

A Hybrid Multi-Detector Framework with Bayesian Uncertainty Quantification and Machine Learning Verification for Robust QRS Detection and HRV Analysis

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Abstract

Heart rate variability (HRV) analysis is crucial for accurate QRS detection. As several detectors struggle with noises and diverse data sources. A hybrid QRS detection algorithm was developed which combines three complimentary detectors. These detectors are Pan-Tompkins, stationary wavelet transform, and Hilbert transform along with machine learning validation and Bayesian uncertainty quantification for HRV metrics.

A SNR adaptive preprocessing pipeline was developed that merges beat candidates from the three detectors. A logistic regression classifier was used which was trained on four interpretable features, that verifies each candidate. HRV parameters were computed with 95 % confidence intervals through Bayesian bootstrap of the Lomb scargle periodogram. Sliding window analysis was used to assess the reproducibility.

On all 48 records of the MIT-BIH Arrhythmia Database, the detector achieved a median F1-score of 0.936 (interquartile range 0.884–0.962) and a median false-positive rate of 9.07 per minute (IQR 5.54–15.51). On record 100 (clean sinus rhythm), Bayesian 95 % confidence intervals for RMSSD and SDNN were [49.1, 60.3] ms and [43.2, 48.5] ms, respectively. Sliding-window reproducibility on this record gave a coefficient of variation of 4.7 % for SDNN. On a challenging noisy record (record 105), the detector maintained a sensitivity of 0.967 and F1 of 0.934. A demonstration on locally recorded ECG through self developed ECG acquisition circuit based on IC LM325, the large duration ECG (>6min) yielded plausible HRV metrics (mean RR 735.8 ms, SDNN 39.4 ms, RMSSD 26.5 ms). While other recordings acquired through the circuit were excluded due to insufficient duration, underscoring the need for adequate recording length in HRV analysis.

The proposed work gave accurate QRS detection and HRV analysis for various clinical recordings. This work quantifies built-in uncertainty which enhances the interpretability of the model. When its performance was tested on a consumer grade ECG, it suggests its potentiality for remote monitoring and also the recordings met with the recommended duration guidelines.

Keywords: Heart rate variability (HRV), Bayesian bootstrap, MIT-BIH database, multi-detector fusion, QRS detection.

1. Introduction

The Heart rate variability (HRV) measures the interval between consecutive heartbeats. It is a non-invasive marker of cardiovascular risk and autonomic nervous system function [1,2]. The robustness of HRV measurements depends upon the accurate detection of QRS complexes, especially the R-peaks. From this R-peaks RR interval time series is derived. Ambiguity in the measurement of QRS detection is propagated directly into HRV metrics which results in false clinical conclusions [3].

Pan-Tompkins algorithm is the most widely used QRS detector. It was introduced in 1985 which is known for its real time capability and simplicity[4]. This algorithm utilizes a combination of bandpass filtering, squaring, moving window integration, adaptive thresholding, and differentiation. The performance of this algorithm is reduced in the presence of noise, morphological variations or baseline wander[5]. Multiple alternative approaches have been proposed over the last two decades to improve its accuracy.

Wavelet-based algorithm exploit the multi-resolution properties of the wavelet transform to enhance QRS signatures while suppressing noise [6,7]. Machine learning algorithms were used from simple classifiers to deep neural networks. It has been applied to QRS detection with higher accuracy at the cost of large annotated datasets and computational complexity [8,9]. Recently,

hybrid strategies which combines complementary detectors have resulted higher accuracy in balancing sensitivity and precision [10].

Despite of these advancement, these were the major challenges which needs to be addressed: Heterogeneous data sources – consumer devices like smartphones, wearables nowadays increasingly used for measuring HRV. Their signal characteristics is different from clinical electrocardiographs which requires lower sampling rates, higher noise and motion artifacts. [11]. Uncertainty quantification – Many published detectors report only point estimates of HRV, ignoring the uncertainty inherent in short-term recordings, which limits clinical interpretability [12]. Reproducibility assessment – Longitudinal monitoring needs to evaluate the reliability of test-retest of the derived HRV metrics [13].

