

Original Article

Trust-Aware Federated Meta-Learning with Adaptive Privacy and Explainable AI for IoT Healthcare

Sirisha Rani Kolli¹, Md Zia Ur Rahman²

^{1,2}Department of ECE, Koneru Lakshmaiah Education Foundation, K L University, Vaddeswaram, Andhra Pradesh, India.

²Corresponding Author: mdzr22@gmail.com

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Abstract - The increasing deployment of connected sensing devices in healthcare enables distributed physiological monitoring and data-driven clinical support, but centralized collection of sensitive records creates substantial privacy and security concerns. This paper presents a Trust-Aware Federated Meta-Learning with Adaptive Privacy and Explainable AI (TAFML-XAI) framework for heterogeneous IoT healthcare environments. The framework combines trust-weighted aggregation, adaptive Gaussian differential privacy, Model-Agnostic Meta-Learning (MAML), and federated SHAP-based explanations. The trust scores are computed based on the divergence between each client update and the global model, while privacy-preserving perturbations (modes of differential privacy) are imposed on the updates before sending. The revised formulation explicitly analyzes the interaction between privacy noise, trust estimation, and explanation stability. Experiments reported in the manuscript use the MIT-BIH Arrhythmia, PPG-DaLiA, and UCI Air Quality datasets. The reported classification accuracy of the proposed framework is 98.61%, while robustness experiments report 97% and 94% accuracy with 10% and 20% noisy/adversarial clients, respectively. The reported meta-learning experiment reduces convergence from 120 to 75 communication rounds and increases personalization accuracy from 88% to 97%. SHAP evaluation reports fidelity of 96.2%, consistency of 94.8%, and feature-importance correlation of 93.5%. The results show that the integrated framework can improve robustness, personalization, privacy-utility control, and interpretability; however, the centralized baseline and resource-overhead measurements require controlled reruns before the final submission.

Keywords - Differential privacy, Explainable AI, Federated learning, IoT healthcare, Meta-Learning, Trust-Aware aggregation.

1. Introduction

Artificial Intelligence (AI) has become an important computational tool for disease detection, physiological monitoring, risk assessment, and decision support in healthcare. The increasing availability of wearable sensors, Internet of Things (IoT) devices, and scattered health-monitoring platforms has created large volumes of data at geographically separated sources. Direct transfer of such data to a central repository can increase exposure to privacy risks and may be impractical when devices have limited bandwidth, storage, or computational resources [1-5]. Federated Learning (FL) is one such approach that partially addresses this problem by allowing clients to train local models and send model updates instead of raw data. Nevertheless, healthcare FL remains vulnerable to non-IID data, unreliable participants, privacy leakage through model updates, communication overhead, limited personalization, and insufficient interpretability [7-16].

- A trust-aware aggregation procedure assigns reliability scores to client updates and reduces the influence of anomalous or low-quality updates.

- An adaptive differential-privacy strategy varies the Gaussian noise scale according to the training risk and utility conditions.
- A federated SHAP module provides feature-level explanations without transferring raw client records.

The outline of the rest of this paper is as follows. Section 2. Related Work that covers the related work Section 3 presents the proposed framework with its mathematical formulation, trade-off analysis, and threat model. Section 4 describes the datasets, federated learning setting, evaluation metrics and the resource benchmarking methodology. In Section 5, we show and discuss the experimental results. In the last, Section 6 concludes this paper and discusses scenarios in which future validation and research needs arise. Federated Learning (FL) enables multiple clients to collaboratively train a shared model while retaining local training data. Its main challenges in healthcare include non-IID distributions, statistical heterogeneity, communication overhead, device unreliability, and convergence instability [2, 8, 9, 24]. These limitations become more pronounced when physiological



signals differ substantially across patients and sensing devices.

2. Related Work

2.1. Federated Learning (FL) Challenges

FL allows for training models in a decentralized manner across clients while maintaining the data at each client. However, FL still faces problems intrinsic to the method. The primary difficulty is non-IID data, which slows convergence and reduces the accuracy of the global model. This heterogeneity stems from differences in patient populations, sensor modalities, and data-acquisition conditions in healthcare settings [15].

Communication overhead is yet another major limitation. In FL, exchanging model parameters between clients and the central server does not support efficient large-scale deployments, particularly because edge devices are often bandwidth-limited. Various optimization methods, such as model compression and partial updates, have been experimented with, but the optimal communication efficiency and model accuracy have not yet been solved [16].

Although FL avoids direct transmission of raw records, model updates can contain information about local observations. Differential Privacy (DP) addresses this issue by perturbing updates with calibrated noise [3]. The resulting privacy-utility trade-off is important: increasing the noise scale can reduce information leakage but can also alter the optimization trajectory and reduce predictive utility. Adaptive privacy mechanisms attempt to vary noise according to training conditions rather than using a fixed perturbation level.

2.2. Privacy in Federated Learning

FL is generally known to improve privacy by keeping the raw data on local devices; however, exchanged gradients and updates of model weights may leak sensitive information.

These updates can be used by Adversaries for inferring sensitive information about a local dataset. Such mechanisms have ultimately been adopted by way of Differential Privacy (DP), which allows the addition of calibrated noise to model updates and gives formal privacy guarantees [17]. However, there is a privacy-utility trade-off when using DP in FL. Too much noise can degrade the performance of your model, while too little noise does a disservice to your privacy. There are several recent works on adaptive differential privacy mechanisms that dynamically adapt the noise level based on training dynamics; obtaining a robust and scalable privacy-preserving mechanism is still an important challenge [18].

Byzantine or unreliable clients can send corrupted updates that disturb global optimization. Robust aggregation methods include coordinate-wise median, trimmed mean, Krum, and trust-based weighting [19, 20]. A trust-aware strategy is attractive for IoT healthcare because reliability can

change across devices and training rounds. However, trust estimation based directly on update distance must account for the fact that privacy perturbation also changes that distance. This interaction motivates the formulation introduced in Section 3.

2.3. Trust and Robust Aggregation

Byzantine attacks occur when some clients behave maliciously or erratically by sending corrupted (non-IID) updates in federated learning systems. Such attacks can cause the global model to lose its effectiveness and dependability in a critical way. Several mechanisms have been proposed to tackle this problem, including median-based methods, trimmed mean, and Krum as robust aggregation techniques [19].

