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An Efficient QRS Detection and Pre-processing by Wavelet Transform Technique for Classifying Cardiac Arrhythmia

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Abstract: An electrocardiogram (ECG) is a recording of the heart's electrical activity. Symptoms of cardiac arrhythmias (CA) include an irregular heart rate. Large noise signal components will affect the acquired raw ECG signal from the MIT-BIH arrhythmia database. An ECG wave undergoes a pre-processing technique to eliminate noise signals and baseline drift. The most prominent characteristics will provide accurate and helpful data on cardiac arrhythmias. The Pan Tompkins technique is a real-time algorithm developed specifically for detecting QRS complexes in ECG signals. As distortion in the reconstructed signal increases, the PSNR metric's numerical value decreases and is used to rank signals from best to worst. Therefore, when PSNR increases, so does the quality of the compressed or reconstructed signal. The wavelet transform can be used for denoising and pre-processing nonstationary ECG signals. Filtering is a vital stage in the processing of ECG data because the current goal of the healthcare sectors is to preserve essential diagnostic information with little noise. This research demonstrates that the wavelet Thresholding approach has an effect on the quality of reconstructed electrocardiograms (ECGs). In this research, we use a discrete wavelet transform to analyse and de-noise an electrocardiogram (ECG) signal. The results of a comparative analysis were used to evaluate the efficacy of the third-level decomposition wavelet Denoising technique in reducing errors. According to the findings of the tests, this technique generates signals that are cleaner and smoother while keeping the essential elements.

Keywords**:** *ECG; DWT; CA; PSNR*.

1. Introduction:

Using electrodes placed on the skin, electrocardiography (ECG or EKG) records the electrical activity of the heart throughout time. Electrodes like these detect depolarization and repolarization patterns in the heart muscle's electrophysiology, which manifest as subtle electric changes in the skin. It is typically done to detect heart problems [1]. In a standard 12-lead electrocardiogram, 10 electrodes are attached to the patient's skin on their arms, legs, and chest. Twelve separate angles ("leads") are then used to record the average electric capacity of the heart over a given time period (often 10 seconds). Each stage of the cardiac cycle captures the significance and trajectory of electrical depolarization of the heart in this way. This non-invasive clinical approach generates an electrocardiogram, which is a graph of voltage variation with relation to time. An electrocardiogram (ECG) is made up of three main parts. The P wave represents atrial depolarization, the QRS complex represents ventricular depolarization, and the T wave represents ventricular repolarization [2]. Figure 1 shows the electrocardiogram waveform of a healthy heart.

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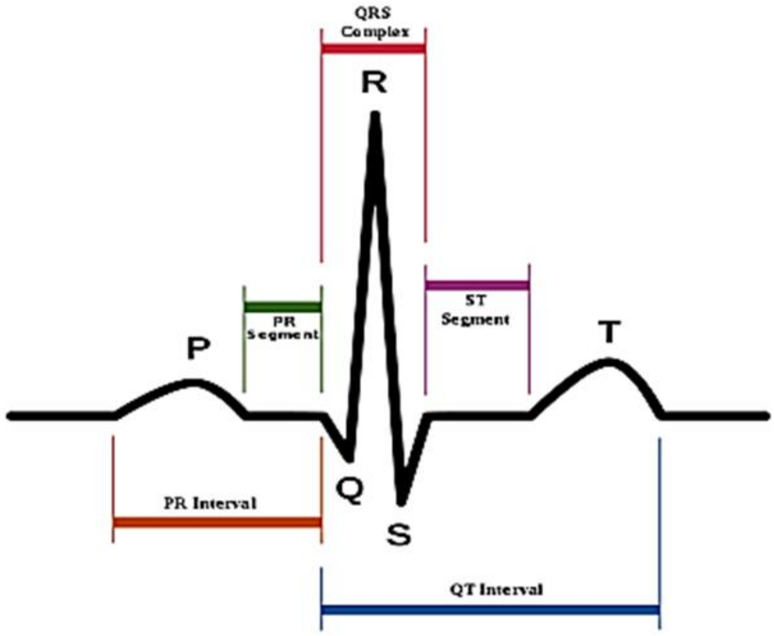

Fig 1: ECG of Normal Heart Beat.

