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R-Peak Detection in Electrocardiogram Signal Using Stationary Wavelet Transform

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ABSTRACT: Electrocardiogram (ECG) signal is used to measure the electrical activity of heart as blood circulate from chamber to rest of the body. ECG signal is basically having three waves viz. P-wave, QRS-wave, and T-wave. Among three waves QRS wave is important in which R-wave is responsible for detecting any existing heart disease. Detecting that R-peak with precision help to professional to solve many real-life problems. The accurate R-peak is utmost important for detecting heart diseases before any casualty. The proposed work is utilizing Stationary Wavelet Transform (SWT) for signal pre-processing followed by a Random Forest (RF) classifier to identify R-peak candidates. In SWT, a Symlet 4 wavelet is used in which decomposition levels can jointly perform signal denoising and extraction of the QRS band energy. It helps to precisely determine R peak candidates by the use of adaptive energy thresholding. The proposed work efficiently applied physiology inspired post processing to accurately confirm identified R peaks. After getting the R-peaks, model is trained and 10 features are evaluated that shows the property of the waveform. From candidate peaks, window size of 20ms is selected and then extracted all 10 features for that. These features are then put into RF to increase the efficiency. Further, fine tuning of the parameters is done and repeat this step until whole signal is trained. The proposed algorithm obtained higher values of performance evaluating parameters viz. an overall classification accuracy (ACC) of 97.54%, sensitivity (SEN) of 98.41%, positive predictive value (PPV) of 98.54%, and F1-score (F1-S) of 98.47% those are higher than other benchmark algorithms.

I. INTRODUCTION

Heart diseases are one of the major causes of death in all age groups. Therefore, continuous monitoring of heart signals plays a critical role in the early detection of cardiac conditions [1]. Electrocardiogram (ECG) signal is considered the most reliable and one of the cheapest tools to observe the heart rate variability (HRV). The most important step to observe HRV is to find the correct location of R-peaks. Unfortunately, different errors are encountered in the recorded ECG signal due to noncardiac components such as baseline wander (BLW) arising from breathing, electrode movement, weak signal quality in wearable and mobile devices, power line interference (PLI), motion artifacts, and muscle noise differences in ECG shape from one patient to another [2]. Many papers [3-9] have been published and still technologies are evolving around it to reduce the error on it. Real-world ECG recordings are frequently affected by above mentioned noncardiac components. Earlier detection methods were relied on fixed thresholds, slope calculations, or derivative-based rules are good but have its limit.

Classical algorithms such as Pan Tompkins and its improved variants have widely used for QRS detection [3, 4]. While these approaches perform better on clean signals, their accuracy drops considerably when noise increases or when the signal shape varies significantly between patients.

Recent work has found out machine learning and deep learning solutions for ECG analysis. Approaches including near sensor delineation systems, wearable-focused detectors, and deep neural networks have demonstrated strong results [5-7]. Similar machine-learning approaches have also demonstrated their potential for automated biomedical disease detection and classification using performance measures such as accuracy, sensitivity, specificity, and F1-score [8]. Deep learning models such as Bi-LSTM have shown good capability in capturing peaks in ECG signal [9]. Also, some researchers utilized time-domain techniques for processing ECG signals, however these methods tend to show less accuracy and robustness in presence of noise and artifacts [10]. Some other researchers developed frequency-domain techniques, which face the problem of spectral leakage that causes false positive detection [11]. Beyond ECG analysis, recent clinical research has also explored artificial intelligence and machine-learning methods for automated medical image interpretation and clinical decision support, highlighting the broader application of data-driven models in healthcare [12].

The system developed in this study meets these requirements by combining Stationary Wavelet Transform (SWT) with a Symlet-4 wavelet to extract a QRS energy signal from the raw ECG. Candidate R-peak positions are identified from this energy signal using an adaptive threshold set at six times the mean energy.

A set of ten local features is then extracted around each candidate and passed to a Random Forest (RF) classifier for training and testing on 80% and 20%, respectively. After classification, a 250ms refractory period filter removes duplicate detections, and a local amplitude refinement step corrects each peak to its true maximum positive value. This combination of signal processing and machine learning allows the system to capture both time-frequency characteristics and nonlinear patterns in ECG morphology, resulting in reliable and accurate R-peak detection.

II. ITERATURE REVIEW

ECG signal processing has been working area of research for a decade now, mainly focuses on accurate R-peak detection [13]. Wavelet Transform is a very popular tool used in this field, as it breaks the signal into different frequency component consist of a cascaded system of high pass filter and low pass filter. V. Gupta et al. [14] showed that wavelet-based denoising can effectively clean ECG signals while keeping the sharp features of the QRS complex intact. Fundamental studies of time frequency methods help to give accurate feature extraction but not include machine learning. The proposed work can be integrated with hardware like smartwatches to perform effective for real time ECG signal analysis applications [15, 16].

Movement of human during the analysis can cause a noise referred as motion artifact [17]. It was addressed in the next subsequent research works by combining moving horizon estimation with filtering applied across different frequency sub bands. While this improved overall signal quality but not built to directly improve R-peak accuracy.

As classical machine learning is in use, deep neural network model is not far behind in this race. Architecture such as residual U-Net models and Bi-LSTM CNN frameworks have shown strong classification results by learning complex signal patterns automatically [18, 19]. The drawback of this neural network is that it requires vast amount of data and high computational cost, and its interpretability is less. Tree-based machine learning methods, like Decision tree, Random Forest and gradient boosting classifiers, have been applied to biomedical signal classification task. Random forest can learn nonlinear relation between features and showcases incredibly good results considering needed handcrafted input features. Recent healthcare-oriented machine-learning research has similarly evaluated Random Forest and other classification algorithms for disease prediction and clinical decision-support applications [20]. This model provided good balance of interpretability and transparency for pattern recognition without the need of large dataset.

