A Novel Framework for ECG Signal Processing and Robust Arrhythmia Detection

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***Abstract*: Cardiovascular diseases are still one of the most important public health issues that the world is facing today. Early identification of heart problems can help with early diagnosis. Analyzing the electrical signals created by the heart can provide important insight into how well a person's heart is functioning. The electrical signals generated by the heart can be disrupted by noise and interference, which effects the interpretation of these signals. This paper reveals a novel approach to process bio signals to uncover the presence of abnormal heart rhythms based on abnormally fast, slow, or irregular heartbeat patterns. The results of the experimental evaluations demonstrate that out of total 10 participants, 6 individuals have a normal heart pattern while the heart rate analysis of remaining 4 individuals indicates that they are having arrhythmia. Thus, the method used in this study successfully distinguishes between normal and abnormal cardiac conditions. This publication provides an overview of the potential use of signal processing to assist with early diagnosis of heart problems and improve ongoing monitoring of patients' health in both clinical and remote settings.**

***Keywords:* cardiovascular disease (CVD), ECG, abnormal heart rhythms, filtration, reducing noise, analyzing features**

I. INTRODUCTION

Cardiovascular Disease (CVD) are still the leading cause of death in the world with millions of people died each year [1],[2]. It encompasses a wide variety of conditions impacting both the heart and blood vessels. Included within CVD are the following: coronary arteries, heart failure and arrhythmias (rhythm problems) [1]-[5]. Atherosclerosis, Hypertension (high blood pressure), Diabetes Mellitus, Smoking, and a Sedentary Lifestyle are the multiple factors that deteriorate the cardiac health. As the heart becomes less efficient at pumping blood, these factors could ultimately result in conditions including Myocardial Ischemia (reduced flow of oxygenated blood to the heart), Ventricular Dysfunction (inability of the ventricles to contract), or Sudden Cardiac Death [1], [2]. Patients with declining cardiac output (CO) become fatigued, and have difficulty in breathing (dyspnea)[6]. They do not tolerate excessive physical activity, even their ambulation pattern is altered resulting in decreased step length [7]. Untreated myocardial infarction (MI, or heart attack) and malignant arrhythmia's lead to urgent medical situations that may have a very high likelihood of sudden death [1],[3].

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Arrhythmia is a condition in which heart beat is altered and is categorized into Bradycardia and Tachycardia. The Bradycardia is a condition when a person's heart beats slower than the normal, usually less than 60 times per minute (bpm). This decreases the cardiac output (CO), which in severe cases may result in dizziness, fainting (syncope), low blood pressure (hypo-tension), and in extreme cases heart failure or asystole [2],[3]. Tachycardia is when a person's heart beats too fast usually greater than 100 bpm [2][4]. Conversely, long-term fast heart rates increase diastolic filling time (DFT) and the MYO_2 demand on the heart thereby increasing the likelihood of ischemia (inadequate blood flow), the development of tachycardia-induced cardiomyopathy (disease of the heart muscle due to rapid heart beat) and the occurrence of premature ventricular contractions (PVCs) and sudden cardiac death (SCD)[2][3]. Abnormalities in heart rates are usually associated with changes in the shape of the QRS complex (QRS morphology) and changes in the beat-to-beat intervals (RR-interval variability), both of which are critical elements in current frameworks for feature extraction such as Efficient QRS Morphology (E-QRSM) for the classification of PVCs [1],[3]. Thus, analyzing these waves are crucial to forecast the activity of heart.

An electrocardiogram is a non-invasive tool to record the heart's electrical impulses. The P wave shows that the atria have been depolarized; the QRS complex indicates that the ventricles have been depolarized; and the T wave shows that the ventricles have been repolarized [3]-[5]. An ECG during bradycardia may show RR interval (that is the interval between R peaks) being prolonged, heart rate being significantly less than the average (in BPM). The output also displays the following "rhythms" that may have occurred during the ECG: sinus pauses, escape beats, and conduction delays; e.g. prolonged PR interval (AV nodes for Atrial Ventricular Conduction) or Bundle Branch Block (BBB) which can easily be identified by measuring a QRS that is greater than 120 ms in duration[2]. When someone has tachycardia, their RR (R-to-R) intervals shorten and there are several RR's separated by longer than usual amounts of time (i.e., several QRS complexes). In the case of supraventricular tachycardia (SVT), when taking the lead II ECG, the QRS complex is narrow; whereas when taking a ventricular tachycardia (VT) lead II ECG, the QRS complex widens and have an abnormally large, rounded morphology [2],[3]. To explore these differences accurately, advanced filtering techniques must be incorporated that remove noise caused by random motion of the heart muscle or skeletal muscles (electromyography noise - EMG noise), 50/60Hz powerline interference (PLI), or any other forms of noise. Along-with the filtration technique during the processing of bio-signals, denoising filter techniques must also be employed including the stationary wavelet transform (SWT), notch filter, and robust Neville aggregation (RNA) operator so that the most diagnostically important features of the ECG, namely the P-, QRS-, and T-waveforms, are preserved for measuring the following intervals: PR, QT, QRS, and RR.[3],[4]. In parallel with this, time-

