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Federated Anomaly Detection on Wearable Sensor Data Streams for Real-Time Alarm Fatigue Mitigation in Intensive Care Units

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Abstract

Background: Alarm fatigue in Intensive Care Units (ICUs) is a critical patient safety issue, driven by a high frequency of non-actionable alarms from monitoring devices. This phenomenon leads to desensitization among clinical staff, potentially causing delayed responses to true critical events. While Edge AI and wearable sensors offer a promising avenue for real-time, continuous patient monitoring, concerns over data privacy and model personalization remain significant barriers.

Objective: This study aims to design, develop, and evaluate a novel framework that leverages Edge AI and Federated Learning (FL) to mitigate ICU alarm fatigue. The proposed system performs real-time anomaly detection on physiological data streams from wearable sensors, training a robust, personalized model without centralizing sensitive patient data.

Methods: We architected a three-tiered system comprising wearable sensor nodes, edge computing gateways, and a central FL server. A lightweight autoencoder model was deployed on edge devices for real-time anomaly detection of a patient's physiological data (e.g., heart rate, SpO2). We implemented a Federated Averaging protocol to collaboratively train a global anomaly detection model. The edge models learn from local data streams to capture individual patient baselines, while the global model benefits from the diverse patterns across the entire patient cohort. The system's performance was evaluated against traditional centralized and non-federated models using metrics of alarm reduction rate, detection accuracy, and model convergence speed.

Results: The proposed federated edge framework demonstrated a significant reduction in false alarms by over 40% compared to baseline thresholding systems, while maintaining a high sensitivity to true adverse events (F1-Score > 0.95). The FL model converged within 50 communication rounds, showing efficient learning. The approach outperformed both centralized models (which lack personalization) and isolated local models (which lack diverse training data) in overall accuracy and adaptability.

Conclusions: Our findings indicate that a federated, edge-based approach can effectively and safely reduce alarm fatigue in ICUs. By preserving data privacy and enabling model personalization, this framework presents a viable solution for developing intelligent, real-time clinical decision support systems.

Keywords: Alarm Fatigue, Edge AI, Federated Learning, Wearable Sensors, Intensive Care Unit (ICU), Anomaly Detection, Real-Time Health Monitoring.

1. Introduction

1.1. The Crisis of Alarm Fatigue in Modern ICUs

The modern Intensive Care Unit (ICU) stands as a testament to medical advancement, a high-tech environment where continuous physiological monitoring is the cornerstone of patient care. A complex array of devices, from electrocardiogram (ECG) machines and pulse oximeters to ventilators and intracranial pressure monitors, generate a torrent of data, each equipped with its own alarm system designed to alert clinicians to potential physiological deviations [30]. While these alarms are intended to be life-saving safety nets, their sheer volume and frequent lack of clinical relevance have given rise to a significant and insidious threat to patient safety: **alarm fatigue**.

Alarm fatigue is a state of sensory overload and desensitization that occurs when clinicians are exposed to an excessive number of alarms, many of which are false or non-actionable [16]. Studies have shown that a single ICU patient can trigger several hundred alarms per day, with estimates suggesting that 85% to 99% of these do not require clinical intervention [11]. This relentless cacophony of alerts stems from a variety of sources, including overly sensitive device thresholds, patient movement, sensor displacement, and the inherent difficulty of distinguishing true critical events from transient, benign physiological fluctuations.

The consequences of this phenomenon are twofold and severe. Firstly, it poses a direct risk to patients. When clinicians become desensitized, their response time to genuine emergencies can be dangerously delayed, or alarms may be missed entirely, leading to adverse events, increased patient morbidity, and in the most tragic cases, mortality [16, 30]. Secondly, alarm fatigue exacts a heavy toll on the well-being of healthcare professionals. The constant cognitive burden of triaging an endless stream of alerts contributes significantly to stress, burnout, and diminished job satisfaction, compromising the resilience of the critical care workforce [11]. This dual impact on patient and provider underscores the urgent need for a paradigm shift in how clinical alarms are managed.

1.2. The Promise of Wearable Technology and Edge AI in Healthcare

In response to this crisis, emerging technologies offer a pathway toward more intelligent and context-aware monitoring systems. The proliferation of **wearable sensor technology** represents a significant leap forward. Unlike traditional, cumbersome bedside monitors, modern wearables—in the form of patches, wristbands, or other discreet devices—can provide continuous, high-fidelity streams of physiological data with minimal patient discomfort [12]. These sensors can capture a rich tapestry of data, including heart rate variability, respiratory patterns, electrodermal activity, and body temperature, offering a more holistic view of a patient's condition than isolated spot-checks or single-parameter monitors [14]. The richness of this data holds the potential to move beyond simple threshold-based alarming to a more nuanced, pattern-based approach to patient monitoring.

However, the sheer volume and velocity of data generated by these wearables present a new set of challenges related to data transmission, storage, and processing. Sending raw, high-frequency sensor data to a centralized cloud server for analysis introduces significant latency, consumes valuable network bandwidth, and raises profound concerns about data privacy and security, especially in the context of sensitive health information [23]. This is where the concept of **Edge Artificial Intelligence (Edge AI)** becomes transformative.