The strengths of the proposed system are as follows

- The SWT preserves temporal alignment (shift invariance), which is essential for precise peak localization an advantage over the standard DWT.
- Symlet-4 wavelet resembles QRS complex more closely, thus allowing the system to better identify true R peak positions.

- Ten features include information about signal characteristics such as amplitude, variance, energy, and behavior, which provides the classifier with better data on the ECG signal.
- Random forest classifier allows for determining importance of each feature, which makes the algorithm analysis easier.
- Refractory filtering and local peak amplitude improvement are examples of post-processing steps used to decrease the number of false positives and increase accuracy of detection of R peaks position. The complete system is implemented in Python using standard open-source libraries, making it easier to reproduce, modify, and extend for future work.

III. PROPOSED METHODOLOGY

The proposed system processes raw ECG signals following blocks: wavelet-based energy extraction, candidate detection, feature extraction, machine learning classification, and peak refinement. The overall workflow is illustrated in Fig. 1. Each of these blocks are explained further in detail.

A. Stationary Wavelet Transform (SWT) and Energy Signal

Traditional methods require a filter in pre-processing step but here we directly use the SWT to both filtering the signal i.e., denoising and extracting the information from the signal in the single step.

The raw ECG signal is decomposed using the Symlet-4 wavelet at four levels of decomposition. The wavelet we used here is Symlet-4 also known as “least asymmetric”, it resembles like QRS waveform. It is an orthogonal wavelet family designed to increase symmetry compared to Daubechies wavelet. While \$ refers to the order provide great smoothness. This property makes it suitable for accurate peak localization.

An energy signal is a signal with finite total energy and zero average power. It is calculated by taking an amplitude square. As peak is the highest amplitude means should have highest energy too.

The ECG signal $x(t)$ is decomposed into approximation and detail coefficients. Mathematically expression of SWT is:

$$x(t) \rightarrow \{A_j(t), D_j(t)\}, \quad j = 1, 2, 3, 4 \quad (1)$$

where:

- $A_j(t)$ = Approximation coefficient at level j
- $D_j(t)$ = Detail coefficient at level j

Only levels 3 and 4 detail coefficients are retained.

Reconstructed SWT Signal: The filtered reconstructed signal is:

$$x_r = ISWT(D_3(t) + D_4(t)) \quad (2)$$

Where ISWT is inverse stationary wavelet transform.

Energy Signal: Energy signal is the square of amplitude, can be said as square of signal under curve:

$$E(t) = |x_r(t)|^2 \quad (3)$$

This filtering step helps remove low-frequency components while preserving the amplitude and shape of the QRS complexes.

B. Candidate Peak Detection

Candidate peaks refer to potential of signal peaks that are independent before final validation. Here, for its calculation we multiplied the mean of energy signal with six times.

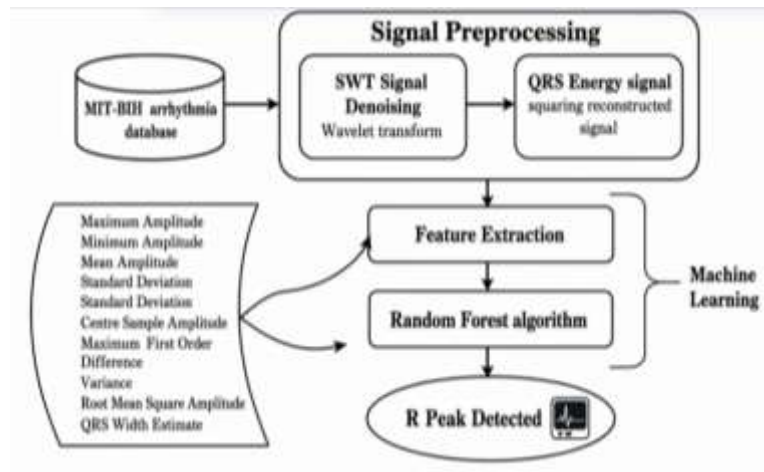


Fig. 1. Proposed methodology

$$T = 6 \times \text{mean}(E(t)) \quad (4)$$

C. Feature Extraction

For each candidate position in the signal, we have taken the window size of 20 samples then find out all 10 features and repeat the cycle again till got the features of whole signal.

$$w = \{x(p-10), x(p-9), \dots, x(p), \dots, x(p+9)\} \quad (5)$$

Feature 1: Maximum Amplitude:

$$f1 = \max(w) \quad (6)$$

This captures the peak height of the signal within the window. A true R-peak typically have highest energy.

Feature 2: Minimum Amplitude:

$$f2 = \min(w) \quad (7)$$

This captures the lowest amplitude helpful as in QRS- complex R have maximum amplitude while P and T have lower amplitude values.

Feature 3: Mean Amplitude:

$$f3 = \frac{1}{N} \sum_{i=0}^{N-1} w(i) \quad (8)$$

This gives the average value of all the samples, where peak is present value will be in higher as compared to place where peak is not present.

Feature 4: Standard Deviation:

$$f4 = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} (w(i) - f3)^2} \quad (9)$$

This measures the spread of a signal relative to its mean. QRS complex contain steep rise and fall showcase the presence of R-peak.

Feature 5: Sum of Absolute Values:

$$f5 = \sum_{i=0}^{N-1} |w(i)| \quad (10)$$

This represents the total sum of signal energy within the window. QRS complexes naturally show higher total value than the noise dominated windows.

Feature 6: Centre Sample Amplitude:

$$f6 = w(10) = x(p) \quad (11)$$

This gives the amplitude of ECG signal at candidate position. Since the candidate was identified from the energy signal as a local peak, its centre amplitude directly reflects whether the original signal also has a strong positive value at that exact point.

