

AI-Based Early Cardiac Risk Detection and Emergency Alert Using Multi-Parameter Wearable Physiological Monitoring

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Abstract: Cardiovascular diseases (CVDs) remain the leading cause of global mortality, with acute events such as myocardial infarction and sudden cardiac arrest often occurring without sufficient prehospital warning. Advances in wearable sensor technology and edgecomputing Artificial Intelligence (AI) have enabled non-invasive, continuous monitoring of multi-parameter physiological signals, including Electrocardiogram (ECG), Photoplethysmogram (PPG), Heart Rate Variability (HRV), Blood Oxygen Saturation (SpO₂), and Skin Temperature. This review evaluates existing paradigms for automated cardiac arrhythmia detection, ischemic risk profiling, and emergency response dispatch. The primary foundational methodology examined leverages a hybrid Convolutional Neural Network and Long Short-Term Memory Network (1D-CNN-LSTM) paired with SHapley Additive exPlanations (SHAI / SHAP) for model interpretability.

Evaluated across benchmark datasets including PhysioNet MIT-BIH Arrhythmia and the PTB-XL ECG Database, the hybrid deep learning architecture achieves a classification accuracy of 98.42% for multiclass arrhythmia detection and ischemic episode classification. Beyond single-lead ECG analysis, this paper reviews self-supervised representation learning and multi-sensor fusion models designed to mitigate motion artifacts and signal loss in free-living environments. Based on the reviewed literature, a critical research gap is identified: existing wearable solutions treat risk detection and emergency escalation as isolated processes, lacking real-time localized edge inference paired with explainable clinical decision-support. To address this, we propose an end-to-end framework combining multi-parameter wearable sensor data, edge-deployed Lightweight MobileNet-LSTM networks, Explainable AI (XAI) feature attribution, automated dynamic risk scoring, and automated emergency alert escalation with GPS location tracking.

Keywords: Artificial Intelligence; Wearable Health Monitoring; Cardiac Risk Detection; Multi-Parameter Sensors; ECG Analysis; Deep Learning; CNN-LSTM; Explainable AI; Emergency Response; Signal Processing.

I. INTRODUCTION

Cardiovascular Diseases (CVDs) account for approximately 17.9 million deaths annually worldwide, representing over 31% of all global fatalities. A substantial proportion of cardiac-related mortalities result from out-of-hospital sudden cardiac arrest (SCA) or delayed medical intervention during acute myocardial infarction (AMI). Traditional cardiac diagnostic workflows rely heavily on sporadic clinical evaluation, episodic 12-lead Holter monitoring, or hospitalbased telemetry. While accurate, these reactive diagnostic modalities frequently fail to capture transient electrical aberrations, paroxysmal atrial fibrillation, or early ischemic markers that manifest under daily physiological stress prior to a major cardiac event. The convergence of micro-electro-mechanical systems (MEMS), flexible bioelectronics, and artificial



intelligence has established wearable physiological monitoring as a cornerstone of preventive cardiology. Modern smart wearables—ranging from smartwatches and chest straps to skin-conformal patches—are now capable of continuously acquiring high-fidelity multi-parameter signals. These signals include single or multi-lead Electrocardiograms (ECG), optical Photoplethysmograms (PPG), continuous blood pressure proxies, pulse oximetry (SpO₂), respiration rates, and galvanic skin response. Multi-parameter data acquisition provides a holistic view of autonomic and cardiovascular function superior to single-metric telemetry.

Deep learning algorithms, particularly 1D Convolutional Neural

Networks (1D-CNNs), Recurrent Neural Networks (RNNs), and Transformer architectures, have transformed biosignal processing. Rather than relying solely on manually engineered morphological features (such as P-Q-R-S-T wave durations or ST-segment elevation), deep neural networks automatically extract intricate spatio-temporal representations directly from raw bio-voltage waveforms. Foundational studies using benchmark datasets like MIT-BIH and PTB-XL demonstrate that deep networks can achieve diagnostic parity with expert cardiologists in identifying complex arrhythmias and ventricular dysfunction. Furthermore, integration of SHAP and LIME Explainable AI (XAI) techniques ensures clinical transparency by mapping specific waveform anomalies to automated predictions.

