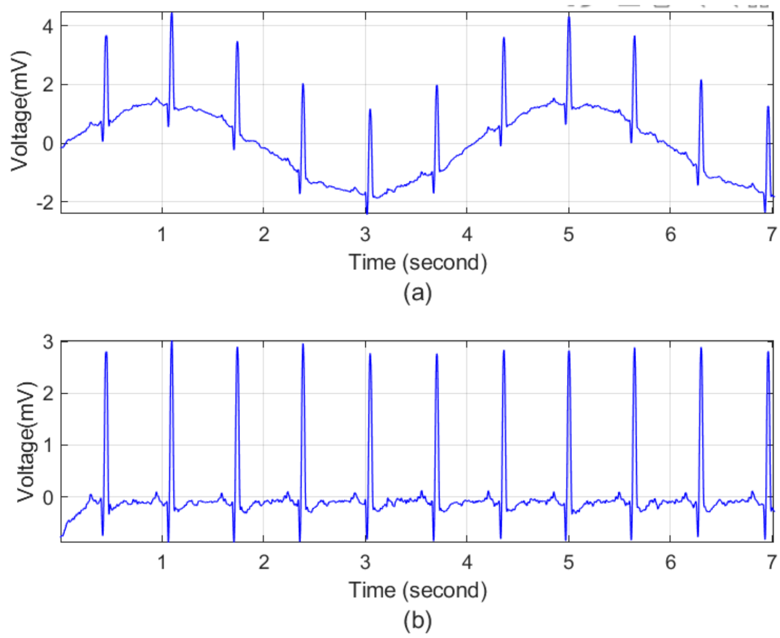

Fig.(5):- (a) An ECG data contaminated with wander noise. (b) The same ECG signal after being filtered to remove wander noise using the Discrete Wavelet Transform (DWT).

Table (2): -Comparison of Wander Noise Removal using the Discrete Wavelet Transform (DWT) and a Low-Pass Filter (LPF).

#	Wander Amplitude (mA)	SNR_{in} (dB)	SNR_{out} (dB)		MSE		$SNR_{improvement}$ (dB)		$SNR_{Enhancement}$ (%)
			DWT	LPF	DWT	LPF	DWT	LPF	
1	0.25	10.13	20.10	18.58	0.0030	0.0043	9.99	8.58	14
2	0.50	4.10	20.13	18.41	0.0030	0.0044	16.03	14.42	10
3	0.75	0.58	20.05	18.16	0.0030	0.0047	19.47	17.70	9
4	1.00	-1.92	19.87	17.85	0.0032	0.0051	21.79	19.88	9
5	1.25	-3.86	19.59	17.48	0.0034	0.0055	23.46	21.46	9
6	1.50	-5.45	19.25	17.08	0.0037	0.0060	24.69	22.64	8

The examples in this study featured signals of the same length but varied in terms of the amplitude of the noise. It is evident that signals with lower noise amplitudes, such as example #1, were not denoised as effectively as those with higher noise amplitudes, such as example #6. The Signal-to-Noise Ratio (SNR) was significantly improved, from -5.45 dB to 19.25 dB, resulting in a total improvement of 24.7 dB, which is 8% higher than what could be achieved using a Low Pass Filter alone. On average, the signal-to-noise ratio (SNR) improved by 19 dB, which is within the desired range. This means that the original signal could be successfully reconstructed with very high accuracy. The applied Discrete Wavelet Transform (DWT) filtering method yielded promising results, with a maximum attainable SNR of approximately 24.69 dB, depending on the signal length and the level of baseline wander. This new method for analysing ECGs is more accurate and effective than previous methods because it can remove noise from the signal.

4.2 Power-Line Interference Removing

Figure 5 demonstrates the outcomes of

denoising an ECG signal through the application of a Packet DWT filter to eliminate Power Line Interference (PLI) noise. Meanwhile, Table 3 provides a comprehensive overview of Signal-to-Noise Ratio (SNR) measurements for ECG signals following the removal of power line frequency noise using the Packet DWT Filter to eliminate the 50 Hz component. These results are juxtaposed with those obtained using a conventional IIR notch filter designed to eliminate a 50 Hz frequency from a signal sampled at 360 Hz. In this study, the filter's bandwidth was specified by setting the Q factor to 35, as detailed in the work by (Rahmatillah, 2017).

