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Federated Learning for Early Cardiac Anomaly Prediction in Cross-Silo IoMT Environments

Michael Georgiades
ISLab, CS, Neapolis University & Infostrada Communications
Cyprus
m.georgiades@nup.ac.cy

Lakis Christodoulou, Andreas Chari
R&D, Technology, and Innovation Biomed Medical Systems
Cyprus
lakis.christodoulou, andreaschari88@gmail.com

Kezhi Wang
Department of Computer Science Brunel University of London
UK
kezhi.wang@brunel.ac.uk

Kin-Hon Ho
Department of Business Administration Hong Kong Shue Yan University
Hong Kong SAR, China
khho@hksyu.edu

Yun Hou
Department of Computer Science Hang Seng University of Hong Kong
Hong Kong SAR, China
aileenhou@hsu.edu.hk

Wei Koong Chai
Department of Computing and Informatics Bournemouth University
UK
wchai@bournemouth.ac.uk

***Abstract*—Early detection of cardiovascular anomalies remains critical for proactive patient care, especially within the growing ecosystem of Internet of Medical Things (IoMT) devices. This study explores the application of Federated Learning (FL) to predict early cardiac events using electrocardiogram (ECG) signals across heterogeneous IoMT silos without centralized data sharing. We focus on Premature Ventricular Contraction (PVC) as an example of early event prediction. Using three real-world ECG datasets (PTB-XL, Chapman-Shaoxing, and MIT-BIH), we simulate cross-silo environments where local models are trained independently and aggregated through FL. Our experiments demonstrate that local models can already achieve high classification performance, but global models obtained via FL lead to consistent improvements in macro precision, recall, and F1-scores across datasets. Visual analysis of early ECG segments further highlights inter-dataset variability, emphasizing the importance of silo-specific characteristics. The results validate that FL is a promising strategy to enable scalable, privacy-preserving, and accurate early cardiovascular event prediction in IoMT systems, bridging clinical silos while safeguarding sensitive patient data.**

***Index Terms*—Federated Learning, IoMT, ECG, Early Event Prediction, Cross-Silo Learning, Cardiovascular Anomaly Detection**

I. Introduction

Cardiovascular diseases (CVDs) continue to represent the leading cause of global mortality, accounting for approximately 20.5 million fatalities in 2021 [1]. Projections suggest that the global burden of CVDs will increase by over 90% between 2025 and 2050, potentially resulting in more than 35 million cardiovascular-related mortalities annually by mid-century [2]. These alarming trends highlight the critical need for early detection, preventive care, and scalable diagnostic solutions capable of supporting proactive patient management.

Advancements in healthcare technologies have ushered in a paradigm shift toward more data-centric and intelligent systems, particularly in the realm of cardiovascular disease monitoring and diagnosis. In this context, machine learning (ML) algorithms applied to biomedical data such as electrocardiograms (ECGs) have gained increasing prominence. However, traditional centralized learning approaches pose substantial privacy risks due to the sensitive nature of medical data [3]–[5].

FL, first formalized by McMahan et al. [6], introduced a decentralized approach to collaboratively train models without centralizing sensitive data, addressing privacy concerns while enabling efficient distributed learning [7]–[12].

Applications of FL in healthcare span a wide range of modalities, from medical image classification to sensor-based vital sign analysis. In particular, ECG-based diagnosis of arrhythmias and other cardiac abnormalities has become a focal area, owing to the proliferation of wearable sensors and mobile ECG devices [13], [14]. These technologies enable real-time monitoring and early intervention, crucial for improving patient outcomes in both clinical and remote settings [15], [16].

Meanwhile, the IoMT ecosystem is rapidly expanding. The global IoMT market was valued at approximately USD 230.69 billion in 2024 and is projected to reach USD 658.57 billion by 2030, driven by the widespread adoption of connected health devices and remote monitoring systems [17]. Specifically, the market for wearable ECG monitors is expected to grow from USD 3.29 billion in 2023 to USD 4.01 billion in 2024, representing a compound annual growth rate (CAGR) of 21.7

In this work, we specifically target cross-silo IoMT environments, where healthcare institutions such as hospitals, clinics, and remote care facilities utilize IoMT devices—for example, wearable ECG monitors and portable diagnostics—for local data collection. Each institution maintains its own siloed dataset and collaborates to train a shared global model without exposing raw patient data [18]. This paradigm is particularly relevant in IoMT ecosystems, where resource constraints and privacy concerns hinder the deployment of traditional centralized machine learning approaches.