frequency transforms of greater sophistication (such as continuous wavelet transform (CWT), short-time Fourier transform (STFT), and plotting of FFT-derived spectra) are being widely applied to generate two-dimensional scalograms or spectrograms from one-dimensional ECG waveforms, with the intent of capturing the arrhythmia both temporally and spectrally [5].

Numerous well-established ECG repositories provide large-scale electrocardiographic data (e.g., MIT-BIH AR and PTB DB) and routinely demonstrate that the majority of patients from diverse backgrounds exhibit at least one form of clinically significant arrhythmia [1],[3],[5].For digital signal processing of ECG either the data from these repositories are extracted or can directly fetch from hospitals. Recent studies indicate that QRS-feature-extraction software applications (e.g., E-QRS-M) and advanced versions of the R-peak detectors have enhanced performance compared to the legacy method. Additionally, contemporary technology allows use of complex methods (e.g., SWT-based filters, RNA-based PLI suppression, CWT/FFT/STFT) that utilize sequential, 2D convolutional neural network (CNN) calculation methods, which have provided significant improvements over conventional techniques for detecting arrhythmias from short segment ECG [1],[5]. The technology's emergence demonstrates how AI-enabled ECG analysis systems are becoming an essential part of CAD that will alleviate the burden on physicians' workloads as well as provide for earlier medical interventions that reduce the risk of morbidity and death associated with CVDs [1]-[5].

II. LITERATURE REVIEW

An electrocardiogram (ECG) is widely used to diagnose cardiac disorders. Many algorithms have been employed to improve the analysis of ECG signal so that maximum information regarding cardiac condition can be extracted. Some of the latest approaches to dig out the bio-signal evaluation are listed here along with the algorithms implemented. D. Zhai et al.,[8] employed the Pan-Tompkins algorithm in detecting the QRS complex. It shows the optimum results but its performance is limited because of fixed threshold and its sensitivity to noise .

Due to the non-stationary nature of ECG signals, wavelet-based techniques are widely used for ECG signal processing. The Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) enable the analysis of multi-resolution ECG signals, facilitating the accurate detection of different ECG components, such as P, Q, R, S, and T waves [9], [10]. The unique properties of Wavelet Transforms allow the alleviation of noise while retaining the most significant Morphological Characteristics of ECG Signals. Along with the implementation of multiple bio signal processing techniques in time & frequency domain, the advent of Machine Learning and Deep Learning has transformed the automatic interpretations of ECG signal. Thus, merging these time & frequency domain approaches with machine learning and deep learning model boosts the performance. S. C. Mohonta et al.,[9] et al. proposed a hybrid deep learning framework for ECG-based arrhythmia classification that integrates the Continuous Wavelet Transform (CWT) with a two-dimensional Convolutional Neural Network (2D-CNN). The ECG signals were obtained from the MIT-BIH Arrhythmia Database, comprising 23 recordings of 30 minutes duration each, sampled at 360 Hz. The study highlighted the effectiveness of CWT in multi-resolution signal analysis, as it preserves detailed time–frequency information while mitigating motion artifacts that commonly affect FFT and STFT methods, particularly at low frequencies. The proposed CWT-RGB model (TN4) demonstrated superior performance, achieving an average sensitivity of 98.87%, specificity of 99.85%, and overall accuracy of 99.65%. Despite these results, the approach is limited by the restricted diversity of arrhythmia classes and the relatively small dataset, consisting of approximately 7,500 signal segments derived from only 23 recordings. Hybrid Models, such as developing a Combined Statistical, Spectral and Morphological Feature Set and a Machine Learning Classifier, for example, SVM and ANFIS, have been shown to improve classification performance for arrhythmias [11],[12].

