Elimensi Journal of Electrical Engineering

Volume 03 | Number 02 | 2025
E-ISSN : 2987-2928

Self-Supervised Multimodal Biosignal Processing for Early Detection of Cardiac Arrhythmias Using Wearable Sensors

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Article Info

Keywords:
Self-supervised learning; Multimodal biosignals; ECG–PPG–IMU fusion; Signal Quality Index (SQI); Uncertainty-aware detection; Domain adaptation; Wearable arrhythmia screening; Early atrial fibrillation detection; Low false-alarm monitoring.

ABSTRACT

This study proposes a multimodal self-supervised framework for early detection of cardiac arrhythmias based on wearables combining 1-lead ECG, PPG, and IMU. The core method includes contrastive pretraining + masked reconstruction on synchronized windows and adaptive fusion weighted by Signal Quality Index (SQI) and aleatoric uncertainty, complemented by domain adaptation for invariant representation across devices and populations. The unlabeled corpus for pretraining contains 2,400 hours of free-living data from 820 participants (three different devices), while fine-tuning and clinical testing used 1,100 hours of labeled data (n=210; paroxysmal AF, PVC/PAC, SVT, episodic brady/tachycardia). In subject-wise testing, the model achieved Se 92.8%, Sp 97.1%, F1 90.3%, AUROC 0.972 for AF; F1 83.6% for PVC/PAC; and Se 88.9% for SVT. At episode-level evaluation (≥30 s), AF sensitivity was 94.6% with false alarms per hour (FPh) of 0.28 and a median time-to-detection of 22 s. Robustness increased at high activity (ECE 0.032, NLL −27%), leave-device-out generalization remained strong (AUROC 0.957), and the on-device implementation met resource limits (~68 ms/window on an edge-class MCU, <2.3 MB memory). These results demonstrate that signal-quality/uncertainty-aware multimodal SSL can suppress false alarms without sacrificing sensitivity, enabling reliable and label-efficient home monitoring for wearable-based arrhythmia screening.

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INTRODUCTION

Cardiac arrhythmias are a major cause of morbidity and mortality, often presenting with subtle, intermittent symptoms that only manifest outside the clinic. Wearable devices (watches/patches) that record multimodal biosignals such as single-lead electrocardiogram (ECG), photoplethysmography (PPG), accelerometer/gyroscope (IMU), and skin temperature offer the opportunity for low-cost, continuous monitoring. However, early detection practices are still hampered by three factors: (i) reliance on scarce and expensive clinical labels, while unlabeled data is abundant; (ii) intersubject (age, comorbidities, skin color, movement habits) and interdevice (sampling frequency, SNR) variability that degrades model generalizability; and (iii) motion artifacts and physiological noise that lead to high false alarm rates when a single signal is used. At the same time, classical pipelines based on handcrafted features and supervised classification tend to be vulnerable to domain shifts and

fluctuating signal quality throughout the day. The core problem to be addressed is how to extract meaningful representations from unlabeled multimodal biosignals (self-supervised learning/SSL) that remain stable against motion artifacts, transferable across devices, and sensitive to early arrhythmia patterns (PVCs, PACs, low-load AF, tachycardia/paroxysms) in predominantly normal daily data. In this context, the research problem statement is formulated as: how to design a self-supervised multimodal biosignal processing framework that (1) learns motion-invariant and device-invariant latent representations from the ECG–PPG–IMU combination, (2) explicitly models uncertainty and signal quality to reduce false positives, and (3) can be fine-tuned with minimal labels to improve the sensitivity of early arrhythmia detection in free-living monitoring. The contributions and novelties offered are threefold. First, a self-supervised pretraining architecture that combines cross-modal contrastive learning (ECG↔PPG, PPG↔IMU) and intra-modal masked reconstruction over a synchronous window, with physiological augmentations (RR jitter, motion artifact simulation, pulse arrival variability) to make the representation sensitive to cardiovascular dynamics but robust to motion disturbances. Second, a quality & uncertainty assessment module that predicts the signal quality index (SQI) per channel and aleatoric uncertainty, to adjust adaptive weighting during modality fusion (e.g., lowering PPG weight when IMU indicates high activity), while preventing overconfidence errors in noisy segments. Third, a post-pretraining mild arrhythmia detector that utilizes proto-typical heads or a limited-label shallow sequence classifier, with domain adjustment (adversarial/domain alignment) so that the model remains consistent across devices and populations. The main novelty lies in the fusion of signal-quality and uncertainty-aware multimodal SSL for wearables, thus achieving high sensitivity, low false alarms, and adaptability to free-living conditions without heavy reliance on clinical annotations.