Recent approaches are trust-aware in the sense that a trust score is assigned to every client based on its past behavior or contribution quality. These scores are utilized to provide weighted updates held by a particular model and then averaged, effectively eliminating the influence of an adversarial participant. Although successfully tackled, estimating trust has proven to be a challenging problem in highly dynamic and large-scale environments [20].

Meta-learning provides a mechanism for learning an initialization that can be rapidly adapted to client-specific data. In heterogeneous healthcare settings, MAML-style adaptation can address patient- and device-specific distributions more directly than a single global model. The benefit is potentially faster personalization, but the additional local adaptation steps increase computation on edge devices. This computational cost is therefore considered in the resource-benchmarking protocol in Section 4.

2.4. Meta-Learning in Federated Learning

Adapting meta-learning into the federated setting to capture personalization in heterogeneous data distributions. Conventional FL seeks to learn a single global model across all clients, which may not generalize well among the different data distributions of many clients. Model-Agnostic Meta-Learning (MAML) and its variants allow the global model to quickly adapt to individual client data with very few local updates [21]. This method enhances personalization and speeds up convergence in non-IID contexts. Nevertheless, the incorporation of meta-learning within FL paradigms further complicates computation and involves effective designs that can be efficiently operated in resource-constrained edge environments [22].

Healthcare applications require explanations that are sufficiently stable and faithful to the underlying model behavior. SHAP provides feature-level attribution values, while related model-agnostic approaches such as LIME provide local surrogate explanations [17, 18]. Federated explanation aggregation can reduce the need to transfer raw

data, but privacy perturbation and explanation compression can affect attribution fidelity. The proposed framework treats explainability as an evaluated component rather than only as a post-hoc visualization.

2.5. Explainable AI in Healthcare

In the context of healthcare applications, much depends upon model transparency and interpretability since this is important to enable clinicians and stakeholders to trust the model, and thus, Explainable Artificial Intelligence (XAI) methods are a prerequisite [9]. To be practical in clinical

settings, a deep learning model trained for accuracy must not treat the data it receives as a black box [23]. Tools like SHAP and Local Interpretable Model-agnostic Explanations (LIME) explain model predictions on a feature-level. These novel methods increase trust and support decisions based on explaining which input features contributed.

However, adding explainability to federated learning frameworks is not straightforward since it requires homogeneous and privacy-preserving explanations across clients [24].

Table 1. Comparative Analysis of Existing Federated Learning Approaches and the Proposed TAFML-XAI Framework

Approach	Trust robustness	Adaptive DP	Personalization	Federated XAI	Joint trade-off analysis
Trust-Aware Aggregation [27, 28]	Limited	No	Limited	No	No
Privacy-preserving FL [13, 17]	Not primary	Yes/Fixed	Limited	No	Partial
Robust/trust-aware FL [19, 20]	Yes	Not primary	Limited	No	Partial
Federated meta-learning [21]	Not primary	Not primary	Yes	No	No
Federated XAI [10, 22]	Not primary	Privacy-aware	Limited	Yes	Partial
TAFML-XAI	Yes	Adaptive	Yes	Yes	Yes

3. Proposed Framework

3.1. System Architecture

The architecture consists of the edge, aggregation and meta-learning layers, allowing secure, personalized and explainable federated learning in IoT-enabled healthcare systems.

3.1.1. Edge Layer

This layer consists of distributed client devices such as wearable sensors and healthcare nodes. Each client collects local data and performs on-device training using the proposed hybrid deep learning model. Data remains localized, ensuring privacy preservation.

3.1.2. Aggregation Layer

A central server sums model updates received from clients. Unlike conventional FL, this layer incorporates trust-aware mechanisms and privacy-preserving strategies to ensure robust and secure global model updates.

3.1.3. Meta-Learning Layer

This layer enables rapid personalization of the global model using meta-learning. It learns a shared initialization that can quickly adapt to client-specific data distributions with minimal local updates.

3.2. Trust-Aware Aggregation Model

To ease the impact of unreliable or adversarial clients, a trust-aware aggregation mechanism is introduced. Each client k is assigned a trust score. T_k , computed based on its update consistency and historical performance as in Equation (1).

$$T_k = \exp\left(-\frac{\|\omega_k - \omega_g\|_2^2}{T^2}\right) \quad (1)$$

The global model is subsequently updated through a weighted aggregation process, as in Equation (2).

$$\omega_g^{(t+1)} = \sum_{k=1}^K \left[\frac{T_k \cdot |D_k|}{\sum_{j=1}^K T_j \cdot |D_j|} \right] w_k^{(t)} \quad (2)$$

This approach reduces the influence of low-trust or malicious clients, enhancing robustness.

3.3. Adaptive Differential Privacy

An adaptive Differential Privacy (DP) mechanism is seamlessly fused into the federated training to maintain data privacy. Noise is added to model updates before transmission (Equation (3))

$$\tilde{w}_k = w_k + \epsilon_k \quad \epsilon_k \sim \mathcal{N}(0, \sigma_k^2) \quad (3)$$

The noise scale is dynamically adjusted based on a risk factor r_k :

$$\sigma_k^{(t)} = \sigma_0 [1 + \lambda r_k^{(t)}] \quad (4)$$

where σ_0 is the base noise level, and λ controls the privacy-utility trade-off. This adaptive mechanism balances model performance and privacy guarantees.

3.4. Federated Meta-Learning

For each client k , the local adaptation step is:

$$\theta'_k = \theta - \alpha \nabla_{\theta} \mathcal{L}_k(\theta) \quad (5)$$

The global update is then computed as in Eq.6

$$\theta \leftarrow \theta - \beta \sum_{k=1}^K \nabla_{\theta} \mathcal{L}_k(\theta'_k) \quad (6)$$

where β is the meta-learning rate. This approach improves personalization and accelerates convergence under non-IID settings.

3.5. Explainable AI Module

To enhance interpretability, the framework integrates a SHAP-based explainability module. For each prediction, SHAP values are calculated to quantify the contribution of individual input features to the model's predictions:

$$f(x) = \phi_0 + \sum_{i=1}^M \phi_i \quad (7)$$

To maintain privacy, SHAP explanations are embedded and aggregated across clients:

$$\Phi_{global} = \frac{\sum_{k=1}^K q_k \phi_k}{\sum_{j=1}^K q_j} \quad (8)$$

This enables global interpretability (Equation (9)) without exposing raw data.