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Nonetheless, despite its advantages, FL still faces challenges related to data heterogeneity, communication costs, model personalization, and explainability [3], [4]. Recent studies propose architectural innovations, such as microservices-based platforms [19] and transfer learning-enhanced FL frameworks [13], to address these barriers.

The objective of this study is to demonstrate the practical benefits of FL in cross-silo IoMT settings, with an emphasis on early cardiovascular event prediction using ECG signals. Through experimental evaluation across distinct datasets, we illustrate how smaller entities—such as community hospitals, clinics, and rural care centers—can significantly enhance their predictive performance while preserving sensitive data privacy.

This article is organized as follows: Section II reviews related work on FL in ECG analysis and heart disease prediction. Section III describes the datasets and the cross-silo FL setup. Section IV presents the system model, including data preprocessing, local model architecture, and federated training procedures. Section V presents and analyzes the evaluation results, emphasizing accuracy, robustness, and privacy preservation. Section VI concludes the paper with key findings and outlines directions for future research.

II. Related Work

The growing body of literature in FL for ECG-based diagnostics demonstrates its transformative impact on healthcare AI systems. Numerous methodologies have been proposed to enhance the privacy, scalability, and diagnostic performance of cardiovascular models in distributed environments.

Several studies focus on improving arrhythmia classification and cardiovascular disease detection through FL. Pal et al. developed CardioNet, employing transfer learning for ECG arrhythmia classification [20], while Mane et al. proposed a lightweight FL system for arrhythmia detection on edge devices [21]. Sakib et al. explored asynchronous federated approaches to improve latency in ECG analysis [22], and Zhang et al. addressed non-IID data challenges in arrhythmia detection [23]. Similarly, Jimenez Gutierrez et al. applied FL to classify arrhythmias from 12-lead ECGs [24], while Meqdad et al. introduced a Gaussian-based aggregation module to handle data heterogeneity [25].

To personalize and optimize model performance, Tang et al. aligned feature distributions for individualized classification [26], and Park et al. designed a personalized FL system for mobile sensor data [15]. Similarly, Phan et al. presented an FL framework that balances privacy with ECG signal classification performance [14], while Zeleke et al. leveraged Kolmogorov-Arnold networks for explainability in ECG models [27].

Recent frameworks also address scalability and architectural modularity. Atitallah et al. proposed a microservice-oriented FL framework [19], and Yuan et al. developed an FL system tailored for IoMT devices [7]. Raza et al. combined transfer learning with explainable AI (XAI) [13], and Khan et al. hybridized FL with the Artificial Bee Colony algorithm in IoMT systems [28].

Efforts to benchmark and generalize FL models include Zhang et al.'s FedCVD benchmark on real-world CVD data [29], Hwang et al.'s practical utility evaluation across datasets [11], and Agrawal et al.'s multi-hospital analysis using differential privacy [30]. Complementarily, Antunes et al. provided a comprehensive taxonomy of FL systems [4], and Gafni et al. emphasized the signal processing underpinnings [10].

In specialized studies, Santos et al. explored atrial fibrillation detection with federated neural networks [31], and Alreshidi et al. developed Fed-CL for atrial fibrillation prediction [32]. Ying et al. proposed FedECG, integrating semi-supervised learning [33], while Asif et al. introduced weighted aggregation for ECG anomaly detection [34]. Other notable contributions include FedSDM by Rajagopal et al. [35], Couto et al.'s arrhythmia-focused system [36], and Lin et al.'s FedCluster framework for cross-device classification [37].