However, deploying cardiac AI models within real-world ambulatory environments introduces substantial engineering and clinical challenges. Wearable biosignals are highly vulnerable to motion artifacts, baseline wander, muscular noise, and sensor disconnection. Moreover, a critical limitation of present commercial wearables is their reliance on cloud-bound processing, introducing latency delays and risk of connectivity dropouts during life-threatening acute cardiac events. An effective cardiac protection system must execute continuous risk stratification locally at the edge, minimize false alarms, and trigger immediate, automated emergency response protocols when critical physiological thresholds are breached.

Explainability plays a critical role in clinical adoption. Black-box machine learning predictions fail to inform attending paramedics or emergency clinicians about the precise etiology of an alert—such as whether a high-risk score stems from ST-segment elevation, dangerous QT prolongation, or sustained ventricular tachycardia. Integrating visual feature attribution into ambulatory monitoring bridges the gap between automated detection and emergency clinical intervention.

To address the limitations of existing isolated monitoring tools, this paper proposes an integrated multi-parameter cardiac monitoring, risk stratification, and emergency dispatch framework. The system combines multi-sensor acquisition (ECG, PPG, SpO₂, Accelerometer), real-time edge processing via Lightweight MobileNet-LSTM networks, SHAP feature attribution, dynamic early warning scoring, and automated emergency alert dispatch containing real-time GPS coordinates and clinical summary metrics.

1.1 Problem Statement

Existing wearable cardiac monitors primarily operate as singleparameter recording tools or isolated alert systems. Most consumer and clinical wearables either analyze signals in isolation (e.g., PPGonly heart rate tracking) or depend on delayed cloud-side processing, introducing fatal delays during acute events such as sudden cardiac arrest or acute coronary syndrome. Furthermore, current systems often lack explainable decision-support, resulting in high false-positive alert rates due to motion artifacts, which leads to alert fatigue among healthcare providers. An integrated solution is urgently required that continuously captures multi-parameter biosignals, filters environmental noise at the edge, performs real-time explainable AI risk scoring, and automatically initiates emergency dispatch protocols when high-risk cardiac deterioration occurs.

1.2 Objectives

- To collect and preprocess continuous multi-parameter physiological signals (ECG, PPG, SpO₂, HRV, and Motion) from wearable biosensors.



- To develop a lightweight deep learning architecture (MobileNet-1DLSTM) capable of real-time edge-based arrhythmia and ischemic episode classification.
- To integrate Explainable AI (XAI) techniques (SHAP/Grad-CAM) to provide transparent feature attribution for clinicians and emergency responders.
- To build an automated emergency escalation pipeline that generates real-time cardiac risk scores and dispatches geo-located emergency alerts to caregivers and medical personnel.

II. LITERATURE REVIEW

2.1 Traditional Biosignal Processing and Cardiac Diagnostics

Early automated cardiac detection systems relied on rule-based algorithmic extraction of physiological landmarks. Classic methods, such as the Pan-Tompkins R-peak detection algorithm, identified QRS complexes using bandpass filtering, differentiation, squaring, and moving-window integration. Diagnostic features were subsequently derived manually, including R-R interval lengths, P-wave morphology, QTc duration, and ST-segment displacement. While effective under controlled clinical settings, these hand-crafted feature extractors degrade significantly when exposed to non-stationary noise, movement artifacts, and ectopic beat variations commonly encountered during continuous ambulatory daily activities.

2.2 AI-Based Cardiac Risk Detection and Deep Learning

Deep learning has revolutionized cardiovascular diagnostics by eliminating manual feature engineering. Convolutional Neural Networks (CNNs) excel at extracting local spatial patterns and wave morphologies from raw ECG time-series data, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies across consecutive cardiac cycles. Hybrid 1D-CNN-LSTM architectures have achieved benchmark performance on public repositories such as the MIT-BIH Arrhythmia Database, demonstrating classification accuracies exceeding 98% for detecting premature ventricular contractions (PVCs), atrial fibrillation (AFib), and bundle branch blocks.