Feature 7: Maximum First-Order Difference:

$$f7 = \max(|w(i+1) - w(i)|), i = 0, 1, \dots, N-2 \quad (12)$$

This measures the steepest sample-to-sample change within the window. The upstroke of the R-peak is one of the fastest transitions in the entire ECG signal. A large maximum difference indicates a sharp, sudden rise which is characteristic of a true QRS complex rather than a smooth T-wave or baseline noise.

Feature 8: Variance:

$$f8 = \frac{1}{N} \sum_{i=0}^{N-1} (w(i) - f3)^2 \quad (13)$$

Variance is the square of the standard deviation. While standard deviation and variance carry similar information. This can help separate QRS complexes with moderate sharpness from very flat noise regions where variance is close to zero.

Feature 9: Root Mean Square Amplitude:

$$f9 = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} w(i)^2} \quad (14)$$

RMS amplitude is a classic measure of signal power. Unlike the mean, it is not affected by cancellation between positive and negative values because every sample is squared before averaging. A QRS window will have a significantly higher RMS value than a noise or baseline window of the same length.

Feature 10: QRS Width Estimate:

$$f10 = \sum_{i=0}^{N-2} I[|w(i+1) - w(i)| > 0.05] \quad (15)$$

Where $I[\cdot]$ is an indicator function that is equal to 1 when the condition is true and 0 otherwise. This counts how many consecutive samples within the window have a difference greater than 0.05 mV. A genuine QRS complex has several rapidly changing samples in succession, producing a high count. This feature effectively estimates how wide and active the QRS region is within the window.

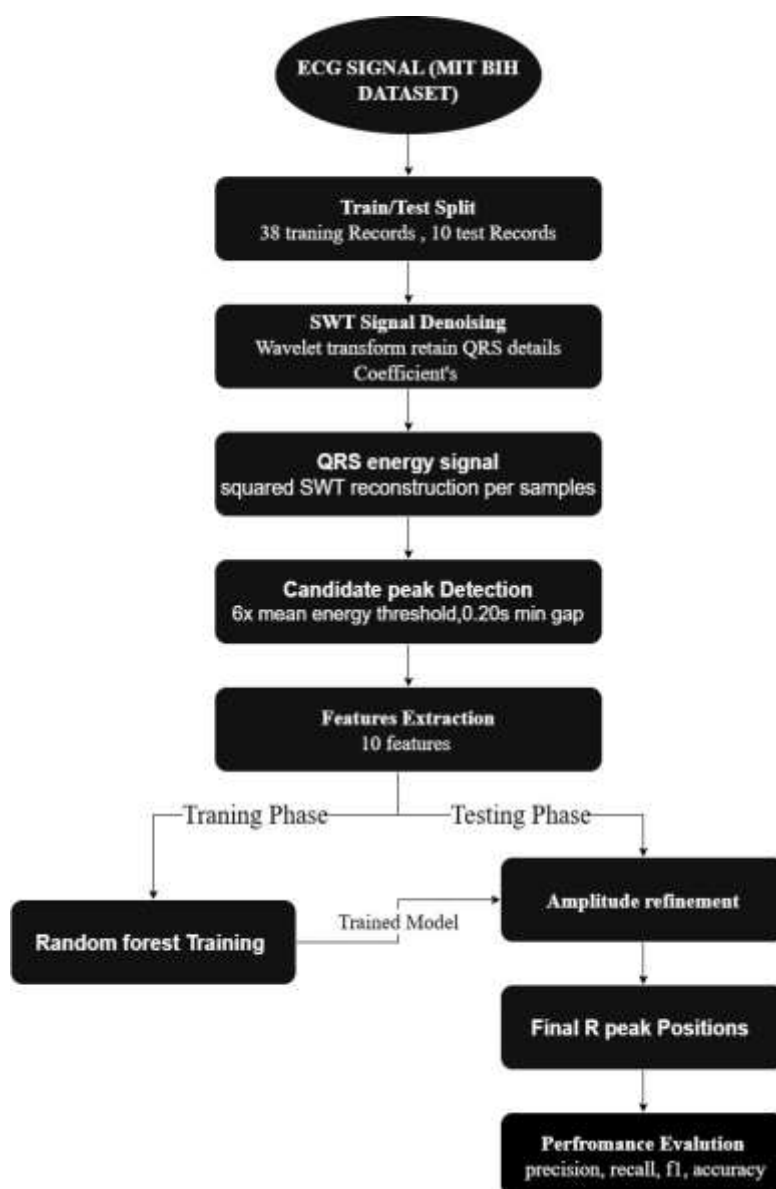


Fig. 2. Block Diagram of ECG Signal Processing

D. Random Forest Classification

After the ten features are extracted for each candidate position, the next step is to decide whether that candidate is a true R-peak or not. This is a binary classification problem, where the output is either 1 for R-peak or 0 for not R-peak. A Random Forest classifier is used for this purpose.

$$P(f) = \frac{1}{T} \sum_{t=1}^T h_t(f) \quad (16)$$

Where: $P(f)$ is the final averaged probability;

$T = 400$ is the total number of trees;

$h_t(f)$ is the probability from the t^{th} tree.

Classification Decision: Once the final probability is computed, a threshold of 0.48 is applied:

$$\hat{y} = \begin{cases} 1 & \text{if } P(f) \geq 0.48 \\ 0 & \text{if } P(f) < 0.48 \end{cases} \quad (17)$$

Where: $\hat{y} = 1$ means the candidate is accepted as a true R-peak; $\hat{y} = 0$ means the candidate is rejected; 0.48 is the probability threshold.

E. Post Processing

After classification, two post-processing steps are applied to improve the final detection quality.