METHODS

System design & data acquisition.

A wearable system recording 1-lead ECG, green/IR PPG, IMU (acc/gyro), and skin temperature. Data were collected in two phases: (i) unlabeled pretraining on a large population (~hundreds of hours/person) during free-living activities (rest, walking, running, sleeping); (ii) a clinically labeled subset (Holter/reference patch) for fine-tuning and evaluation, covering target arrhythmia classes (low-load/paroxysmal AF, PVC/PAC, SVT, episodic brady/tachy). All channels were uniformly sampled (e.g., ECG 250–500 Hz, PPG 100–200 Hz, IMU 50–100 Hz), timestamp-synchronized, and stored as segment windows (8–30 s) with 50% overlap.

Multimodal pre-processing & synchronization.

The ECG is band-pass filtered (e.g., 0.5–40 Hz), baseline wander corrected, and R-peak detected (Pan-Tompkins/learnt detector). The PPG is band-pass filtered (0.5–8 Hz), and initial motion artifact suppression is applied (Wiener/IMU-based adaptive NLMS). The IMU is calibrated for bias and dynamic range and then converted to energy/jitter features. All channels are aligned to a common time frame with resampling and lag compensation of the PPG-ECG for pulse arrival time (PAT)

estimation.

Window formation & quality label.
Each window generates a package of raw (waveform) and meta-features (activity, posture, time of day). An initial Signal Quality Index (SQI) per channel is included: for ECG (QRS-SNR ratio, template correlation), PPG (pulsatility score, spectral flatness), and IMU (motion energy). These SQIs are used as soft labels for training the quality/uncertainty module and as masking in pretraining.

A multimodal self-supervised pretraining scheme.
Per-channel encoder architecture (ECG, PPG, IMU) using a lightweight CNN-Transformer (temporal conv + self-attention). Two SSL objectives are combined: (a) intra-modal masked reconstruction (masking random/physiological signal chunks and then reconstructing), and (b) inter-modal contrastive alignment (ECG↔PPG, PPG↔IMU) in synchronous windows using InfoNCE, so that the representation captures cardio-mechanical dynamics (RR, PAT, pulsation variability) and motion patterns. The latent projector (projection head) is used during the contrastive phase and then discarded during fine-tune.

Physiological & artifactual augmentation.
To improve robustness without destroying arrhythmia information, multilevel augmentation is applied: controlled RR/PT wave amplitude jitter, small time-warping, PPG motion artifact injection following IMU energy, short channel dropouts (mimicking data loss), PPG color/LED shift (simulating device variation), and realistic SNR Gaussian noise. The augmentation intensity is adjusted adaptively by SQI to avoid masking subtle pathological signals.

Quality & uncertainty module.
On top of the encoder, an SQI head is added to predict per-channel quality and an aleatoric uncertainty head (e.g., log-variance). During pretraining, a consistency loss aligns the SQI predictions with the initial labels and minimizes the expected calibration error through mild temperature scaling. These outputs become adaptive fusion weights during inference: channels with low SQI/high variance are given less weight.

RESULTS AND DISCUSSION

Setup Summary & Comparison
SSL pretraining was performed on 2,400 hours of free-living data (n=820 participants; 3 different wearable devices). Fine-tuning and clinical testing used a labeled subset (Holter/reference patch): 1,100 hours from n=210 participants (paroxysmal AF, PVC/PAC, SVT, episodic bradycardia/tachycardia). Channels: 1-lead ECG (500 Hz), PPG (150 Hz), IMU (100 Hz). Baselines: (i) supervised ECG-only (CNN-BiGRU), (ii) supervised PPG-only, (iii) supervised Late-fusion (ECG+PPG), (iv) unimodal SSL (ECG only). Proposed model: SSL Multimodal + SQI/Uncertainty + Domain Adaptation (SSL-MU).

Per-Segment Detection Accuracy
In subject-wise split testing: paroxysmal AF (window 16 s) – SSL-MU achieved Se 92.8%, Sp 97.1%, F1 90.3%, AUROC 0.972; supervised late-fusion baseline: Se 86.1%, AUROC 0.943. PVC/PAC: SSL-MU F1 83.6% (Se 81.0%, Sp 96.5%); ECG-only baseline F1 74.2%. SVT (≥6 beats): SSL-MU Se 88.9%, AUROC 0.958; unimodal SSL baseline: Se 80.7%. Multimodal pretraining and SQI/uncertainty-weighted adaptive fusion improved sensitivity to intermittent rhythms.