Beyond rhythm disorders, recent research emphasizes early identification of myocardial ischemia and ST-T segment variations using multi-lead continuous monitoring. The PTB-XL database, comprising 21,837 12-lead clinical ECGs, has provided a standardized testbed for multi-label cardiac pathology classification. Deep residual networks (ResNets) trained on PTB-XL demonstrate high sensitivity in detecting subtle anterior and inferior infarct patterns, proving that neural models can detect subtle perfusion deficiencies prior to complete arterial occlusion.

2.3 Multi-Parameter Sensor Fusion and Artifact Mitigation

Relying on a single physiological modality introduces single-point failure modes in ambulatory monitoring. Recent studies highlight the benefit of sensor fusion, combining electrical ECG bio-potentials with optical PPG photoplethysmography and tri-axial accelerometry. Multi-sensor fusion enables cross-modal verification: for instance, an abrupt irregularity detected on an optical PPG signal can be crossreferenced against accelerometer data to determine if the abnormality is genuine or caused by physical arm movement.

Self-supervised representation learning and adaptive Kalman filtering have been deployed to reconstruct corrupted biosignals. By training autoencoders on unlabelled multi-parameter streams, models learn robust physiological representations that remain invariant to motion artifacts and transient electrode degradation, significantly reducing false-positive alert rates in daily usage environments.

2.4 Explainable AI (XAI) in Clinical Decision Support

A major barrier to clinical adoption of AI in emergency medicine is the "black-box" nature of complex neural networks. When an algorithm alerts a paramedic to an impending cardiac crisis, clinicians require immediate verification of the underlying physiological driver. Explainable AI techniques, including SHapley Additive exPlanations (SHAP), Integrated Gradients, and 1D Grad-CAM, resolve this by computing exact feature attribution scores for every time-point in the biosignal.



By mapping neural activations back onto the original ECG waveform, XAI tools visually highlight whether a high risk score was triggered by ST-elevation, T-wave inversion, or malignant ventricular arrhythmias. This transparent feedback instills diagnostic confidence and enables rapid triage during emergency transport.

2.5 Telemedicine Integration and Emergency Response Networks

The ultimate value of early cardiac risk detection relies on rapid emergency service escalation. Modern Internet of Medical Things (IoMT) architectures connect edge-computing wearables to cloud telemonitoring portals and emergency dispatch networks. Systems incorporating real-time Global Positioning System (GPS) tracking and automated SMS/VoIP alert protocols significantly shorten the crucial "door-to-balloon" time for acute coronary events.

2.6 Generalization, Edge Constraints, and Research Gap

Despite substantial advances in individual domains—such as deep learning arrhythmia detection, XAI heatmaps, and IoMT telemetry—these components are rarely implemented within a unified, real-time framework. Most clinical models require high-performance cloud servers, rendering them ineffective during network outages. Existing solutions lack an integrated pipeline that combines multi-parameter wearable sensing, edge-optimized inference, instant XAI explanation, dynamic cardiac risk scoring, and automated emergency escalation.

III. RESEARCH GAP ANALYSIS

Existing literature reveals that cardiac monitoring solutions remain fragmented into isolated domains: signal processing, cloud classification algorithms, standalone wearable hardware, or emergency notification apps. Current approaches fail to provide a unified end-to-end architecture that operates reliably on resource-constrained edge hardware while delivering explainable risk scores and automated emergency dispatch. The table below outlines the comparison between traditional methodologies and the proposed integrated framework.