The first step is refractory period filtering. Based on the physiological constraint that the human heart cannot produce two consecutive beats within less than 250ms, any two detected peaks that fall within this interval are compared by their classifier probability scores. The candidate with the lower probability is discarded, and only the higher-confidence detection is retained.

The second step is local amplitude refinement. Because the energy-based candidate position may not correspond exactly to the true R-peak in the original ECG signal, each accepted candidate is adjusted by searching within a window of 40 milliseconds on either side and locating the sample with the highest positive amplitude. This corrected position is used as the final R-peak location.

These two steps together reduce false detections caused by noise and correct small positional offsets introduced during the energy-based candidate detection stage. Additionally, the detected peaks were refined by searching for the local maximum within a $\pm 50\text{ms}$ interval. In the proposed work python programming language is used. Dataset was taken from MIT-BIH arrhythmia database of total size of 788,423 samples and class distribution contain 675,807 non-peaks, 112,616 R-peaks

IV. RESULT AND DISCUSSION

High precision indicates that the model produces very few false peak detections, whereas the recall value indicates that most actual R-peaks are successfully identified. Performance consistency across 48 records demonstrates generalization capability despite morphological diversity. The proposed model is tested on MIT-BIH arrhythmia dataset with whole 48 records. The results are mentioned below in table 1 and evaluated the model using confusion matrix in Fig.3.

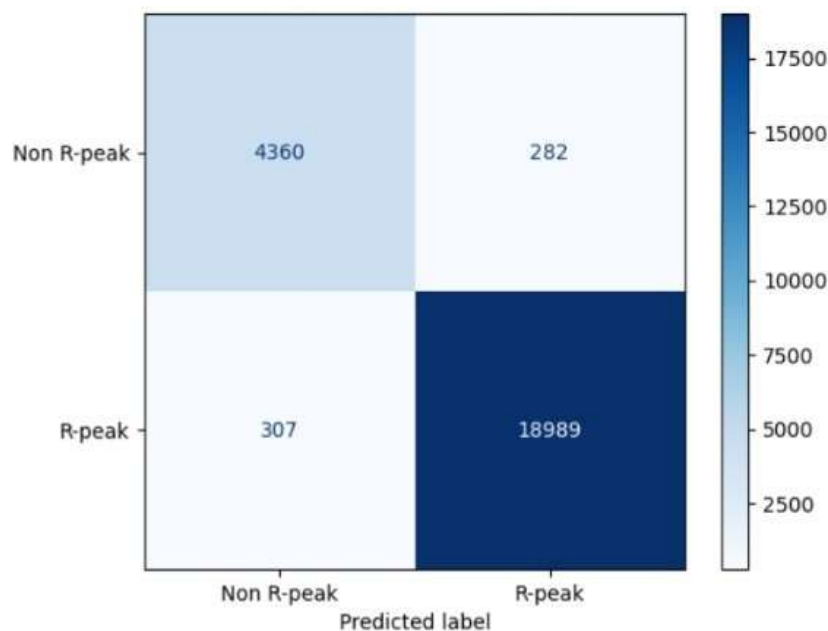


Fig.3. Confusion Matrix

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN} = 97.54\%$$

$$\text{Sensitivity (SEN)} = \frac{TP}{TP + FN} = 98.41\%$$

$$\text{Positive Predictive Value (PPV)} = \frac{\text{TP}}{\text{TP} + \text{FP}} = 98.54\%$$

$$\text{F1 - Score (F1 - S)} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} = 98.47\%$$

These indicators demonstrate the performance, robustness and reliability of the model. Confusion matrix calculation gave the accuracy of 97.54%, sensitivity of 98.41%, PPV of 98.54% and F1-score of 98.47%. These results showcases that the model built performs effectively and can be considered for practical real-world applications. Confusion matrix evaluation highlights its potential for deployment in intelligent decision-making system and providing real world problem solutions.

Fig. 4 shows gives the visualization from ECG raw signal to find the R-peak, showing each step involve in it such as-(1) the original ECG signal, (2) the SWT-reconstructed signal, (3) the energy signal, (4) the candidate peaks detected using SWT and energy thresholding, and (5) the final R-peaks after post-processing. Here x-axis denote time and y-axis denote amplitude. This figure shows the processing stages of Record 102 for a segment containing approximately 11 R-peaks.

Table I. Per-Record Detection Performance On MIT-BIH Arrhythmia Database

Record	TP	FP	FN	Acc	Se	PPV	F1
100	2253	0	0	1.000	1.000	1.000	1.000
101	1865	3	2	0.997	0.999	0.998	0.999
102	2027	57	0	0.973	1.000	0.973	0.986
103	2082	0	1	1.000	1.000	1.000	1.000
104	1958	133	4	0.938	0.998	0.936	0.966
105	2203	31	2	0.987	0.999	0.986	0.993
106	1673	4	0	0.998	1.000	0.998	0.999
107	2103	9	0	0.996	1.000	0.996	0.998
108	1208	36	45	0.971	0.964	0.971	0.968
109	2473	2	1	0.999	1.000	0.999	0.999
111	1368	20	3	0.989	0.998	0.986	0.992
112	2513	1	5	0.998	0.998	1.000	0.999
113	1794	0	0	1.000	1.000	1.000	1.000
114	1844	0	2	0.999	0.999	1.000	0.999
115	1953	0	0	1.000	1.000	1.000	1.000
116	2383	6	0	0.998	1.000	0.997	0.999
117	1522	4	2	0.998	0.999	0.997	0.998
118	2263	10	0	0.996	1.000	0.996	0.998
119	1556	18	2	0.990	0.999	0.989	0.994
121	1339	0	88	0.977	0.938	1.000	0.968
122	2467	1	1	0.999	1.000	1.000	1.000
123	1516	2	0	0.999	1.000	0.999	0.999