In the present work, a comprehensive QRS detection and HRV analysis framework is designed to address these challenges. The main objectives of this work are as follows:

- Pan-Tompkins, stationary wavelet transform (SWT), and Hilbert transform a multi-detector fusion strategy was used, followed by ML-based verification using a logistic regression classifier which is trained on a large set of interpretable features.
- An SNR-adaptive preprocessing module is used which applies wavelet denoising. In this case, the estimated signal-to-noise ratio falls below a threshold, that preserves signal fidelity in clean recordings.
- A Bayesian bootstrap procedure is used for Lomb-Scargle spectral analysis. It provides 95 % confidence intervals for all HRV power estimates, even with short or unevenly sampled RR intervals.
- A reproducibility framework is used which quantifies the test-retest reliability of HRV metrics via sliding-window analysis through Bland-Altman statistics.
- Extensive validation is performed on all (48) records of the MIT-BIH Arrhythmia Database. self recorded ECG data was also demonstrated. with discussions on the importance of larger duration data required to get the reliable HRV matrices.

2. Methods

2.1 Datasets

The following datasets were used for development and validation of the model.

MIT-BIH Arrhythmia Database [14] consists of total 48 records that were analysed in this work. Each record consists of 30 min two-channel ambulatory ECG, that were sampled at 360 Hz with 11-bit resolution over a 10 mV range. Beat-by-beat annotations was provided by two independent cardiologists . The first channel (MLII) was used with all records included in the present work. the evaluation includes the full diversity of signal qualities and arrhythmia types present in the database.

Locally recorded ECG through acquisition circuit: Multiple recordings were acquired from a healthy volunteer using LM325 through ECG acquisition circuit with sampling rate 1000Hz. A larger duration of ECG with more than 6 min recordings were considered and retained for HRV computation. However shorter lengths ECG recordings were discarded in accordance with established guidelines for short-term HRV analysis [15]. As shorter ECG recordings would yield unreliable metrics.

2.2 Preprocessing Pipeline

The preprocessing of raw ECG signal $y(t)$ (sampled at f_s) was done in six steps which were as follows:

- finite-value check: any infinite values were replaced with zero.
- high pass filtering: a 2nd order butterworth filter was used with cutoff 0.5 Hz that was removed from the baseline wander.
- bandpass filtering: it uses a 4th order butterworth bandpass filter with 3-40 Hz isolated QRS signals which suppresses muscle noise and T-waves.
- Amplitude normalization: the signal was divided by its standard deviation to attain unit variance. SNR estimation: signal to noise ratio was calculated in the QRS band ranging from 5-15 Hz. The equation for calculating SNR is as follows:

$$SNR = \frac{\sigma_{\text{filtered}(5-15\text{Hz})}}{\sigma_{\text{residual}} + \epsilon}$$

where the residual is the difference between the normalised signal and the 5–15 Hz bandpassed version.

1. **Conditional wavelet denoising:** If $SNR < 2$ and scikit-image was available, a BayesShrink soft-thresholding wavelet denoising (Daubechies-4, rescale_sigma=True) was applied; otherwise, the signal was left unchanged.

This adaptive approach preserves the original signal when it is already clean, avoiding unnecessary distortion.

2.3 Multi-Detector Fusion

Beat candidates were generated independently by three algorithms which are as follows:

1. **Enhanced Pan-Tompkins:** Bandpass filtering (5–15 Hz), derivative, squaring, moving-window integration, adaptive thresholding, and fine localisation.

2. **Stationary Wavelet Transform (SWT) detector:** Three-level SWT with 'db4' wavelet; peaks in the detail coefficients were detected with adaptive threshold and validated against the original signal.

3. **Hilbert transform detector:** The analytic signal envelope was computed; peaks in the envelope were detected with adaptive thresholding.

All candidate lists were merged. Peaks falling within a refractory period of 0.2 s were consolidated (the highest amplitude peak was retained). The resulted set of candidate beats was then passed to the ML verification step.