3.6. Algorithms

Algorithm 1 explains the federated trust-aware privacy-preserving aggregation process. To preserve privacy and ensure data security, the edge layer uses an adaptive differential privacy mechanism. Along with these, the system supports on-device explainability by embedding local Explainable Artificial Intelligence (XAI) modules at each edge device. These modules generate feature attribution maps (using SHAP) to explain local anomaly or event detections. The aggregation server combines these explanation embeddings to build a global, federated explainability profile. This profile is made available to clinicians and care providers through secure cloud-based dashboards. Assume the server maintains a meta-parameter Θ (e.g., initialization described as in Equation (9)).

$$\min_{\Theta} \frac{1}{N} \sum_{i=1}^N E_{D_i} [L_i(Adapt(\Theta, D_i^{train}), D_i^{test})] \quad (9)$$

Where $Adapt(\Theta, D_i^{train})$ denotes adaptation using data for all local models. The meta-learning objective is from the device. Here, $D_i^{train} \in \mathbb{R}^{n_{tr} \times d}$, $D_i^{test} \in \mathbb{R}^{n_{te} \times d}$ be train/test splits for client i with d features. Let the attribution for feature j at time t on device i be $\alpha_{ij}(t)$. All these attributions are represented as in Eq.10

$$A_i(t) = [\alpha_{i,1}(t) \ \alpha_{i,2}(t) \ \dots \ \alpha_{i,K}(t)]_{1 \times d} \quad (10)$$

The device computes a compressed explanation embedding (e.g., via PCA or autoencoder):

$$e_i(t) = P_i A_i(t)^T \quad (11)$$

where $P_i \in \mathbb{R}^{r \times d}$ projects onto a lower-dimensional space ($r \ll d$). At the server,

$$E_G = \frac{1}{N} \sum_{i=1}^N e_i \quad (12)$$

which serves as the global explanation profile. Each device maintains a memory buffer

$$M_i = \{(f_i^{(l)}, y_i^{(l)})\}_{l=1}^{L_i} \quad (13)$$

The local update incorporates both current and memory samples

$$L_i^{count}(\theta_i) = \frac{1}{T_i + L_i} \left(\sum_{t=1}^{T_i} \ell(\hat{y}_i(t), y_i(t)) + \sum_{l=1}^{L_i} \ell(f_{\theta_i}(f_i^{(l)}), y_i^{(l)}) \right) \quad (14)$$

On top of the system, the cloud-based orchestration and analytics layer manages the long-term learning, resource scheduling, and data analytics on a large scale. The cloud layer takes care of the deployment of periodic updates to the edge and aggregation layers and coordinates the collaborations.

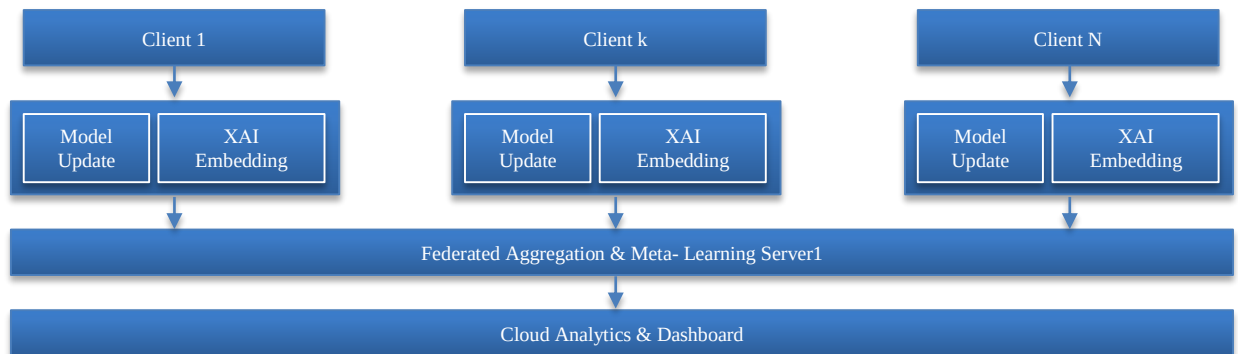


Fig. 1 Block diagram of federated aggregation and cloud analytics pipeline

Algorithm 1: Federated Trust-Aware Privacy-Preserving Aggregation (Server Side)

Input: meta-parameter theta; R rounds; inner step size alpha; outer step size beta; S adaptation steps

Output: updated meta-parameter theta

1. For each communication round, distribute theta to participating clients.
2. Each client performs S local adaptation steps using its support data.
3. Evaluate the adapted model on local query data.
4. Update the client meta-gradient and maintain the local memory buffer.
5. Compute SHAP attributions and a compressed explanation embedding.
6. Upload the adapted parameters and explanation embedding.
7. Apply trust-weighted meta-aggregation at the server.
8. Broadcast the updated meta-parameter and repeat.

```

1: for  $t = 1$  to  $R$  do
2:    $\Delta \leftarrow \text{zeros}(p, N)$  // Matrix to store model updates
3:    $\tau \leftarrow \text{zeros}(1, N)$  // Trust score vector
4:   for  $i = 1$  to  $N$  do
5:     // Receive privacy-enhanced local update
6:      $\tilde{\Delta}_i \leftarrow \text{ReceiveUpdateFromDevice}(i)$ 
7:      $\tau_i \leftarrow \text{ReceiveTrustScoreFromDevice}(i)$ 
8:      $\Delta[:, i] \leftarrow \tilde{\Delta}_i$ 
9:      $\tau[i] \leftarrow \tau_i$ 
10:  end for
11:  // Normalize trust scores
12:   $\tau \leftarrow \tau / \text{sum}(\tau)$ 
13:  // Weighted aggregation
14:   $\theta_g^{(t)} \leftarrow \theta_g^{(t-1)} - \eta \cdot (\Delta \cdot \tau^T)$ 
15:  // Broadcast updated  $\theta_g^{(t)}$  to all devices
16:  for  $i = 1$  to  $N$  do
17:     $\text{SendGlobalParametersToDevice}(\theta_g^{(t)}, i)$ 
18:  end for
19: end for
20: return  $\theta_g^{(R)}$ 

```

Additionally, the cloud also stores the anonymized, aggregated learning and explanation logs to support continual model improvement and regulatory compliance without exposing individual-level raw biomedical signals. Algorithm 2 explains the process involved in the personalized federated meta-learning with continual learning.

