FEASIBILITY OF ECTOPIC BEAT DETECTION AND COUNT ESTIMATION FROM SMARTWATCH-BASED PHOTOPLETHYSMOGRAPHY

Baiying Lu[1,2,*] *Quan Dong*[1] *Sharanya Desai*[1] *Hao Zhou*[1]
Cyrus Tanade[1] Simon Lee[1] Chaoyi Kang[1]

[1]Samsung Research America, Mountain View, CA, USA, [2]Dartmouth College, Hanover, NH, USA

ABSTRACT

Ectopic beats (EBs) are common cardiac irregularities associated with risks of atrial fibrillation (AF) and sudden cardiac death, highlighting the need for reliable long-term monitoring. Electrocardiogram (ECG)-based methods remain the clinical gold standard, but their limited monitoring duration and patient burden restrict long-term daily use. In contrast, smartwatch photoplethysmography (PPG) enables passive, long-term data collection and offers a promising alternative for daily monitoring. In this study, we developed a pipeline using free-living smartwatch PPG data for ectopic beat detection and count estimation. Performance was evaluated under three experimental scenarios reflecting different application contexts. The pipeline achieved an F1 score of up to 0.884 in distinguishing ectopic beats from sinus rhythm and a mean absolute error as low as 0.042 per segment, while AF emerged as a major confounding factor. These findings demonstrate the feasibility of smartwatch-based PPG for ectopic beat monitoring in free-living conditions, providing a foundation for future long-term, passive monitoring solutions.

***Index Terms*—** Ectopic beat detection, Ectopic burden estimation, PPG signal processing, Deep learning, Smartwatch.

1. INTRODUCTION

Ectopic beats are common cardiac irregularities associated with increased risks of AF and sudden cardiac death, underscoring the need for reliable long-term monitoring[1, 2]. The two major types of EBs are premature atrial contractions (PACs) and premature ventricular contractions (PVCs) [3, 4]. Clinically, ectopic beats are detected using prescription-based wearable ECG patches [5]. Although effective for short-term diagnostics as the gold standard, these devices cannot provide long-term daily monitoring and often impose additional burden on patients, including discomfort from daily wear, cost, and the need for annual follow-up visits [5]. PPG, in contrast, is a passive sensing modality already integrated into most commercial smartwatches, offering a feasible approach for long-term monitoring of ectopic beats [6, 7, 8, 9].

Smartwatch-based PPG has already proven effective in arrhythmia detection, particularly AF, but extending it to ectopic beat detection and burden estimation presents additional challenges[6, 10]. In free-living conditions, smartwatch PPG signals often suffer from motion artifacts, inconsistent sensor contact, and noise, which reduce data quality and make ectopic patterns harder to distinguish from sinus rhythm (SR) or other arrhythmias[6, 11]. Most prior studies on EB detection have relied on fingertip PPG collected in controlled settings, where the signal is higher resolution and less affected by free-living factors[12, 13]. In addition, in real-world monitoring, quantifying ectopic activity over time is more clinically meaningful than classifying individual beats [14]. Existing studies have primarily focused on binary detection or beat-by-beat identification [6, 8, 15, 16, 17], leaving long-term quantification as an open area for further research. Together, these considerations highlight the unique challenges of applying smartwatch-based PPG to ectopic beat monitoring in daily life and motivate the need for further investigation.

In this study, we present a pipeline that uses free-living PPG data from smartwatches for ectopic beat monitoring under three experimental scenarios designed to reflect different application contexts. As shown in Fig 1, PPG signals were paired with reference ECG annotations, preprocessed, input into convolutional neural network (CNN) models, and evaluated at segment and participant levels separately. The main contributions of this study are:

- We demonstrate, on free-living PPG from commercially available smartwatches, that ectopic beats can be effectively identified from both SR and other arrhythmias by CNN-based models, despite challenging signal conditions.
- We move beyond binary classification by estimating ectopic beat counts per 30-second PPG segment, providing a foundation for future burden estimation in real-world applications.
- We conducted a comprehensive evaluation across three experimental scenarios at both segment and individual levels, demonstrating feasibility in varied real-life contexts and identifying confounding factors such as AF.