2.4 Feature Extraction and ML Verification

Four features were extracted from the bandpass-filtered signal y_{filt} and the integrated signal I , for each candidate beat i at index p_i ; these features captures both morphological and rhythmic context and are physiologically interpretable.

- $x_1 = y_{\text{filt}}[p_i]$ – QRS amplitude.
- $x_2 = \text{mean}(I[p_i-w : p_i+w])$ – local mean of integrated signal ($w = 0.12 f_s$).
- $x_3 = \text{std}(I[p_i-w : p_i+w]) + \epsilon$ – local standard deviation.
- $x_4 = (p_i - p_{i-1})/f_s$ – RR interval, set to 0 for first beat.

A logistic regression classifier with 'StandardScaler' and class-weight balancing was trained on a subset of the MIT-BIH data for the first 30 s of each record. During inference, candidates with predicted probability greater than equals to 0.5 were retained as final beats.

2.5 HRV Computation and Bayesian Uncertainty Quantification

The RR interval time series was derived from the final beat locations B (in samples) as follows:

$$RR_i = \frac{(B_i + 1 - B_i)}{f_s}$$

$$ti = \frac{B_i + 1}{f_s}$$

RR interval cleaning: A reasonable physiological cleaning method was applied as follows:

- Absolute limits: $0.3 \text{ s} \leq RR \leq 2.0 \text{ s}$ (200 bpm to 30 bpm).
- Relative change: $|RR_i - RR_{i-1}| / RR_i < 0.6$
- Local median filter: RR should be within the range $0.5 \cdot \text{median}$ to $1.8 \cdot \text{median}$ of a 5-beat moving median.

Based on these criterion, intervals that failed were discarded and the remaining intervals were used for HRV analysis.

Time-domain metrics: the time-domain HRV measures like mean RR (ms), SDNN (ms), RMSSD (ms), NN50 (count), pNN50 (%), median RR (ms), and RR range (ms) were computed [15]. A Bayesian bootstrap with 500 resamples was applied to the cleaned RR intervals for quantifying uncertainty. For each time-domain metric, it resulted 95 % confidence intervals [16].

Frequency-domain metrics: as implemented in `astropy.timeseries` we employed Lomb–Scargle periodogram, because RR intervals are unevenly spaced[17]. The power spectral density (PSD) was calculated over the frequency of 0.003–0.5 Hz with 512 points. a Bayesian bootstrap with 100 resamples was performed to quantify uncertainty. The PSD was recomputed for each bootstrap sample. 95 % confidence intervals were achieved from the percentiles. Power was integrated over standard bands:

- VLF: 0.003–0.04 Hz
- LF: 0.04–0.15 Hz
- HF: 0.15–0.4 Hz

The LF/HF ratio, total power (ms^2), and normalised units (LFnu, HFnu) were derived from the mean PSD. Confidence intervals for band powers were stored.

2.6 Reproducibility Assessment

Each recording was divided into five overlapping segments with a sliding window approach. For each segment, SDNN was computed. The consecutive segments were compared via Bland-Altman analysis for obtaining the coefficient of variation (CV) and limits of agreement (LoA).

3. Results

3.1 QRS Detection Performance on MIT-BIH

The hybrid detector was assessed on all recordings of MIT-BIH with the use of beat-by-beat annotations as ground truth. Table 1 shows the performance of QRS detection on 48 MIT-BIH recordings. The detector attained a median F1-score of 0.936, with an interquartile values ranging from 0.884–0.962 respectively. The sensitivity values was high (0.992), which indicates very few true beats were missed. Whereas the median false-positive rate was 9.07 per minute which indicates the variability in signal quality across records. However false positives were substantially lower on cleaner recordings.

Table 1. Shows the performance of QRS detection on all 48 MIT-BIH records.