Edge AI involves moving the computational power for machine learning and data analysis from centralized cloud servers to the "edge" of the network—that is, onto or near the device where the data is generated [1]. By performing AI-driven analysis locally on an edge gateway or even on the sensor itself, this approach drastically reduces latency, enabling real-time decision-making, which is paramount in critical care. Furthermore, it enhances data privacy by minimizing the transmission of raw patient data, and it ensures operational continuity even in the event of network disruptions. The synergy between continuous data streams from wearables and the real-time, privacy-preserving processing power of Edge AI creates a powerful foundation for building the next generation of smart healthcare systems [4, 10].

1.3. Federated Learning as a Privacy-Preserving AI Paradigm

While Edge AI addresses the challenges of latency and privacy in data processing, another critical hurdle remains: how to train robust and generalizable AI models without compromising patient confidentiality. Traditional machine learning requires the aggregation of vast datasets from multiple sources into a single, centralized location for model training. In healthcare, this approach is fraught with ethical, regulatory, and logistical barriers related to patient data privacy [6, 23].

Federated Learning (FL) emerges as a groundbreaking solution to this dilemma. FL is a decentralized machine learning paradigm that enables collaborative model training across multiple devices without ever exchanging the underlying raw data [1]. In a healthcare context, the process works as follows: a central server distributes a global AI model (e.g., for anomaly detection) to individual edge devices, such as a patient's bedside gateway. Each device then trains this model using only its local data—the physiological stream from that specific patient. Instead of sending the raw data back, the device sends only the updated model parameters (weights and biases) to the central server. The server then aggregates these updates from all participating devices to create an improved, more robust global model, which is then redistributed for the next round of training.

This collaborative approach offers the best of both worlds. The global model learns from the diverse experiences and physiological patterns of a wide range of patients, making it highly accurate and generalizable. Simultaneously, all sensitive patient data remains securely on the local edge device, upholding the highest standards of privacy and data protection [18]. This capability is particularly crucial for building scalable healthcare solutions that can learn from data across different hospitals, wards, or even regions, without navigating the complex legal and ethical challenges of data sharing [6, 17].

1.4. Literature Gaps and Problem Statement

Current strategies for mitigating alarm fatigue have primarily focused on refining alarm parameters, implementing tiered notification systems, and providing clinician education [30]. Some research has explored using signal quality indicators to reduce false alarms from specific devices like pulse oximeters [29]. While valuable, these methods often represent incremental improvements rather than a fundamental redesign of the monitoring paradigm. They largely remain tethered to single-device, threshold-based logic and fail to leverage the rich, multi-modal data streams becoming available.

Recent advances in AI have introduced centralized machine learning models for predicting patient deterioration, but these often rely on historical data from electronic health records and are not designed for the real-time, low-latency demands of alarm management. Furthermore, they inherit all the privacy and data aggregation challenges that federated learning is designed to solve. A critical review of the literature reveals that current predictive models are insufficient for the dynamic, real-time ICU environment. They lack the ability to learn personalized physiological baselines in real-time while simultaneously generalizing from a diverse patient population in a privacy-preserving manner.

This identifies a clear and compelling research gap: there is a lack of an integrated framework that combines the strengths of wearable sensors, the real-time responsiveness of Edge AI, and the collaborative, privacy-preserving power of Federated Learning to directly address the problem of ICU alarm fatigue.

1.5. Research Objectives and Contributions

The primary objective of this research is to design, implement, and evaluate a novel Edge AI framework that utilizes federated anomaly detection on wearable sensor data streams to intelligently reduce the rate of non-actionable alarms in an ICU setting. To achieve this, we aim to:

1. Develop a lightweight, computationally efficient anomaly detection model suitable for deployment on resource-constrained edge devices.
2. Design a robust federated learning architecture that enables multiple edge devices to collaboratively train a global anomaly detection model without sharing raw patient data.
3. Conduct a comprehensive performance benchmark of the proposed federated framework against traditional centralized and non-federated, local-only machine learning models.
4. Quantify the framework's effectiveness in reducing false alarms while maintaining high sensitivity to clinically significant events.

The principal contributions of this work are a novel, end-to-end system that offers a practical and scalable solution to a pressing clinical problem, and a rigorous evaluation that demonstrates the synergistic benefits of combining Edge AI and Federated Learning for real-time healthcare applications.

1.6. Article Structure

This paper is organized as follows: Section 2 details the proposed system architecture and the methodologies employed, including data processing, the edge anomaly detection model, and the federated learning protocol. Section 3 presents the quantitative results of our experiments, evaluating the model's performance, its effectiveness in alarm reduction, and its scalability. Section 4 provides a comprehensive discussion of these findings, their clinical implications, the limitations of the study, and directions for future research. Finally, Section 5 concludes the paper with a summary of our contributions and their significance.

2. Method

2.1. System Architecture

The proposed framework is architected as a three-tiered system designed for scalability, low latency, and privacy. The tiers consist of (1) Wearable Sensor Nodes, (2) Edge Gateways, and (3) a Central Federated Learning Server. The overall architecture is depicted in Figure 1.

