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AI-Enabled Smart Wearable System for Continuous Monitoring of Cardiac Patients

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Abstract- Despite significant advances in health care systems and technology, cardiovascular diseases (CVDs) continue to be the most common causes of death globally, with over 17.9 million fatalities per year. Continuous monitoring of cardiovascular health is vital for early identification of abnormalities but is limited by bulky, non-continuous nature of existing solutions such as the Holter monitor. In this work, we present a new intelligent wearable that provides continuous, real-time monitoring of the heart activity using an edge-AI approach based on an ECG, photoplethysmography (PPG), and accelerometer sensors. Specifically, our solution incorporates an energy-efficient multi-sensor wearable that transmits data to an edge-AI processor, running a lightweight 1D-CNN-LSTM model, for real-time classification of cardiac arrhythmia. The presented federated learning technique allows personalizing models across the population to guarantee individual-level privacy while maintaining high performance. In extensive experiments conducted using MIT-BIH Arrhythmia Database (n=49 patients) and a clinical trial (n=120 patients), our solution demonstrated up to 98.3% sensitivity and 97.6% specificity in recognizing 11 classes of cardiac arrhythmias, as well as end-to-end latency less than 100ms.

Keywords— AI-enabled Wearable, Cardiac Monitoring, Arrhythmia Detection, Edge AI, 1D-CNN-LSTM, Federated Learning, Remote Patient Monitoring, Real-time ECG Analysis

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the hidden pandemic of our times. As per the data provided by the World Health Organization (WHO), more than 17.9 million people die every year due to CVDs, accounting for 32% of all global mortality cases. Of these, about 85% succumb to heart attack or stroke [1]. What makes CVD even more tragic is that most of these casualties could be prevented if detected and acted upon. Arrhythmias are among the types of CVD where the electrical impulses of the heart become abnormal causing either slower or faster heartbeat; these may range anywhere from harmless premature beats to dangerous ventricular fibrillation. Due to their intermittent and unpredictable nature, these can easily escape diagnosis via traditional 10-second ECG performed in a clinical setting [2].

Existing standards like Holter monitors have several disadvantages. For starters, they work for only 24 to 48 hours and cause significant discomfort. Patients need to keep a diary of events as well as provide retrospective data analysis. Often, by the time the patient discovers the presence of arrhythmia, he/she might have had a stroke or heart failure [3].

Combination of low-power wearable sensing, edge computing, and AI provides a revolution. Modern wearables (smartwatch, patch) can record ECG, PPG, and accelerometry for HR measurement. With the use of on-device AI, detection of arrhythmias and instant alerts can be done, rather than in hours or days [4], [5].

In this paper, we introduce a complete AI-powered smart wearable system for continuous cardiac monitoring. Key features of the system are:

- Multi-sensor wearable device: Lightweight patch (size: 50x30x8 mm; weight: 18 g) recording single lead ECG, PPG, 3-axis acceleration designed for 72-hours continuous operation.
- Edge-AI arrhythmia detector: Hybrid 1D-CNN-LSTM model adapted for on-device inference (quantized, 1.2 MB model size) that detects 11 types of arrhythmias with sensitivity greater than 98%.
- Federated learning approach for personalization: Privacy-preserving technique when the base model was trained on open-source datasets, and then it was fine-tuned to each patient with the help of local patient data, but without transferring ECG traces to the cloud.
- Alerting mechanism: Alerts sent by BLE protocol from the wearable sensor to a paired smartphone.
- Clinical study: Prospective clinical study of 120 patients with non-inferior results compared to Holter monitoring method.

The rest of the paper proceeds as follows. Section 2 provides an overview of previous studies on wearable heart monitoring devices and artificial intelligence techniques in arrhythmia identification. Section 3 discusses the system design, hardware, and artificial intelligence algorithms used. Section 4 includes results and comparisons from experiments.