* Work done as an intern at Samsung Research America

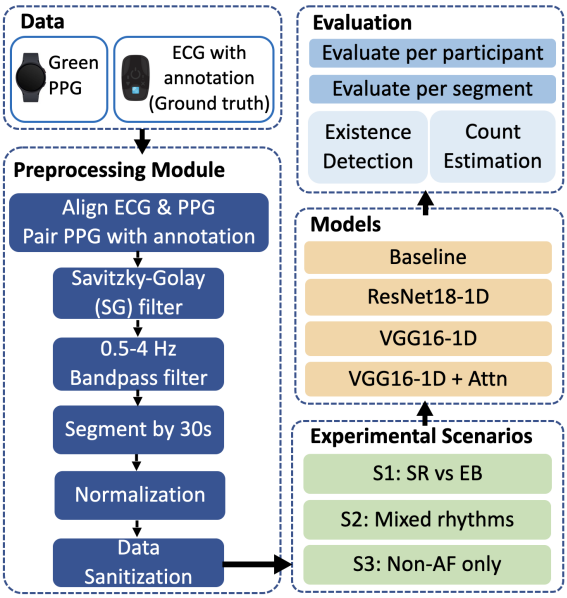


Fig. 1. Overview of the proposed pipeline for ectopic beat detection and count estimation from smartwatch-based PPG.

2. RELATED WORKS

Prior work on PPG-based ectopic or PVC detection has followed two main directions: (i) extracting temporal or spectral features (e.g., interbeat intervals, and power ratios) from PPG pulses and applying machine learning classifiers [6, 8, 15, 18], or (ii) using deep neural networks directly on PPG segments for multi-arrhythmia classification [16, 17, 19]. Feature-based studies often relied on high-resolution or fingertip PPG collected in controlled settings or ICU (e.g., MIMIC dataset) [12, 13], which is different from free-living data conditions. While deep learning approaches have primarily targeted arrhythmia classification[16, 17, 19], rather than identifying the number or burden of ectopic beats. Therefore, quantifying ectopic activity based on free-living PPG from smartwatches still worthwhile for exploration and feasibility verification.

3. METHOD AND EXPERIMENT

3.1. Dataset

We analyzed a proprietary dataset of 140 participants aged 22 to 84, 44% African American and 56% Caucasian, with varying levels of ectopic activity. Each participant was monitored under free-living conditions with simultaneous PPG and ECG for an average of 12.4 days (± 1.84 standard deviation). Green-channel PPG signals were recorded using the Samsung Galaxy Watch 6 at 25 Hz, while ECG was captured with BodyGuardian™ remote cardiac monitors at 250 Hz. Annotations of ectopic events were generated by the BeatLogic™ cardiac algorithm, which provided event-level timestamps in milliseconds, marking the occurrence of ectopic beats identified from ECG with high accuracy and agreement with human visual inspection[20, 21]. These event annotations were used to construct reference labels for model training and evaluation. Across the monitoring period, the number of ectopic beats per participant ranged from 74 to 116,037. In addition to ectopic beats, the dataset included up to 38 distinct arrhythmia types as identified by BeatLogic. All data collection and de-identification were conducted in compliance with Institutional Review Board requirements.

3.2. Preprocessing

To transfer the annotations from ECG to the PPG, data alignment was achieved using synchronization event log files that recorded broadcasting exchanges between the BodyGuardian™ mobile application and a companion application designed for Galaxy Watch data collection. After alignment, PPG signals were first smoothed using a Savitzky–Golay (SG) filter (polyorder = 3, window length = 1.5 × 25 Hz) and a 0.5–4 Hz Butterworth bandpass filter to suppress noise outside the physiological heart-rate range. Denoised signals were split into non-overlapping 30-second segments and normalized to [0,1]. PPG segments were excluded if they met any of the following sanitization criteria: (1) missing aligned ECG data; (2) presence of significant motion artifacts flagged by the Galaxy Watch algorithm; (3) watch-off events indicated by the watch; or (4) artifacts, low-quality ECG, or electrical disconnection identified by the BeatLogic™ algorithm. After applying these filters, 22.8% of PPG segments were retained for model training and evaluation, ranging from 116 to 12,443 segments per participant. In this case, we prioritized high-quality segments to reduce instability and remain consistent with real-world smartwatch PPG monitoring systems.