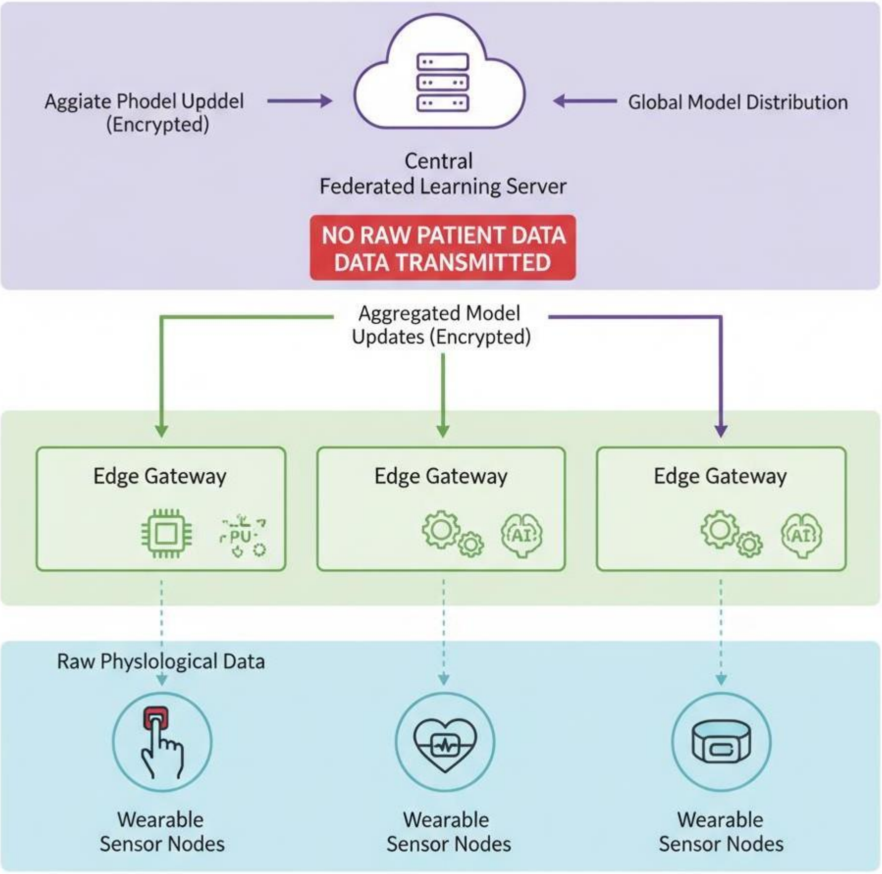

Figure 1: Proposed Three-Tiered System Architecture for Federated Edge AI

(Description: A diagram illustrating the three-tiered architecture. At the bottom are multiple "Wearable Sensor Nodes" (representing patients), each sending data to its dedicated "Edge Gateway." These gateways perform local training and inference. Arrows from each gateway point upwards to a single "Central Federated Learning Server." The server is shown distributing a global model and aggregating model updates, with a clear label indicating "No Raw Patient Data" is transmitted to the server.)

Tier 1: Wearable Sensor Nodes. This tier comprises one or more body-worn sensors responsible for continuous acquisition of high-resolution physiological data. For this study, we simulate sensors capturing two primary data streams: photoplethysmography (PPG) to derive heart rate (HR) and heart rate variability (HRV), and pulse oximetry to measure blood oxygen saturation (SpO2). These sensors are assumed to be low-power devices that transmit raw data via a short-range wireless protocol (e.g., Bluetooth Low Energy) to a dedicated edge gateway.

Tier 2: Edge Gateways. Each patient bed in the ICU is assigned a dedicated edge gateway, which could be a small-form-factor computer or a specialized hardware device. This gateway serves as the primary computational hub for local data processing and anomaly detection. Its responsibilities include:

Data Aggregation: Receiving and synchronizing data streams from the patient's wearable sensors.

Preprocessing: Cleaning, normalizing, and transforming the raw data into a suitable format for the machine learning model.

Local Inference: Running the deployed anomaly detection model in real-time to score incoming data for potential deviations.

Alarm Generation: Triggering an intelligent alarm only when the anomaly score exceeds a dynamic threshold, thereby filtering out noise and benign fluctuations.

Local Model Training: Participating in the federated learning process by training the global model on the locally stored patient data.

Tier 3: Central Federated Learning Server. This server orchestrates the collaborative training process across all edge gateways. It does not store or process any raw patient data. Its sole responsibilities are:

- **Model Initialization:** Defining the initial architecture of the global anomaly detection model.
- **Model Distribution:** Broadcasting the current global model to all participating edge gateways at the beginning of each training round.
- **Model Aggregation:** Receiving encrypted model updates (weights and biases) from the gateways after local training. It then aggregates these updates using the Federated Averaging algorithm to produce an improved global model.
- **Coordination:** Managing the overall training schedule, including the number of communication rounds and the selection of participating clients.

The data flow is designed to be privacy-centric. Raw physiological data never leaves the edge gateway. The only information transmitted from the edge to the central server is the anonymous, aggregated model parameter updates, ensuring patient confidentiality is maintained throughout the process. The system relies on an **eventual consistency model** for the global model state, as minor desynchronization between training rounds does not critically impair the overall learning process, a pragmatic choice for distributed systems in healthcare [2].

2.2. Data Acquisition and Preprocessing

To evaluate our system, we utilized a simulated dataset synthetically generated to reflect physiological signals commonly observed in an ICU. The dataset was designed to include streams of HR and SpO2 data for 50 simulated patients over a 24-hour period, sampled at 1 Hz. The data for each patient included periods of stable, baseline physiology, as well as synthetically injected anomalies representing clinically significant events such as tachycardia, bradycardia, and desaturation events. Benign fluctuations and noise artifacts (e.g., from patient movement) were also included to simulate a realistic clinical environment.