S. Abagaro et al.,[12] in a research study proposes a hybrid ECG-based arrhythmia classification framework that integrates morphological and dynamic features to improve diagnostic performance. Morphological characteristics are extracted from individual heartbeats using the Discrete Wavelet Transform (DWT), followed by Independent Component Analysis (ICA) for dimensionality reduction, resulting in a compact set of representative features. Dynamic information is derived from RR intervals, with nonlinear temporal behavior captured using the Teager Energy Operator (TEO) and multiple RR-based descriptors, including previous, subsequent, average, and local intervals. The combined feature set is classified using a deep feedforward neural network with ReLU and sigmoid activation functions. The approach demonstrates high performance on benchmark MIT-BIH arrhythmia datasets, achieving an average accuracy of 99.75% along with strong sensitivity and specificity under a class-oriented evaluation scheme. However, the study notes that performance for rare arrhythmia classes remains challenging and emphasizes that subject-oriented evaluation strategies are necessary for reliable real-time clinical deployment.

Subsequently, R.Kumar and V. Chakrapani, presents an ECG-based arrhythmia classification system that employs Fast Fourier Transform (FFT) for frequency-domain feature extraction in conjunction with an enhanced AlexNet convolutional neural network for deep learning–based classification. Using ECG signals from the MIT-BIH Arrhythmia Database, the proposed approach classifies four types of arrhythmia and reports an approximately 20% improvement in deviation detection compared with conventional methods, highlighting the potential of integrating spectral features with deep neural networks for noninvasive and early cardiac diagnosis. Despite these promising results, the methodology exhibits several limitations, including reliance on a single feature extraction technique that may neglect important temporal dynamics, classification restricted to a limited number of arrhythmia classes, and dependence on a single dataset without cross-database validation. Additionally, the study lacks comprehensive performance metrics and statistical validation, provides limited insight into computational requirements and model interpretability, and does not address real-time deployment, robustness to noise, or subject-oriented evaluation, thereby constraining its generalizability and clinical applicability [13].More advanced DL models have employed FFT-based spectral learning [14] and hybrid CNN–LSTM structures [15] for wearable cardiac monitoring applications. Reviews have also highlighted the importance of using hybrid-domain frameworks for enhancing interpretability and real-time processing [16].

Denoising techniques using DWT in combination with Butterworth and Notch filters have demonstrated satisfactory denoising and anomaly detection performance [17]. Deep learning architectures, including residual CNNs [18] and hybrid fusion-based models [19], have improved classification performance on multi-lead ECG datasets. The ensemble learning approach has further increased robustness and diagnostic accuracy [20]. Recent advances in self-supervised learning have demonstrated high accuracy using a small amount of labeled data, thereby improving the scalability of the method for telemedicine applications [21].

In summary, so far, the best combination seen in the state-of-the-art for arrhythmia detection and classification is the combination of wavelet transformation, frequency-domain analysis, and machine or deep learning techniques. Using these in combination with MATLAB real-time systems develops the efficient and interpretable ECG diagnostic tool but the main constraint is the excess time consumption. So there is a need to design a simpler

framework for cardiac health monitoring without AI Models to save time.

III. METHODOLOGY

The methodology comprises multiple steps, from data acquisition to signal pre-processing and then to detection. The layout starts with the system framework yielding the specifications of each stage of processing, then the Processing Pipeline demonstrating the flow of signal from taking input to detection of arrhythmia in heart beat and in last Signal Analysis depicting the diagnosis of heart condition via waveform.

A. System Framework

1. Data Acquisition

The ECG data are extracted from the MIT-BIH Arrhythmia Database, present in the PhysioNet archive, a public repository of physiological data relevant to biomedical research. The ECG signal contained in the file '103m.mat' is part of a recording originally sampled at 360 Hz, which is the typical sampling frequency of the MIT-BIH database.
The dataset can be accessed at:

https://physionet.org/content/?topic=MIT-BIH+Arrhythmia+Database%2C+

When the .mat file is loaded, the ECG signal can be retrieved through the variable val, which indicates the amplitude values of the ECG waveform over time. This signal is normalized (dividing by 200) and gives rise to the var ecgsig, which is subsequently subjected to several preprocessing steps.