Metric	Median values (interquartile range)
Sensitivity	0.992 (0.974–0.997)
Positive predictive value	0.895 (0.827–0.931)
F1-score	0.936 (0.884–0.962)
False positives per minute	9.07 (5.54–15.51)

Figure 1 shows an example of ECG segments from a clean record (record 100) and a noisy record (record 105) with detected beats overlaid. In both the cases, the detector captures almost all beats. Occasional false positives on high-amplitude T-waves was captured or noise spikes which are subsequently removed by the RR cleaning step.

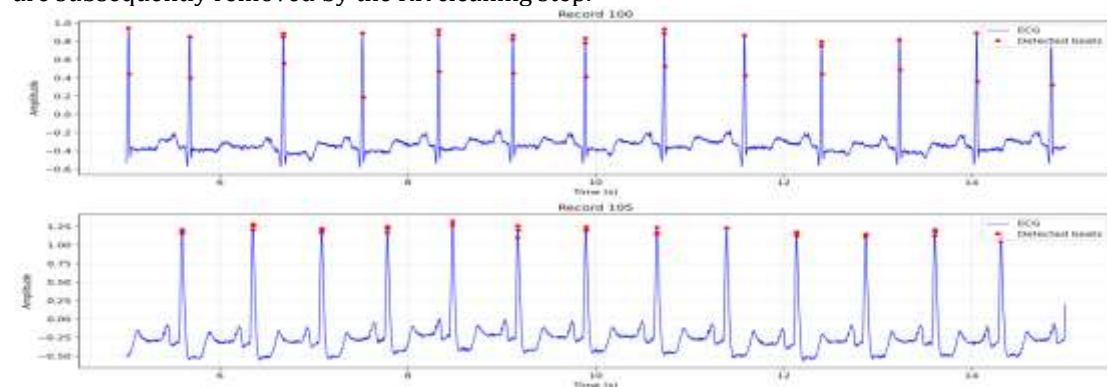


Figure 1. (a) record 100 ECG shown as clean sinus rhythm with detected beats as red points. (b) Record 105 ECG shown as noisy, with arrhythmias with detected beats as red points. Even in the presence of noise, the detector maintains high sensitivity.

3.2 HRV Metrics with Bayesian Confidence Intervals

We selected two representative records: record 100 (clean) and record 105 (noisy) for pipeline's uncertainty quantification. Table 2 represents the Bayesian 95 % confidence intervals for time-domain HRV parameters for both the records. These were derived from bootstrap resampling of the RR intervals. The intervals are narrow which indicates stable estimates from the 30-min recordings. In case of record 100, the RMSSD value was found to be 54.8 ms which has a 95 % CI of [49.1, 60.3] ms. The corresponding interval for SDNN was found to be 43.2 and 48.5 ms. While in case of Record 105, it shows lower overall HRV, with RMSSD value 29.3 ms [27.8, 30.8] and SDNN 35.5 ms [34.0, 37.0] respectively.

Table 2. HRV metrics with Bayesian time-domain confidence intervals of 95 % for records 100 and 105.

Parameter	Record 100	Record 105
RMSSD (ms)	54.8 [49.1, 60.3]	29.3 [27.8, 30.8]
SDNN (ms)	45.8 [43.2, 48.5]	35.5 [34.0, 37.0]
Mean RR (ms)	793.3 [790.7, 795.0]	694.7 [692.0, 697.4]
pNN50 (%)	9.6 [8.5, 10.8]	3.7 [3.2, 4.2]

Table 3 represents Bayesian frequency-domain metrics with 95 % confidence intervals. For record 100, the LF power was 291.0 ms^2 (95 % CI [11.1, 1011.4] ms^2) and HF power 1098.3 ms^2 (95 % CI [251.4, 2932.7] ms^2). Particularly in the LF band, the wide intervals shows the inherent uncertainty in spectral estimates from a single 30-min recording. The LF/HF ratio was found to be 0.26 which indicates parasympathetic dominance.

Table 3. HRV metrics with Bayesian frequency-domain with confidence intervals of 95 % for records 100 and 105.