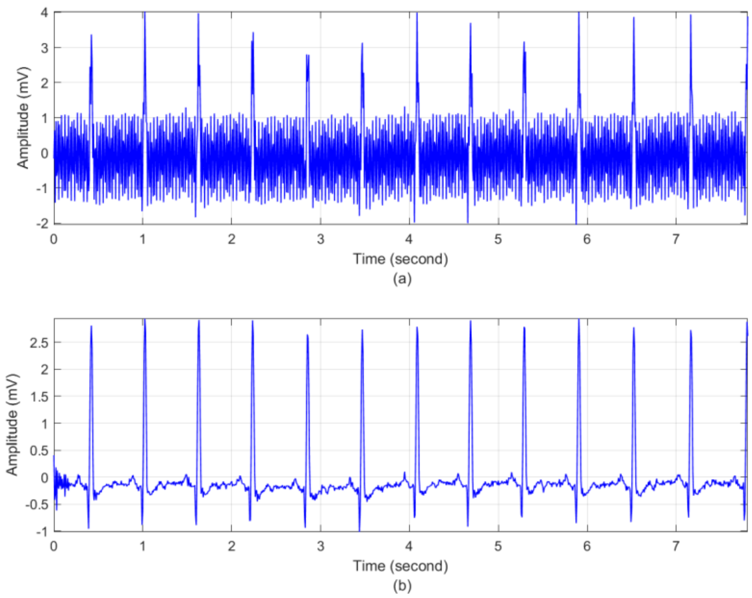

Fig.(5):- (a) A heart signal that has been distorted by noise from the power grid. (b) The same ECG signal after being filtered using a three-level Packet Discrete Wavelet Transform (DWT).

Table (3): -Comparison of Power Line Interference (PLI) removal using Packet DWT and a Notch Filter.

#	PLI Noise Amplitude (mA)	SNR_{in} (dB)	SNR_{out} (dB)		MSE		$SNR_{improvement}$ (dB)		$SNR_{Enhancement}$ (%)
			Packet DWT	Notch Filter	Packet DWT	Notch Filter	Packet DWT	Notch Filter	
1	0.25	9.92	27.25	34.69	0.0006	0.0001	17.31	24.75	-43
2	0.50	3.91	25.96	30.34	0.0008	0.0003	22.04	26.42	-20
3	0.75	0.39	24.42	27.23	0.0011	0.0006	24.02	26.83	-12
4	1.00	-2.11	22.90	24.89	0.0016	0.0010	25.00	26.99	-8
5	1.25	-4.05	21.50	23.03	0.0022	0.0015	25.54	27.07	-6
6	1.50	-5.63	20.24	21.49	0.0029	0.0022	25.86	27.12	-5

The incorporation of the Packet Wavelet Transform (PWT) noticeably improved the effectiveness of the denoising technique employed for cancelling PLI, as demonstrated by the substantial improvements in Signal-to-Noise Ratio (SNR). Achieving a maximum attainable SNR of around 24 dB for a band-stop at 50 Hz, depending on the signal's amplitude, highlights the power of PWT. The denoised SNR, which reached up to 23 dB in this study, suggests that the Packet Wavelet Transform almost perfectly reconstructs the ECG waveform. This outcome underscores the method's value and its ability to produce highly effective results.

4.3 White Noise Removing

Figure 6 illustrates the results of introducing white noise to an ECG signal and the subsequent filtration procedure using a DWT filter. In contrast, Table 4 provides detailed measurements of Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE) for ECG signals following the application of the DWT filter to eliminate white noise. It's evident from Table 4 that the SNR of the filtered signal is influenced by both the duration of the noisy signal and the variance of the white noise, as demonstrated.