124	1602	8	0	0.996	1.000	0.995	0.998
200	2058	52	24	0.974	0.988	0.975	0.982
201	1876	0	56	0.975	0.971	1.000	0.985
202	1764	1	13	0.994	0.993	0.999	0.996
203	1073	131	46	0.909	0.959	0.891	0.924
205	2620	2	1	0.999	1.000	0.999	0.999
207	1584	20	21	0.980	0.987	0.988	0.987
208	2021	51	4	0.976	0.998	0.975	0.987
209	2979	3	5	0.998	0.998	0.999	0.999
210	2398	10	3	0.995	0.999	0.996	0.997
212	2686	16	2	0.994	0.999	0.994	0.997
213	3088	14	1	0.995	1.000	0.995	0.998
214	2024	11	4	0.993	0.998	0.995	0.996
215	3119	5	4	0.997	0.999	0.998	0.999
217	2148	1	1	0.999	1.000	1.000	1.000
219	2141	1	0	1.000	1.000	1.000	1.000
220	2048	0	0	1.000	1.000	1.000	1.000
221	1952	76	2	0.969	0.999	0.963	0.980
222	2179	3	95	0.959	0.958	0.999	0.978
223	2361	2	1	0.999	1.000	0.999	0.999
228	1473	39	18	0.975	0.988	0.974	0.981
230	2245	11	4	0.994	0.998	0.995	0.997
231	1566	0	0	1.000	1.000	1.000	1.000
232	1773	0	3	0.999	0.998	1.000	0.999
233	2757	60	3	0.981	0.999	0.979	0.989
234	2722	1	3	0.999	0.999	1.000	0.999