2. ECG Signal Preprocessing

Various preprocessing methods are applied to the raw ECG signal (ecgsig) in order to suppress artifacts:

a) Baseline Wander Removal:
This is implemented using the biorthogonal wavelet transformation. The ECG signal is decomposed into approximation and detail coefficients using the wavedec function and the 'bior3.7' wavelet, up to level 9. The detailed coefficients from levels 1 to 9 are aggregated using wrcoef to reconstruct the baseline wander component, which is saved in y0 (baseline-corrected ECG), effectively eliminating low-frequency baseline drift.

b) Powerline Interference Removal:
Powerline interference, typically present at 50 Hz, is addressed with a notch filter. An IIR notch filter is designed using an IIR notch, set with a notch frequency (Fnotch) of 50 Hz, a bandwidth (BW) of 100 Hz, and a passband attenuation (Apass) of 1 dB. This filter is applied to the signal from which the baseline wander has been removed (y0), and the resulting output is recorded in y1 (ECG after powerline noise removal).

c) High-Frequency Noise Reduction:
Additional noise removal is conducted by breaking down y1(ECG after powerline noise removal) with the 'bior3.7' wavelet using wavedec up to level 2. The approximate component obtained at level 2 is reconstructed through wrcoef and saved as y2 (denoised ECG signal), thereby smoothing the signal by eliminating high-frequency components.

d) Bandpass Filtering:
A bandpass filter is applied to y2 (denoised ECG signal) to preserve the clinically significant frequency components of the ECG signal, which typically range from 0.5 Hz to 50 Hz. A second-order Butterworth filter is created using butter with cutoff points set at 0.5 Hz and 50 Hz, normalized by half the sampling frequency (Fs/2). This filter is now applied to y2 (denoised ECG), and the final cleaned ECG signal is stored in y3 (denoised ECG).

The ECG signal (y3) is used to identify the morphological features of the ECG signal.

e) Feature Extraction:

The ECG signal (y3) is used to identify the morphological features of the ECG signal.

i. R-peaks Detection:
R-peaks are identified using the find peaks function, where the minimum peak height is set to 0.4 and the minimum distance between peaks is 50 samples. This allows each heartbeat to be detected and its R peak to be found. The location of the R-peaks is stored in locs_r.

ii. P, Q, S, T Waves Detection:
The locations and amplitudes of other key waveforms (P, Q, S, T) are found with respect to the located R-peaks. The steps are shown below.

- *S wave:* Found as the lowest point of the segment obtained after the R-peak (15 samples).
- *Q wave:* The lowest point in the segment between the R-peak and the following R-peak, within 15 samples.
- *P wave:* The highest point in a window before the Q wave (within 60 samples).
- *T wave:* The highest point in the window before the next R-peak after the S wave (within 130 samples).

The peak amplitudes and positions are saved in Speaks, locs_s, Ppeaks, locs_p, Tpeaks, and locs_t.

f) Interval Calculation:

Using the identified peak positions, the following intervals are determined:

- *RR intervals:* The time between successive R-peaks. diff(locs_r) ./ Fs (seconds).
- *QRS durations:* Time between the S-wave and Q-wave positions. locs_s - locs_q (seconds).
- *PR intervals:* Time between the location of the R-wave and the P-wave. locs_r - locs_p (seconds).
- *QT intervals:* Time between the T-wave and the Q-wave positions. locs_t - locs_q (seconds).

All the interval arrays are truncated to the minimum length so that they have the same length downstream.

Heart Rate and HRV Calculation

- *Heart Rate:* The heart rate, expressed in beats per minute (BPM), is the average of the RR intervals.

$$\text{Heart Rate (BPM)} = \frac{60}{\text{Mean RR interval (s)}}$$

- *Heart Rate Variability (HRV):* HRV is the standard deviation of the RR intervals (Std_RR) divided by the average RR interval:

$$\text{HRV} = \frac{\text{Std-RR}}{\text{Mean-RR}}$$

g) Arrhythmia Detection:

Arrhythmias are detected based on the heart rate and morphological characteristics of the signal.

These are identified by applying thresholds to the heart rate and morphological characteristics.

- *Tachycardia:* Heart rate above 100 BPM.
- *Bradycardia:* Heart rate below 60 BPM
- *Atrial Fibrillation:* Std_RR > 0.15 seconds.
- *Ventricular Arrhythmia / Bundle Branch Block (BBB):* Indicated when the average QRS duration (Mean_QRS) surpasses 0.12 seconds.

