2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) | 979-8-3503-7149-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/EMBC53108.2024.10782098

Federated Learning for Enhanced ECG Signal Classification with Privacy Awareness

Quoc Bao Phan[1], Linh Nguyen[1], Ngoc Thang Bui[2], Dinh C. Nguyen[3], Lan Zhang[1], and Tuy Tan Nguyen[1]

***Abstract*—This paper presents a novel approach for classifying electrocardiogram (ECG) signals in healthcare applications using federated learning and stacked convolutional neural networks (CNNs). Our innovative technique leverages the distributed nature of federated learning to collaboratively train a high-performance model while preserving data privacy on local devices. We propose a stacked CNN architecture tailored for ECG data, effectively extracting discriminative features across different temporal scales. The evaluation confirms the strength of our approach, culminating in a final model accuracy of 98.6% after 100 communication rounds, significantly exceeding baseline performance. This promising result paves the way for accurate and privacy-preserving ECG classification in diverse healthcare settings, potentially leading to improved diagnosis and patient monitoring.**

I. Introduction

Cardiovascular diseases continue to be a leading cause of morbidity and mortality worldwide, underscoring the critical importance of accurate and timely diagnosis in healthcare [1]. Among the diagnostic modalities, the electrocardiogram (ECG) signal is a fundamental tool for monitoring cardiac activity. Its intricate waveform provides valuable insights into the heart's electrical activity, aiding clinicians in identifying abnormalities and making informed decisions about patient care. The advent of machine learning (ML) has revolutionized medical diagnostics, offering the potential to enhance the accuracy and efficiency of ECG signal classification [2], [3]. ML models, when trained on vast datasets, can discern subtle patterns and anomalies in ECG signals that may elude conventional diagnostic methods. This transformative capability has paved the way for more precise and timely cardiac diagnoses, contributing to improved patient outcomes.

However, the utilization of ML models in healthcare raises concerns about data privacy and security. To address these challenges, federated learning (FL) emerges as a promising paradigm [4]. FL enables the training of ML models across decentralized devices without sharing sensitive data centrally. In the context of ECG signal classification, the integration of FL not only safeguards patient privacy but also facilitates collaborative model training across diverse healthcare institutions [5], [6].

This material is based upon work supported by the National Science Foundation under Grant No. 2348464.

[1]School of Informatics, Computing, and Cyber Systems, Northern Arizona University, Flagstaff, AZ 86011, USA. (e-mail: bqp7@nau.edu, ln522@nau.edu, lan.zhang@nau.edu, tuy.nguyen@nau.edu).

[2]Department of Radiology, Mayo Clinic, Rochester, MN 55905, USA. (e-mail: bui.ngoc-thang@mayo.edu).

[3]Department of Electrical and Computer Engineering, The University of Alabama in Huntsville, Huntsville, AL 35899, USA (e-mail: dinh.nguyen@uah.edu).

This paper explores the intersection of healthcare, ML, and FL, aiming to advance the field of ECG signal classification. By leveraging the power of ML models and the privacy-preserving capabilities of FL, we seek to enhance the accuracy and security of cardiac diagnoses, ultimately contributing to more effective and patient-centric healthcare practices. Our contributions are described as follows:

- We introduce novel ML models with convolutional neural networks (CNNs) for ECG signal classification, enhancing the accuracy and efficiency of cardiac diagnoses.
- We integrate an FL system to address privacy concerns, ensuring decentralized model training and safeguarding sensitive patient data.
- We offer insights into the nuances of accuracy variations between local and server-side implementations, furnishing valuable information for the deployment of FL-enhanced models in real-world healthcare scenarios.
- We conduct a comprehensive comparison with existing work to demonstrate the efficiency of our classification approach.

II. System Design and Implementation

Our presented FL framework designed for healthcare places a primary emphasis on safeguarding data privacy and fostering collaborative learning. Fig. 1 presents an overview of the proposed system, offering a detailed portrayal of its fundamental structure and components specifically crafted for healthcare applications. This depiction encompasses essential elements, including distributed nodes, model training processes, and the aggregation of a global model. Furthermore, the illustration delves into the communication protocol employed within the system, underscoring the secure exchange of global model updates among the nodes actively participating in the collaborative learning process.