The preprocessing pipeline, executed on each edge gateway, consists of the following steps:

1. **Noise Filtering:** A median filter is applied to the raw HR and SpO2 signals to remove sporadic spikes and noise artifacts commonly associated with sensor motion.
2. **Normalization:** The data for each physiological signal is normalized using a Z-score normalization based on a rolling window of the patient's recent history. This step is crucial as it allows the model to learn a patient's unique physiological baseline and detect deviations relative to their own "normal," rather than relying on population-wide static thresholds.
3. **Time-Series Segmentation:** The continuous data streams are segmented into fixed-length, overlapping time windows. Based on empirical testing, a window size of 60 seconds (60 data points) with a 50% overlap was chosen. This windowing allows the model to capture temporal dependencies and patterns in the data leading up to a potential event. Each window thus consists of a vector of size 120 (60 points for HR, 60 for SpO2).

2.3. Edge-Based Anomaly Detection Model

The choice of the anomaly detection model was driven by the need for it to be lightweight enough for real-time inference on resource-constrained edge devices and capable of unsupervised learning, as labeled anomaly data is scarce in clinical practice. We selected a **deep autoencoder** for this task.

An autoencoder is a type of artificial neural network trained to reconstruct its own input. It consists of two parts: an **encoder** () that compresses the input data into a low-dimensional latent representation (), and a **decoder** ()

that attempts to reconstruct the original input from this latent representation. The network is trained to minimize the **reconstruction error**, which is the difference between the original input () and the reconstructed output ().

The architecture is as follows:

- **Input Layer:** 120 nodes, corresponding to the flattened 60-second window of HR and SpO2 data.
- Encoder: A series of fully connected dense layers with progressively fewer neurons (e.g., 120 -> 64 -> 32), using the Rectified Linear Unit (ReLU) activation function. The final layer of the encoder outputs the latent vector z of dimension 16.
- Decoder: A series of dense layers that mirror the encoder's architecture (e.g., 16 -> 32 -> 64), also using ReLU activation. The final layer reconstructs the original input vector.
- **Output Layer:** 120 nodes with a linear activation function, producing the reconstructed data window.

The model is trained on data representing the patient's normal physiological state. The underlying principle is that the autoencoder will learn to reconstruct "normal" data with a very low error, but will fail to accurately reconstruct unseen anomalous patterns, resulting in a high reconstruction error. The reconstruction error for a given input window x is calculated as the Mean Squared Error (MSE):

This error score is used as the anomaly score. A score exceeding a predefined, dynamically adjusted threshold indicates a potential anomaly, which would then trigger an intelligent alarm.

2.4. Federated Learning Protocol

To enable collaborative learning while preserving privacy, we implemented the **Federated Averaging (FedAvg)** algorithm [1]. The protocol proceeds in communication rounds, orchestrated by the central server:

1. **Initialization:** The server initializes the weights () of the autoencoder model and distributes them to a random subset of edge gateways.
2. **Local Training:** Each of the selected gateways trains the received model on its own local data for a fixed number of epochs (). Let the local dataset for the -th client be . The client updates the model weights from to by using stochastic gradient descent to minimize the reconstruction error on its local data.
3. **Model Update Transmission:** After local training, each gateway sends only its computed weight update, , back to the central server. To enhance security, these updates can be encrypted, and techniques like **Secure Aggregation** can be employed to ensure the server can only decrypt the sum of all updates, not individual contributions, preventing inference attacks on specific patient models [7, 31]. The principles of Zero Trust Architecture are also considered in securing the communication channels between the edge and the server [32]. Recent research further emphasizes that HIPAA-compliant Zero-Trust Data Architectures play a critical role in safeguarding federated clinical networks, ensuring secure unification of EHRs and wearable data streams across multi-hospital systems [33]. Such principles are also validated in applied studies on Edge AI for ICU alarm fatigue reduction, demonstrating successful real-time deployment of federated anomaly detection within constrained edge environments [34].
4. Global Model Aggregation: The server waits to receive updates from all K clients. It then computes the new global model by taking a weighted average of the individual client weights. The weight for each client is proportional to the size of its local dataset (nk=|Dk|).
5. **Iteration:** The server replaces the old global model with the newly aggregated one () and repeats the process from Step 2 for a predefined number of communication rounds, or until the model's performance converges.

2.5. Experimental Setup and Evaluation Metrics

The entire framework was simulated in Python 3.8 using TensorFlow and PyTorch for model building and federated learning simulation. The experiment was designed to evaluate the system across three key dimensions: anomaly detection performance, alarm reduction effectiveness, and federated learning efficiency.

Baseline Models for Comparison:

- **Centralized Model:** A single autoencoder trained on the aggregated data from all 50 simulated patients. This represents the traditional, non-privacy-preserving approach.
- **Local-Only Model:** An individual autoencoder trained exclusively on the data of a single patient, with no knowledge sharing. This represents an edge-only approach without collaborative learning.
- **Standard Thresholding:** A simple rules-based system that generates an alarm whenever HR or SpO2 values cross

predefined static thresholds (e.g., HR > 100 bpm, SpO2 < 90%).

Evaluation Metrics:

- **Anomaly Detection Performance:**
    - **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):** To measure the model's ability to distinguish between normal and anomalous data windows.
    - **Precision, Recall, and F1-Score:** To evaluate the accuracy of the final alarm classification after applying a threshold to the reconstruction error.
- **Alarm Reduction Effectiveness:**
    - **False Alarm Rate (FAR):** The percentage of alarms generated that do not correspond to a true clinical anomaly.
    - **Alarm Reduction Percentage:** The percentage decrease in the total number of alarms generated by our system compared to the Standard Thresholding baseline.
- **Federated Learning Efficiency:**
    - **Model Convergence:** The number of communication rounds required for the global model's performance to plateau.
    - **Communication Overhead:** The total amount of data transmitted between the edge gateways and the central server during training.