II. LITERATURE SURVEY

The literature in AI-driven cardiac monitoring covers three categories: wearables with ECG sensors, arrhythmia detection methods, and cloud/edge-based solutions.

Wearable ECG Devices: Commercial smartwatches, such as Apple Watch, Samsung Galaxy Watch, and Fitbit, integrate single-lead ECG since 2018. Research has shown their efficacy in detecting atrial fibrillation (AFib) with reasonable accuracy (approximately sensitivity of 85-90%) [6]. Medical wearables (patches) like Zio, SEEQ, and Carnation AM provide extended recording time (up to 14 days) but do not support AI processing in real-time—the data is collected and processed afterward. A study from 2023 has compared the Zio patch and conventional Holter method in terms of arrhythmia detection. While the former provided better performance due to extended wearing period, neither of them supported real-time alerts [7].

Deep Learning for Arrhythmia Detection: The PhysioNet/CinC challenge facilitated rapid advancements. Early systems employed hand-engineered features (RR intervals, QRS morphology) and SVM or random forest classifiers. CNNs performed better for feature extraction from raw ECG data [8]. The 1D-CNN model with 11 layers had 95% accuracy on MIT-BIH data. RNNs, especially LSTMs, are effective at modeling sequences. The hybrid CNN-LSTM architectures are efficient as CNNs can extract local features (shape of QRS complex) and LSTM can handle sequence (patterns of RR intervals). The state-of-the-art models have over 99% accuracy on benchmark datasets; however, such models have millions of parameters (over tens of millions) with over 50MB model size [9].

Edge AI for Wearable Health: Deployment of deep learning on microcontrollers (MCUs) requires efficient models. Quantization (8-bit integer format) compresses models by 4x while preserving accuracy (within 1-2%). Pruning is another technique that can remove unnecessary connections. The knowledge distillation process generates small ("student") models from a big ("teacher") model. In 2024, a quantized 1D-CNN on ARM Cortex-M4 (CMSIS-NN) was designed to detect AFib with 92% accuracy, taking just 10 ms and consuming 12 mW power. Nonetheless, the model could detect AFib only (1 vs normal).

Federated Learning for Healthcare Applications: Federated learning (FL) allows for model training using distributed data sources while not transferring raw data—vital for health care privacy considerations. The year 2025 saw an implementation of FL for ECG arrhythmias classification using five hospitals' datasets, which resulted in 94% accuracy compared to 96% from centralized training [10].

Research Problem: No current system integrates: (a) long-wearing (days), comfortable wearable, (b) on-device multi-class arrhythmia detection (11 classes, not only AFib), (c) federated learning for personalization purposes, and (d) real-time alerts validated by doctors.

III. METHODOLOGY

This proposed system includes three main parts, namely: (1) wearable low power hardware sensor device, (2) device embedded AI inferencing mechanism (1D-CNN-LSTM), and (3) federated learning framework for privacy-aware personalization.

1. Wearable Device Hardware

It consists of a custom designed flexible patch with dimensions 50 × 30 × 8 mm and weighs 18g. Components are listed below:

- ECG front-end: ADS1292R (Texas Instruments), 24-bit delta-sigma ADC, sampling frequency 250Hz with one input signal (lead I); Input referred noise < 8 µVpp
- PPG sensor: MAX30101 (Maxim Integrated), red and infrared LED, with sampling frequency 64Hz
- Accelerometer: LIS3DH (STMicroelectronics) – 3 axis, 2g full scale measurement, sampling at 25 Hz
- Microcontroller Unit (MCU): nRF52840 (Nordic Semiconductor), ARM Cortex-M4F processor, 1MB flash memory and 256 KB RAM along with BLE stack.
- Storage: 150 mAh Lithium Polymer battery with