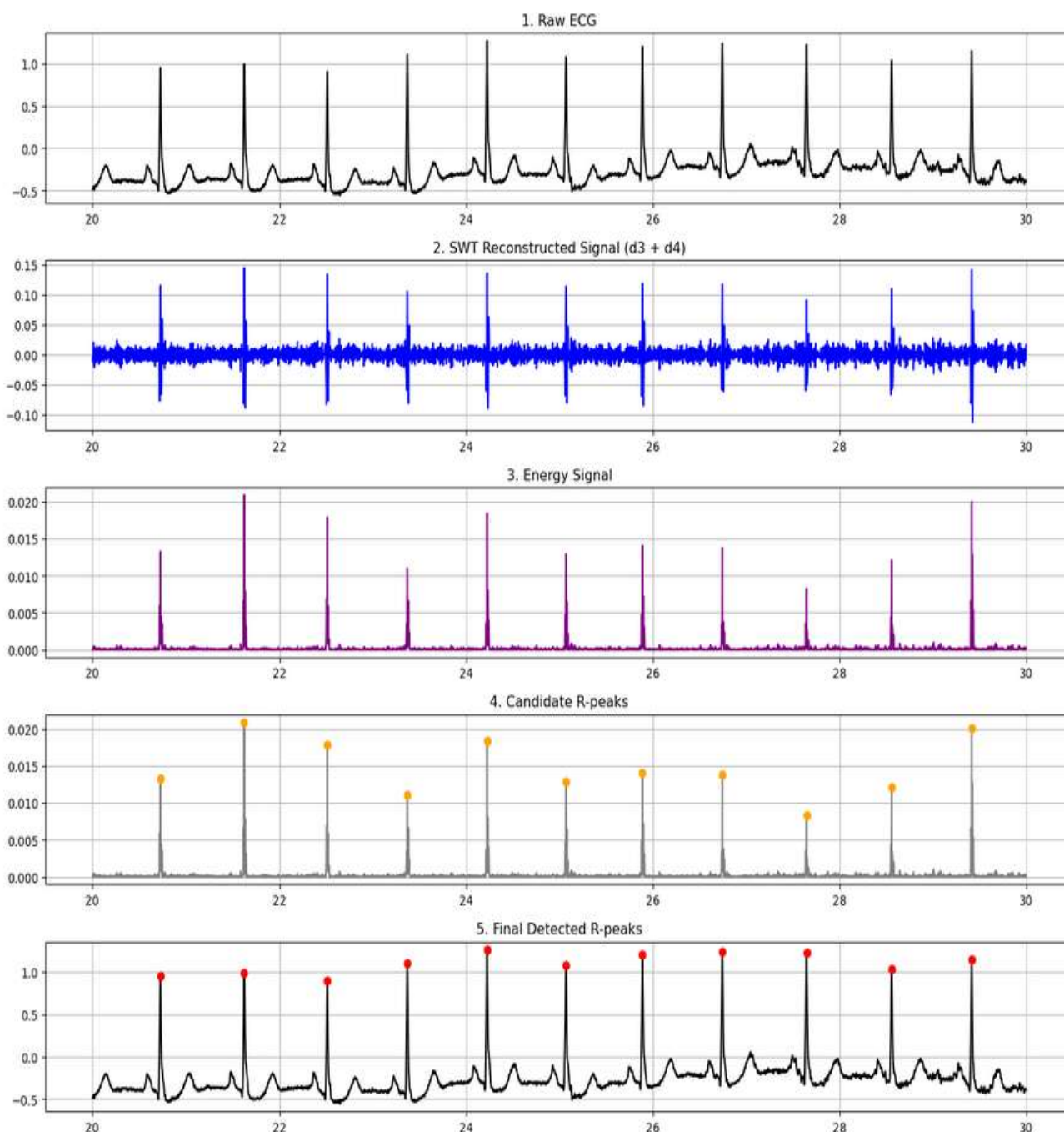


Figure 4 Step-by-Step ECG Processing and R-Peak Detection for Record 102

For this record, system secured TP of 2027, FP of 57, and FN of 0, resulting in ACC of 97.3%, SEN of 100%, PPV of 97.3%, and F1-S of 98.6%. All true R-peaks were detected successfully, although some false positive detections (say FP of 57 and FN of 0) slightly reduced PPV (Precision) and ACC. Fig.5 shows the processing stages of record 105 for a segment containing approximately 12 R-peaks. For this record, system achieved TP = 2203, FP = 31, and FN = 2, resulting in ACC of 98.7%, SEN of 99.9%, PPV of 98.6%, and F1-S of 99.3%. The algorithm maintained highly reliable detection despite minor false and missed detections (say FP of 31 and FN of 2). Fig. 6 shows the processing stages of Record 210 for a segment containing approximately 15 R-peaks. For this record, system achieved TP of 2398, FP of 10, and FN of 3, resulting in ACC of 99.5%, SEN of 99.9%, PPV of 99.6%, and F1-S of 99.7%. The proposed algorithm successfully identified nearly all R-peaks while

maintaining a very low false alarm rate (say FP of 10 and FN of 3). These results demonstrate excellent detection capability and consistency. Fig. 7 shows the processing stages of Record 234 for a segment containing approximately 16 R-peaks. For this record, the system achieved TP of 2722, FP of 1, and FN of 3, resulting in ACC of 99.9%, SEN of 99.9%, PPV of 100%, and F1-S of 99.9%. The algorithm demonstrated outstanding performance by correctly detecting almost all R-peaks with only negligible errors. The combination of high SEN, perfect PPV, and excellent F1-S confirms the robustness and reliability of the proposed R-peak detection framework.

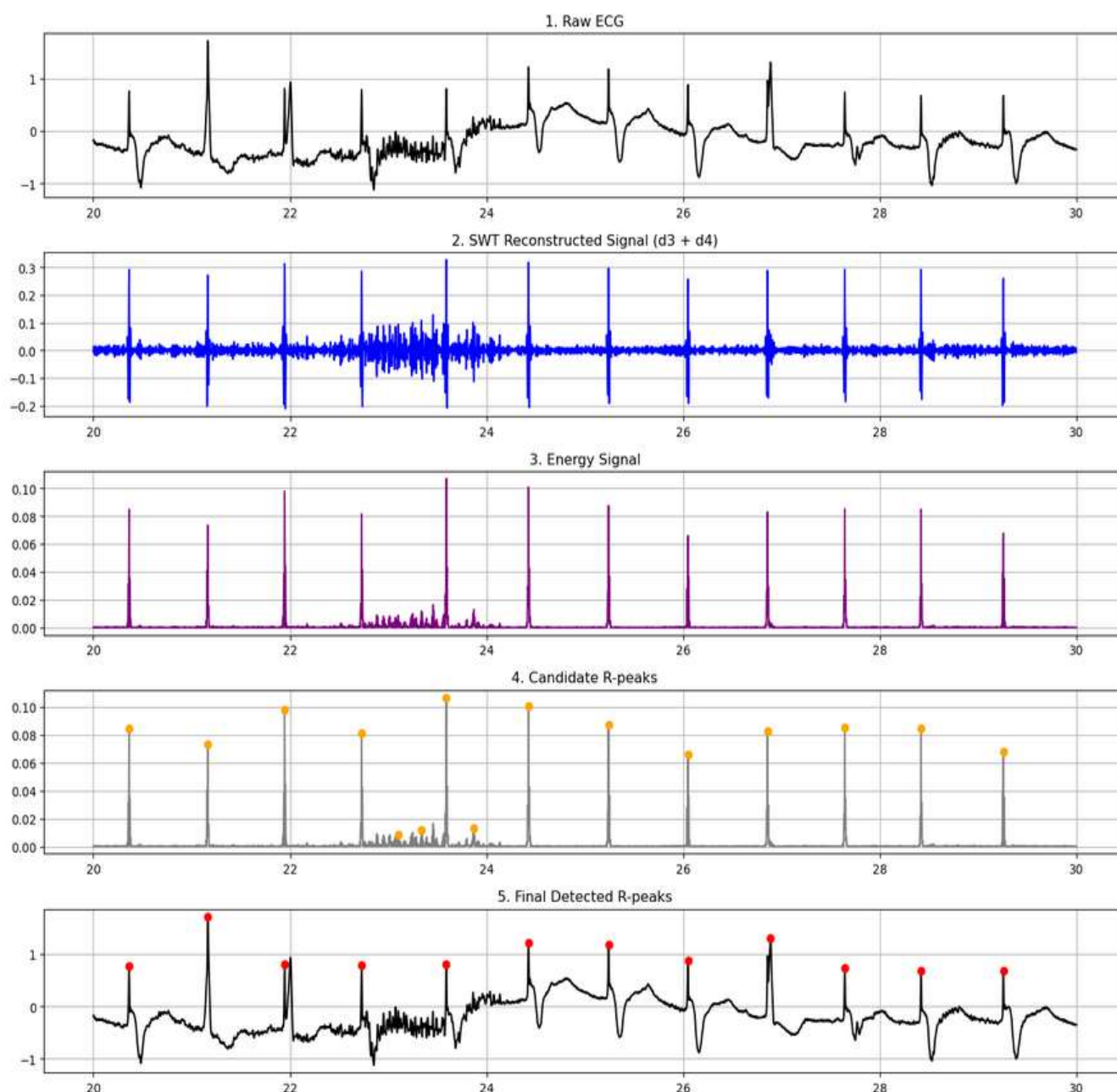


Figure 5 Step-by-Step ECG Processing and R-Peak Detection for Record 105

Table II reveals that the proposed work has achieved SE of 98.47% and ACC of 97.54, those performance parameters are very much higher as compared to existing research work viz. SE of 82.75%, 93.70%, and 95.8% in [21], [22], and [24], and ACC of 91.56%, 95%, and 96.84% in [21], [23], and [24], respectively.