Further developments include Khan et al.'s asynchronous FL for improved cardiovascular prediction [38], Zou et al.'s UNet++-based approach for heart failure detection [39], and Qiu et al.'s paradigm for heart sound classification [40]. Semmadi and Bahhou provided an overarching discussion on FL's role in IoMT [41], and Elayan et al. examined FL sustainability in Internet of Things (IoT) systems [12].

Several large-scale datasets underpin these studies. The PTB-XL dataset [42], [43], the MIT-BIH arrhythmia database [44], and Zheng et al.'s 12-lead ECG dataset [45] are frequently employed. Goldberger et al.'s PhysioNet platform further enhances data accessibility [46].

Finally, systems-level and implementation perspectives are provided by Gupta et al. [9], Rani et al. [8], and Yoo et al. [47]. Federated radar applications are explored in Jiang et al.'s FedRadar system [48]. Cross-device and unsupervised learning approaches are examined by Kapsecker and Jonas [49], while Christodoulou et al. highlight real-time cardiovascular monitoring with FL integration [50]. Goto et al. proposed a multinational FL framework combining ECG and echocardiogram data for hypertrophic cardiomyopathy detection [51], and Gupta et al. applied LSTM (Long short-term memory) and CNN-based models in a federated setting for heart disease prediction [52]. Additional strategies were introduced by Ulver et al. for FL in clinical cardiovascular prediction [53], and Rao and Muneeswari, who proposed an IoT-integrated FL framework for CVD prediction [54]. Ensemble learning techniques were examined by Islam et al. [55], while Alahmadi et al. focused on mental stress detection using a privacy-preserved FL approach in IoMT systems [56]. Scalable FL architectures for healthcare sensors were also proposed by Sun and Wu [57], as well as Lee and Shin which assessed performance trade-offs using clinical benchmark datasets [5].

Despite these advancements, there remains a critical gap in validating FL systems under real-world, cross-silo healthcare scenarios, where privacy concerns, regulatory constraints, and institutional authorizations present significant barriers—underscoring the need for practical, use-case-driven investigations such as the one pursued in this study.

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III. Datasets and Cross-Silo FL Setup

For our cross-silo FL experiments, we utilize three major open-access ECG datasets: **MIT-BIH Arrhythmia Database** [44], **PTB-XL** [42], [43], and the **Chapman-Shaoxing ECG Dataset** [45].

MIT-BIH provides a collection of long-term ECG recordings annotated with heartbeat-level symbols, such as "N" (normal), "V" (premature ventricular contraction), and "A" (atrial fibrillation). Signals are segmented around annotated events, allowing flexible extraction of pre-event or event-centered samples.

PTB-XL consists of over 20,000 12-lead ECG records labeled according to the SCP-ECG coding standard, covering diagnoses like atrial fibrillation (AFIB), atrial flutter (AFLT), premature ventricular contractions (PVC), and normal sinus rhythm (SR).

Chapman contains more than 45,000 ECG recordings labeled using SNOMED CT clinical codes. It captures a broad range of cardiac conditions across diverse clinical settings, similarly covering arrhythmic events such as AFIB, AFLT, and PVC.

To maintain alignment across heterogeneous coding systems, we focus on **Premature Ventricular Contractions (PVC)** as a shared clinical target across all three datasets. Table I summarizes the distribution of total records and PVC-specific cases per dataset. Although labeling systems differ, PVC events offer a common diagnostic endpoint for federated training and evaluation.

Additionally, Figure 1 visually compares examples of PVC signals across the three datasets, highlighting morphology and amplitude differences that motivate the need for FL strategies capable of handling cross-silo heterogeneity.

Cross-silo FL enables decentralized model improvement without direct data sharing, a crucial capability for sensitive healthcare environments [13], [19], [20], [33], [35].

IV. System Model

In this study, we model early detection of PVCs using a Federated Learning (FL) framework applied to decentralized IoMT client datasets. Each client (hospital, clinic, or device) retains local ECG signals without sharing raw patient data. The high-level workflow is illustrated in Figure 2 and follows a five-step process aligned with our evaluation.