The pacemaker cells in the sinoatrial node initiate depolarization during each heartbeat, which then travels through the atrium, the atrioventricular node, the bundle of His, and the Purkinje fibres before spreading downward and to the left in the ventricles [3]. An ECG may tell a lot about the heart's structure and electrical conduction system to a competent practitioner. An electrocardiogram (ECG) signal can be interpreted from many different angles, including measuring heart rate and rhythm, measuring heart chamber size and location, detecting damage to the heart's muscle cells or conduction system, gauging the effectiveness of a heart capsule, and measuring the performance of an implanted pacemaker.

Depolarization is a continuous process that allows an electrical impulse to go through excitable tissue [4]. When cardiac muscle fibres are repeatedly depolarized, a substantial ionic current is generated. The voltage drops when the current flows through the body's naturally resistant tissues. The voltage drop is too great for the electrodes to feel as they press against the skin. Myocardial depolarization results in a passage of ions across the skin, which is recorded as an ECG signal. The P-wave is a result of the dispersion of the electrical impulse into the atrial myocardium, which occurs after atrial depolarization [5]. As a result, the QRS complex represents the propagation of the electrical impulse across the ventricular myocardium after ventricular depolarization, and the T wave represents the repolarization of the ventricular muscle after ventricular repolarization.

The Sino-Atrial node, located in the upper portion of the atrium, and the Atrial-Ventricular node, situated in the interatrial septum, make up the human heart's conduction system. The AV node is responsible for controlling the ventricles and auricles. When the impulse signal from the Sino atrial node travels over the auricles, it causes the atriums to contract. These impulses are then emitted into the ventricles of the heart, where they are transformed into the force that propels blood to the lungs and the rest of the body [6]. The SA node controls the heart's impulse to the right places.

In the absence of any abnormality or disease in the morphology of the ECG wave, the normal rhythm of the cardiac muscle is referred to as Normal Sinus Rhythm (NSR). Those with NSR often have a heart rate between 60 and 90 beats per minute. Sinus tachycardia describes a heart rate of 100 or more beats per minute that originates in the sinus node. This is not an abnormal cardiac rhythm but rather a physiological response to a situation that calls for increased blood flow. Bradycardia is a condition in which the heart rate is dangerously low, which can have serious consequences for other bodily functions [7]. The study of an electrocardiogram rhythm can be performed quickly and painlessly by monitoring. The patient is made to adhere to a small number of leads, and the ECG machine checks each and every heartbeat.

In order to gain a deeper understanding of ECG, knowledge of the signal output by the leads that are authenticating the heart is essential. The ECG pattern confirms each heartbeat signal. We can tell what kind of cardiac arrhythmias, if any, are occurring by looking for certain characteristics. The dissimilarities in the P, QRS complex, and T wave parts of the signal allow for a thorough analysis of the various arrhythmias in this work. Differences in the cardiac signal are measured in terms of wave width and height.

2. Existing Work Done:

Cardiovascular diseases, such as those caused by smoking, diabetes, obesity, stress, high or low blood pressure, etc., have been a leading cause of death in recent years. In humans, ventricular and atrial arrhythmias are one of the most common and serious complications of cardiovascular disease [8].

Researchers have hypothesised that the minute variations in amplitude and time duration inherent in an ECG signal make it extremely challenging to extract and analyse the hidden data included in the signal. Therefore, advice is provided on how to diagnose with the help of computer software, and the retrieved data can be used by doctors in subsequent treatment. Researchers have proposed a classification learning algorithm for six distinct types of ECG beats, including normal, LBBB, RBBB, APC, VPC, and paced beats, with 86% sensitivity for APC beats and 97% sensitivity for the other five types of beats [9]. Researchers have also presented a machine learning system for classifying five distinct types of ECG beats, with a success rate of 93.97 percent.

The authors have successfully classified 6 different forms of ECG arrhythmias using the Particle Swarm Optimisation and Wavelet Transform methods, with an overall accuracy of 88.84%. Using a neuro-fuzzy approach and the Hermite Coefficients of ECG signal beats, they were able to achieve a 96% accuracy in their classification. The authors present a system in which the ECG signal is analysed for two distinct types of abnormalities and then classified using the Gaussian Mixture Model (GMM), achieving an accuracy of greater than 94% in both cases [10]. The scientists have also suggested an ECG SVM classifier model based on wavelet transform and principal component analysis, which has been shown to distinguish between normal and pathological heartbeats with an accuracy of 95.6%.