- *First-degree AV Block / Prolonged PR Interval:* Noted if the average PR interval (Mean_PR) exceeds 0.2 seconds.
- *Long QT Syndrome / Prolonged QT Interval:* Indicated if the average QT interval (Mean_QT) goes beyond 0.44 seconds.

h) Frequency-Domain Analysis:

Results of the detections are shown with the heart rate class (Normal, Tachycardia, Bradycardia) if there is any atrial fibrillation, QRS duration abnormality, prolonged PR interval, prolonged QT interval, bundle branch block.

i) Tools and Software:

The entire study is done in MATLAB. These functions of the Signal Processing Toolbox are used :

- wavedec and wrcoef (for removing noise using wavelets)
- iirnotch (for notch filtering)
- butter (for designing Butterworth)
- filter (for applying designed filters)
- findpeaks (for finding R-peaks) f) fft (for doing frequency domain analysis)

B. Processing Pipeline of the Proposed System

The Processing Pipeline is a step-by-step approach to accurately check for heart rhythm problems using ECG signals. First, ECG data is collected from public databases, which show how the heart's electrical activity changes over time. These signals have different types of noise, so filtering is used to remove unwanted parts like baseline shifts, electrical interference from power lines, and muscle movement. This helps keep important parts of the ECG, such as the P wave, QRS complex, and T wave, clear and useful. After cleaning the data, features that describe the shape, height, and length of these ECG parts are taken to find any signs of heart rhythm issues. Then, time-based measurements like RR, PR, QRS, and QT intervals are calculated to reveal the heart beat and it's conduction. In addition to looking at time-based data, frequency-based features are also analyzed using methods like the Fast Fourier Transform to find rhythm problems that aren't obvious in the time domain. Using these features, the system tells the difference between normal heart rhythms and abnormal ones. The final results are shown in a way that's easy to understand, helping doctors make better decisions about patient care. The given figure 1. depicts this whole procedure.

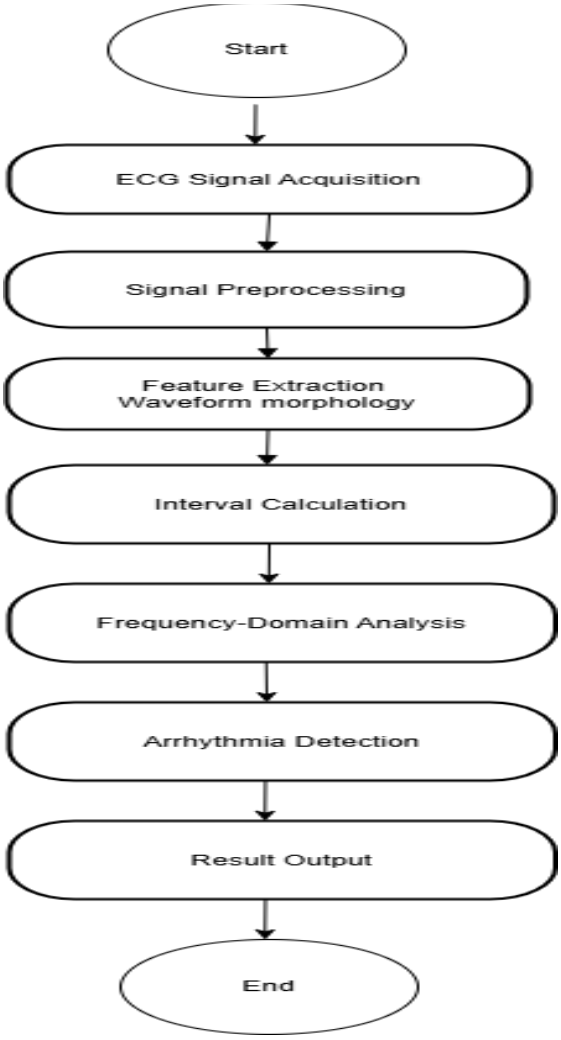

Figure 1:Flowchart illustrating the overall methodology of ECG signal processing and arrhythmia detection.

C. Digital Signal Processing for ECG Denoising & Signal Analysis

Denoising, heart rate, and QRS complex results are obtained from the ECG signal processing framework phases in various steps. The results of the processed ECG signal and extracted features are presented in Figure 2 below. The diagram illustrated how the ECG signal is processed through successive stages to filter out interference and other unwanted disturbances, resulting in a noise free signal waveform.