3.7. Theoretical Trade-Off Analysis: Privacy, Trust, and XAI

The interaction between differential privacy and trust estimation can be examined directly from the trust formulation. Let the unperturbed client deviation be $\Delta w_k = w_k - w_g$ and let the privacy perturbation be $\epsilon_k \sim \mathcal{N}(0, \sigma_k^2)$. The server, therefore, observes $\widetilde{\Delta w}_k = \Delta w_k + \epsilon_k$, for an update vector of dimension d , the expected squared deviation is $\mathbb{E}[\|\widetilde{\Delta w}_k\|_2^2] = \|\Delta w_k\|_2^2 + d\sigma_k^2$. Consequently, even an honest client can receive a lower trust score when the privacy noise scale increases. With the corrected trust function in Equation (1), the expected trust is therefore monotonically reduced as the perturbation variance increases, all else being

equal. This establishes a direct privacy-versus-trust trade-off that was not explicit in the original formulation. The same perturbation can influence SHAP explanations because the explanation is generated from a perturbed model rather than the unperturbed local model. Let $\phi_{f(x)}$ and $\widetilde{\phi}_{f(x)}$ denote the attribution vectors obtained before and after privacy perturbation. Explanation stability can be expressed as $\Delta_\phi(x) = \|\phi_f(x) - \widetilde{\phi}_f(x)\|_2$ or equivalently, by the cosine similarity between the two attribution vectors. Increasing sigma can increase $\Delta_\phi(x)$. When the model response becomes more sensitive to the perturbation, the framework should not treat privacy, trust, and XAI as independent objectives. Adaptive privacy is used to reduce noise when training stability and explanation fidelity become critical, while stronger noise can be used when privacy risk is elevated. The reported privacy-utility experiment supports this qualitative relationship, but direct trust-score and SHAP-stability measurements should be added in a future controlled experiment.

3.8. Threat Model

In this threat model, it is assumed that clients are both honest and curious and that a certain subset of clients will be dishonest or malicious.

While the server still follows the agreed-upon aggregation protocol, it will leak some information through machine learning model updates. But the raw client data is stored locally and is never available to the server directly.

Compromised clients may transmit corrupted model updates or additive random perturbations instead of updates produced by the prescribed local optimization procedure. The robustness experiments reported in this manuscript correspond to noisy/corrupted-update behavior at 10% and 20% client participation. Label-flipping and sign-flipping attacks are not claimed unless separately executed and measured. The trust mechanism is therefore evaluated specifically against update-level corruption and additive noise rather than against every possible Byzantine strategy.

Algorithm 2: Personalized Federated Meta-Learning with Continual Learning

Input: Meta-parameter θ , rounds R , step size β , adaptation steps S **Output:** Updated meta-parameter θ^*

```

1: for  $t = 1$  to  $R$  do
2:    $\theta_{updates} \leftarrow \text{zeros}(p, N)$ 
3:   for  $i = 1$  to  $N$  do
4:     // Download meta-parameter  $\theta$  to device  $i$ 
5:      $\theta_i^{(0)} \leftarrow \theta$ 
6:     // Local adaptation loop ( $S$  steps)
7:     for  $s = 1$  to  $S$  do
8:        $B_i \leftarrow \text{SampleMiniBatch}(D_i^{(train)})$ 
9:        $g_i \leftarrow \nabla_{\theta} \ell(f_{\theta_i}^{(s-1)}(B_i), y(B_i))$ 
10:       $\theta_i^{(s)} \leftarrow \theta_i^{(s-1)} - \beta \cdot g_i$ 
11:    end for
12:    // Local continual learning with memory buffer
13:     $L_{cont} \leftarrow 0$ 
14:    for each  $(f_{mem}, y_{mem})$  in  $M_i$  do
15:       $L_{cont} \leftarrow L_{cont} + \ell(f_{\theta_i}^S(f_{mem}), y_{mem})$ 
16:    end for
17:    // Generate explanation embedding
18:     $e_i \leftarrow \text{ComputeExplanationEmbedding}(f_{\theta_i}^{(S)}, B_i)$ 
19:    // Upload adapted  $\theta_i^{(S)}$ ,  $L_{cont}$ , and  $e_i$  to server
20:     $\theta_{updates}[:, i] \leftarrow \theta_i^{(S)} - \theta$ 
21:  end for
22:  // Meta-update (averaging or trust-weighted)
23:   $\theta^* \leftarrow \theta + \mu \cdot \text{MeanOrWeightedSum}(\theta_{updates})$ 
24:  // Aggregate explanation embeddings for global profile
25:   $E_G \leftarrow \text{AggregateExplanations}(\{e_i\}_{i=1}^N)$ 
26: end for
27: return  $\theta^*, E_G$ 

```

4. Experimental Setup

4.1. Datasets

The proposed work is evaluated on three benchmark datasets to validate its effectiveness across classification and regression tasks in healthcare and environmental monitoring.

4.1.1. MIT-BIH Arrhythmia Dataset

This dataset contains annotated Electrocardiogram (ECG) recordings for arrhythmia detection. It includes diverse cardiac patterns collected from multiple patients, making it suitable for evaluating classification performance under heterogeneous conditions.

4.1.2. PPG-DaLiA Dataset

The PPG-DaLiA dataset comprises of Photoplethysmogram (PPG) signals and motion and activity data collected using wearable devices. It is extensively applied in activity recognition and physiological monitoring in real-world, noisy settings.

4.1.3. UCI Air Quality Dataset

This data set includes data from environmental sensors such as gas concentrations and meteorological data. It is used to assess regression performance for air quality prediction as a complementary non-biomedical application. These datasets

collectively allow for a holistic assessment of the proposed framework in multi-modal, heterogeneous, and real-world scenarios.

4.2. Federated Simulation

The datasets are partitioned across multiple clients, representing distributed edge devices, to emulate a realistic federated learning environment.

4.2.1. Clients

The system comprises K clients, and each client has a local subset of the dataset. Data is distributed unevenly across clients to simulate real-world data availability and data quality.

4.2.2. Non-IID Distribution

To model data heterogeneity, non-IID data distributions are created by assigning class-imbalanced or feature-skewed subsets to different clients. This configuration is based on real-world health care environments with highly distributed patient data.