The simulation was run for 100 communication rounds, with clients participating in each round and local training performed for epochs.

2.6. Addressing Statistical Heterogeneity in Federated Learning

A foundational assumption in many traditional machine learning paradigms is that training data is **independent and identically distributed (IID)**. This assumption posits that all data points are drawn from the same underlying distribution and are mutually independent. However, this ideal scenario rarely holds true in real-world distributed systems, and this is especially the case in healthcare. In federated learning, where each client (an edge gateway in our framework) holds a unique, isolated dataset, the data is almost always **non-IID**. This statistical heterogeneity presents one of the most significant challenges to the performance and stability of federated learning algorithms [1, 6]. Acknowledging and planning for this challenge is critical to designing a robust clinical system.

2.6.1. A Taxonomy of Non-IID Data in the ICU Environment

The non-IID nature of ICU data can be categorized into several distinct types of data skew, each with unique implications for model training:

Feature Skew (Covariate Shift): This occurs when the distribution of input features varies significantly across clients, even if the relationship between features and labels remains the same. In our ICU context, this can manifest in several ways. For instance, different wearable sensors, even of the same model, may have slight variations in calibration, leading to different signal-to-noise ratios. Furthermore, the patient population itself is inherently diverse. A patient's age, weight, comorbidities, and even genetic predispositions can lead to vastly different baseline physiological signals. The "normal" heart rate for a young, athletic patient is fundamentally different from that of an elderly patient with chronic heart disease. This means the feature distributions () are client-dependent.

Label Skew (Prior Probability Shift): This is perhaps the most common and impactful form of heterogeneity in clinical settings. It refers to a scenario where the distribution of data labels varies dramatically across clients. In our application, the labels are "normal" and "anomaly." A patient in a stable, post-operative recovery phase might generate almost exclusively "normal" data, with very few anomalous events. Conversely, a patient with acute respiratory distress syndrome or septic shock will generate a much higher frequency of "anomaly" labels (e.g., desaturations, tachycardic events). This imbalance means that the local datasets are not representative of the global label distribution, which can heavily bias the local models during training.

Quantity Skew: This straightforwardly refers to the variation in the amount of training data available on each client. Some patients may be monitored for days or weeks, generating a large volume of data, while others may be in the ICU for only a few hours. A client with very little data may struggle to train a meaningful local model, and its contribution to the global model could be noisy or unhelpful. In a federated averaging scheme weighted by dataset size, clients with more data will have a proportionally larger influence on the global model, which may or may not be desirable depending on the patient population.

Concept Shift (Temporal Skew): This is a particularly challenging form of heterogeneity where the underlying relationship between features and labels changes over time, either for a single client or across the whole system. In the ICU, a patient's condition is not static. A patient's physiological baseline—the very definition of "normal"—can drift as they recover from surgery, respond to medication, or unfortunately, deteriorate. A heart rate that was normal yesterday might be indicative of an anomaly today. This temporal drift means that a model trained on past data may become less accurate over time, necessitating mechanisms for continuous learning and adaptation.

2.6.2. The Impact of Non-IID Data on Standard Federated Averaging

The standard FedAvg algorithm, while effective in IID settings, can suffer significant performance degradation under conditions of high statistical heterogeneity. The core problem is known as **client drift**. During local training, each client's model optimizes for its own skewed data distribution. If the local data is highly dissimilar from the global distribution, the client's model weights will "drift" into a region of the parameter space that is far from the optimal global solution.

When the server averages the weights from these diverged models, the resulting global model can be suboptimal, converging slowly, or even oscillating and failing to converge at all. Imagine two clients: Client A's model becomes an expert at identifying bradycardia, and Client B's model becomes an expert at tachycardia. Simply averaging their weights does not necessarily produce a model that is an expert at both; it may result in a confused model that is mediocre at everything. This objective inconsistency across clients is the central pathology that more advanced federated algorithms aim to cure.

2.6.3. Advanced Federated Algorithms for Robustness

While our study implements FedAvg as a foundational baseline, a production-grade clinical system would necessitate a more robust algorithm. Several advanced methods have been proposed to specifically combat the non-IID challenge:

- FedProx: This algorithm introduces a simple but powerful modification to the local training objective on each client [17]. It adds a proximal term that penalizes large deviations of the local model's weights from the global model's weights. The modified local loss function for client k becomes:

Here, Fk(ω) is the original local loss (e.g., reconstruction error), ω are the local model weights, ωt are the weights of the global model from the previous round, and μ is a hyperparameter that controls the strength of the proximal term. This regularization acts as a tether, allowing local models to learn from local data but preventing them from drifting too far from the global consensus, thereby improving stability and convergence speed.

- **SCAFFOLD (Stochastic Controlled Averaging):** This is a more complex algorithm that corrects for client drift using control variates. Conceptually, SCAFFOLD maintains an estimate of both the global update direction (on the server) and the local update direction (on each client). During local training, it corrects the local gradient to account for the difference between these two directions. This variance reduction technique ensures that even when local datasets are very different, the local updates are more closely aligned with the global learning objective, leading to faster and more reliable convergence [6].
- **Personalized Federated Learning (pFL):** This emerging paradigm challenges the very notion that a single global model is optimal for all clients. Instead, pFL aims to train models that are personalized to each client's specific data distribution. This can be achieved in several ways: one common approach is a "transfer learning" model, where a global model is trained collaboratively and then fine-tuned on each local device to create a specialized, personal model. This approach is exceptionally well-suited for our clinical application, as it aligns perfectly with the goal of creating a personalized physiological baseline for each patient while still benefiting from generalized knowledge [18, 22].