Pre-processing techniques are conducted to enhance the ECG's overall quality for better analysis and measurement. The ECG could be considerably affected by ambient noise, leaving any subsequent results dubious. Baseline Wander (BW), as proposed by researchers is a low-frequency type of noise that results from breathing and body movement; high-frequency random noises result from main interference (50 or 60Hz) and muscular activity; and random shifts in the amplitude of the ECG signal are caused by poor electrode contact and body movement [11].

Filters have received a lot of research and development time to eliminate disturbances like baseline wander and power line interference, which necessitate the development of a narrowband filter [12]. Since the ECG and muscle noise share a great deal of the same frequency spectrum, removing the noise caused by muscular activity is another crucial filtering problem. The presence of muscle noise in the ECG signal can be mitigated by employing methods that take use of the fact that the ECG is a recurring signal when suitable [13].

The standard ECG signal spans from 0.05 Hz to 100 Hz in frequency. The elimination of artefacts is a crucial step in ECG signal processing [14]. If artefacts are present in the ECG signal, it is more challenging for the professional to diagnose the disorders. The goal of any device designed to capture ECG signals is to do it with as little noise as possible. The ECG parameters can be extracted from the noisy ECG signal using a number of different techniques [15].

3. The Proposed Work:

This study discusses the use of wavelet transforms for denoising or pre-processing electrocardiogram (ECG) signals. For the purpose of identifying QRS complexes in ECG signals, a real-time algorithm known as the Pan Tompkins method has been created. It uses digital studies of slope, amplitude, and width to consistently identify QRS complexes. False positives generated by noise in the ECG signals are reduced with a specialised digital band pass filter. This filtering makes it possible to employ low thresholds, which in turn improves the detection sensitivity. In order to account for variations in QRS shape and heart rate in the ECG, the algorithm regularly modifies the thresholds and parameters. Traditional wavelet threshold de-noising selects all wavelet coefficients for threshold processing, but the proposed method selects only those wavelet coefficients that need threshold de-noising based on the wavelet energy and leaves the rest unmodified.

The QRS complexes are detected using two different thresholds. The filtered ECG signal and the signal generated by the integration of moving windows are both subject to thresholding. utilising thresholds on both signals increases detection reliability compared to when utilising a single waveform. By applying this digital band pass filter as a pre-processor to the raw ECG signal, the signal-to-noise ratio is enhanced, allowing for lower thresholds to be used. As a result, there is a greater ability to detect. The algorithmic detection thresholds are superimposed on the background noise. This method lessens the occurrence of false positives due to noise types that mimic the QRS complex.

The algorithm employs a dual-threshold approach to eliminate false negatives when searching for missed beats. Each threshold set consists of two individual thresholds. Each tier is equivalent to another's half. Because they are derived from the most recent signal and noise peaks found in the continually processed data, the thresholds continuously adapt to the features of the signal.