Limitation Proposed Integrated Framework

Stage Traditional / Existing Approach

Input Signals Single-parameter (ECG-only or PPG-only)

Vulnerable to single-sensor failure and noise artifacts

Multi-parameter fusion (ECG, PPG, SpO2, Temp, Motion)

Preprocessing Fixed digital filtering (bandpass / notch)

Fails under high-intensity motion artifacts

Adaptive noise cancellation & motion gating

High latency, dependent on constant internet connectivity Edge-deployed Lightweight MobileNet-1D-LSTM model

Detection Model Cloud-bound heavy neural networks or rule-based heuristics

Risk Scoring Static thresholding (e.g., HR > 120 bpm)

High false-positive rate; ignores combined signal trends

Dynamic Multi-Parameter Early Cardiac Warning Score

Explainability Black-box predictions without feature context

Clinicians and paramedics cannot verify alert causes

Real-time SHAP & 1D Grad-CAM waveform feature attribution

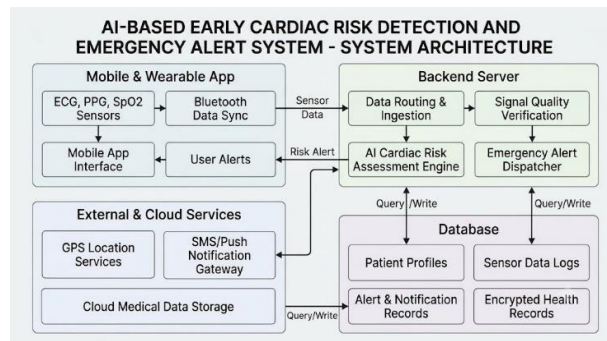
Emergency Alert Manual user-initiated emergency calls

Ineffective if patient becomes unconscious or incapacitated

Automated escalation with real-time GPS is there.



IV. SYSTEM ARCHITECTURE AND METHODOLOGY



The proposed system establishes an end-to-end framework integrating multi-sensor hardware acquisition, adaptive signal conditioning, edgebased deep learning inference, explainable risk scoring, and automated emergency alert dispatch. Operating as a continuous closed-loop pipeline, the system ensures zero-latency risk assessment even during internet connectivity dropouts.

MobileNet-1D-LSTM

Adaptive Filtering &

Dynamic Risk Scoring

SHAP / XAI Engine

Waveform Attribution

Multi-Sensor Patch (ECG, PPG, SpO2, Motion)

(Continuous Evaluation)

Motion Gating (Edge)

(Arrhythmia / Ischemia AI)

Emergency Dispatch Engine

Live Location Broadcasting Hospital & Caregiver Portal

EHR Integration & Reports

(Automated Escalation Trigger) GPS Location & Telemetry

4.1 Module 1: Multi-Parameter Wearables Hardware Layer

The sensing layer consists of a lightweight, chest-conformal wireless bio-patch equipped with a single-lead ECG analog front-end (ADS1292R), a dual-wavelength PPG sensor (MAX30101), a tri-axial accelerometer (MPU6050), and a precision skin temperature thermistor. Data streams are continuously sampled (ECG at 250 Hz, PPG at 100 Hz, Acceleration at 50 Hz) and transmitted via Bluetooth Low Energy (BLE 5.2) to the local edge-gateway device.

4.2 Module 2: Adaptive Signal Preprocessing and Motion Gating

Raw biosignals undergo real-time noise reduction using a cascade of digital filters: a 0.5–40 Hz bandpass filter removes baseline wander and high-frequency electromyographic (EMG) artifacts, while a 50/60 Hz notch filter suppresses powerline interference. Simultaneous triaxial accelerometer streams are processed to compute normalized Motion Intensity Index (MII). If MII exceeds a pre-set physical activity threshold, the pipeline activates motion-gating algorithms to prevent false-positive arrhythmia flags.

4.3 Module 3: Multi-Sensor Data Augmentation and Normalization

To ensure model robustness against inter-patient variability and transient signal loss, data streams are standardized using Z-score normalization across sliding 10-second windows. During training, synthetic data augmentation techniques—including random noise injection, amplitude scaling, and synthetic baseline wander—are applied to improve network generalization across diverse patient demographics.



