

Beyond ECG: Robust Deep Learning-enabled Atrial Fibrillation Detection in HSATs with PPG

Jan Wodnicki, BSc*, Chris Fernandez, MSc*, Yoav Nygate, MSc*, Nick Glattard, MSc*, Matt Sprague, MSc*, Tom Vanasse, PhD*, Fred Turkington, BSc*, Sam Rusk, BSc*, Krishna Sundar, MD***, Nathaniel F. Watson, MD, MSc**

* EnsoData Research, EnsoData, Madison, WI, USA, ** Department of Neurology, University of Washington School of Medicine, Seattle, WA, *** UC Davis Medical Center

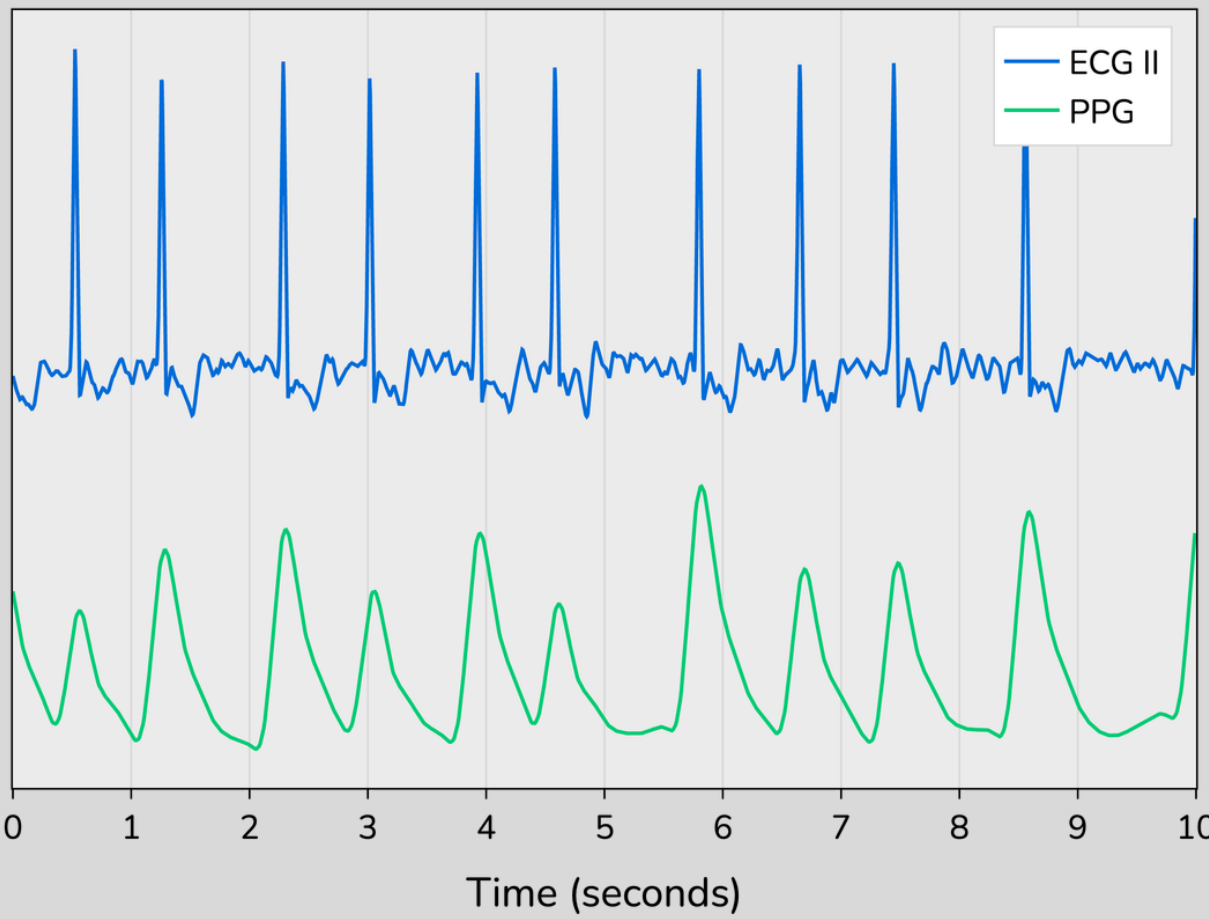


Introduction

Atrial fibrillation (AFib) is a prevalent and frequently underdiagnosed comorbidity in patients with obstructive sleep apnea (OSA), and sleep-disordered breathing is mechanistically linked to cardiac arrhythmias¹. This makes the sleep study a natural setting for arrhythmia screening, yet detection of AFib and atrial flutter (AFL) conventionally requires electrocardiography (ECG), which is absent from most home sleep apnea tests (HSAT).