3.3. Experimental Scenarios

The models were trained and evaluated under three experimental scenarios, each defined by distinct data inclusion criteria and sampling strategies.

Scenario 1 (SR vs. EB): Only segments labeled as SR or EB were included, with all other arrhythmia types excluded. To ensure that participants with abundant data do not dominate training and evaluation while still accommodating people with fewer valid segments, up to 1,500 segments were randomly sampled per participant; if fewer were available, all valid segments were retained. This scenario reflects a screening setting in healthy users, focusing on distinguishing ectopic beats from SR.

Scenario 2 (Mixed rhythms): Segments containing other arrhythmias were included in addition to SR and ectopic beat. As in Scenario 1, up to 1,500 segments were randomly sampled per participant. This scenario represents real-world monitoring in patients with multiple arrhythmias, where ectopic beats might be detected alongside other rhythms.

Scenario 3 (Non-AF participants): To reduce the confounding effect of AF identified in error analysis of Scenario 2, only participants without AF ($n = 83$) were included. For these participants, 2,000 segments each were sampled to increase training and evaluation size. This scenario corresponds to monitoring in non-AF populations, reducing AF-related confounding to focus on ectopic beats.

3.4. Model Architectures

We focused on CNN architectures for ectopic beat detection and count estimation from real-world smartwatch PPG, different from traditional feature-based methods that require high-quality signals. CNNs are widely used in time-series and biomedical signal analysis because they can effectively capture local temporal patterns[7, 22]. To provide a fair comparison, we evaluated one shallow baseline and three established deep CNN backbones.

Baseline: A lightweight 3-layer CNN was used as a simple reference against deeper architectures.

VGG16-1D[23]: VGG networks have been successfully applied to arrhythmia detection from PPG [16]. Similarly, we adapted the VGG16 backbone into a one-dimensional form to model temporal PPG sequences and identify ectopic beats.

ResNet18-1D[24]: Residual networks can stabilize training and improve feature learning, and have also been used in PPG-based arrhythmia detection [17, 19]. We therefore refactored ResNet18 into a one-dimensional variant to evaluate its effectiveness for ectopic beat estimation.

VGG16-1D with Attention: To further enhance temporal representation, we extended VGG16-1D with a convolutional block attention module (CBAM) and attentive statistics pooling, allowing the model to emphasize informative regions in the PPG signal[25, 26].

3.5. Model Training

Participants were randomly split into training, validation, and test sets (6:2:2). Models were trained with SmoothL1Loss ($\beta = 1$) using the Adam optimizer (learning rate 3×10^{-4}, batch size 32) for up to 50 epochs. To address sampling imbalance, we selected two weighting strategies based on extensive experimental evaluation: (i) individual-level weights for participants with fewer than the preset number of samples, and (ii) segment-level weights scaled inversely to ectopic count frequency with a logarithmic adjustment, normalized to an expected value of one. For higher-count groups ($\geq$9 beats), weights were capped to the same level as $count = 9$ to prevent excessive influence of rare tails. All experiments were implemented on an NVIDIA T4 GPU (16 GB).

3.6. Evaluation Tasks and Metrics

Model performance was evaluated on two tasks using the same trained models, which output ectopic beat counts per 30s segment. The first task, beat detection, assessed whether a segment contained one or more ectopic beats, with performance measured by F1 score, sensitivity, specificity, and precision, consistent with prior studies [6, 15, 16, 17, 19]. The second task, count estimation, quantified the number of ectopic beats per segment using mean absolute error (MAE) across all segments, MAE on non-zero segments, and the correlation between true and estimated counts. Evaluation was performed at both segment and participant levels: segment-level metrics were computed across all test segments, while participant-level metrics were calculated for each individual.