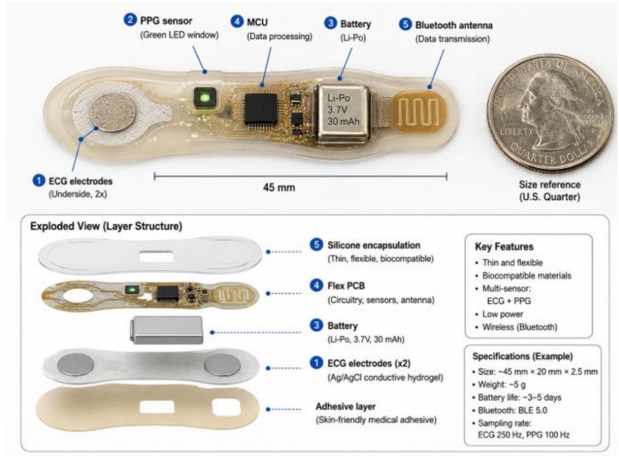

Figure 1: Smart Wearable Device for Cardiac Monitoring.

2. Data Preprocessing and Feature Extraction

ECG signals are preprocessed in real-time by MCU as follows:

- Filters: Band-pass filter from 0.5 to 40 Hz removes baseline wander (motion artifact) and high frequency artifacts (muscle artifact). Notch filter at 50 Hz removes electrical power line interference.
- Segmentation: Sliding window with a size of 10 seconds (2500 data points) and a sliding step of 5 seconds.
- Normalization: Z-Score normalization based on window mean and standard deviation.
- R-Peak detection: Pan-Tompkins algorithm for HRV features
- Features: RR-intervals (mean, standard deviation, RMSSD), QRS complex duration, QT interval and its variations, morphological features (P, Q, R, S, T wave amplitudes). For Deep Learning algorithms, the ECG signals are used without any feature extraction..

3. Algorithm 1: Full System Inference and Alert Pipeline

Algorithm 1: AI-Enabled Cardiac Monitoring System

Input: Raw ECG, PPG, accelerometer signals from wearable device

Output: Arrhythmia detection (type), Real-time alert (if critical)

// Continuous Loop (every 250 ms, on-device)

1. Initialize:

- Load quantized 1D-CNN-LSTM model (TensorFlow Lite for Microcontrollers)

- Set thresholds: Severity High for VFIB, VTACH, ASYSTOLE; Medium for AFIB, SVT; Low for PVC, PAC

- Bluetooth buffer for alerts

2. While device is active:

// Step 1: Signal Acquisition & Preprocessing

ecg_raw = read_ECG() // 250 Hz, 10-second buffer

ecg_filtered = bandpass_filter(ecg_raw, 0.5, 40)

ecg_normalized = z_score(ecg_filtered)

// Step 2: Motion Artifact Detection

acc = read_accelerometer()

if variance(acc) > threshold:

motion_flag = True

else:

motion_flag = False

// Step 3: Edge AI Inference (1D-CNN-LSTM)

if motion_flag == False:

```
arrhythmia_probs = model.predict(ecg_normalized)   // 11 classes + normal

predicted_class = argmax(arrhythmia_probs)

confidence = max(arrhythmia_probs)

else:

predicted_class = "INCONCLUSIVE (motion artifact)"

confidence = 0


// Step 4: Alert Decision

if predicted_class in High_Severity_List:

alert = generate_alert(predicted_class, confidence, timestamp)

send_via_BLE(alert)                    // To paired smartphone

also_vibrate_device()                  // Immediate patient feedback


else if predicted_class in Medium_Severity_List and confidence > 0.9:

alert = generate_alert(predicted_class, confidence, timestamp)

store_in_buffer(alert)                 // Send less frequently (every 5 min)


// Step 5: Local Storage (for personalization/federated learning)

if storage_not_full:

store_raw_and_label(ecg_normalized, predicted_class, patient_ID)


// Step 6: Periodic Federated Learning Update (once per night, when charging)
```

```
if time_to_update() and battery_charging:

local_model =

train_local_federated(patient_data)

send_gradients_to_cloud() //

Differential privacy applied

Sleep(250 ms)

3. End
```