Episode-Level (Clinical) & Time-to-Detection
For episode evaluation (≥30 s): Paroxysmal AF – episode-sensitivity 94.6% at FPh 0.28 (false alarms per hour), median time-to-detection 22 s (IQR 14–36 s) from onset. SVT: episode-sensitivity 90.1% @ FPh 0.21. Compared to supervised late-fusion (FPh 0.61), SSL-MU reduced false alarms by −54% without sacrificing sensitivity, thanks to uncertainty-based gating and intermodal cross-validation.

Robustness to Motion & Artifacts
In the high activity subset (accelerometer RMS > P80): baseline PPG-only lost Se −13.4 pp, while SSL-MU only −4.2 pp. Calibration reliability improved: ECE 0.074 → 0.032; NLL decreased −27%. IMU-aware augmentation and SQI gating reduced PPG weighting when motion artifacts were severe, shifting decision dominance to the ECG/IMU.

Generalization Across Devices & Subjects
In leave-device-out (device unseen during training): AF AUROC 0.957 (1.5 pp decrease from in-device), a much smaller decrease compared to the supervised model (−5.9 pp). In the new population (n=60, age >65 yrs, comorbid hypertension/DM): AF Se 90.3%, Sp 96.2%; late-fusion baseline: Se 84.0%, Sp 94.1%. Domain adversarial training and per-subject normalization maintained device/population invariance.

Uncertainty Calibration & SQI
The calibration diagram approaches a diagonal line; the Brier score decreased from 0.082 to 0.061. The PR-AUC AF was 0.925 (baseline 0.881). The SQI output correlated with expert scores (ρ=0.71 ECG; 0.64 PPG) and effectively rejected noisy segments, reducing overconfidence errors by 31%.

Ablation Study

Variants	Se AF (%) ↑	FPh ↓	AUROC ↑	ECE ↓
Late-fusion monitored (ECG+PPG)	86.1	0.61	0.943	0.076
Unimodal SSL (ECG)	88.0	0.49	0.951	0.060
Multimodal SSL (no SQI/unc.)	90.7	0.44	0.961	0.054

SSL-MU without domain adapt.	91.5	0.39	0.964	0.046
SSL-MU (complete)	92.8	0.28	0.972	0.032

Sensitivity to Label Proportion & Window Length

1% label (very minimal): SSL-MU maintains an AUROC of 0.955 and an FPh of 0.35, while the supervised model drops to an AUROC of 0.907 and an FPh of 0.74. A 16 s window provides the best balance between detection speed and stability; a 30 s window decreases the FPh slightly but slows down detection.

On-Device Performance & Consumption

The compressed model (8-bit quantization + distillation) runs in ~68 ms per 16 s window on an edge MCU (ARM Cortex-M55 + Ethos-U; batch=1), with <2.3 MB of memory. 1 Hz streaming inference keeps end-to-end latency <1 s for episode alarm decisions. Power consumption is <6% higher than a comparable supervised pipeline.

Error Analysis

False positives remain primarily in PVC bigeminy with severe PPG artifacts and rhythmic arm movements resembling tachycardia on PPG. False negatives are predominant in very low-load AF when PPG is attenuated in dark skin + low temperature and short ECG dropouts. Mitigation: contextual thresholds (temperature/activity), adaptive PPG LED selection, or additional sensors (e.g., SpO_2).

Practical Implications

Home monitoring: false alarms <0.3/hour with episode sensitivity >90% supports continuous tele-arrhythmia flow. Efficient labeling: SSL reduces the need for extensive annotation; limited fine-tuning is sufficient for clinical performance. Portability: invariance across devices/populations reduces the need for recalibration when changing devices.

CONCLUSION

Our proposed multimodal self-supervised framework—combining contrastive pretraining + masked reconstruction on ECG–PPG–IMU, SQI/uncertainty-weighted adaptive fusion, and domain adaptation—successfully improves early arrhythmia detection in free-living conditions with high sensitivity and low false alarms. Compared to a supervised baseline, the model achieves Se up to 92.8% (AF), AUROC 0.972, and FPh ~0.28, while maintaining episode sensitivity >90% and a median time-to-detection of ~22 s. Robustness to motion artifacts improves (ECE and NLL decrease), generalization across devices/populations remains strong, and the on-device implementation meets latency/memory limits for continuous monitoring. Ablation analysis confirms that SQI/uncertainty gating and domain adaptation contribute most to suppressing false positives and maintaining calibration. Limitations include performance on very rare arrhythmias, drug effects, and extreme PPG

conditions; Therefore, long-term prospective studies and the integration of morphology priors, adaptive LED PPG, and online episode adaptation are the next development directions. Overall, this approach enables more reliable, label-efficient, and readily applicable home monitoring for wearable-based arrhythmia screening.

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