A. Step 1: Data Preparation

Given a set of local ECG recordings $\{(x_i, y_i)\}_{i=1}^{N}$ from each client, we preprocess the signals by:

- Selecting the first $L = 90$ samples (early prediction focus), corresponding to approximately 0.25 seconds of ECG signal at 360 Hz sampling,
- Normalizing each signal:

$$\tilde{x}_i = \frac{x_i - \mu(x_i)}{\sigma(x_i) + \epsilon},$$

where $\mu(x_i)$ and $\sigma(x_i)$ denote the mean and standard deviation of x_i, respectively, and $\epsilon = 10^{-6}$ prevents division by zero,

- Assigning binary labels:

$$y_i = \begin{cases} 1 & \text{if PVC detected,} \\ 0 & \text{otherwise.} \end{cases}$$

B. Step 2: Model Initialization

Each client receives a shared initialization of a lightweight 1D convolutional neural network (CNN) f_θ, parameterized by weights θ. This model, referred to as TinyECGCNN, consists of:

- Two convolutional layers with ReLU activations:

$$h_1 = \text{ReLU}(\text{Conv1d}(x)), \quad h_2 = \text{ReLU}(\text{Conv1d}(h_1)),$$

- A flattening layer and fully connected classification head:

$$\hat{y} = \text{Softmax}(W h_2 + b),$$

where W and b are trainable parameters. The model is designed for edge deployment and used to demonstrate the benefits of FL. Each client minimizes the standard cross-entropy loss:

$$\mathcal{L}_{\text{CE}}(\theta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}).$$

C. Step 3: Local Model Training

Each hospital client independently trains its local copy of TinyECGCNN using its own preprocessed ECG samples for a few epochs. No raw data is exchanged between clients or with the server.

D. Step 4: Federated Aggregation

Once local training is complete, each client k transmits its learned model weights θ_k to a central aggregator. The global model is updated using Federated Averaging (FedAvg):

$$\theta_{\text{global}} = \frac{1}{K} \sum_{k=1}^{K} \theta_k,$$

where K is the number of participating clients. No raw patient data is transferred during this process.

E. Step 5: Fine-Tuning and Evaluation

After aggregation, the global model can be optionally fine-tuned locally by each client to improve adaptation to site-specific characteristics. In our experimental setup, fine-tuning was performed on MIT-BIH to simulate adaptation at a smaller hospital.

Model performance is then evaluated using standard classification metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad \text{Precision} = \frac{TP}{TP + FP},$$

$$\text{Recall} = \frac{TP}{TP + FN}, \quad \text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

This five-step design enables early detection of PVC abnormalities in a privacy-preserving, distributed manner across heterogeneous IoMT hospital clients.

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TABLE I
DISTRIBUTION OF TOTAL RECORDS AND PVC CASES ACROSS FL CLIENTS (MIT-BIH, PTB-XL, CHAPMAN). PVC = PREMATURE VENTRICULAR CONTRACTION. ALTHOUGH CODING SYSTEMS DIFFER ACROSS DATASETS (E.G., SCP-ECG, SNOMED CT, MIT ANNOTATIONS), PVC EVENTS PROVIDE A SHARED CLINICAL TARGET FOR CROSS-SILO FL EXPERIMENTS.

Client (Dataset)	#Records	Code Type	Diagnosis	Description
MIT-BIH	19,386	Annotation Symbols (Various)	All ECG Classes	Full sample size after early signal segmentation, including PVC, Normal, AFIB, and other heartbeat categories.
PTB-XL	25,590	SCP-ECG Labels (Various)	All ECG Classes	Full set of clinical 12-lead ECG recordings with multiple cardiac diagnoses based on SCP-ECG labeling standards.
Chapman	45,152	SNOMED CT Codes (Various)	All ECG Classes	Comprehensive ECG dataset covering a wide range of SNOMED-coded cardiac conditions across multiple settings.
MIT-BIH	644	Annotation Symbol ("V")	PVC	Early abnormal ventricular beats identified in MIT-BIH via the "V" annotation symbol (ventricular ectopic beats).
PTB-XL	1,143	SCP-ECG Label ("PVC")	PVC	Premature ventricular contractions annotated according to the SCP-ECG clinical guidelines in resting ECGs.
Chapman	1,091	SNOMED CT Code ("427172004")	PVC	Ventricular premature beats detected using SNOMED CT coding in Chapman dataset ECG recordings.