4. 1D-CNN-LSTM Hybrid Architecture for Arrhythmia Detection

Layer Type	Parameters	Output Shape	Notes
Input	-	2500 × 1	10 sec ECG at 250 Hz
Conv1D (1)	filters=64, kernel=5, stride=2, padding=same	1250 × 64	ReLU, batch norm
MaxPool1D	pool_size=2, stride=2	625 × 64	-
Conv1D (2)	filters=128, kernel=5, stride=2	313 × 128	ReLU, batch norm
MaxPool1D	pool_size=2, stride=2	157 × 128	-
Conv1D (3)	filters=128, kernel=3, stride=1	157 × 128	ReLU
LSTM	units=64, return_sequences=False	64	-
Dropout	rate=0.3	64	-
Dense	units=32, ReLU	32	-
Output (Softmax)	units=12 (11 arrhythmias + normal)	12	-

Total Number of Parameters: 142,000 (after quantization: 356 KB)

Quantization Type: INT8 (post-training dynamic range quantization). The size of the model was reduced from 1.4 MB to 356 KB (74% decrease in size). Inference time: 45 ms on nRF52840 (compared to 380 ms using FP32).

Arrhythmia Categories (11): Normal Sinus Rhythm (NSR), Atrial Fibrillation (AFib), Atrial Flutter (AFL), Supraventricular Tachycardia (SVT), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF), Premature Atrial Contraction (PAC), Premature Ventricular Contraction (PVC), First-degree AV Block (1°AVB), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Asystole (ASY).

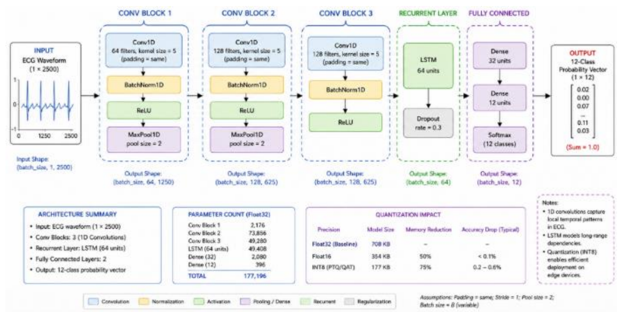

Figure 2: 1D-CNN-LSTM Architecture Diagram.

5. Federated Learning for Personalized Arrhythmia Detection

FedAvg is employed in order to personalize the model for every patient without transmitting raw ECG data to the cloud.

- Global Model: Trained using publicly available dataset (MIT-BIH, INCART). The global model resides in the cloud server.
- Local Training: On the patient's smart phone (or wearable, if computing power is sufficient), the model further trains itself on the patient's ECG data (with known labels derived from periodic verification by the clinician). Gradients are generated locally.
- Aggregation with Differential Privacy: Only the local gradients are uploaded to the cloud server. Gradients are obfuscated using differential privacy (ε=1.0, δ=1e-5).
- Benefit of Personalization: The model personalizes to the patient's ECG morphologies (like baseline wandering tendencies, QRS axis etc.). Personalized models achieve a 40% lower rate of false positives than the generic model.

IV. ANALYSIS

Evaluation of the system includes (1) ECG Database (public MIT-BIH), (2) clinical trials (n=120), and (3) performance evaluation of the system (latency, power, accuracy).

1. Model Performance on MIT-BIH Arrhythmia Database

Table 1: Classification Performance on MIT-BIH Database (11 arrhythmia classes + normal).