Photoplethysmography (PPG) is recorded in nearly every polysomnogram (PSG) and HSAT, and pulse-based methods have shown feasibility for arrhythmia detection². However, accurate, automated AF detection from PPG at clinical scale remains unmet.

AFib in Simultaneous ECG and PPG



Objective: Develop and evaluate a deep learning model to detect AF events (AFib and AFL combined) from PPG alone, offering a scalable solution for high-accuracy, routine arrhythmia detection within large clinical sleep cohorts.

Materials & Methodology

Burden Estimation: AFib burden, the percentage of study epochs classified as AFib, was estimated across the clinical PSG/HSAT database using a validated open-source ECG model.

Datasets: Studies with ECG and PPG were sampled across the AFib burden range, yielding a cohort of 10,496 studies. The cohort was split into Training N=7,550, Validation N=1,888, and Test N=1,058.

Reference Labels (Ground Truth): Definitive AF labels (AFib and AFL) were derived from a validated ECG analysis algorithm applied to single-lead ECG II. This algorithm, distinct from the open-source model used for stratification, served as the gold-standard for training and evaluation.

Cohort Characteristics

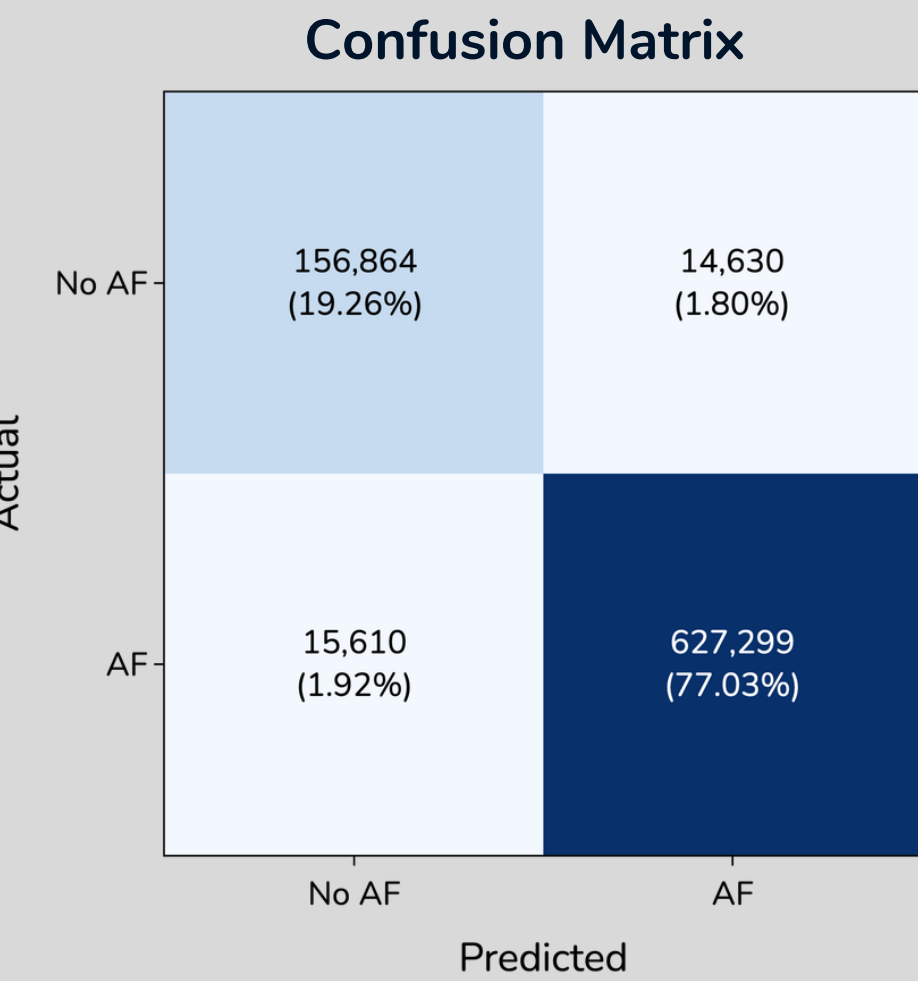
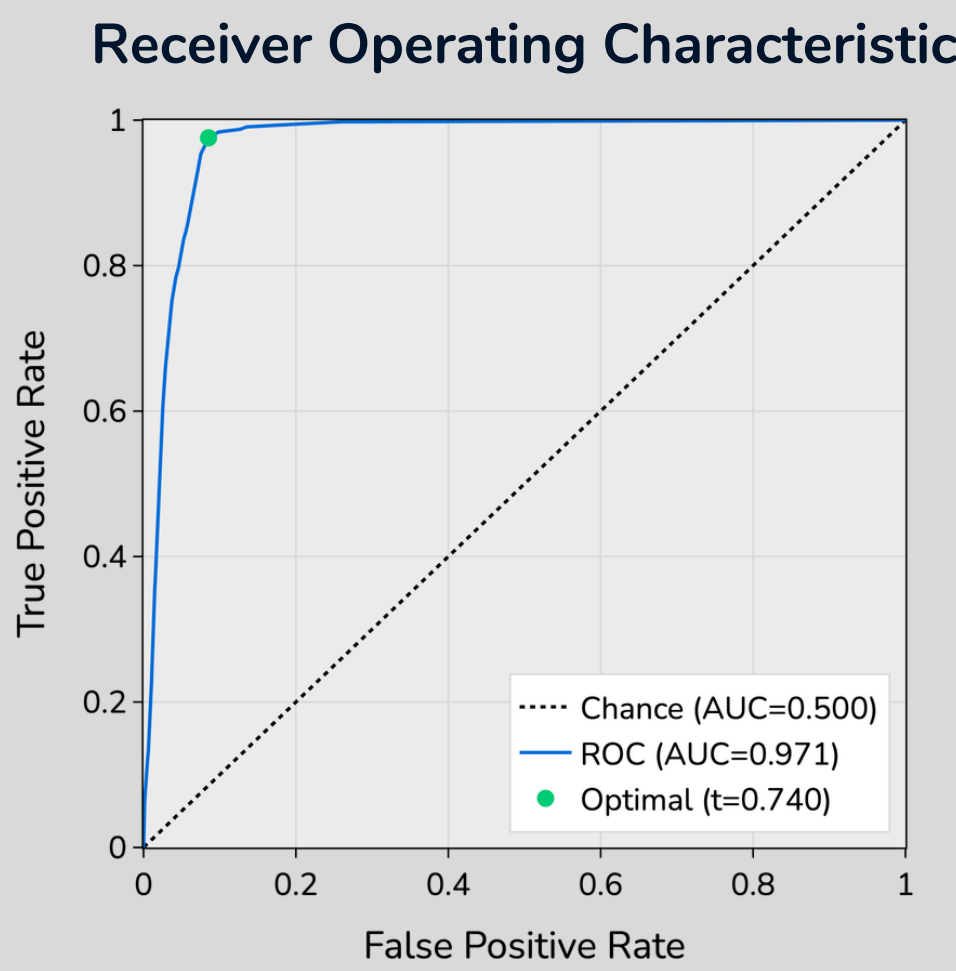
Variable	Value
Total patients, N	10,496
Female, n (%)	3,009 (28.7%)
Age, mean ± SD (years)	67.8 ± 12.6
BMI, mean ± SD (kg/m²)	33.7 ± 7.5
AFib epochs, n (%)	7,090,480 (80.1%)