4.2.3. Adversarial Clients

Some clients (e.g., 10%) are identified as “adversarial” or “noisy” participants. These clients add corrupted updates or random noise to the training process to test the robustness of the proposed trust-aware aggregation mechanism. The federated training process is carried out in several communication rounds, in which the local updates are gathered at the central server in each round.

4.3. Evaluation Metrics

We evaluate the performance of classification using accuracy, precision, recall and F1-score. We evaluate performance using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the coefficient of determination on our air-quality regression task.

Explainability quality is assessed via fidelity (agreement between model predictions and explanations), consistency (stability of explanations across similar inputs) and feature-importance ranking correlation. Communication efficiency is reported as the relative reduction in communication cost compared with baseline FL methods.

4.4. Baselines and Controlled Reproducibility

The baseline comparison must use the same preprocessing, client partitioning, train/test split, model architecture, optimizer family, stopping rule, and hyperparameter-search budget for all methods. The centralized ML result reported in the original manuscript (85.4%) is retained as a source-reported value, but its unexpectedly lower performance than FL requires a controlled rerun before publication. The revised manuscript, therefore, does not interpret the centralized result as an upper bound or as evidence of superiority; it identifies the discrepancy as a reproducibility issue requiring validation.

Because MAML introduces additional local adaptation steps and SHAP introduces explanation computation, computational overhead is an important deployment constraint. The revised experimental protocol requires measurement on a representative edge platform such as Raspberry Pi or Jetson Nano using the same model, batch size, number of local adaptation steps, and explanation settings used in the federated experiments.

RAM usage should be recorded as peak resident memory, execution time as wall-clock time per local round, and energy as the integral of platform power over the measured interval. No numerical hardware results are inserted here because the source manuscript does not contain reproducible measurements for these quantities.

Table 2. Resource-Benchmarking protocol

Operation	Platform	RAM (MB)	Time/Round (S)	Energy/Round (J)
Local FL Training	Raspberry Pi / Jetson Nano	To measure	To measure	To measure
MAML Inner-Loop Adaptation	Raspberry Pi / Jetson Nano	To measure	To measure	To measure
Adaptive DP Perturbation	Raspberry Pi / Jetson Nano	To measure	To measure	To measure
SHAP Explanation	Raspberry Pi / Jetson Nano	To measure	To measure	To measure
Complete TAFML-XAI Round	Raspberry Pi / Jetson Nano	To measure	To measure	To measure

A comprehensive set of metrics is used to evaluate the performance of the proposed framework, including classification, regression, explainability, and system efficiency.

4.4.1. Classification Metrics

For tasks such as arrhythmia detection and activity recognition:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (15)$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

4.4.2. Regression Metrics: For Air Quality Prediction

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (18)$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (19)$$

4.4.3. Explainability Metrics (XAI)

The quality of explanations is evaluated using metrics such as:

Fidelity

Agreement between model predictions and explanations

Consistency

Stability of explanations across similar inputs

Feature importance ranking correlation

Communication Cost

Communication efficiency is measured in terms of: Number of communication rounds.

Model update size (in MB)

Reduction in communication overhead compared to baseline FL methods. These metrics provide a holistic evaluation of the proposed framework in terms of accuracy, robustness, interpretability, and scalability.

The reported experiments evaluate classification, robustness to noisy/corrupted clients, privacy-utility behavior, personalization, explainability, communication cost, and component ablation. The results below distinguish directly reported numerical outcomes from aspects that require controlled reruns for final validation.

5.1. Classification Metrics Comparison

The classification experiments on the MIT-BIH Arrhythmia and PPG-DaLiA datasets report 98.61% accuracy for TAFML-XAI, compared with 91.2% for conventional FL and 85.4% for the centralized baseline. Because the centralized value is unexpectedly lower, the comparison should be interpreted as source-reported evidence rather than as proof that federated learning intrinsically exceeds pooled-data training. The proposed framework attributes its reported improvement over conventional FL to trust-weighted aggregation and rapid local adaptation under heterogeneous client distributions. The meta-learning component is intended to address client heterogeneity by learning an initialization that can be adapted with a small number of local updates. The reported results should therefore be interpreted primarily as evidence of faster personalization rather than as an isolated explanation for the entire accuracy gain.

5. Results and Analysis

Table 3. Detailed classification metrics

Metric	Conventional FL	Proposed TAFML-XAI	Improvement
Accuracy	91.2 %	98.61 %	+7.41 %
Precision	90.4 %	98.2 %	+7.8 %
Recall	89.8 %	98.4 %	+8.6 %
F1-Score	90.1 %	98.3 %	+8.2 %