4. RESULTS AND DISCUSSION

4.1. Performance on segment level

From Table 1, model performance varied substantially across the three experimental scenarios. In Scenario 1 (SR vs. EB), models achieved their best results, with F1 score up to 0.884 and the lowest MAE values (0.042 per segment, 0.188 on non-zero segments). This indicates that ectopic beats can be reliably distinguished from sinus rhythm when no other arrhythmias are present.

Table 1. EB detection and count estimation performance across three evaluation scenarios on segment level.

Scenario / Metric	Baseline	VGG16	ResNet18	VGG16+Attn
S1: SR vs. EB				
Existence detection				
F1 score	0.478	0.884	0.879	0.884
Sensitivity	0.540	0.842	0.832	0.831
Precision	0.429	0.931	0.931	0.943
Specificity	0.929	0.994	0.994	0.995
Count estimation				
MAE/seg	0.278	0.044	0.043	0.042
MAE/non-zero	1.308	0.204	0.189	0.188
S2: Mixed rhythms				
Existence detection				
F1 score	0.482	0.715	0.737	0.713
Sensitivity	0.511	0.751	0.766	0.789
Precision	0.456	0.682	0.711	0.651
Specificity	0.905	0.959	0.963	0.950
Count estimation				
MAE/seg	0.327	0.114	0.107	0.133
MAE/non-zero	1.306	0.378	0.394	0.372
S3: Non-AF participants				
Existence detection				
F1 score	0.710	0.844	0.852	0.835
Sensitivity	0.721	0.855	0.832	0.803
Precision	0.699	0.833	0.873	0.871
Specificity	0.959	0.990	0.993	0.993
Count estimation				
MAE/seg	0.162	0.051	0.050	0.052
MAE/non-zero	0.843	0.482	0.542	0.500

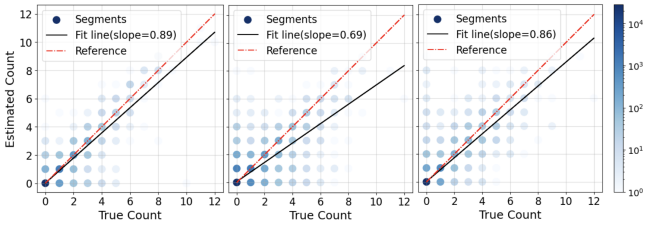
In Scenario 2 (mixed rhythms), performance declined across all metrics, with F1 scores reduced to 0.715–0.737 and precision showing the largest drop, reflecting more false positives. Error analysis showed that 83.7% of false positives

were AF segments, although AF accounted for only 15.3% of the test set, confirming AF as the dominant confounder.

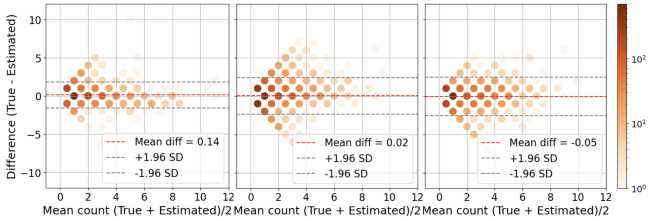
In Scenario 3 (non-AF participants), excluding AF improved performance markedly (F1: 0.844–0.852; lower MAE than Scenario 2), validating AF's disruptive effect. Nonetheless, non-zero MAE remained relatively high, highlighting challenges in quantifying ectopy under diverse rhythms.

Fig. 2 illustrates regression results for VGG16-1D. In Scenario 1, scatter points align closely with the reference line (fit slope 0.89), whereas in Scenarios 2 and 3 they are more dispersed, consistent with wider limits of agreement in Bland–Altman plots. These findings reinforce the scenario-level trends observed in Table 1.