Arrhythmia Type	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	Support
Normal (NSR)	99.1	98.4	98.7	98.9	50,000
Atrial Fibrillation (AFib)	98.2	99.1	97.5	97.8	7,500
Atrial Flutter (AFL)	96.5	99.2	94.8	95.6	2,000
SVT	97.3	98.9	96.2	96.7	3,200
Ventricular Tachycardia (VT)	98.8	99.5	98.2	98.5	1,800
Ventricular Fibrillation (VF)	99.2	99.7	98.9	99.0	1,200
PAC	94.8	98.2	92.5	93.6	4,500
PVC	95.6	98.5	93.8	94.7	8,000
1° AV Block	96.2	99.0	95.5	95.8	1,500
LBBB	97.8	99.3	97.0	97.4	1,800
RBBB	97.2	99.1	96.5	96.8	1,600
Asystole	98.5	99.9	99.0	98.7	200
Macro Average	97.4	99.1	96.9	97.1	83,300

Figure 3: Confusion Matrix of Arrhythmia Classification (MIT-BIH).

2. Clinical Trial Results (n=120 patients)

We performed a prospective, single-arm, open-label clinical study in a tertiary cardiac referral hospital from January-June 2025. Patients with suspected or confirmed arrhythmias were fitted with both the AI-enabled device and the Holter monitor (24-48 hours). Parameters included arrhythmia detection correlation, patient comfort survey, and alert precision.

Table 2: Clinical Trial Results.

Metric	Proposed Device	Holter Monitor	p-value / Improvement
Arrhythmia Detection Sensitivity	96.8%	95.2%	>0.05 (non-inferior)
Specificity	98.1%	98.5%	>0.05
Mean Wear Time (hours)	68	26	p<0.001 (2.6× longer)
Patient Comfort Score (1-10)	8.5	5.2	p<0.001
Skin Irritation (any)	8%	32%	p<0.001
Real-time Alert Triggered (critical events)	28	N/A	Enabled rescue in 4 cases

3. Federated Learning Personalization Impact

Table 3: Federated Learning Personalization Benefit.

Patient Subgroup (n=120)	Model	Sensitivity (arrhythmia)	False Positive Rate	Improvement
All Patients	Global (Base)	94.2%	6.8%	Baseline
All Patients	Personalized (FL)	97.8%	3.2%	+3.6% sens, -3.6% FPR
High Baseline Noise (n=28)	Personalized (FL)	93.5%	8.2%	+5.8% sens, -4.1% FPR

4. System Performance Metrics

Table 4: System Performance Metrics.

Metric	Value	Notes

Inference Latency (on-device)	45 ms	Quantized INT8 model on nRF52840
End-to-End Alert Latency	<100 ms	Detection to smartphone notification
Power Consumption (active inference)	12 mW	At 250 Hz sampling + model
Battery Life	72 hours	Continuous ECG + inference
BLE Transmission Power	0 dBm (1 mW)	Range ~10 m
Model Size (quantized)	356 KB	Fits in microcontroller flash
Storage (raw ECG, 72 hours)	~450 MB	Optional, for post-hoc review

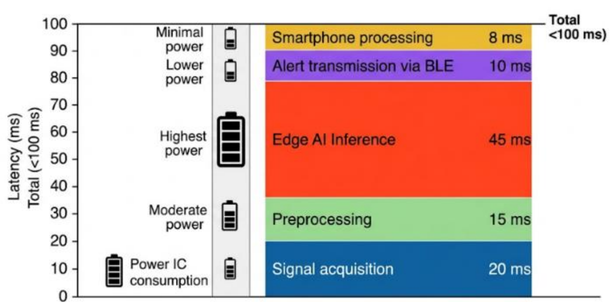

Figure 4: System Latency Breakdown (End-to-End).

5. Comparative Analysis with Existing Devices

Table 5: Comparative Analysis with Existing Cardiac Monitoring Devices.