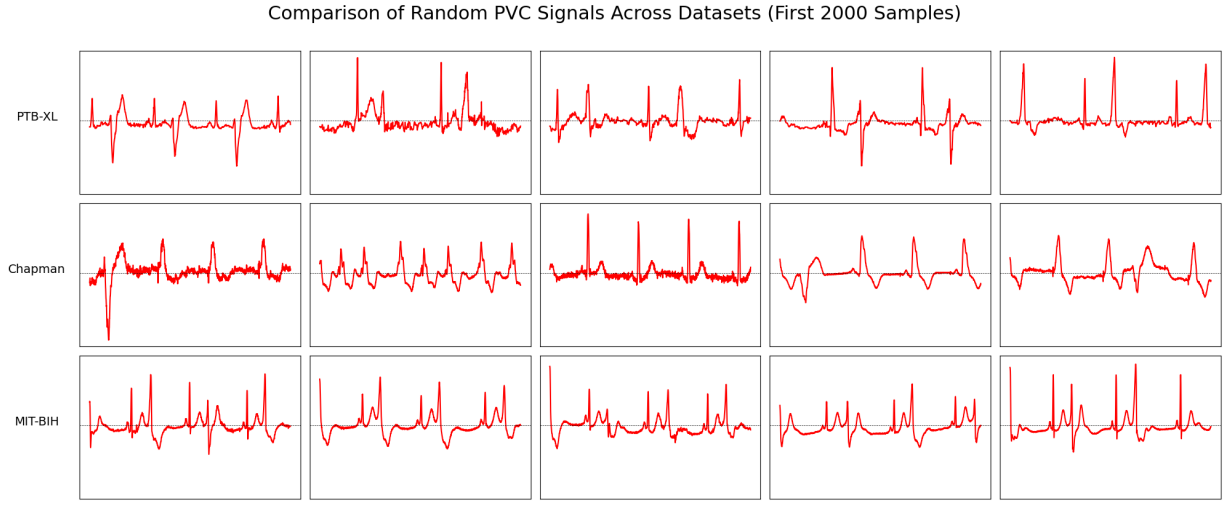

Fig. 1. Comparison of random PVC signals across the PTB-XL, Chapman, and MIT-BIH datasets (first 2000 samples shown). Differences in signal shape, noise, and amplitude are evident across the three silos.

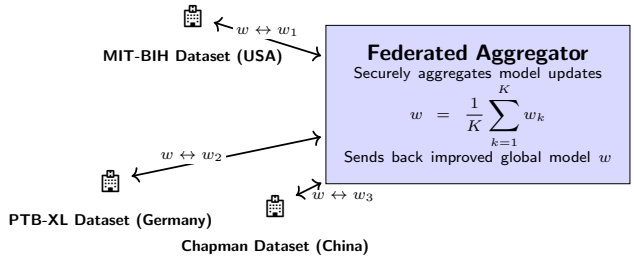

Fig. 2. FL across three hospital silos. Each hospital trains a local TinyECGCNN on early segmented MIT-BIH PVC signals, exchanges only model updates with the federated aggregator, and receives global model improvements.

V. EVALUATION AND DISCUSSION

This section evaluates the five-step Federated Learning (FL) framework introduced in Section IV, focusing on early-stage PVC prediction across decentralized IoMT silos. The evaluation simulates a realistic healthcare scenario in which each institution has limited ECG data and privacy constraints. To enable early detection, only the first 90 samples (approximately 0.25 seconds at 360Hz) are extracted from each ECG trace—prior to any arrhythmia onset.

Step 1: Dataset Preparation. PVC-labeled records were extracted from three sources: MIT-BIH (symbol "V"), PTB-XL ("PVC"), and Chapman (SNOMED code "427172004"). All records were normalized and segmented to retain only early signals. This process produced **682 early PVC signals** from MIT-BIH, with proportionally processed subsets from PTB-XL and Chapman for simulation purposes.