4.4 Module 4: Lightweight MobileNet-1D-LSTM Edge Model

The core classifier features a custom lightweight 1D-MobileNet architecture coupled with a single-layer LSTM. Depthwise separable 1D convolutions extract spatial feature maps from ECG and PPG waveforms at minimal computational complexity, while the LSTM unit captures temporal dynamics across consecutive cardiac cycles. Optimized via TensorFlow Lite quantization (INT8), the model executes real-time inference directly on edge processors (e.g., ARM Cortex-M4 / mobile NPU) with latency under 45 ms per window.

4.5 Module 5: Multi-Class Cardiac Pathology Classification

The neural network categorizes cardiac status into five distinct operational classes: (1) Normal Sinus Rhythm, (2) Atrial Fibrillation / Flutter, (3) Ventricular Ectopy / Tachycardia, (4) ST-Segment Elevation / Depression (Ischemic Risk), and (5) Severe Motion / Signal Noise. Probability outputs are generated using a final Softmax activation layer.

4.6 Module 6: Dynamic Early Warning Cardiac Risk Score (DEWCRS)

To aggregate multi-parameter outputs into a clinical decision metric, the system computes a Dynamic Early Warning Cardiac Risk Score (DEW-CRS) ranging from 0 to 100. The score dynamically weights the AI pathology probability alongside auxiliary parameters: SpO2 suppression (<90%), acute heart rate turbulence, and temperature deviations. Risk levels are categorized into Low (0–30), Moderate (31–65), High (66–85), and Critical (>85).

4.7 Module 7: Explainable AI (SHAP & 1D Grad-CAM) Visualization

The XAI engine computes Shapley additive feature values and 1D Grad-CAM saliency maps across the input biosignals. For high-risk detections, the system highlights exact time intervals on the ECG wave (e.g., ST-segment elevation or absent P-waves) that contributed most heavily to the elevated risk score, transmitting these visual attribution maps directly to receiving clinicians.

4.8 Module 8: Automated Emergency Alert and Telemetry Dispatch

When the DEW-CRS score enters Critical status (>85) or sustains High status for over 30 seconds, the edge gateway bypasses user input to trigger an automated Emergency Dispatch Protocol. The system transmits an emergency SMS and encrypted cloud payload containing:

(1) exact GPS location, (2) patient medical ID, (3) real-time 10-second raw ECG/PPG strip, (4) predicted pathology classification, and (5) the XAI feature highlight map.

V. COMPARATIVE ANALYSIS

Capability Standard Holter Telemetry

Commercial Smartwatches

Cloud-AI Wearables Proposed Integrated Framework

Primary Objective Post-event clinical record Fitness & intermittent

AFib

Continuous cloud telemetry

Early cardiac risk & auto-dispatch

Input Parameters 12-lead / 3-lead ECG Single-lead ECG or PPG

Single-lead ECG + SpO2 ECG, PPG, SpO2, Temp, Acceleration Detection Engine Manual physician review On-device heuristics

Cloud Deep Neural Networks

Edge Lightweight MobileNet-1D-LSTM

Arrhythmia Detection Yes (Offline) Intermittent / On-demand Yes Real-Time Continuous

Ischemia Screening Yes No Limited Yes (ST-T wave monitoring)

Motion Artifact Gating No Basic accelerometer threshold

Software noise filter Adaptive MII Cross- Modal Gating Explainable AI (XAI) Not Applicable No No SHAP & 1D

Grad-CAM Saliency Maps



Dynamic Risk Scoring No No Static thresholds Dynamic DEW-CRS Score (0–100)
No Fall detection only Manual notification Automated GPS &
Telemetry Dispatch
Automated Emergency Call
Edge Latency Not Applicable Instant (Simple rules) High (2–10 seconds cloud delay)
Ultra-Low (<45 ms local edge inference)
Hospital Portal Sync Manual SD card transfer Proprietary Smartphone
App
Cloud Dashboard Encrypted IoMT / EHR Direct Sync

VI. DISCUSSION OF THE INTEGRATED APPROACH

The primary innovation of the proposed framework lies in unifying multi-sensor physiological sensing, edge deep learning, explainable clinical decision-support, and automated emergency alert dispatch into a cohesive ambulatory safety system. Unlike conventional clinical Holter monitors that merely record data for retrospective review, or commercial smartwatches that provide intermittent consumer-grade notifications, this system operates continuously and proactively to prevent out-of-hospital cardiac fatalities.