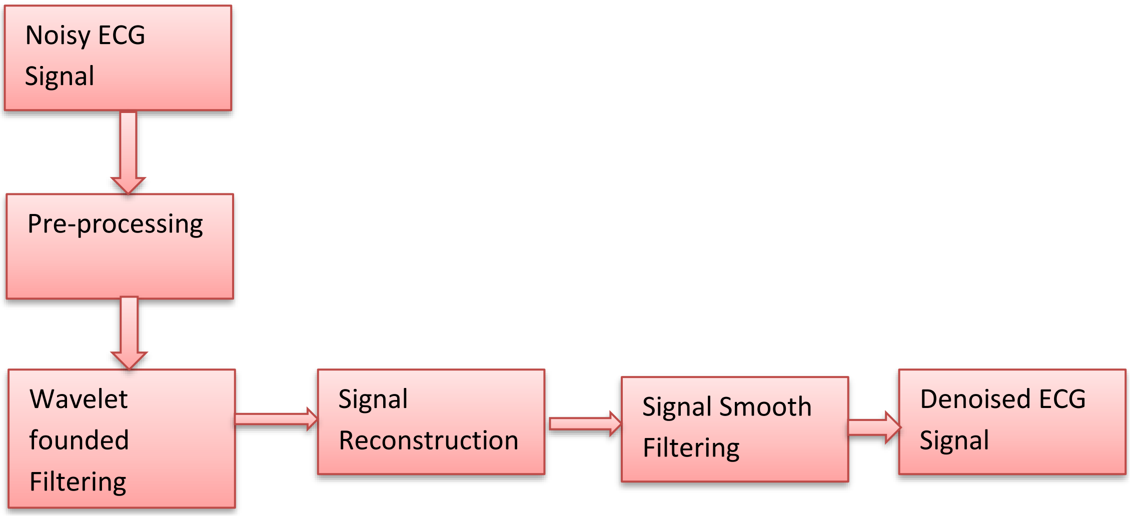

Fig 2: The Proposed Algorithm.

Denoising is carried out using the wavelet transform method following QRS detection. Instantaneous and time-varying signals are common applications of the wavelet transform. While the traditional Fourier transform can capture the gist of a signal's meaning, the way it's expressed is often baffling. Wavelet transform is an alternative to the Fourier transform for decomposing signals into smaller size components. Depending on the processing goal, a suitable decomposition scale can be chosen. Additionally, both the time and frequency domains can be found at the same time. It is most useful for analysing signals that change over time.

Further, it analyses the signal through the lens of the wavelet basis, rather than independently, leading to spurious frequencies and significant loss of information. While it is possible to increase the number of decomposition layers in Noisy ECG pre-processing denoising in order to acquire additional wavelet coefficients, doing so can easily lead to the erroneous frequency components. Each layer's detail coefficients are determined first using Matlab's detcoef function, and then the energy represented by those coefficients is determined. This is the formula for figuring it out:

$$E_j = \mathrm{Log}_e\left(\sum_{i=0}^{N} \mathrm{Cof_i}^2\right) \quad (1)$$

Where Ej is the energy of the jth-layer detail coefficient, N is the number of jth-layer detail coefficients, and cofi is the ith-layer detail coefficient.

As indicated before, the QRS complex in the denoised ECG data is detected using Pan and Tompkins, a real time QRS detection technique. The Pan Tomkins algorithm has been shown to have the abilities of acquiring derivatives, rectification/absolute operation, average integration moving, and threshold operations. Once the QRS Complex has been detected, the 100 samples before and after the QRS peak as well as the QRS peak itself are added together to form the 200-sample segment that constitutes a single beat for the purposes of further analysis.

4. Result and Discussion:

Metrics including mean squared error, mean absolute error, signal-to-noise ratio, peak-to-average ratio, cross correlation, and computational time have been calculated to assess the efficacy of the aforementioned algorithms. In order to use these signals for proper real-time diagnosis, we've selected these measurements, keeping in mind that denoising algorithms should be both accurate and fast. The following provides a quick summary of each metric.

4.1. Mean Square Error (MSE):

The mean squared error (MSE) is a common statistic for measuring the quality of denoising. The more closely the denoised signal matches the original signal, the lower the MSE value should be. If the MSE is low, the denoised signal is accurately denoised since the procedure has preserved the essential features of the original signal.

$$\mathrm{MSE} = \frac{1}{XY}\sum_{i=0}^{X-1}\sum_{j=0}^{Y-1}[B(i,j) - b(i,j)]^2$$
(2)

4.2. Mean Absolute Error (MAE):

The Mean Absolute Error (MAE) is a major statistical metric for determining the reliability of a projected system.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - x_i}{y_i}\right| \quad (2)$$

4.3. Peak to Signal Ratio (PSNR):

It is calculated by taking the square root of the Mean Square Error (MSE) between the noisy and the original image and dividing it by the maximum potential intensity value of the image (10log10). The mathematical definition of PSNR is:

$$\text{PSNR} = 10.\log_{10}\frac{\text{Max}_i}{\sqrt{\text{MSE}}} \quad (3)$$

4.4. Cross Correlation:

The degree of similarity between two time series can be determined by using cross correlation. The denoised signal and the noisy signal are very similar if the value of cross correlation (i.e. xcorr) is near to 1. Using the above symbol convention, we can write the definition of the cross correlation as:

$$\text{Corr}\left(\frac{A}{B}\right) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{i,j}-\hat{A})(B_{i,j}-\hat{B})}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{i,j}-\hat{A})^2\sum_{i=1}^{m}\sum_{j=1}^{n}(B_{i,j}-\hat{B})^2}}$$

(4)

Complex functions, including as wavelets, mother wavelets, analysing wavelets, and scaling functions, constitute the basis of the wavelet transform. During wavelet analysis, the signal is decomposed into scaled and shifted iterations of the mother wavelet. The multi-resolution nature of the wavelet transform makes it well suited for analysis of non-stationary signals like the ECG signal. By expanding and contracting its basis functions, the wavelet transform can provide representations of the signals at varying granularities. Figure 3 depicts the original raw ECG signal.