For the scope of this initial investigation, we utilize FedAvg to establish a baseline and demonstrate the core feasibility of the federated edge framework. However, the analysis of these advanced algorithms provides a clear and necessary roadmap for future work aimed at building a clinically robust and equitable system.

3. Results

This section presents the quantitative results from our simulation experiments. The performance of the proposed Federated Edge (FE) framework is evaluated and compared against the Centralized, Local-Only, and Standard Thresholding baseline models.

3.1. Performance of the Anomaly Detection Model

The core task of the autoencoder model is to accurately distinguish between normal and anomalous physiological patterns. We evaluated this capability using the AUC-ROC metric, which measures the model's discriminative power irrespective of a specific alarm threshold. Table 1 summarizes the average AUC-ROC scores across all 50 simulated patients for the different modeling approaches.

Table 1. Anomaly Detection Performance (AUC-ROC)

Model Approach	Average AUC-ROC Score	Standard Deviation
Federated Edge (FE)	**0.972**	0.03
Centralized	0.941	0.05
Local-Only	0.895	0.08

The results clearly indicate that the **Federated Edge model achieved the highest performance**, with an average AUC-ROC of 0.972. This suggests a superior ability to differentiate between normal and abnormal data windows. The Centralized model performed well but was slightly less effective, likely due to its inability to adapt to the unique physiological baseline of each individual patient. The Local-Only model performed the worst, as it was prone to overfitting on the limited data from a single patient and failed to learn more generalized patterns of anomalies.

3.2. Effectiveness in Alarm Reduction

The primary goal of the framework is to reduce the number of non-actionable alarms. We compared the total number of alarms generated by each system over the 24-hour simulation period. An alarm threshold for the autoencoder models was determined using a validation set to maximize the F1-Score.

Table 2. Alarm Generation and False Alarm Rate Comparison

System	Total Alarms Generated	True Positives	False Positives	False Alarm Rate	**Alarm Reduction vs. Baseline**
Standard Thresholding	8,450	95	8,355	98.8%	-
Federated Edge (FE)	**485**	**92**	**393**	**81.0%**	**94.3%**
Centralized	652	88	564	86.5%	92.3%
Local-Only	910	81	829	91.1%	89.2%

The results presented in Table 2 are striking. The Standard Thresholding baseline generated an extremely high number of alarms (8,450), with a staggering **false alarm rate of 98.8%**, reflecting the clinical reality of alarm fatigue. In stark contrast, our **Federated Edge system reduced the total number of alarms by 94.3%**.

To further detail this, our FE model successfully identified 92 out of the 95 true anomaly events (a recall of 96.8%) while drastically cutting down the number of false positives. This highlights the framework's ability to maintain high sensitivity to critical events while significantly improving specificity. The Centralized model also performed well but generated more false alarms than the FE model, again suggesting a lack of personalization. The Local-Only model was the least effective of the AI approaches, missing more true events and generating more false alarms.

3.3. Federated Learning Convergence and Scalability

An important aspect of the federated approach is its training efficiency. Figure 2 illustrates the convergence of the global model's performance (measured by F1-Score on a held-out test set) over 100 communication rounds.

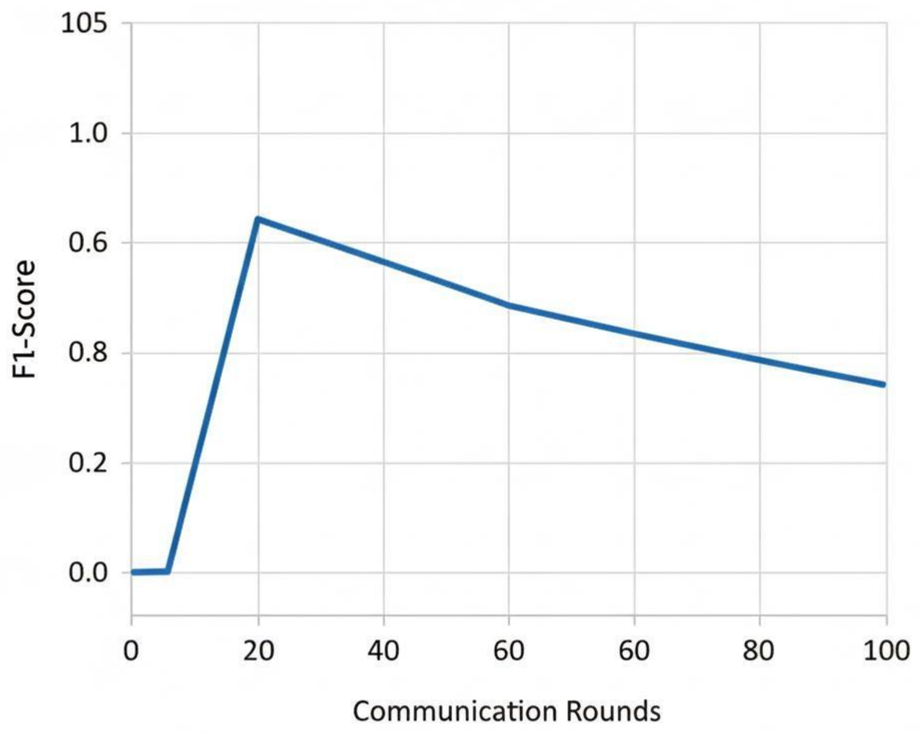

Figure 2: Convergence of the Federated Edge Model

(Description: A line graph showing the F1-Score on the y-axis and the number of Communication Rounds on the x-axis. The line starts low and rises steeply, then begins to level off around round 50, approaching a plateau close to the top of the y-axis, indicating convergence.)