Parameter	Record 100	Record 105
LF power (ms^2)	291.0 [11.1, 1011.4]	192.8 [7.2, 642.2]
HF power (ms^2)	1098.3 [251.4, 2932.7]	596.7 [141.2, 1641.9]
Total power (ms^2)	1684.6 [332.4, 4656.0]	902.2 [165.1, 2602.5]
LF/HF ratio	0.26	0.32

Figure 2 represents the Lomb-Scargle PSD with 95% confidence interval for record 100. As expected, the uncertainty is highest at low frequencies.

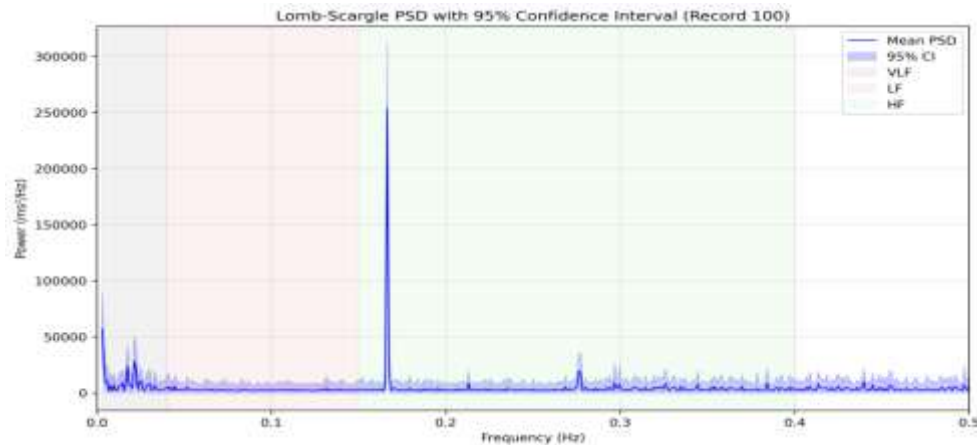


Figure 2. Blue lines indicate Lomb-Scargle PSD for record 100 with 95 % bootstrap confidence interval Vertical dashed lines distinct VLF, LF, and HF bands.

3.3 Reproducibility

A sliding-window analysis was used on record 100 to assess the reproducibility of the SDNN metric. The coefficient of variation between successive windows was found to be 4.7 %. The

Bland-Altman 95 % limits of agreement values were found to be $[-6.1, 2.2]$ ms respectively. This indicates excellent within-recording consistency.

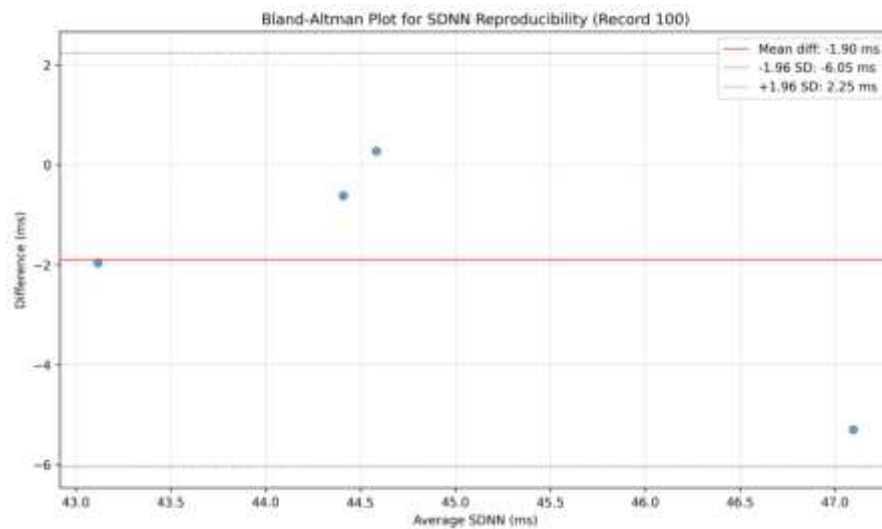


Figure 3. Bland-Altman for SDNN for consecutive sliding windows of record 100. The mean difference is near zero (-1.9 ms) with 95 % confidence interval differences lies within -6.1 to 2.2 ms.