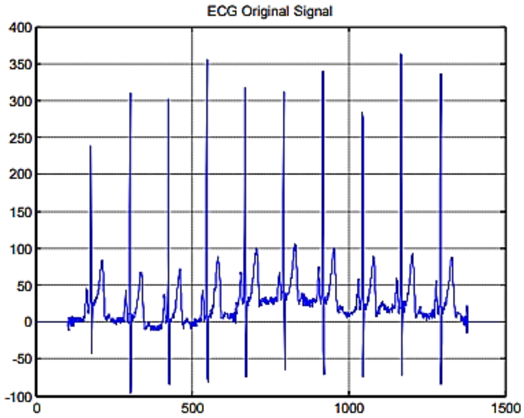

Fig 3: Pure EEG Signal.

The wavelet scales and translations of the numerous data points that make up an electrocardiogram can be set according to predetermined rules. The noisy ECG signal was first decomposed using a wavelet transform (DWT).

Band pass filters are shown in Figure 4 to correct the baseline drift. The original signal must be decomposed using consecutive Low-Pass Filters (LPF) and High-Pass Filters (HPF), as per Wavelet Transform (WT). For both low-pass and high-pass filters, the sampling frequency will serve as the cutoff. Figure 4 shows the resultant normalised ECG signal. One of the microcomputer systems takes a sample of the ECG database being played back from an FM recorder and analyses it using the QRS detection method. A pulse is produced if a QRS complex is recognised. Figure 5 shows the R peak that was identified.

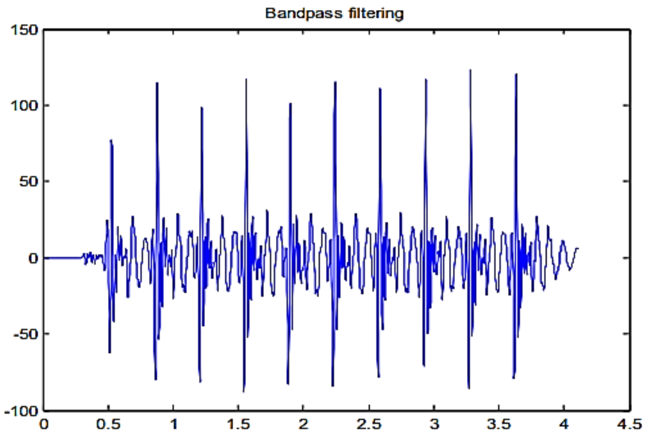

Fig 4: Pre-processed ECG signal.

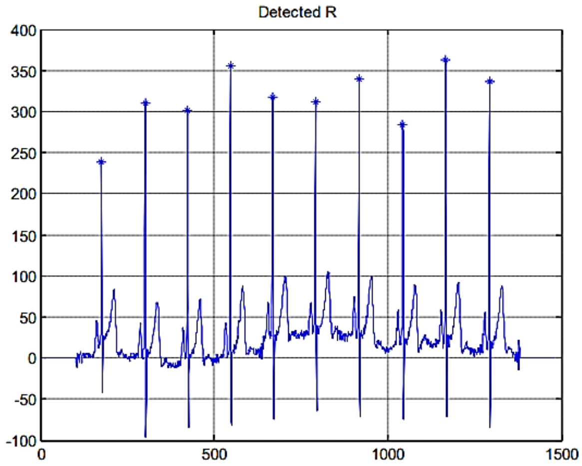

Fig 5: Detected R Peak in ECG signal.

Before processing the signal, it is first decomposed using Discrete Wavelet Transform (DWT). After selecting a wavelet and settling on an appropriate level of decomposition for the wavelet transform N, the N-layer wavelet decomposition of the signal s (n) can be carried out. Thus, the decomposed signal is presented in Figure 6 .