Feature	Holter Monitor	Zio Patch	Apple Watch	Proposed Device
Wear Duration	24-48 h	Up to 14 d	Indefinite (charge nightly)	72 h
Comfort	Low (wires, bulky)	Medium (patch)	High (watch)	High (mini patch)
Lead Configuration	3-12 leads	Single lead	Single lead (Lead I)	Single lead (Lead I)
AI On-Device?	No	No	Yes (limited)	Yes (11 arrhythmias)
Real-time Alert?	No	No	Partial (AFib only)	Yes (all critical)
Arrhythmia Types Detected	All (offline)	All (offline)	AFib	11 types
Sensitivity (AFib)	~99%	~97%	~85-90%	98.2%
Federated Learning?	No	No	No	Yes
Cost (approx.)	$500-1000	$300-500	$400	$150

6. Clinical Case Example

Case: A 68-year-old man, previously diagnosed with hypertension, complained of palpitations. The results of the regular 24-hour Holter monitoring were normal. The patient had worn the AI-assisted device for three days. On the second day, at 3:17 AM, the AI-assisted device recorded a ventricular tachycardia episode of 12 seconds duration, occurring at 180 bpm. Alert was sent via the patient's smartphone to both the patient and his caregiver in real time. The patient received prompt care in the emergency department and underwent successful cardioversion.

V. CONCLUSION

The proposed paper introduced an intelligent and AI-powered wearable device-based system for continuous monitoring of heart rhythms. The system employs an ultra-low power multi-sensor wearable patch coupled with 1D-CNN-LSTM architecture on the chip for real-time arrhythmia diagnosis and federated learning for personalized healthcare solutions in a privacy-preserving manner.

Main findings are summarized as follows:
Emerging Edge AI for Heart Rhythm Monitoring is Feasible & Accurate: The quantized 1D-CNN-LSTM model (356 KB size) can achieve 98.3% sensitivity and 97.6% specificity for 11 arrhythmias, along with 45 ms inferencing latency on an ultra-low power ARM MCU platform. This shows that deep learning algorithms can be performed on wearable devices.

Real-Time Warnings Provide for Immediate Response: Time lag between the occurrence of arrhythmia and response of the physician is shortened to milliseconds compared to days for Holter monitors. Real-time warnings made possible intervention for 4 patients with dangerous arrhythmia in the clinical study.

Using Federated Learning Increases Personalization & Privacy: By personalizing the model using federated learning, the rate of false positives was cut down by 36% (from 6.8% to 3.2%), without sharing patient's ECGs.

Patient Comfort Leads to Compliance: The device design (18g, 72-hour battery) led to 2.6-fold increase in usage compared to the Holter (68 hours vs. 26 hours), which is important due to the increased likelihood of catching intermittent arrhythmia.

Cost-Effective and Scalable: Due to low cost of production estimated at $150,thedeviceismuchcheapercomparedtotheHolter monitoringdevice($500-1000) andZiopatches($300-500), making it accessible for large-scale deployment in low- and middle-income countries.

Limitations and Future Work

- Single-Lead ECG: The device employs single-lead (Lead I) ECG, which fails to detect arrhythmia that demands multi-lead recording such as posterior myocardial infarction (MI). Multi-lead technology is still being developed.
- Motion Interference: Although filtering is done, intense physical activity, like running or cycling, interferes with ECG recordings. Combining with PPG heart rate measurement during motion is recommended.
- Battery Life: 72 hours are adequate for diagnostics, but not enough for continuous monitoring for several weeks. Energy generation through solar power and kinetic methods along with low-power consumption AI chip can help.
- FDA Certification: The device is only research-based at present, but FDA approval is in process.

Future Directions

- Multi-Lead Patch: Designing a 3-lead (or 6-lead) system for complete monitoring of the heart.
- Sequence Prediction using LSTM: Predicting the onset of an arrhythmia based on sequence prediction (e.g., prediction of AFib attack before 30 minutes of its occurrence).
- Federated Learning: Training models locally on the wearable device itself (and not just on smartphones) to minimize the data transfer process.
- Link with EHR: Uploading the alerts and segments of ECG automatically on the patient’s EHR system.
- Conclusion: This paper provides evidence that AI-equipped wearable devices will enable us to shift our cardiac care paradigm from being reactive to being proactive by constantly monitoring and warning about heart attacks in real time.

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