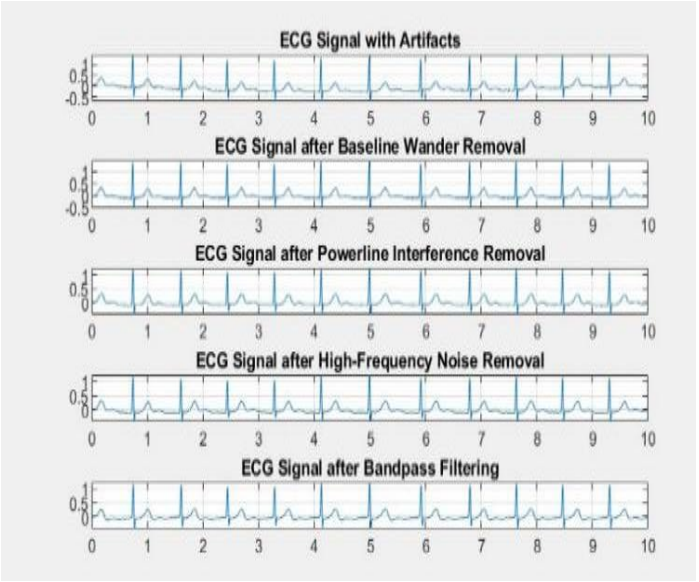

Figure 2: ECG signal with artifacts and then after filtration

(i) ECG Signal Denoising and Enhancement

The first ECG signal acquired in Figure 2. is contaminated with different types of noise including Baseline Wande, Powerline Interference and high-frequency noise originating either from breathing, bodily movements and from muscle activity or external influences. The sequence of filtering operations are applied to the ECG signal as:

- ECG Signal with Artifacts: The first ECG signal exhibited significant low-frequency drift and noise, obscuring the individual components of the ECG waveform (P wave, QRS complex, T wave).
- After Powerline Interference Removal: The high amplitude 50/60 Hz sinus interference(comingfrom medical devices) is removed and the waveform became a much more uniform signal without the unnatural jumps.
- After High-Frequency Noise Removal: Trivial, fast variations are removed from the signal, making the R-peaks and other ECG morphology more visible.
- After Bandpass Filtering: A bandpass filter (typically, between 0.5–100 Hz) is used to retain the clinically relevant signal frequency range. This last step made the signal sharper, enabling high-quality ECG waveform morphology analysis and filtering out the non-cardiovascular.

The filtering process ensured that the interference is removed from the signal without damaging the cardiac signal itself, enabling accurate clinical interpretation of the signal as well as further signal processing.

(ii) Heart Rate Analysis

In Figure 3, the heart rate changes over time is observed (in BPM - beats per minute). Heart rate is calculated over time, and in the proposed methodology R-peak is detected and RR interval is calculated.

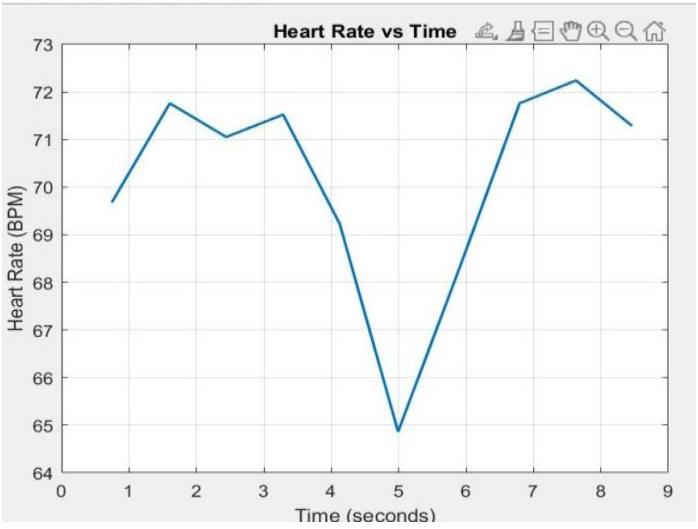

Figure 3: Variation in heart rate with time

Heart rate varied between 64 BPM and 72 BPM in above figure indicating normal heart rate(at rest). However,there is a small drop around the 5 seconds (around 64 BPM). This is caused by a long RR interval. Long RR intervals refers to natural HRV. There is no bradycardia (HR < 60 BPM) or tachycardia (HR > 100 BPM). This graph shows that the subject has a normal sinus rhythm, beating with a healthy variation from one beat to the next. The effective and accurate finding of the R-peaks proves the efficiency of the denoising and the peak detection algorithms.