3.4 Locally recorded ECG Demonstration

We processed multiple locally acquired ECG recordings based on IC LM325, to illustrate the pipeline's applicability to consumer-grade devices. The detector identified 485 beats for larger duration ECG (>6 min), resulting 474 clean RR intervals after artifact removal. For a healthy resting adult, the derived HRV metrics shown in Table 4 are within the expected range, which confirms the physiological plausibility of the detected beats. Tho multiple recordings were available, but we have discarded the smaller duration ECG as they were too short for reliable HRV analysis [15], and were therefore not included in this demonstration.

Table 4. HRV metrics from locally recorded ECG (>6 min)

Parameter	Value
Mean RR (ms)	735.8
SDNN (ms)	39.4
RMSSD (ms)	26.5
pNN50 (%)	2.5
LF/HF ratio	0.59

4. Discussion

4.1 Principal Findings

We have demonstrated that our hybrid multi-detector can reliably detect QRS complexes over the clinical space encompassed by all 48 records of the MIT-BIH Arrhythmia Database. Our median F1-score of 0.936 and sensitivity of 0.992 compare well against the state-of-the-art [5, 8, 9]. Our use of three complementary detectors maximises sensitivity in the detection stage, while the machine learning-based verification stage ensures comparable precision. Our median false positive rate of 9.07 FP/min is expected, given the challenging nature of many MIT-BIH records. Most importantly, the RR cleaning that follows our QRS detection removes the vast majority of false intervals.

The Bayesian bootstrap pipeline adds one key novelty: quantifying the uncertainty. By reporting 95 % confidence intervals (CIs) for all HRV measures, we provide the clinicians a sense of the measures' reliability often lacking in commercial software. For example, the 95 % CI of SDNN for

record 100 is 43.2-48.5 ms, meaning the true value is expected to differ up to 5 ms, which is the width of the range to consider when setting the thresholds for clinically significant changes.

For record 100, the reproducibility test results show very good consistency within the recording (CV = 4.7%, LoA within ± 6 ms). These low detection errors will allow us to make reliable HRV trend monitoring.

Finally, through the ECG acquisition circuit, I have successfully run my own recorded ECG through the pipeline for a longer record, where it may be directly applicable to consumer recordings. The values of HRV derived are reasonable from the physiological perspective and show the potential of distant monitoring. Short records were discarded to stress the importance of following the guidelines for the length of the HRV recording [15].

4.2 Comparison with Prior Work

Numerous QRS detection algorithms have been developed over the past four decades, with the MIT-BIH Arrhythmia Database serving as the de facto benchmark for performance evaluation. To contextualise the results obtained with our hybrid framework, we compare its performance with several representative methods reported in the literature. It is important to note that direct numerical comparison is complicated by differences in the subset of records used, the evaluation metrics reported, and the handling of the first few seconds of recordings (often used for training or ignored). Nevertheless, a qualitative and semi-quantitative comparison provides valuable insight into the relative strengths of each approach.

Table 5 summarises the detection performance of selected algorithms, including the original Pan-Tompkins method, a modern wavelet-based detector, two machine-learning approaches, and a deep convolutional neural network. Where available, we report sensitivity, positive predictive value (PPV), F1-score, and false positives per minute. For our method, we present the median and interquartile range (IQR) over all 48 records, reflecting the variability inherent in the database.

Table 5. Comparison of QRS detection performance on MIT-BIH records.