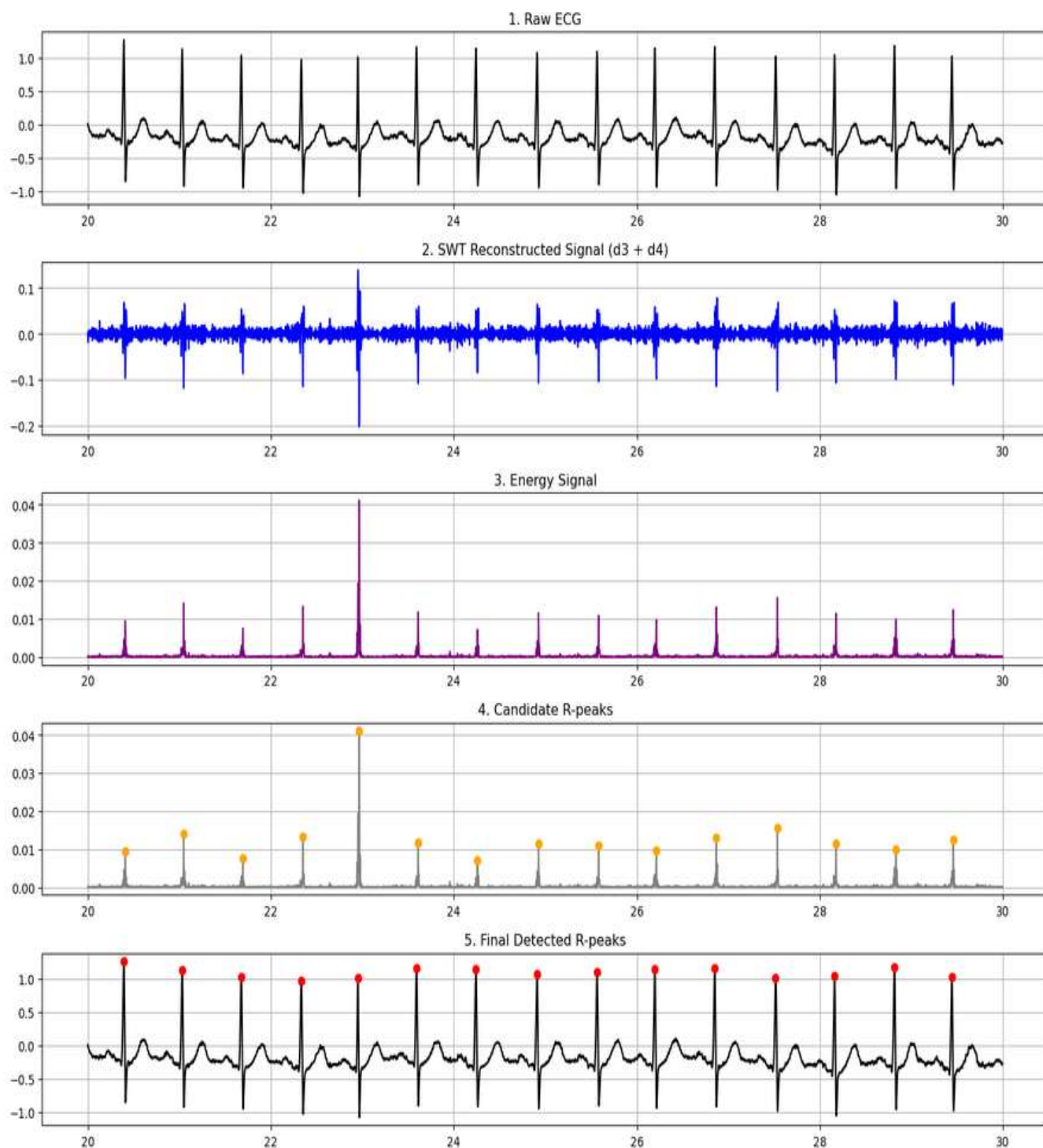


Figure 6 Step-by-Step ECG Processing and R-Peak Detection for Record 210

The major limitations and challenges of the proposed work are as follows-

- The method is trained and evaluated exclusively on the MIT-BIH Arrhythmia Database. Even though the MIT-BIH database is one of the most popular databases to benchmark the accuracy of the ECG R-peak detection, the system has never been evaluated using data obtained using different types of equipment, different electrodes or in other patients including pediatric patients.

- The biggest problems with detecting peaks happen when it comes to hard records such as 203 and 108 due to the presence of high levels of noise and rare arrhythmia. Moreover, the feature extraction algorithm that was manually developed is good but can be biased and based on domain knowledge.