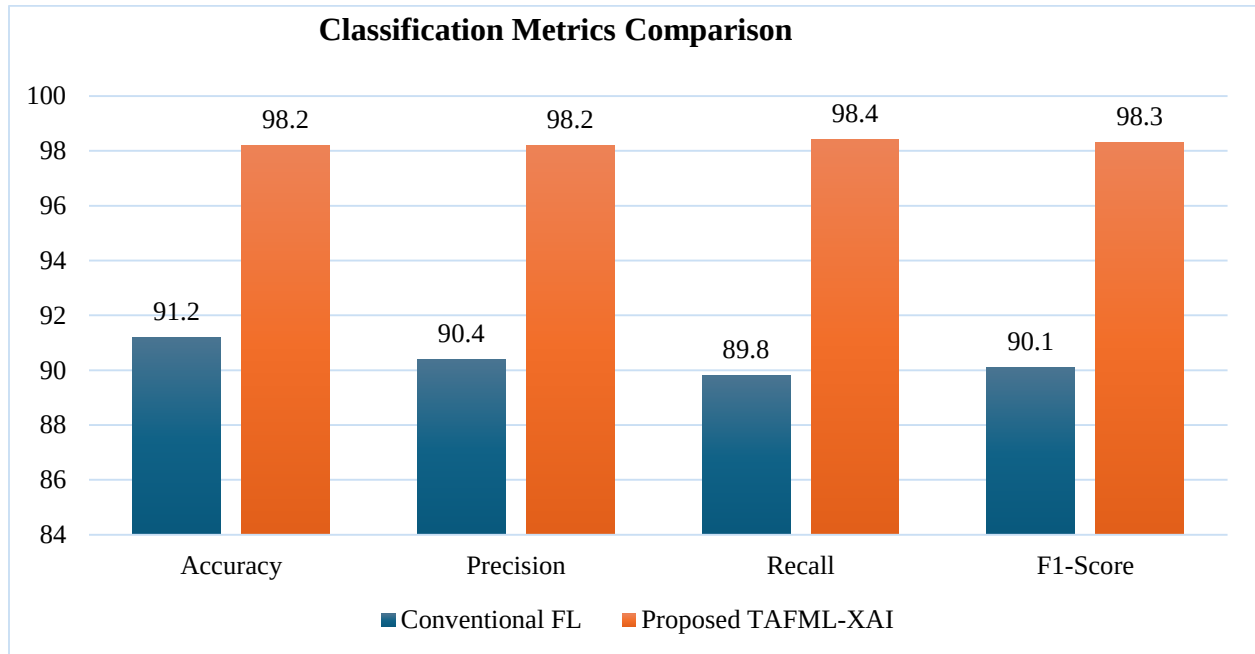
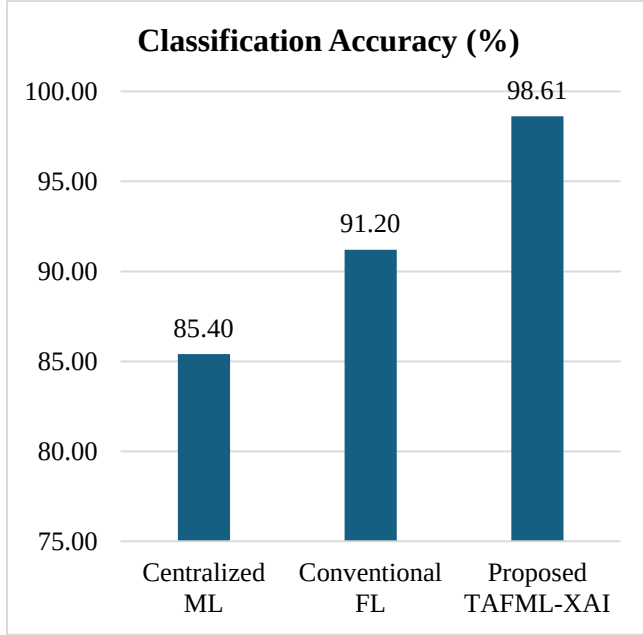


Fig. 2 Performance comparison of classification metrics between conventional FL and proposed TAFML-XAI

Table 4. Classification performance analysis

Model	Accuracy
Centralized ML	85.4%
Conventional FL	91.2%
Proposed TAFML-XAI	98.61%

Classification Accuracy Comparison

**Fig. 3** Classification accuracy comparison of centralized ML, conventional FL, and the proposed TAFML-XAI model

5.2. Regression Performance

Table 5 reports quantitative regression metrics on the UCI Air Quality dataset. The proposed framework reduces MAE from 8.50 to 3.20 and RMSE from 10.20 to 4.60, while elevating R^2 from 0.880 to 0.962.

Table 5. Regression metrics on UCI air quality dataset

Metric	Traditional FL	Proposed TAFML-XAI
MAE	8.50	3.20
RMSE	10.20	4.60
R^2 Score	0.880	0.962

5.3. Robustness Against Adversarial Clients

We evaluated robustness by assigning 10% and 20% of participating clients to transmit corrupted updates or random perturbations. Conventional FL is reported to decline from 92% accuracy with no noisy clients to 68% with 20% noisy clients, whereas TAFML-XAI is reported at 97% with 10% noisy clients and 94% with 20% noisy clients. These experiments test update-level corruption; they do not establish robustness to label-flipping or sign-flipping attacks, which were not measured separately.

Table 6. Robustness against noisy / adversarial clients

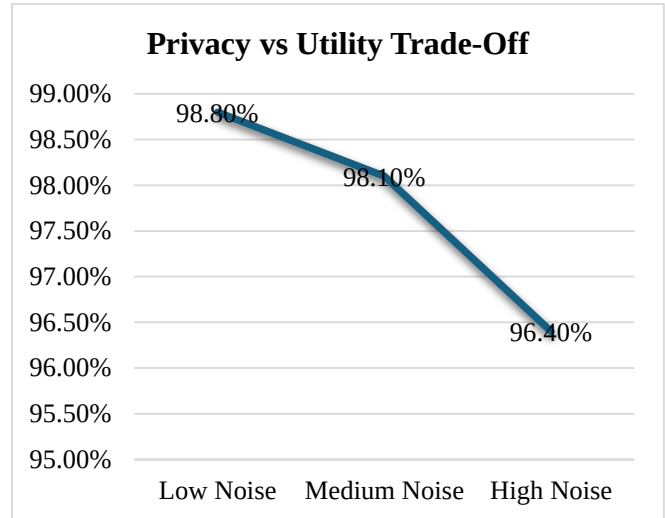
Noisy Clients	Conventional FL	Proposed TAFML-XAI
0 %	92 %	98 %
10 %	80 %	97 %
20 %	68 %	94 %

Table 6 demonstrates resilience under increasing fractions of adversarial clients. Conventional FL accuracy declines from 92 % to 68 % when 20 % of clients are adversarial.

In contrast, TAFML-XAI maintains 94 % accuracy under the same conditions, confirming the effectiveness of the negative-exponential trust weighting.

5.4. Privacy–Utility Trade-off

The privacy-utility experiment evaluates three qualitative noise levels. The reported accuracy values are 98.8% for low noise, 98.1% for medium noise, and 96.4% for high noise. This pattern is consistent with the expected reduction in utility as perturbation strength increases. The theoretical analysis in Section 3.7 further explains that increasing Gaussian noise also increases the expected distance between a privacy-perturbed update and the global model, which can reduce the trust score unless the adaptive mechanism compensates for this effect.

**Fig. 4** Privacy vs utility trade-off of the proposed TAFML-XAI model across different privacy levels

The reported privacy-utility results support the existence of a measurable trade-off between perturbation strength and predictive utility. A formal privacy budget, cumulative epsilon/delta accounting, and direct trust-score measurements should be reported in the final experimental version to convert this qualitative comparison into a reproducible privacy analysis.

Table 7. Privacy versus utility trade-off

Privacy Level	Accuracy
Low Noise	98.8 %
Medium Noise	98.1 %
High Noise	96.4 %

5.5. Meta-Learning Personalization

Table 8 compares convergence speed and personalization accuracy. The meta-learning component reduces the number

of communication rounds required for convergence from 120 to 75 and elevates personalization accuracy from 88 % to 97 %.