Across all scenarios, the three deep CNNs consistently outperformed the shallow baseline, but their differences were minor. This suggests that CNN depth is important for the task, while architectural variations yield limited additional benefit.



(a) True vs. estimated counts with linear fit lines.



(b) Bland–Altman plots on non-zero segments.

Fig. 2. Model performance on ectopic beat count estimation across three scenarios (S1–S3, left to right). Darker dots indicate higher segment distribution density.

4.2. Performance on individual level

Fig. 3 displays participant-level F1 distributions in a box plot, showing large variance across individuals. The standard deviations reported in Table 2 further highlight this variability. Beyond F1, both non-zero MAE and the correlation between true and estimated ectopic counts varied widely. Two factors largely explain this pattern. First, some participants had very few ectopic events, making evaluation unstable since a small number of errors disproportionately affected metrics. Second, participants with confounding rhythms such as AF, first-degree heart block, or bradycardia exhibited PPG patterns that overlapped with ectopic morphology, leading models to misclassify these segments as ectopic beats.

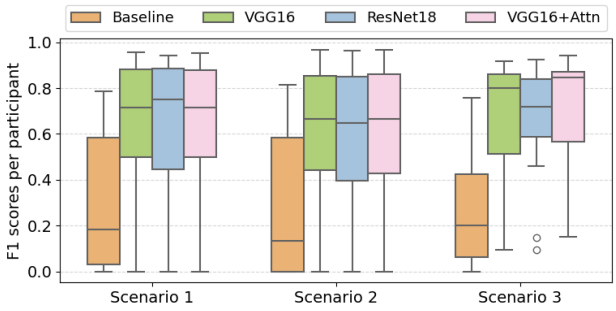


Fig. 3. Participant-level F1 score distributions across scenarios, highlighting the large variability across individuals.

Table 2. Individual-level EB count estimation across three scenarios (mean ± SD).

Scenario / Metric	Baseline	VGG16	ResNet18	VGG16+Attn
S1: SR vs EB				
MAE/non-zero seg	0.803 (0.29)	0.428 (0.27)	0.420 (0.27)	0.423 (0.28)
Corrcoef (r)	0.296 (0.31)	0.642 (0.28)	0.648 (0.28)	0.666 (0.25)
S2: Mixed rhythms				
MAE/non-zero seg	0.941 (0.41)	0.560 (0.38)	0.514 (0.37)	0.477 (0.35)
Corrcoef (r)	0.287 (0.30)	0.551 (0.34)	0.555 (0.33)	0.561 (0.33)
S3: Non-AF only				
MAE/non-zero seg	0.867 (0.29)	0.334 (0.27)	0.392 (0.26)	0.332 (0.26)
Corrcoef (r)	0.274 (0.24)	0.646 (0.26)	0.670 (0.24)	0.668 (0.25)

4.3. Limitation and future works

This study has two main limitations. One is that PVCs and PACs were combined into a single ectopic class. However the distinction is clinically important since PVCs carry greater risk[27, 28]. Second, we only estimated ectopic counts per segment rather than deriving participant-level burden over the study period. Future work will address both limitations and compare results against clinical standards for PVC burden estimation.

5. CONCLUSION

This study demonstrates the feasibility of using smartwatch-based PPG for ectopic beat monitoring in free-living conditions. We developed a pipeline evaluated under three experimental scenarios and showed that ectopic beats can be reliably distinguished from sinus rhythm, with F1 scores up to 0.884 and MAE as low as 0.042 per segment. Performance declined in mixed arrhythmia settings, where atrial fibrillation emerged as a major confounder, but improved again when AF participants were excluded. Overall, our results highlight smartwatch-based PPG as a promising modality for scalable, passive, long-term ectopic beat detection and quantification, providing a foundation for future real-world monitoring solutions, particularly as a smartwatch wellness feature that reports ectopic burden to support users' cardiovascular health awareness.

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