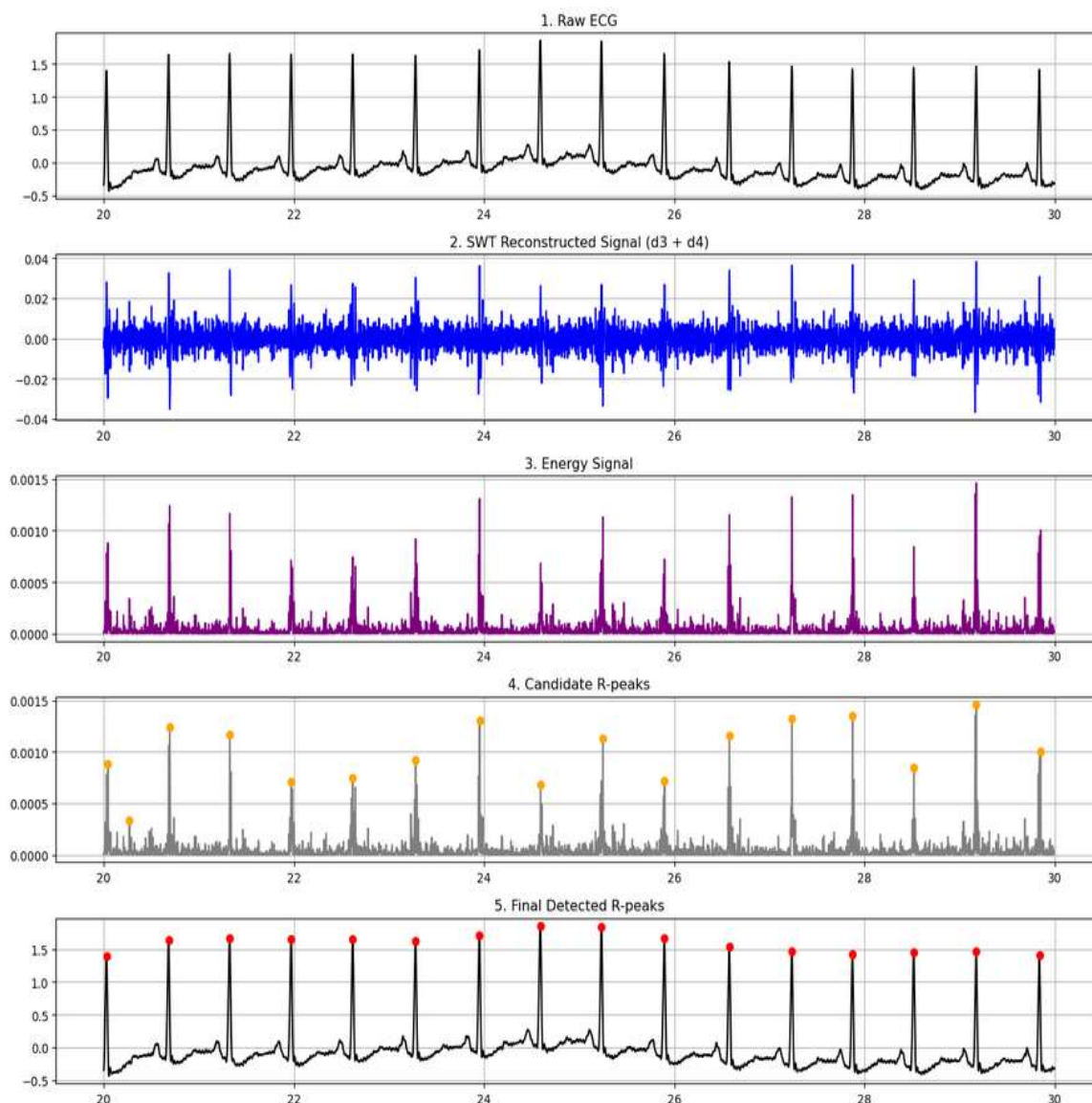


Figure 7 Step-by-Step ECG Processing and R-Peak Detection for Record 234

Table II. Comparison of Current and Existing Techniques Based On SE

Ref	Technique	SE (in %)	ACC (in %)
[18]	Wavelet and Support Vector Machine (SVM) classifier	82.75	91.56
[19]	POT-DPC	93.70	-
[20]	Wireless Electrocardiograms	-	95
[21]	FAWT and LEE features	95.8	96.84
Proposed	SWT+Random Forest	98.47	97.54

V. CONCLUSION

The proposed work introduced a principled and practical framework to automatically detection of R-peaks in the ECG signal by utilizing the Stationary Wavelet Transform for signal pre-processing followed by a Random Forest classifier to identify R-peak candidates. The proposed work efficiently applied physiology inspired post processing to accurately confirm identified R peaks. It is also revealed that a Symlet 4 wavelet decomposition levels can jointly perform signal denoising and extraction of the QRS band energy, thereby helping to precisely determine R peak candidates by the use of adaptive energy thresholding. As used by the current approach, followed by the identification of each candidate window's features and classification via a Random Forest ensemble classifier, requiring limited training data unlike deep neural networks. By processing all 48 ECG records of the MIT BIH Arrhythmia database, the proposed algorithm obtained higher values of performance evaluating parameters *viz.* an overall classification ACC of 97.54%, SEN of 98.41%, PPV of 98.54%, and F1-S of 98.47% those are higher than other benchmark algorithms. The significant level of performance is achieved for all data sets with multiple morphological changes and noises. This robustness and good generalization of the algorithm shows that it is a promising method for potential application for medical devices.

VI. FUTURE SCOPE

The proposed system has been trained on MIT-BIH dataset. In future other datasets those are widely used in medical field may also be utilized. The proposed model is to be deployed with embedded devices for ease of computational cost that will be performed quite easily. Adaptive selection of wavelet can be introduced to improve performance across ECG signal that can vary with patient.

In addition to testing and training of the system on the MIT-BIH Arrhythmia database, other ECG datasets like the MIMIC-III waveform database and clinical ECGs from various patients can be added to increase reliability of the algorithm across various datasets. Integration of the proposed method into the cloud infrastructure can enable remote ECG analysis by health professionals through telemedicine systems.

DECLARATIONS

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Availability of data and materials: It is arranged and developed by present authors.

Code Availability: It is accomplished by corresponding author.

Permission of Clinical Trial: This study is not related to any clinical trial.

Authors Contributions: Varun Gupta is writing original draft. Kamal Kishor Upadhyay, Corresponding Author performed all simulations work in this manuscript. Literature survey is done by Himanshu Saini. Datasets and results were validated by Kirti Pal.

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Consent to Publish: All present authors are giving their consent for publishing the paper.

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