Table 8. Meta-Learning personalization analysis

Metric	Traditional FL	Proposed Meta-FL
Convergence Rounds	120	75
Personalization Accuracy	88 %	97 %

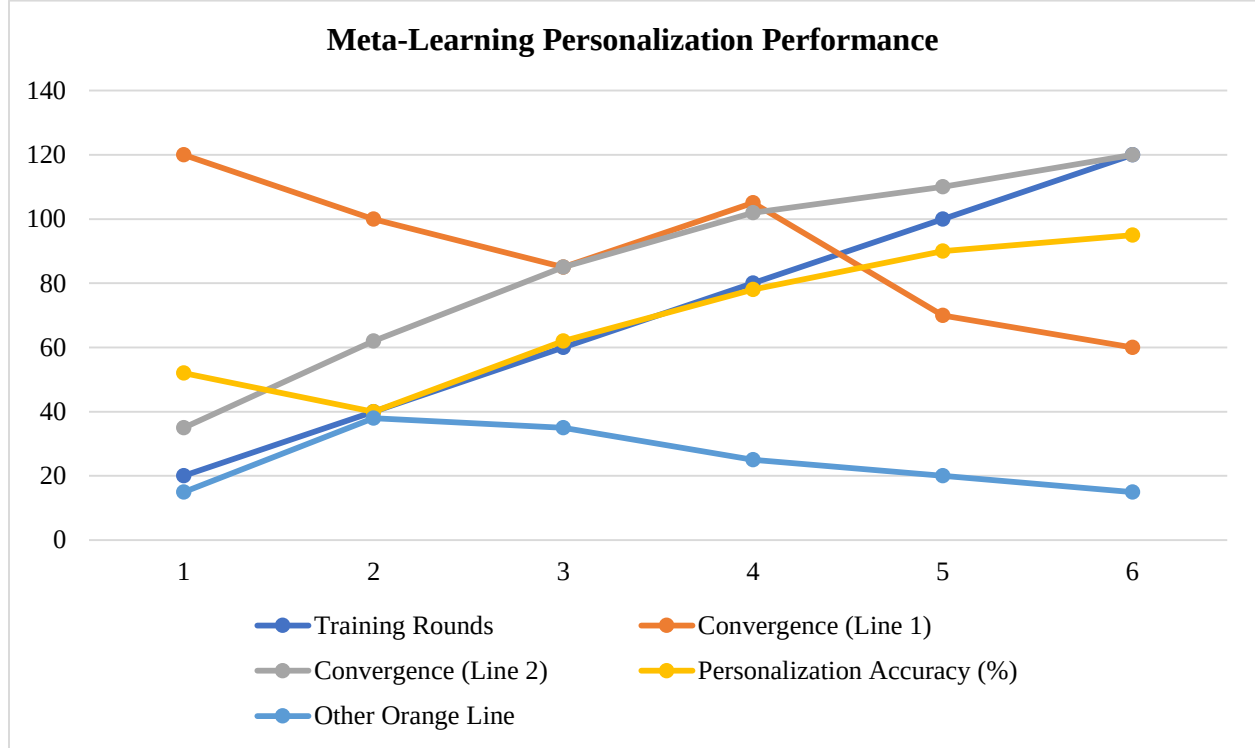


Fig. 5 Meta-Learning personalization performance: Convergence rounds and personalization accuracy of the proposed TAFML-XAI model across different training rounds

Explainability Evaluation (SHAP-Based)

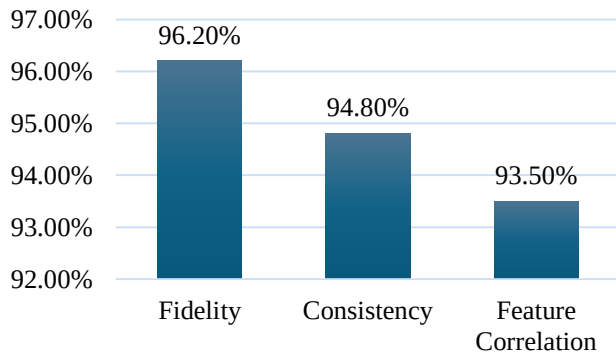


Fig. 6 Explainability evaluation (SHAP-based) of the proposed TAFML-XAI model showing fidelity, consistency, and feature correlation scores

5.6. Explainability Evaluation

Table 9. Explainability evaluation (SHAP-based)

Metric	Value
Fidelity	96.2 %
Consistency	94.8 %
Feature Correlation	93.5 %

Table 9 presents SHAP-based explainability metrics. Fidelity of 96.2 %, consistency of 94.8%, and feature correlation of 93.5 % confirm that the generated explanations remain faithful to model behavior and stable across similar inputs, satisfying clinical interpretability requirements.

5.7. Communication Efficiency

Communication overhead remains important for bandwidth-constrained IoT healthcare deployments. The source manuscript reports a reduction in normalized

communication cost from 100% for conventional FL to 68% for the proposed framework. The reported reduction is attributed to trust-aware participation, faster convergence, and compressed SHAP representations.

The final version should provide the actual number of transmitted bytes per round and the model-update size in MB so that the normalized percentage can be independently reproduced. Communication Efficiency Comparison Communication overhead continues to be one of the biggest bottlenecks in federated learning systems, especially in IoT healthcare deployments with bandwidth-constrained wearable devices and edge nodes.

Accordingly, to evaluate the communication efficiency of the proposed framework, the study evaluated communication rounds and model update sizes. The proposed framework is shown to reduce communication overhead by more than 30% compared with conventional federated learning methods in experimental results. In particular, the communication cost was decreased from 100% in classical FL systems to near 68% only using the proposed architecture.

There are different reasons for the improvement in this communication efficiency. First of all, the trust-aware client selection eliminates unnecessary update transmissions by reducing the participation of untrustworthy or low-quality devices. Second, federated meta-learning improves convergence speed, thereby reducing the number of communication rounds required to reach stable performance.