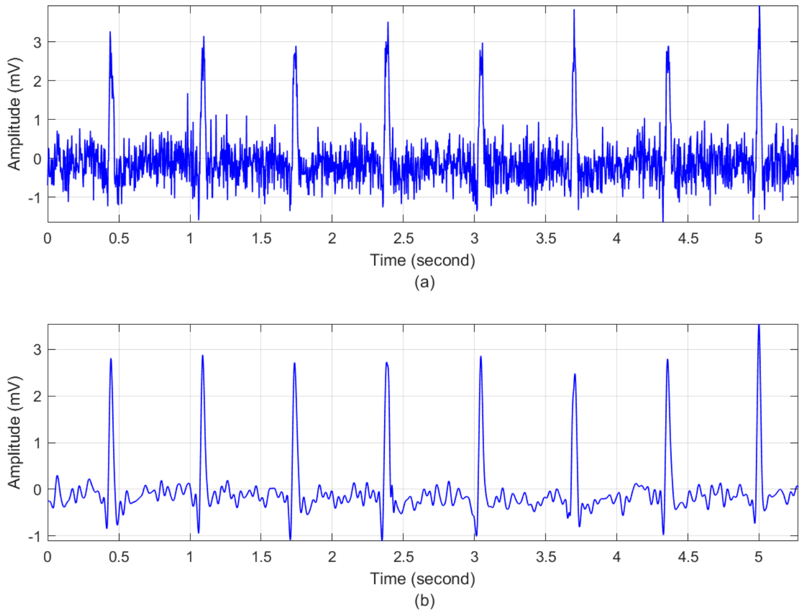

Fig.(6):- (a) An ECG signal contaminated with white noise. **(b)** The same ECG signal after undergoing denoising using a three-level Discrete Wavelet Transform (DWT).

Table (4): -Results of denoising an ECG signal contaminated with white noise.

#	White Noise power-sigma	$SNRi_n$ (dB)	SNR_{out} (dB)		MSE		$SNR_{improvement}$ (dB)		$SNR_{Enhancement}$ (%)
			DWT	Avg. Filter	DWT	Avg. Filter	DWT	Avg. Filter	
1	0.1	14.89	19.17	16.57	0.0037	0.0071	4.28	1.14	73
2	0.2	8.85	14.54	14.16	0.0108	0.0124	5.69	4.63	19
3	0.3	5.27	11.50	12.25	0.0218	0.0193	6.23	5.57	11
4	0.6	-0.65	7.47	7.22	0.0552	0.0615	8.12	4.32	47
5	0.8	-3.05	5.36	5.11	0.0895	0.0999	8.41	3.32	61
6	1	-5.17	3.68	2.64	0.1319	0.1764	8.85	1.40	84

Note: The applied mother wavelet was Bior6.8 in this test.

4.4 Muscle Artefact Noise Removing

Figure 7 illustrates the modelling of muscle noise and the efficacy of Discrete Wavelet Transform (DWT) filtering when applied to a signal with two segments that are corrupted by noise; One is two seconds long and the other is three seconds long. In this example, the Signal-to-Noise Ratio (SNR) improved from 5.39 dB to 8.28 dB. Table 5 provides a detailed breakdown of the SNR measurements for ECG signals after the application of DWT to eliminate muscle noise. Muscle noise typically exhibits short durations, resulting in higher SNR values before filtering, and thus allowing less room for improvement. Muscle noise exhibits random characteristics and lacks a deterministic mathematical description, rendering it challenging to completely restore the original signal shape. Since muscle noise is difficult to remove completely, even the best filtering techniques can only improve the signal-to-noise ratio (SNR) by a limited amount. In other words, even though filtering techniques can help to reduce muscle noise, they will never be able to eliminate it entirely. This means that there will always be some residual noise in the signal, which will limit the amount by which the SNR can be improved. The extent to which the SNR can be improved will depend on a number of factors, including the type of filtering technique used, the severity of the muscle noise, and the specific application. For example, if the muscle noise is very severe, it may not be possible to improve the SNR by very much at all. Despite these limitations, filtering techniques can still be very useful for reducing muscle noise and improving the quality of EMG signals. However, it is important to be aware that they can only offer a restricted enhancement in SNR. Moreover, when dealing with scenarios involving multiple short noisy segments, as demonstrated in example #4, the effectiveness of the method in improving SNR is compromised.

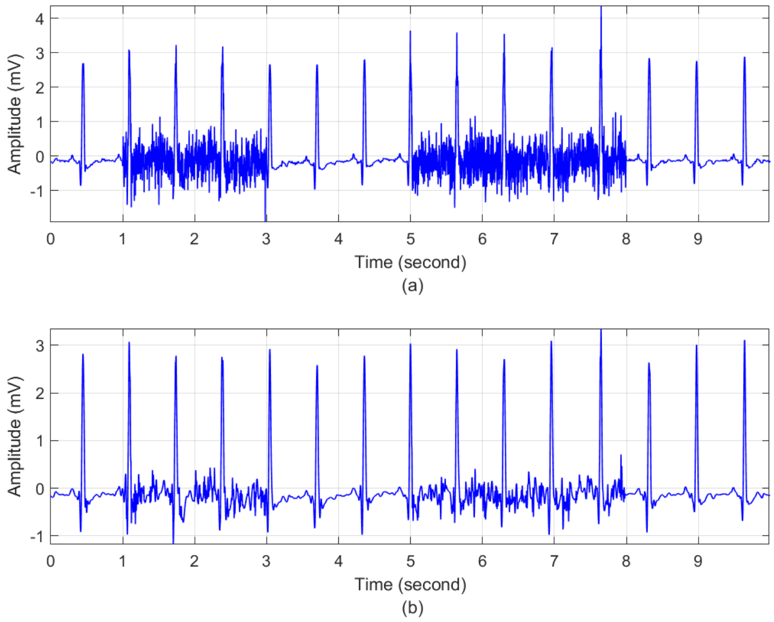

Fig.(7):- (a) ECG signal contaminated with muscle artifact noise. (b) ECG signal after undergoing filtration through a three-level Discrete Wavelet Transform (DWT).