(iii) QRS Duration Analysis

The Line graph, Figure 4. shows the QRS duration measurement over a sequence of 10 cardiac beats.

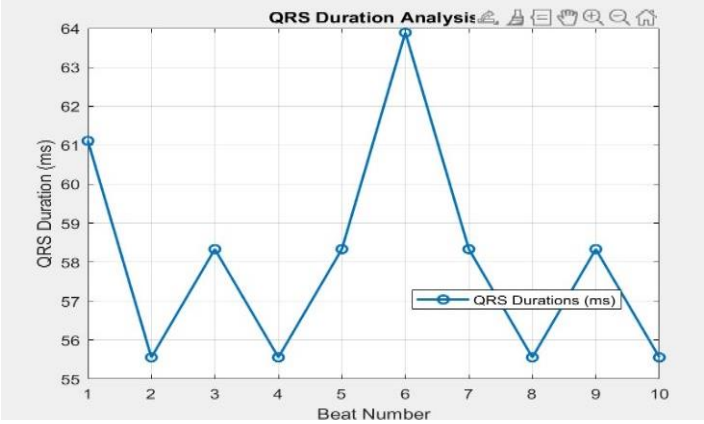

Figure 4: QRS duration Analysis (measured in milliseconds) for 10 cardiac cycles

The above figure illustrates the QRS duration for ten detected heartbeats. The QRS duration signifies the period required for ventricular depolarization and serves as a crucial measure of the heart's electrical conduction. The recorded duration is within the range of 55 ms to 64 ms, which is slightly less than the normal adult range of 70–110 ms, indicating a narrow QRS complex. A narrow QRS complex typically suggested that ventricular depolarization is proceeding normally and swiftly through the His-Purkinje system. There are no indications of an extended QRS duration, which could otherwise imply delays in conduction or blockages in the bundle branches. The uniformity of the QRS duration across the beats further validates the effectiveness of the peak detection algorithm and the temporal stability of the signal after preprocessing. The characteristics of the recorded ECG signal in the frequency domain are assessed by calculating the one-sided amplitude spectrum using a Fast Fourier Transform (FFT). The resulting spectrum is shown in Figure 5. Basic frequency components are observed to be predominantly concentrated within 40 Hz.

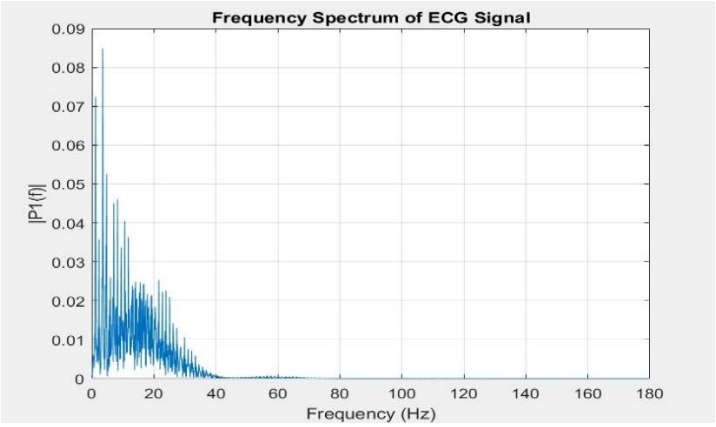

Figure 5: The ECG signal's frequency spectrum

(iv) Dominant Frequency Components

The largest non-DC peak is observed at approximately 1.2 Hz, which is approximately 72 beats per minute (1.2 Hz × 60 s/min). Other peaks around integer multiples (approximately 2.4 Hz, 3.6 Hz, etc.) are the harmonic components of the P–QRS–T cycle.

(v) Energy Distribution

Summing spectral magnitudes give the following cumulative energy spectrum.

- 0–1 Hz (baseline/DC): ~25%
- 1–5 Hz (fundamental + 1st harmonic): ~50%
- 5–15 Hz (details of the QRS complex): ~80%
- 15–30 Hz (T-wave and fine structure): ~95%
- 30 Hz: remaining ~5% (approaching the noise floor)

(vi) High-Frequency Content

Spectral amplitudes fell quickly beyond 40 Hz, so any physiological information content beyond 40 Hz can be considered to be insignificant. There is no significant peaks at 50/60 Hz (power line interference) that would indicate inadequate noise mitigation during data acquisition or preprocessing.