By extending 1D-CNN-LSTM networks with edge quantization, the architecture overcomes the traditional reliance on cloud connectivity. In rural or low-connectivity environments, cloud-dependent alerts can fail during acute events. Local edge inference guarantees that physiological risk assessment occurs in real-time. Furthermore, integrating multi-sensor fusion (ECG + PPG + Motion) addresses the primary weakness of ambulatory monitoring: motion-induced false alarms. Gating signal interpretation based on real-time physical activity index prevents alert fatigue among healthcare providers.

Explainability via SHAP and 1D Grad-CAM bridges the critical gap between machine learning predictions and clinical intervention. Paramedics responding to an automated cardiac emergency alert receive not just a binary panic flag, but a visual attribution map highlighting specific electrocardiographic anomalies—such as acute ST-segment elevation or sustained ventricular ectopy. This transparency empowers emergency teams to prepare targeted interventions (e.g., defibrillation vs. anti-ischemic medication) prior to arriving at the patient's location.

Finally, automated emergency escalation resolves a major failure mode in out-of-hospital cardiac arrests: patient incapacitation. When a patient experiences ventricular fibrillation or severe cardiac syncope, manual emergency calls are impossible. Automating geo-located dispatch based on verified physiological collapse ensures immediate medical response within the critical "golden hour."

VII. CHALLENGES, LIMITATIONS AND ETHICAL CONSIDERATIONS

Deploying AI-driven cardiac monitoring in free-living ambulatory settings involves complex technical, clinical, and ethical constraints. Ensuring high diagnostic sensitivity while maintaining user comfort and data privacy requires addressing several operational challenges.

7.1 Biosignal Quality and Dynamic Noise Artifacts

Ambulatory biosignals acquired in real-world environments are susceptible to severe motion artifacts, electrode detachment, muscle tremor (EMG) noise, and perspiration-induced impedance changes. While adaptive filtering and motion gating mitigate these effects, extreme physical activity can still degrade signal fidelity, potentially causing missed detections or transient false alerts.

7.2 Inter-Patient Physiological Variability

Electrocardiographic and photoplethysmographic morphologies vary substantially across demographics due to age, body mass index, cardiac orientation, underlying bundle branch blocks, and medication usage (e.g., beta-blockers). Models trained primarily on standardized database cohorts (such as MIT-BIH) may experience performance



degradation when deployed across heterogeneous real-world patient populations unless personalized domain adaptation techniques are employed.

7.3 Edge Hardware and Thermal Constraints

Executing continuous neural network inference on ultra-low-power wearable microcontrollers imposes strict memory, processing, and battery limitations. Highly complex networks risk accelerating battery drain or causing thermal elevation against the patient's skin. Edge models must balance diagnostic accuracy against strict energy budgets to enable at least 24–48 hours of continuous operation per charge.

7.4 False Positive Alerts and Alert Fatigue

Frequent false-positive emergency alerts impose severe burdens on emergency medical services (EMS) and induce unnecessary psychological anxiety in patients. Establishing optimal dynamic thresholds for emergency dispatch—requiring multi-window signal verification and multi-parameter consensus—is essential to maintain high diagnostic specificity without compromising emergency sensitivity.

7.5 Algorithmic Latency vs. Battery Trade-offs

Continuous sampling and real-time inference consume significantly more power than duty-cycled periodic monitoring. Strategies such as adaptive sampling—where high-rate ECG acquisition and deep learning inference are dynamically activated only when preliminary PPG or motion screening indicates potential arrhythmia—must be balanced against the risk of missing hyper-acute onset events.