Table (5): -Denoising ECG Signal from Muscle Noise Test Results

#	Noise power level (mA)	SNR_{input} (dB)	SNR_{output} (dB)		MSE		$SNR_{improvement}$ (dB)		$SNR_{Enhancement}$ (%)
			DWT	MA	DWT	MA	DWT	MA	
1	0.20	11.92	17.31	17.31	0.0058	0.0058	5.39	5.40	0
2	0.40	5.75	13.40	12.57	0.0142	0.0172	7.65	6.81	11
3	0.60	2.24	10.42	9.29	0.0282	0.0366	8.18	7.05	14
4	0.80	-0.09	7.85	6.57	0.0510	0.0685	7.94	6.66	16
5	1.00	-2.01	6.27	4.86	0.0734	0.1015	8.28	6.87	17

4.5 Mother wavelets comparison

When employing the Discrete Wavelet Transform (DWT) to remove white noise from ECG signals, multiple mother wavelets are evaluated to determine their effectiveness. Table 6 presents the outcomes regarding the performance of the proposed algorithm when employing various mother wavelets. Agreeing to Table 6, db10 and Bior6.8 stand out as highly effective choices for denoising ECG signals. The enhancement in Signal-to-Noise Ratio (SNR) for the reconstructed ECG signals falls within the range of 4.5 dB to 8.8 dB, accompanied by lower Mean Squared Error (MSE) values.

Table (6): -Filtering White Noise from ECG Signals Using Various Mother Wavelets for Denoising Efforts.

Noise Level	SNR input (dB)	Haar		db10		symlet8		Bior6.8	
		MSE	SNR output (dB)	MSE	SNR output (dB)	MSE	SNR output (dB)	MSE	SNR output (dB)
0.1	14.89	0.0073	1.38	0.005	3.03	0.0037	4.30	0.0037	4.28
0.2	8.85	0.0176	3.57	0.0137	4.68	0.01	6.02	0.0108	5.69
0.3	5.27	0.0334	4.37	0.0251	5.61	0.0214	6.32	0.0218	6.23
0.6	-0.65	0.0817	6.41	0.0582	7.89	0.0558	8.07	0.0552	8.12
0.8	-3.05	0.1294	6.81	0.091	8.34	0.0881	8.48	0.0895	8.41
1	-5.17	0.1798	7.50	0.1421	8.52	0.1337	8.79	0.1319	8.85

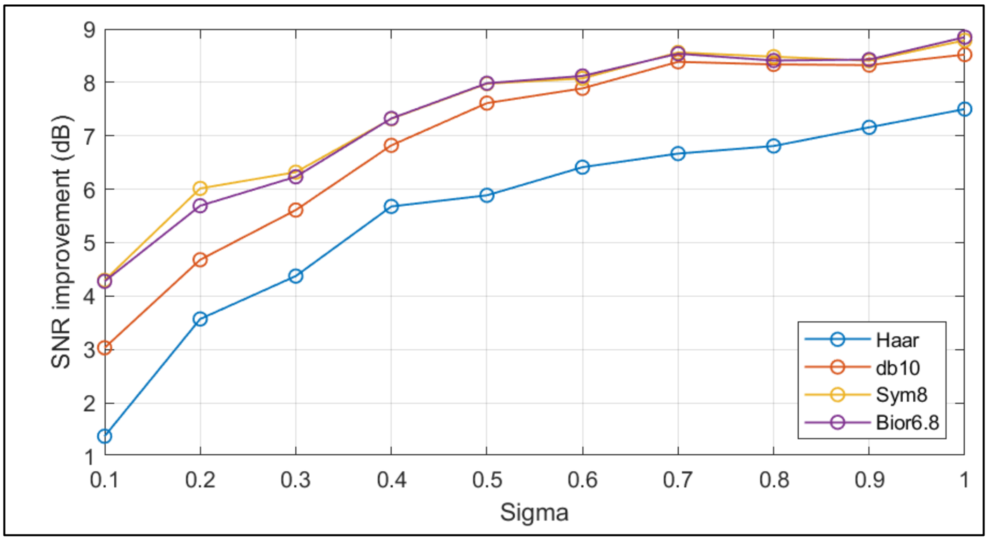

Fig.(8):- Enhancement in Signal-to-Noise Ratio (SNR) through Denoising Using Discrete Wavelet Transform (DWT) in relation to the level of white noise "sigma", as applied to a pristine ECG signal.

