Energy-Aware Federated Learning for Secure and Sustainable IoMT Monitoring

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***Abstract*—Addressing the gap in long-term IoMT sustainability, we propose RemoteCare-EAF, an energy-aware federated learning framework that models per-client battery evolution and role heterogeneity. By integrating a lightweight CNN-GRU dual-stream model with a risk-driven adaptive sensing policy, the system optimises duty cycles based on clinical risk. Results demonstrate role-dependent energy dynamics and an energy-accuracy frontier, establishing a foundation for sustainable, privacy-preserving IoMT monitoring.**

***Index Terms*—Energy-aware, federated learning, IoMT, monitoring, battery sustainability, adaptive sensing.**

I. Introduction

IoMT-based remote care enables continuous monitoring, but it faces a critical constraint: the finite battery life of devices. Energy depletion leads to client dropout, resulting in significant gaps in clinical coverage. While Federated Learning (FL) enhances privacy, current frameworks often optimise for short-term accuracy, neglecting (1) the long-term evolution of battery states and (2) role heterogeneity, where devices consume energy at varying rates [1]. Furthermore, reliable monitoring requires joint modeling of physiological and network behavior [2]. These challenges motivate RemoteCare-EAF, a framework that treats battery sustainability as a primary constraint to ensure secure and valid clinical deployment.

II. Methodology

Fig. 1 illustrates the overall RemoteCare–EAF system architecture, highlighting multimodal sensing at IoMT clients, secure federated training over encrypted channels, and battery-aware coordination at the aggregation server.

A. Dual-Stream Cyber–Clinical Model and System Architecture

RemoteCare-EAF utilizes a dual-stream CNN-GRU architecture, prioritizing the GRU for its low memory footprint and fast convergence on resource-constrained hardware to facilitate joint cyber-physical modeling. [2].

Let X_i^{net} denote network telemetry features and X_i^{phys} physiological measurements for client i. Modality-specific encoders extract representations that are fused for joint inference:

$$h_i = \text{Concat}\Big(f_{\text{cnn}}(X_i^{\text{net}}),\ f_{\text{gru}}(X_i^{\text{phys}})\Big), \tag{1}$$

where $f_{\text{cnn}}(\cdot)$ and $f_{\text{gru}}(\cdot)$ denote lightweight encoders for network and physiological modalities, respectively. The fused representation h_i feeds task-specific heads for cyberattack detection and health-state prediction.

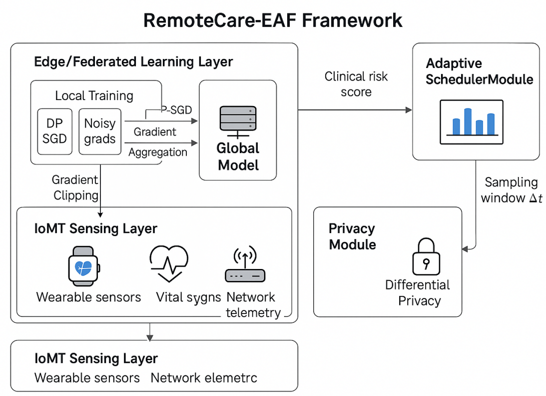

Fig. 1. System architecture of RemoteCare–EAF. IoMT clients perform dual-stream cyber–clinical inference and participate in secure, energy-aware federated learning under battery constraints.

B. Energy-Aware Federated Learning with Battery Evolution

We consider role-heterogeneous clients (attack-only, health-only, hybrid) with finite batteries. Let $E_i^{(r)}$ be client i's energy consumed in FL round r (computation + communication + security overhead). Battery evolves as:

$$B_i^{(r+1)} = \max\Big(0,\ B_i^{(r)} - E_i^{(r)}\Big). \tag{2}$$

This enables explicit sustainability analysis and participation fairness (dropout occurs when $B_i^{(r)} = 0$). The global model is updated via weighted aggregation of participating clients, following standard FedAvg principles [3].

C. Secure Training and Transport

RemoteCare–EAF integrates a deployment-oriented security stack: DP-SGD for privacy, TLS 1.3 for authenticated/encrypted transport, and TEE-based secure aggregation for protected server-side computation. These mechanisms are treated as deployment constraints whose overhead contributes to $E_i^{(r)}$ in (2).