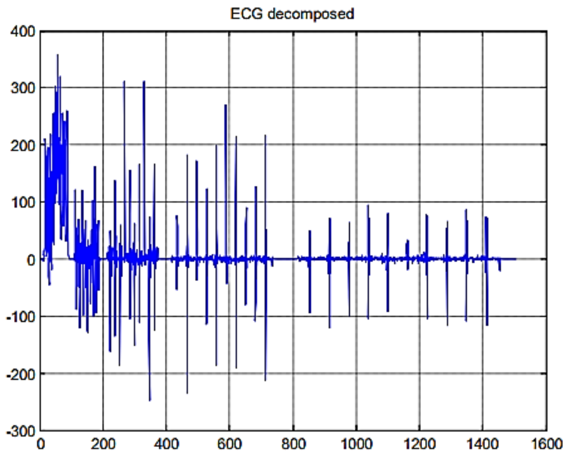

Fig 6: Decomposed ECG Signal.

When it comes time to quantize your wavelet coefficients, use the Thresholding technique and Thresholding rule. After that, the thresholding is done to each stage of the wavelet decomposition, and the wavelet coefficients that are too high are thrown out. The next step is a reconstruction of the denoised signals without losing any of the useful information contained within them. For each level of decomposition, the Inverse Discrete Wavelet Transform (IDWT) is applied to a set of wavelet coefficients to rebuild the original signal. Figure 7 depicts the output of a noise-free ECG signal after smoothing.

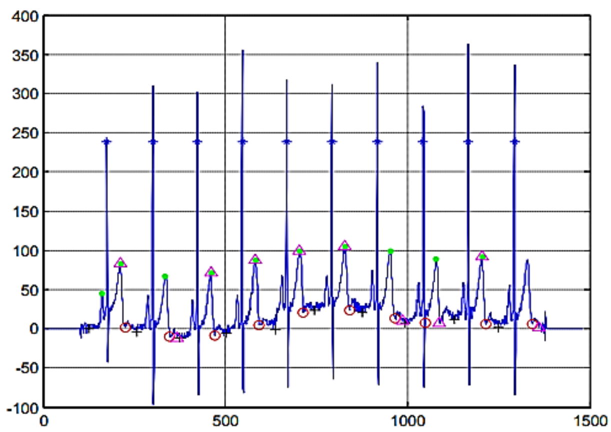

Fig 7: Noise Free ECG Signal.

Table 1: Performance Comparison of raw and denoised ECG signal.

Performance Measures		Mean Square Error	Mean Absolute Error	PSNR (db)	Cross Correlation
Samp. No. 124	Pre-Filtering	0.12	0.38	58.25	0.092
	Post-Filtering	0.001	0.31	64.72	0.056
Samp. No. 205	Pre-Filtering	0.24	0.58	54.47	0.078
	Post-Filtering	0.01	0.45	67.18	0.064
Samp. No. 232	Pre-Filtering	0.093	0.83	55.48	0.082
	Post-Filtering	0.004	0.78	72.59	0.074

Calculating by using Mean Squared Error, Mean Absolute Error, Peak-to-Valley Ratio the reconstruction of the signal is compared to the original signal to make the measurement as shown in table 1.