Step 2: Shared Model Initialization. A lightweight CNN model, referred to as TinyECGCNN, was defined to ensure compatibility with edge-device constraints. This model architecture was initialized centrally and distributed identically to all three client silos.

Step 3: Local Model Training. Each client (MIT-BIH, PTB-XL, and Chapman) independently trained its local copy

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of TinyECGCNN on its respective early PVC dataset for a few epochs (typically 3–5), producing local updates without sharing raw data.

Step 4: Aggregation via FedAvg. The local model parameters were transmitted to a central aggregator and combined using the Federated Averaging (FedAvg) algorithm. This simulated a single round of federated collaboration.

Step 5: Fine-Tuning and Evaluation. The aggregated global model was fine-tuned for two additional epochs using only MIT-BIH data, simulating further training at a smaller hospital site. Model performance was then evaluated on a held-out MIT-BIH test set to assess improvements in early PVC classification.

It is important to note that local models did not need to converge fully before aggregation. Instead, early-stage training across diverse silos was sufficient to produce meaningful global improvements—a typical design principle in FL systems to balance efficiency and generalization.

Two key visualizations summarize the evaluation:

As shown in Figure 3, the local MIT-BIH model achieved reasonable initial performance but exhibited notable misclassifications, particularly for PVC events. Specifically, the local model correctly classified 347 PVC samples, but misclassified 293 PVC instances as "Other," reflecting a substantial false-negative rate. Similarly, 83 "Other" samples were incorrectly classified as PVC, contributing to false positives.

After applying FL aggregation with the PTB-XL and Chapman silos and performing fine-tuning, the global model demonstrated substantial improvements. The number of correctly classified PVC events increased from 347 to 417, while false negatives decreased from 293 to 223. In addition, the global model reduced false positives from 83 to 40, and slightly improved the true negative count, correctly identifying 18,706 "Other" instances compared to 18,663 before FL.

Overall, these results highlight that cross-silo FL training not only enhanced the model's sensitivity to PVC events (true positives) but also improved its specificity by reducing incorrect PVC predictions. The improvements validate the benefits of knowledge sharing across different clinical silos while preserving data privacy.

Performance metrics in Figure 4 reinforce these findings. After FL, the macro-averaged precision increased from 0.8169 to 0.8606, recall rose from 0.7825 to 0.8261, and F1-score improved from 0.7873 to 0.8413. This is particularly notable given the constrained input size and minimal number of training samples.

Key takeaway: *Healthcare-oriented cross-silo FL enables early-stage cardiovascular anomaly prediction from minimal ECG signals, delivering substantial improvements in accuracy, precision, recall, and F1-scores, while safeguarding patient privacy across decentralized institutions governed by distinct administrative domains.*

Overall, the results show that smaller hospitals—such as the one represented by MIT-BIH—can benefit significantly from FL. By collaborating with larger institutions like PTB-XL and Chapman, they achieve notable improvements in early arrhythmia prediction without sharing patient data. These gains in PVC detection are critical for early intervention and could reduce morbidity and mortality associated with arrhythmias. Beyond validating the feasibility of cross-silo FL for ECG-based prediction, these findings emphasize its broader importance for future IoMT healthcare systems. Enabling collaborative model training across heterogeneous, resource-constrained sites allows performance improvements otherwise inaccessible to smaller silos. Notably, this study demonstrates that even with extremely short ECG segments (only 90 samples) and limited local data, meaningful generalization can be achieved without centralizing datasets. This aligns with emerging privacy regulations and supports scalable, privacy-preserving AI deployment across diverse clinical settings.

VI. Conclusion and Future Work

This study presented a practical application of FL for early cardiovascular event prediction in cross-silo IoMT environments. By targeting pre-event PVC prediction using just the first 90 samples (around 0.25 seconds) of ECG data, we showed that minimal, time-constrained input can still enable effective modeling. The experiments confirmed that small hospital silos with limited local data—like MIT-BIH—benefited from FL collaboration with larger datasets such as PTB-XL and Chapman. Through model updates without sharing raw data, FL delivered performance gains in accuracy, precision, recall, and F1-score, validating its role in empowering smaller institutions within distributed healthcare networks.