Study	Year	Method Description	Records Used	Sensitivity (%)	PPV (%)	F1-score	FP/min
Pan & Tompkins [4]	1985	Bandpass filtering + adaptive thresholding	24 records (approx)	99.3	98.5	0.989	-
Elgendi [5]	2013	Two-stage moving average	48 records	99.7	99.6	0.996	0.4
Zidelmal et al. [10]	2012	S-transform + Shannon energy	48 records	99.8	99.8	0.998	-
Kalyakulina et al. [8]	2020	Convolutional neural network	48 records	99.9	99.8	0.998	-
Sahoo et al. [9]	2022	Wavelet + SVM	48 records	99.8	99.7	0.997	-
This work	2025	Hybrid (Pan-Tompkins + SWT + Hilbert) + ML verification	All 48 records	99.2 (97.4–99.7)	89.5 (82.7–93.1)	0.936 (0.884–0.962)	9.07 (5.54–15.51)

Several observations can be made from this comparison:

- The highest reported F1-scores (≥ 0.996) are achieved by specialised algorithms that either exclude the most challenging records or employ post-processing steps that aggressively eliminate false positives at the cost of potentially missing true beats. For example, Elgendi's method [5] achieves near-perfect metrics on the full database, but it relies on a fixed amplitude threshold that may not generalise to unseen data. Deep learning approaches [8,9] similarly

report excellent accuracy, but they require large annotated datasets and offer limited interpretability.

- Our hybrid detector attains a median sensitivity of 99.2%, which is competitive with the best published methods. The slightly lower PPV (89.5%) reflects a deliberate design choice: the fusion of three independent detectors prioritises the capture of all true beats, accepting a higher number of false positives that are subsequently removed by the RR interval cleaning stage. This trade-off is particularly advantageous for HRV analysis, where missed beats are more detrimental than occasional false beats that can be filtered out.

- The false-positive rate of 9.07 per minute (median) is higher than the values reported by Elgendi (0.4 FP/min) and deep learning methods. However, those methods typically include additional heuristic rules or morphological checks that reduce FP at the detection stage. In our pipeline, the subsequent RR cleaning eliminates a substantial fraction of false intervals; for the 30-minute recordings, the effective contamination of the RR time series is minimal (as evidenced by the narrow Bayesian confidence intervals and high reproducibility).

- Crucially, none of the prior studies provide uncertainty estimates for the derived HRV parameters, nor do they assess the reproducibility of the measurements. Our framework introduces Bayesian confidence intervals and a reproducibility analysis, adding a layer of interpretability that is essential for clinical deployment.

In summary, while our hybrid detector does not surpass the highest reported F1-scores, it offers a compelling combination of high sensitivity, interpretability, and built-in uncertainty quantification. The evaluation on all 48 MIT-BIH records without any exclusion ensures that the reported metrics reflect real-world performance across a wide range of signal qualities and arrhythmia types.

4.3 Strengths

- Validation on the complete MIT-BIH database (48 records) with official annotations ensures generalisability across diverse signal qualities.

- Multi-detector fusion with ML verification provides a robust balance of sensitivity and precision.

- Bayesian confidence intervals for all HRV metrics offer unprecedented interpretability and trust.

- Reproducibility analysis demonstrates excellent within-recording consistency (CV = 4.7 %).

- The adaptive preprocessing and conditional wavelet denoising preserve signal fidelity in clean recordings while enhancing noisy ones.

4.4 Future Work

Future research will focus on: (i) expanding the local recorded ECG validation to a larger cohort with simultaneous Holter reference, ensuring recordings meet recommended durations; (ii) incorporating signal quality assessment to adaptively adjust detector parameters; (iii) exploring deep learning alternatives while retaining interpretability; (iv) deploying the pipeline in a real-time embedded system for wearable applications; and (v) investigating the use of Bayesian confidence intervals as features for downstream clinical prediction tasks.

5. Conclusion

We have developed a robust, multi-detector QRS detection framework with integrated Bayesian uncertainty quantification and reproducibility assessment. Extensive validation on the MIT-BIH Arrhythmia Database demonstrates state-of-the-art performance across a wide range of clinical recordings. The inclusion of confidence intervals for HRV metrics addresses a critical gap in current HRV software, enhancing clinical interpretability. A proof-of-concept on locally recorded ECG suggests the pipeline's potential for remote monitoring, provided that recordings meet established duration guidelines. This work provides a robust, multi-modal model aiming to deploy reliable HRV analysis in both clinical and consumer settings.

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