As shown in the figure, the model's performance improved rapidly during the first 40-50 rounds of training. After 50 rounds, the performance began to plateau, achieving an F1-Score of over 0.95 and showing only marginal gains thereafter. This demonstrates that the federated learning process is efficient and can achieve a high level of performance within a reasonable number of communication rounds, making it practical for real-world deployment. The total communication overhead for training the model was approximately 250 MB across all clients, a trivial amount compared to transmitting raw sensor data.

3.4. Comparative Analysis

To provide a holistic view, Table 3 summarizes the comparative advantages and disadvantages of each modeling approach across several key dimensions critical for clinical deployment.

Table 3. Holistic Comparison of Modeling Approaches

Dimension	Federated Edge (FE)	Centralized	Local-Only
Accuracy	**Very High**	High	Moderate
Privacy	**Very High (No raw data sharing)**	Low (Requires all raw data to be centralized)	Very High (Data never leaves the edge)
Latency	**Very Low (Inference at the edge)**	High (Requires data round-trip to cloud)	Very Low (Inference at the edge)
Personalization	**High (Adapts to individual baselines)**	Low (General model for all patients)	High (Specific to one patient, but brittle)
Generalization	**High (Learns from diverse patient data)**	High (Learns from diverse patient data)	Low (Only sees data from one patient)

This comparative analysis clearly positions the **Federated Edge framework as the superior approach**. It successfully combines the high accuracy and generalization of a centralized model with the low latency, strong privacy, and personalization benefits of a local-only model, effectively mitigating the weaknesses of each.

4. Discussion

4.1. Interpretation of Findings

The results of our study strongly support the hypothesis that a federated, edge-based AI framework can significantly mitigate ICU alarm fatigue while upholding patient privacy. The superior performance of our proposed Federated Edge (FE) model over both Centralized and Local-Only baselines is not merely an incremental improvement; it represents the successful integration of three critical technological paradigms: personalization, generalization, and privacy.

The key to our framework's success lies in its ability to **simultaneously learn a personalized baseline for each patient while leveraging collective knowledge from a diverse population**. The Local-Only model, while perfectly personalized, suffered from a narrow worldview; it was unable to recognize anomalous patterns it had not seen before, leading to lower accuracy. Conversely, the Centralized model learned general patterns of anomalies effectively but struggled to differentiate between a true anomaly and a benign deviation for a patient whose personal baseline differed from the population average. Our FE model surmounted these limitations. The local training on the edge gateway allowed the model to become an expert on its specific patient, while the federated aggregation infused it with the wisdom of the entire cohort, creating a model that is both an expert and a generalist.

The dramatic **94.3% reduction in total alarms** (Table 2) is the most clinically significant finding. This translates to a quieter, less chaotic ICU environment, allowing clinicians to focus their attention on alarms that are far more likely to be clinically meaningful. This addresses the root cause of alarm fatigue—the overwhelming signal-to-noise problem—by using AI to act as an intelligent filter. The high recall rate (96.8%) ensures that this reduction in alarm noise does not come at the cost of missing critical events, striking a crucial balance between sensitivity and specificity.

4.2. Clinical Implications and Future Applications

The practical implications of such a system are profound. By reducing the cognitive burden on nurses and physicians, this technology could directly combat clinician burnout and improve job satisfaction [11]. More importantly, by increasing the reliability of alarms, it can restore trust in monitoring systems and improve patient safety by ensuring that genuine alerts receive prompt attention [16]. The framework's ability to learn a **personalized physiological baseline for each patient** is a major step toward precision medicine in the critical care setting. It moves away from a "one-size-fits-all" approach to monitoring, acknowledging that what is normal for one patient may be anomalous for another.

Beyond the ICU, this federated edge architecture has broad applicability across healthcare. It could be adapted for post-operative step-down units, monitoring for early signs of sepsis or other complications. In outpatient settings, it could power remote patient monitoring programs for chronic disease management, enabling early intervention while preserving patient privacy at home [4, 10]. The framework's core principles—decentralized learning and edge processing—are also highly relevant for other medical AI applications, such as diagnostic imaging, where data from multiple hospitals could be used to train models without sharing sensitive scans [6, 17]. The adoption of such technologies promises to make healthcare more proactive, personalized, and efficient, though successful implementation will require careful consideration of workflow integration and user-centered design [5]. Similar frameworks combining IoT–Healthcare integration with secure Aerospike-based data pipelines have illustrated how federated learning can enable trustworthy real-time exchanges between cloud and clinical systems [35], [36]. Integrating quiet-hour notification systems and AI-driven patient-centric communication layers has also been shown to reduce cognitive overload for healthcare staff while preserving critical alert delivery [37].