This work serves as an initial demonstration of how FL in cross-silo IoMT settings improves prediction while preserving privacy. The gains after aggregation highlight the value of shared model knowledge, especially for clinics with limited data access. Our findings suggest that cross-silo FL frameworks are well-suited for early detection tasks in decentralized healthcare, offering equitable access to AI-based diagnostic tools.

Future work will expand the framework beyond binary PVC classification to multiclass cardiac anomalies, integrate explainable AI for clinical interpretation, and explore personalized FL for silo-specific adaptation. Additional directions include anomaly detection, communication optimization, real-time ECG streaming, and applying privacy-preserving methods such as differential privacy and secure aggregation. These enhancements will help evolve the proposed FL system into a deployable, real-time, and trustworthy solution for early cardiac monitoring across diverse healthcare environments.

Acknowledgements

We dedicate this work to the memory of Mr. Christodoulou, whose tragic passing highlights the urgent need for improved real-time remote healthcare and vital signs monitoring. His story reminds us of the importance of advancing accurate and accessible cardiovascular solutions, and we hope this research contributes, in some way, to preventing similar losses.

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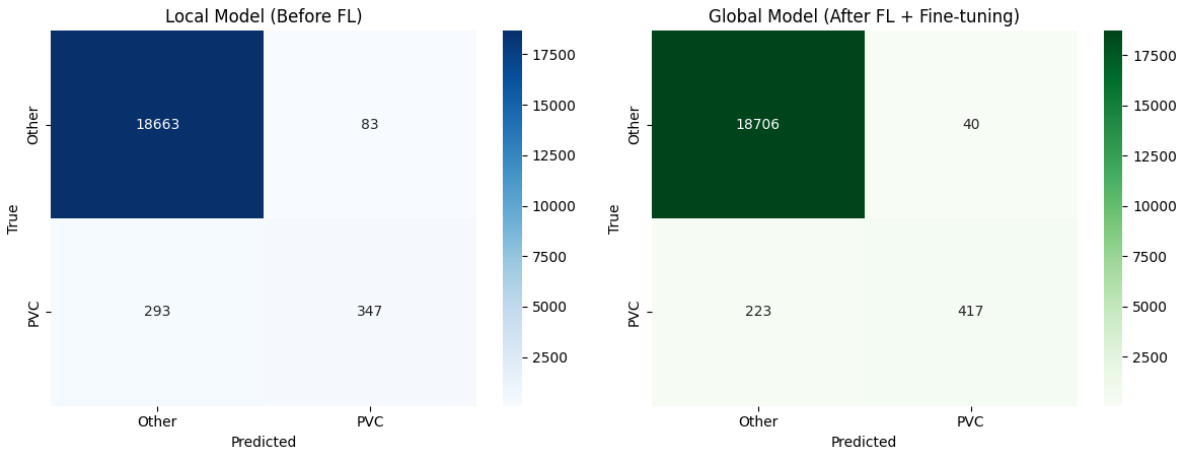

Fig. 3. Confusion matrices comparing the MIT-BIH local model (left) and the global federated model after fine-tuning (right). Models were trained using only the first 90 samples (approximately 0.25 seconds) of ECG traces before the PVC events.

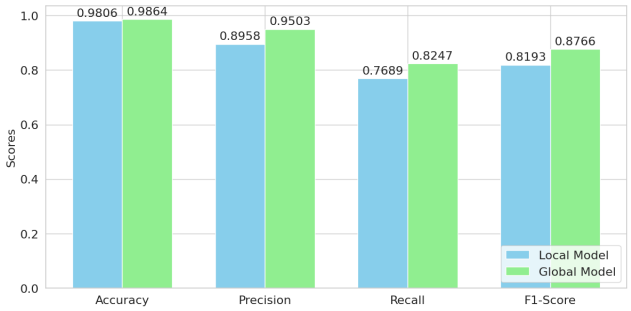

Fig. 4. Comparison of macro-averaged precision, recall, and F1-score between the MIT-BIH local model and the federated global model after fine-tuning.

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