(vii) Implications for Signal Processing

Applying a high-pass filter at around 0.5 Hz removes the baseline wander (25% energy content below 1 Hz) while preserving all of the cardiac signals. Meanwhile, setting a low-pass filter at 40 Hz would remove less than 0.1% of the physiological energy content in the signal, and would reduce any remaining high-frequency noise. Given that there may be no significant content above 50 Hz, the ECG data may safely be downsampling to 100–120 Hz sampling rate with no risk of aliasing. Thus, the relevant physiological information content is observed to be below 40 Hz with a clear fundamental frequency around 1.2 Hz. This spectral information provides a strong clue as to subsequent processing of the signal, including R-peak detection, feature extraction for arrhythmia classification, and time–frequency based using wavelets.

IV. RESULTS

During this study the ECG signal processing pipeline is proposed to profile cardiac health using both morphological and frequency based characteristics. Firstly, the signal is pre-processed to remove baseline drift, powerline interference and high frequency interference using biorthogonal wavelet decomposition in combination with digital filtering. After the denoising process, the P, Q, R, S and T peaks are distinctly marked and relevant intervals RR, PR, QRS, and QT are mined from the ECG signal. The output is displayed as Fig. 6, which shows ECG signal detection as normal, and demonstrates the effectiveness of a combination of wavelet based denoising and feature extraction with a rule based approach to arrhythmia mining.

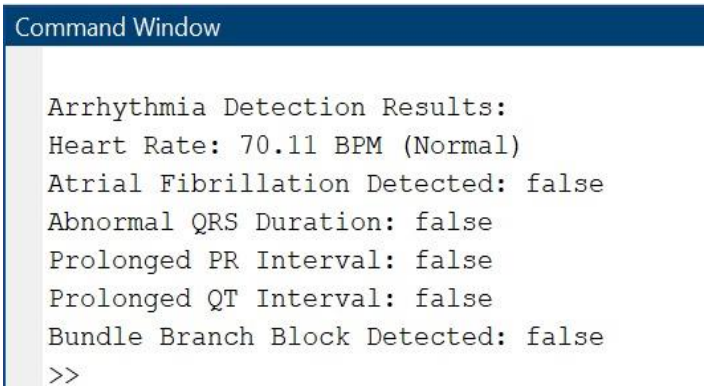

Figure 6: The shown cardiac rhythm analysis showed a regular heart rhythm of 70.11 beats per minute; no abnormalities are detected with regard to the timing and pattern of the cardiac cycle.

In depth analysis of above figure indicates that the automated algorithm for arrhythmia mining returned the following results:

i. Heart rate is on average 70.11 beats per minute (BPM), which is within the normal clinical range.

ii. No signs of atrial fibrillation are detected.

iii. The QRS duration is within the normal range, which indicates no abnormalities are present with regard to ventricular conduction.

iv. The PR and QT intervals are not prolonged, which also indicates no nodal or repolarization abnormalities are present. Finally, no bundle branch block is detected.

V. CONCLUSION

This paper presents a practical framework for the analysis of ECG signals: a way of reconstructing raw physiological results in terms of reliable and automatic cardiac examination. The method consists of the combination of various signal processing features: biorthogonal wavelet denoising, a notch filter to remove interference, adaptive peak detection, and frequency analysis. Used together they succeed in cleaning the ECG signal without destroying the small and valuable waveform features which the clinician makes use of.

One of the merits of the system lies in its ability to detect in real time PQRST segments and also to measure these intervals as RR, PR, QRS, and QT with fairly accurate results. These measurements are important in finding abnormalities in rhythm and conduction. The arrhythmia detection method is grounded in established clinical reference patterns. Preliminary results demonstrate its ability to differentiate between normal sinus rhythm and clinically significant abnormalities, including atrial fibrillation and conduction defects. Although the method is not intended to replace a cardiologist's clinical judgment, it provides a rapid and consistent preliminary assessment that may support clinical decision-making. The frequency domain results also support the findings in the time domain. Concordance between the time-domain and frequency-domain analyses provides assurance that the system's response is not attributable to noise fitting. Also, the response is rapid enough in processing to be applicable to real time monitoring, remote hospital systems, or even to wearables where processing limitations apply. This combination of reliability and computing practicalities can include testing with larger and more varied patient sets in future. Subsequently, implementing deep learning can lead to more depth in the detection of arrhythmia and to move from offline analysis to completely embedded real-time implementations.

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