TABLE I
CENTRALIZED VS. FL PERFORMANCE (**FINAL-ROUND** METRICS).

Setting	**Attack Acc.**	**Health Acc.**
Centralized	0.7563	0.6891
Federated (DP–FedAvg)	0.8756	0.5149

D. Clinical-Risk-Driven Adaptive Sensing

To conserve energy, RemoteCare-EAF employs a risk-driven adaptive sensing policy that modulates the sensing interval $dt_i(t)$ based on the predicted probability of a critical health state $r_i(t)$, extending the interval to $dt_{\max}$ during low-risk periods to reduce duty cycles:

$$r_i(t) = \hat{y}_i^{\text{health}}(\text{Critical} \mid X_i(t)). \tag{3}$$

Then the sensing interval is updated as:

$$dt_i(t) = \begin{cases} dt_{\min}, & r_i(t) > \kappa, \\ dt_{\max}, & r_i(t) \le \kappa, \end{cases} \tag{4}$$

where $dt_{\min} < dt_{\max}$ and κ is a decision threshold.

E. Experimental Setup and Configuration

We simulated $N = 20$ heterogeneous clients using **UNSW-NB15** (network) and **MIMIC-III** (clinical) datasets. Hardware energy profiles $E_i^{(r)}$ represent **Raspberry Pi 4** and **ESP32** devices. FL hyperparameters include 50 communication rounds, $E = 5$ local epochs, learning rate $\eta = 0.01$, and a DP-noise multiplier $\sigma = 0.1$.

III. RESULTS AND DISCUSSION

A. Centralized vs. Federated Benchmarking

Table I compares centralized training against federated training (final-round metrics), showing improved attack detection under FL while highlighting health-task constraints under current pairing and role imbalance, a known challenge in multimodal IoMT settings [2].

B. Battery Sustainability and Energy Fairness

Fig. 2 illustrates the longitudinal battery dynamics enabled by (2). Attack-heavy clients deplete fastest due to larger workloads and security/communication overheads, while lighter roles retain higher residual energy. This motivates role-aware participation policies and energy-aware stopping.

C. Energy–Accuracy Trade-Off (Frontier)

Fig. 3 shows an energy–accuracy frontier: attack accuracy improves with cumulative energy at first, then saturates, indicating diminishing returns. This provides a decision tool for selecting FL horizons under battery constraints, consistent with energy-aware FL design goals [1].

IV. CONCLUSION

RemoteCare–EAF demonstrates that sustainable IoMT RemoteCare requires federated learning designs that explicitly account for battery evolution, client heterogeneity, and security overheads. Results reveal strong role-dependent energy depletion and an energy-accuracy trade-off, motivating energy-aware stopping and role-aware participation policies. Although the evaluation is limited by synthetic hybrid pairing, tabular

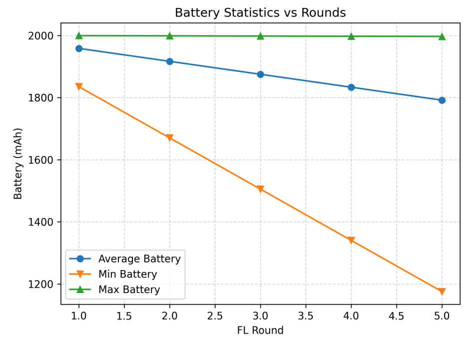

Fig. 2. Residual battery statistics across rounds (mean/min/max over clients). Role heterogeneity yields unequal depletion; high-workload clients approach dropout first.

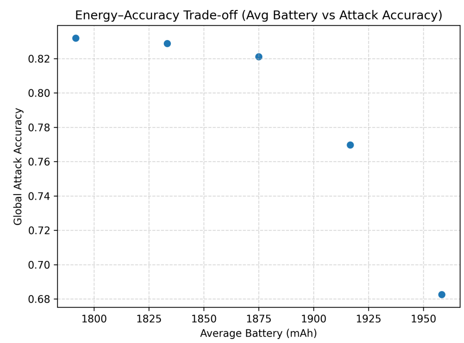

Fig. 3. Energy–accuracy trade-off: accuracy (final-round) vs cumulative energy. Beyond moderate horizons, gains diminish while sustainability cost rises.

physiological features, and the absence of energy harvesting, these constraints bound absolute accuracy without undermining the validity of the proposed energy-aware framework and instead motivate future extensions.

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