Signal Input & Processing: Single-channel PPG was provided as a raw time-series and analyzed on a per-epoch (30-second) basis. 67,023 epochs (7.5%) with insufficient PPG signal quality were excluded from the test set.

Model Architecture: A deep learning (DL) model utilizing convolutional (1D-CNN) and temporal layers, trained exclusively on PPG.

Evaluation: Per-epoch binary classification on a held-out test set, reported as ROC-AUC, sensitivity, and specificity.

Results



On the held-out test set of 1,058 studies (642,909 AF and 171,494 non-AF 30-second epochs), the PPG-only deep learning classifier achieved a strong ROC-AUC of 0.971. At the optimal (Youden’s J) operating point, it reached 97.6% sensitivity and 91.5% specificity for per-epoch AF (AFib/AFL) classification. Sensitivity remained high at lower specificity targets: 98.4% at 90% specificity, and above 95% through 92.5% specificity, but fell sharply as the specificity target increased, dropping to 81.5% at 95% and 59.8% at 97.5% specificity.

Sensitivity Across Specificity Thresholds

Specificity	Sensitivity
90.0%	98.4%
91.5%	97.6%
92.5%	95.3%
95.0%	81.5%
97.5%	59.8%

Conclusions

- A deep learning model detected AF from PPG alone with performance approaching the ECG gold standard (ROC-AUC 0.971).
- Because PPG is ubiquitous in sleep testing, AF detection can be embedded into existing workflows at scale with no additional hardware.
- When operated as a screen with downstream ECG confirmation, the model’s high sensitivity is well suited to first-pass detection that minimizes missed AF.
- Given that AFib is a prevalent and underdiagnosed comorbidity in OSA, routine sleep studies represent a high-volume, underutilized opportunity for scalable screening.

References

- Mehra R, et al. Sleep Disordered Breathing and Cardiac Arrhythmias in Adults: Mechanistic Insights and Clinical Implications: A Scientific Statement From the American Heart Association. Circulation. 2022;146(9):e119-e136.
- Pillar G, et al. Detection of Common Arrhythmias by the Watch-PAT: Expression of Electrical Arrhythmias by Pulse Recording. Nat Sci Sleep. 2022;14:751-763.