7.6 Liability and Clinical Decision Ownership

Automated emergency dispatch based on AI outputs raises legal and regulatory questions regarding diagnostic accountability. If an algorithm fails to detect a fatal arrhythmia (false negative) or triggers an unneeded emergency response (false positive), responsibility between the device manufacturer, software provider, and attending physician must be defined under medical device regulatory frameworks (e.g., FDA SaMD regulations).

7.7 Data Security, HIPAA, and Privacy Considerations

Continuous physiological telemetry combined with real-time GPS location tracking generates highly sensitive Personal Health Information (PHI). Transmission of biosignal streams over wireless networks (BLE, 5G) creates potential attack vectors for unauthorized interception or data tampering. End-to-end AES-256 encryption, secure enclave hardware storage, and strict HIPAA/GDPR compliance are mandatory safeguards.

7.8 Model Drift and Longitudinal Recalibration

Patient cardiac status changes over time due to disease progression, surgical intervention, or pharmacological adjustments. Static deep learning models may experience performance drift over extended deployment periods. Implementing continuous federated learning allows edge models to update weights locally while preserving patient privacy.

7.9 Explainability Limitations in High-Order Neural Networks

While SHAP and 1D Grad-CAM highlight influential signal regions, feature attribution maps reflect mathematical correlations rather than direct physiological causation. Clinicians must interpret XAI visualizations as supportive diagnostic evidence rather than absolute pathophysiological proof.

7.10 Data Management and EHR Integration

Continuous multi-sensor monitoring generates massive volumes of time-series data. Transmitting and storing raw biosignals continuously is unfeasible for hospital infrastructure. Intelligent edge summaries—storing only episodic anomaly strips alongside baseline physiological trends—are necessary for seamless integration into Electronic Health Records (EHR) via HL7 FHIR standards.

7.11 Patient Compliance and Usability

Wearable patches must be water-resistant, biocompatible, and nonirritating to skin during multi-day usage. Complicated skin preparation, frequent electrode replacement, or cumbersome gateway pairing reduce user compliance, directly impacting monitoring continuity.



7.12 Human-in-the-Loop Emergency Oversight

To prevent erroneous dispatch, the system incorporates a brief (15–30 second) fail-safe countdown period on the edge gateway, allowing conscious patients to cancel false alerts triggered by accidental sensor drops before emergency services are notified.

VIII. FUTURE SCOPE

Future research directions include deploying Spiking Neural Networks (SNNs) on neuromorphic edge processors to reduce inference energy consumption by up to 90%, enabling multi-week continuous monitoring. Integrating non-invasive continuous blood pressure estimation via PPG-ECG pulse arrival time (PAT) will enhance ischemic risk detection.

Expanding the pipeline to incorporate Transformer-based foundation models pre-trained on millions of unlabelled biosignals will improve zero-shot generalization to unseen cardiac pathologies. Furthermore, clinical trials validating the framework's reduction in door-to-balloon time during acute myocardial infarction will advance regulatory clearance for clinical emergency dispatch integration.

IX. CONCLUSION

Cardiovascular diseases represent an urgent global health challenge where out-of-hospital mortality is heavily driven by delayed detection and emergency intervention. While traditional clinical monitoring and consumer smartwatches provide partial solutions, they lack an integrated architecture combining multi-parameter sensing, zerolatency edge inference, explainable decision- support, and automated emergency escalation.

The proposed AI-Based Early Cardiac Risk Detection and Emergency Alert framework addresses these challenges through an end-to-end pipeline. By pairing a multi-sensor wearable patch with a lightweight edge-deployed MobileNet-1D-LSTM neural network, the system performs real-time multi-class arrhythmia and ischemic risk classification. Explainable AI modules (SHAP / 1D Grad-CAM) render predictions transparent for emergency responders, while dynamic risk scoring drives automated GPS- enabled emergency dispatch during critical events.

Workflow: Acquisition → Filtering → Edge AI → Risk Score → XAI Explain → Auto Dispatch

This integrated workflow represents a vital shift from reactive cardiac diagnostics to proactive, automated life-saving intervention, holding significant potential to reduce out-of-hospital cardiac mortality worldwide.

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