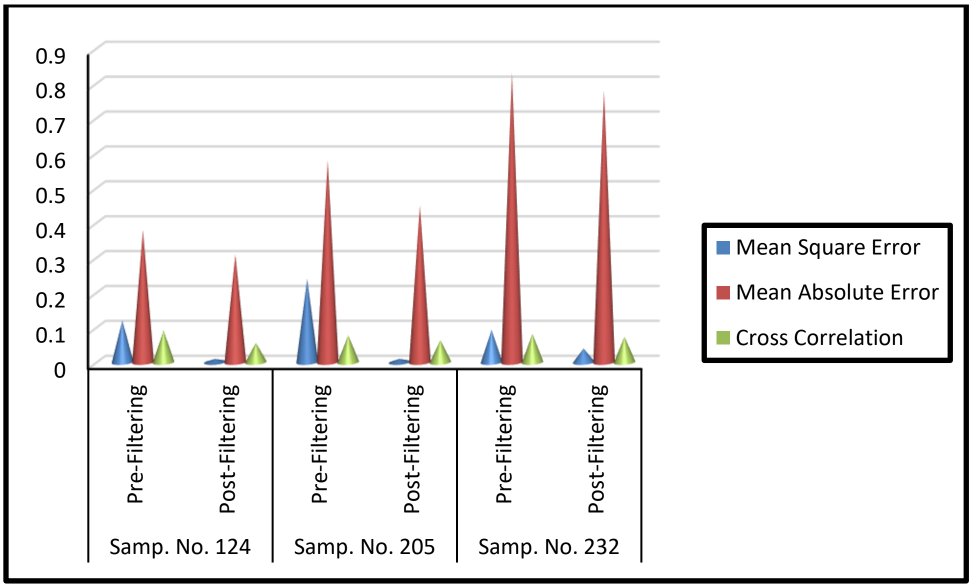

Fig 8: Performance Evaluation of the proposed method.

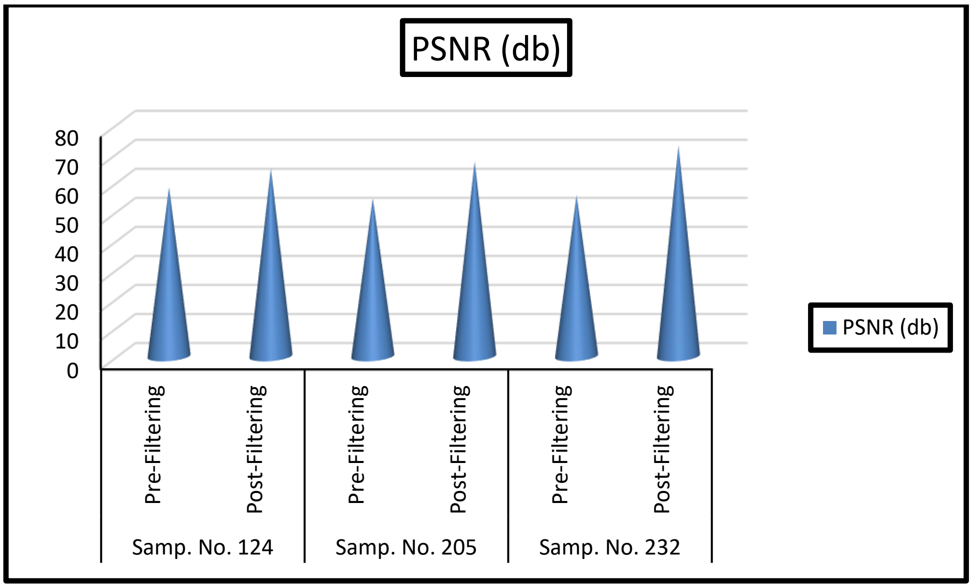

Fig 9: PSNR comparison for Pre and post filtering of proposed method.

A drop in PSNR might be seen as an indication of rising distortion levels in the reconstructed signal, as this quality metric is inversely proportional to distortion. As a result, the quality of the compressed or reconstructed signal improves as the PSNR rises. Nonstationary ECG signals can be denoised and pre-processed using the wavelet transform.

5. Conclusion:

Denoising and pre-processing of electrocardiogram (ECG) signals using the wavelet transform method is the focus of this study. For the purpose of identifying QRS complexes in ECG signals, a real-time algorithm known as the Pan Tompkins method has been created. The PSNR is a metric used to evaluate signal quality, and its numerical value drops as distortion in the reconstructed signal rises. As a result, the quality of the compressed or reconstructed signal improves as the PSNR rises. Nonstationary ECG signals can be denoised and pre-processed using the wavelet transform. Since the present goal of the healthcare sectors is to maintain essential diagnostic information with little noise, filtering is a crucial stage in the processing of ECG signals. Reconstruction quality of an electrocardiogram (ECG) is demonstrated to be affected by the wavelet Thresholding approach applied in this work. In this paper, we analyse how to de-noise an electrocardiogram (ECG) signal using a discrete wavelet transform. Improvement in error reduction was examined by applying the outcomes of a comparative study and taking into consideration the third-level decomposition wavelet Denoising method. The testing results show that this method produces signals that are cleaner and smoother while maintaining crucial features, resulting in a more aesthetically pleasing appearance.

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