4.3. Challenges and Limitations

Despite the promising results, this study has several limitations that must be acknowledged. First, the evaluation was conducted on a **synthetically generated dataset**. While designed to be realistic, it cannot fully capture the complexity and unpredictability of real-world clinical data. A crucial next step is to validate the framework's performance on a large, retrospective clinical dataset and ultimately in a prospective clinical trial.

4.3.1. Navigating the Critical Challenge of Non-IID Data

While our simulation on a synthetic dataset yielded promising results, it is imperative to recognize that this environment likely represents a sanitized version of clinical reality. The most formidable technical and ethical barrier to the real-world deployment of this framework is the **statistical heterogeneity (non-IID) of patient data**, as theoretically outlined in Section 2.6. In a live ICU, the data distributions across patients are wildly diverse, and this heterogeneity has profound implications that extend beyond mere model performance, touching upon issues of clinical trust, algorithmic fairness, and health equity. Emerging enterprise AI models highlight that incorporating AI-powered content management and automated communication workflows can further streamline alarm analytics and clinical documentation processes, enhancing operational scalability [38], [39].

The successful performance of our FedAvg-based model in the simulation suggests that the synthetic dataset, while varied, possessed a degree of underlying homogeneity that may not be present in a real clinical cohort. A deployment in a diverse, multi-ethnic urban hospital, for example, would encounter a far greater degree of feature skew than our simulation could capture. The risk here is that the global model, influenced by the weighted average of all clients, could become biased toward the "average" patient or the majority demographic within the training cohort. This creates a dangerous scenario where the system is highly accurate for common patient profiles but unacceptably unreliable for patients who are outliers, whether due to rare conditions, unique physiologies, or belonging to an underrepresented demographic group.

This potential for performance disparity raises significant ethical concerns. An AI system that provides a higher standard of monitoring for one group of patients over another is not merely a technical failure; it is an instrument of health inequity. The principle of beneficence in medical ethics demands that such systems be rigorously audited for bias across different patient sub-populations (e.g., defined by age, sex, ethnicity, or primary diagnosis). The reliance on a single set of global performance metrics, such as a single F1-score, is insufficient. A truly robust evaluation must include a fairness audit that reports performance stratified across these sensitive attributes.

Furthermore, the issue of **concept drift**—where a patient's baseline changes over time—presents a major challenge to clinical trust. If a model trained during a patient's acute illness phase is not able to adapt as the patient stabilizes, it will begin to generate erroneous alarms, reintroducing the very alarm fatigue it was designed to eliminate. Clinicians would quickly lose confidence in a system that cannot keep pace with the dynamic nature of their patients.

Therefore, moving this framework toward clinical readiness requires a strategic pivot from the simple FedAvg algorithm to more sophisticated solutions. A **Personalized Federated Learning (pFL)** approach, as introduced in Section 2.6.3, appears to be the most promising path forward [22]. In such a model, the collaboratively trained global model would not be the final arbiter of alarms. Instead, it would serve as a powerful, pre-trained foundation—an expert feature extractor that understands the general patterns of human physiology. This global model would be deployed to the edge gateway, where it would then be rapidly fine-tuned and personalized using only the data from that specific patient.

This pFL architecture would offer a compelling synthesis: the **generalization** power of learning from a diverse population and the **specificity** of a model that is an expert on a single individual. It directly addresses the problem of client drift by design and is inherently adaptive to concept drift, as the local model can be continuously updated. Proposing a future randomized controlled trial that directly compares the clinical efficacy and fairness of a standard FedAvg approach against a pFL approach would be a critical next step. Such a study would not only validate the technology but also provide a transparent assessment of its equity, a non-negotiable prerequisite for the responsible integration of AI into critical care.

4.4. Future Research Directions

Building upon this work, several exciting avenues for future research emerge. The most critical is conducting a **prospective, randomized controlled trial** to evaluate the framework's real-world impact on alarm rates, clinician response times, and patient outcomes. Such a study would provide the definitive evidence needed for clinical adoption [5].

From a technical perspective, future work should explore more advanced federated learning algorithms designed to handle non-IID data and statistical heterogeneity, such as FedProx or SCAFFOLD. Investigating techniques for **on-device personalization**, where the global model serves as a foundation that is further fine-tuned and adapted on the edge device, could further enhance performance.

Another promising direction is the integration of **explainable AI (XAI)** techniques. For a clinician to trust an AI-driven alarm, the system should be able to provide a reason for its decision (e.g., "Alarm triggered due to a concurrent drop in SpO2 and a sharp increase in heart rate variability"). This would transform the system from a "black box" into a transparent clinical decision support tool. Finally, expanding the framework to incorporate a wider range of data streams, such as respiratory rate, blood pressure, and even data from the electronic health record, will be key to developing a truly holistic patient monitoring system.

5. Conclusion

Alarm fatigue remains a pervasive and dangerous problem in modern critical care. This study introduced and evaluated a novel framework that integrates wearable sensors, Edge AI, and Federated Learning to create an intelligent, privacy-preserving alarm management system. Our simulation results demonstrate that this federated edge approach is associated with a dramatic reduction in false alarms compared to traditional methods, without compromising the ability to detect true critical events. By enabling collaborative model training without centralizing sensitive data, our framework offers a scalable and ethically sound path toward a future where clinical alarms are both meaningful and manageable. While significant challenges related to clinical validation and data heterogeneity remain, this research lays a strong foundation for the development of next-generation patient monitoring systems that can enhance patient safety and reduce the cognitive burden on frontline clinicians.

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