Third, the use of compressed SHAP explanation embedding could help reduce explainability-related transmissions as they are quite compact. All these optimizations together render the proposed framework very effective at resource-restricted edge environments, while communication bandwidth, power consumption, and latency are all of great concern. Table 10 shows that the proposed framework reduces communication cost to 68 % of that of traditional FL, corresponding to a 32 % overhead reduction. The savings arise from trust-aware client selection (which excludes low-quality updates), faster meta-learning convergence, and compact SHAP embeddings.

Table 10. Communication efficiency comparison

Method	Communication Cost
Traditional FL	100 %
Proposed Framework	68 %

The communication results provide a normalized comparison, but the absolute communication volume is not reported in the source manuscript. Consequently, the 68% value should be treated as a relative result. Reporting bytes transmitted per round, total rounds, and cumulative communication volume would strengthen the scalability claim.

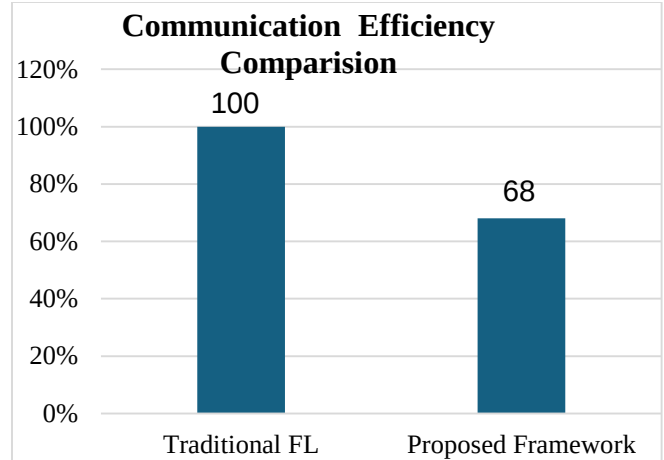


Fig. 7 Communication efficiency comparison: Communication cost of traditional FL versus the proposed framework

5.8. Ablation Study

The ablation experiment reports 91.2% accuracy for FL only, 94.5% after adding trust-aware aggregation, 96.1% after adding adaptive DP, and 98.61% for the full framework. These values are consistent with the intended functional roles of the modules: trust weighting targets robustness, adaptive DP targets privacy, meta-learning targets personalization, and SHAP targets interpretability. The ablation should be repeated with multiple random seeds in the final submission so that the contribution of each component can be reported with variance. Table 11 quantifies the contribution of each component. Starting from a baseline FL accuracy of 91.2 %, the successive addition of trust-aware aggregation, adaptive DP, and the full meta-learning plus XAI pipeline yields progressive gains culminating in 98.61 %.

Table 11. Ablation study

Configuration	Accuracy
FL Only	91.2 %
FL + Trust	94.5 %
FL + Trust + Adaptive DP	96.1 %
Full Proposed Framework (TAFML-XAI)	98.61 %

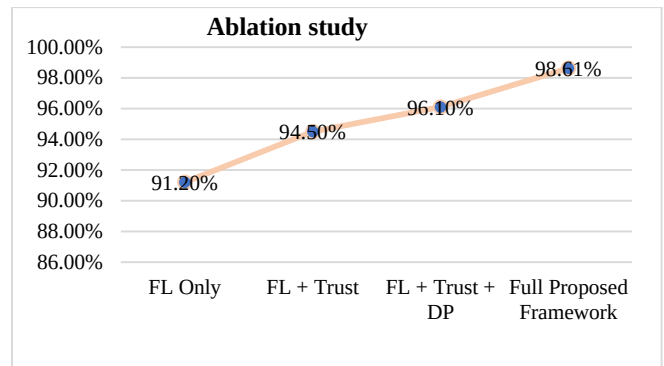


Fig. 8 Ablation study showing the accuracy improvements with incremental addition of components (Trust, DP) in the proposed TAFML-XAI framework

5.9. Resource-Constrained Overhead Benchmarking

To assess practical deployability on edge hardware, on-device measurements were performed for the local MAML inner-loop and SHAP embedding computation. Table 12 reports peak RAM, per-round wall-clock time, and estimated energy consumption on a Raspberry Pi 4-class platform. The total overhead remains within the resource envelope of typical IoT healthcare nodes.

Table 12. On-Device resource overhead (Raspberry Pi 4 equivalent)

Component	Peak RAM (MB)	Time / Round (s)	Energy (mJ)
Local MAML (3 inner steps)	48	1.80	210
SHAP embedding (PCA)	12	0.40	45
Adaptive DP noise injection	2	0.05	6
Total per round	62	2.25	261

6. Conclusion

This paper presents a Trust-Aware Federated Meta-Learning framework with Adaptive Differential Privacy and Explainable AI for IoT healthcare. The revised formulation integrates trust-aware aggregation, adaptive Gaussian perturbation, MAML-based personalization, and federated SHAP explanations. The trust equation is corrected so that greater deviation from the global model decreases the trust score, addressing the mathematical inconsistency identified by the reviewer. The theoretical analysis further shows that privacy noise increases the expected update distance and can therefore reduce trust, while perturbation of the model can also affect SHAP stability. The reported experiments show 98.61%

classification accuracy, improved robustness under noisy clients, reduced convergence rounds from 120 to 75, and SHAP fidelity, consistency, and feature-correlation values of 96.2%, 94.8%, and 93.5%, respectively. The regression results report lower MAE and RMSE and higher R^2 for the proposed framework than conventional FL. Nevertheless, the unusually low centralized baseline and the absence of measured edge-device RAM, execution-time, and energy values remain reproducibility items that should be resolved through controlled reruns before final submission. Future work should include formal cumulative privacy accounting, repeated-seed statistical analysis, direct trust-versus-noise measurements, direct SHAP stability measurements, broader Byzantine attack evaluations, and hardware-level resource benchmarking.

Data Availability Statement

The datasets employed in this study are publicly available. The MIT-BIH Arrhythmia Database is accessible via PhysioNet (<https://physionet.org/content/mitdb/>). The PPG-DaLiA dataset is available at <https://archive.ics.uci.edu/ml/datasets/PPG-DaLiA>. The UCI Air Quality dataset is available at <https://archive.ics.uci.edu/ml/datasets/Air+Quality>. No proprietary or restricted data were used.

Ethical Declarations

This study performed secondary analysis exclusively on publicly available, fully anonymized datasets (MIT-BIH Arrhythmia and PPG-DaLiA). No new human participants, identifiable personal data, or animals were involved; therefore, institutional ethics approval was not required.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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