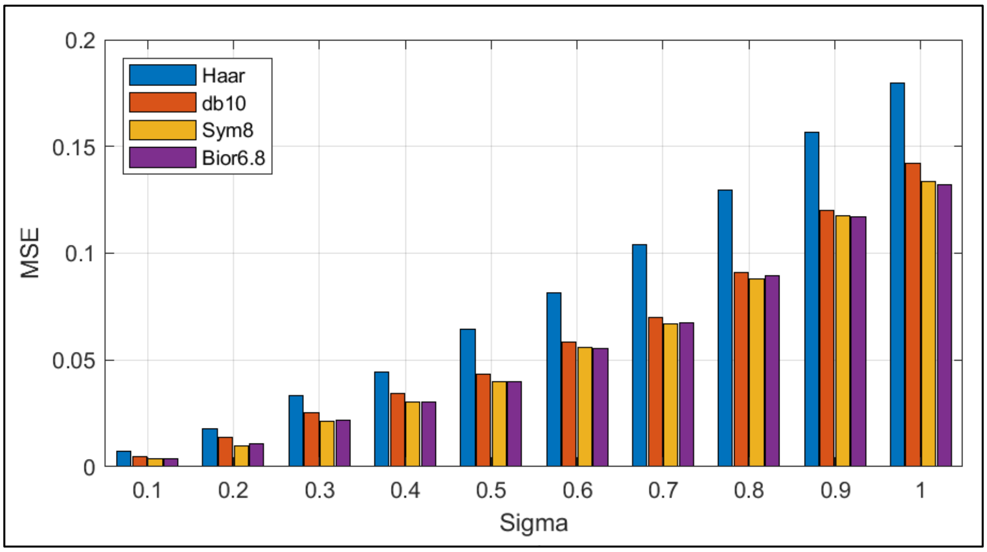

Fig.(9):- MSE vs sigma of white noise for each mother wavelet where used to denoising ECG signal

5. CONCLUSIONS

In this manuscript, one architecture for denoising ECG using DWT is proposed instead of each type of noise being treated separately. The manuscript is focusing on four prominent types of noise commonly encountered in ECG signals: white noise, power line interference, wander noise, and muscle artefact noise. Experiments conducted on the MIT-BIH ECG datasets, which were recorded at a sampling frequency of 360 Hz for durations exceeding 15 seconds, provide compelling confirmation of the efficacy of proposed denoising technology. The results unequivocally establish that our approach successfully suppresses ECG signal distortions while efficiently removing unwanted noise components. The performance of the proposed system is optimised by selecting the parameters of the DWT filter and moving average filter carefully. The results show that our proposed method has better MSE and SNR compared with other traditional filters. The best improvement values in SNR for base-line wander, Power-line Interference and white noise were 25 dB, 26 dB and 9 dB respectively. The MSE range for suggested ECG denoising was between 0.003 to 0.13, which is good and acceptable. Our investigation revealed substantial enhancements in signal-to-noise ratio (SNR) across different noise categories and intensity levels. Notably, the average SNR improvements reached up to 10% for baseline wander, a reduction of -15 dB for power-line interference, and a remarkable 50% increase for white noise when employing low-pass filter, notch filter, and moving average filter techniques, respectively. Consistency in our findings was demonstrated as the enhancements in signal clarity were consistently observed across a range of noise intensities. This highlights a significant improvement in the quality of the signal under different levels of noise interference. The achieved reduction in MSE was substantial, with improvements of 0.003 observed. However, the results of Power-line Interference removal using DWT do not overcome the notch filter but still have good performance and the contribution of the suggested architecture is to dealing with every type of noise in one processing task. According to experimental evaluations and comparisons in this work, the best mother wavelets were bior6.8 and symlt8 in terms of noise reduction, preservation of ECG features like QRS complex, T waves and P waves, and overall reconstructed signal quality improvement. The results of this study will provide valuable insights and guidance for researchers and practitioners in the field of ECG signal processing, paving the way for improved diagnostic accuracy, patient monitoring, and early detection of cardiac abnormalities.

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