A. ECG Classification with Stacked CNN Architecture

In this paper, we present a robust ECG signal classification model using a stacked CNN architecture. Stacked CNNs, chosen for their ability to capture hierarchical features, outperform normal CNNs in ECG classification. The increased depth enables them to excel in learning intricate temporal patterns, automatically extracting nuanced representations from raw data. This depth is crucial for discerning diverse cardiac conditions, whereas shallower architectures of normal CNNs may struggle to capture complex variations. The mathematical formulation of a stacked CNN's forward pass, involving layer-wise computations, further enhances its capacity to model

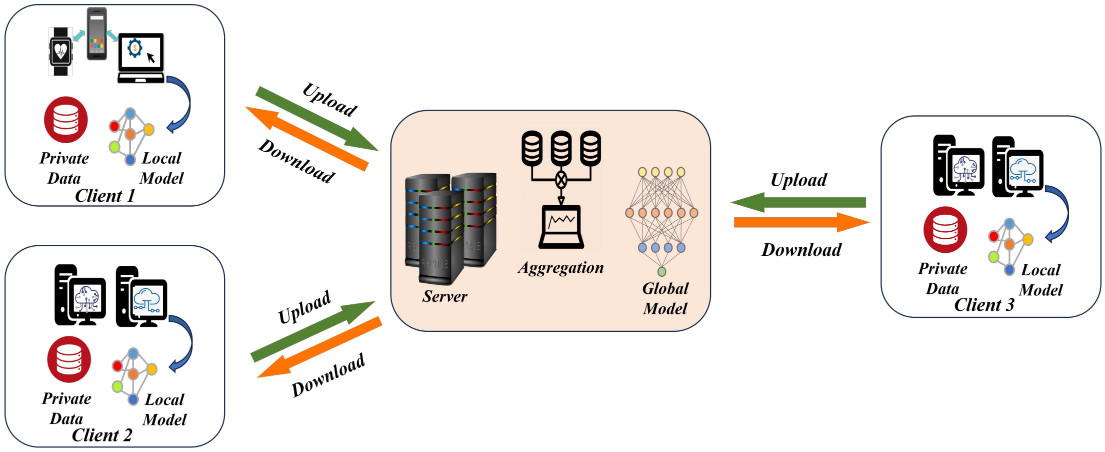

Fig. 1. An overview of the proposed system.

intricate temporal dependencies, contributing to superior ECG classification performance.

- Input layer:
$$\text{Input layer} = X \tag{1}$$
Equation (1) implies the input layer operation where X is the raw ECG signal data.
- Convolutional layers:
$$h_{i,j} = \text{ReLU}\left(\sum_{m,n}(F_{i,j}(m,n) \cdot X(m,n) + b_{i,j})\right) \tag{2}$$
This equation defines the output feature map of the j-th filter in the i-th convolutional layer. It applies the ReLU activation function to introduce non-linearity.
- Activation functions and pooling:
$$a_{i,j} = \text{ReLU}(h_{i,j}), \tag{3}$$
$$P_{i,j} = \text{MaxPooling}(a_{i,j}). \tag{4}$$
Equation (3) represents the output after applying the ReLU activation function, introducing non-linearity. Equation (4) performs max pooling to reduce spatial dimensions while retaining essential information.
- Stacking for depth: The stacked nature of the CNN model facilitates the learning of intricate representations. Deeper layers can comprehend abstract features crucial for discriminating between different ECG signal classes.
- Flattening and fully connected layers:
$$V = \text{Flatten}(P_{\text{final}}), \tag{5}$$
$$Z_{i,j} = \text{ReLU}\left(\sum_{k}(W_{i,j,k} \cdot V_k + b_{i,j})\right). \tag{6}$$
Equation (5) flattens the hierarchical representation into a one-dimensional vector. Equation (6) defines the output of the fully connected layer with ReLU activation.
- Output layer:
$$O = \sigma(Z_{\text{final}}) \tag{7}$$
Equation (7) represents the output probability for the positive class (abnormal ECG) using the sigmoid activation function σ.

B. Federated Operations

To extend our model to a FL system, we consider a scenario where multiple clients $(C_1, C_2, \ldots, C_n)$ collaborate without sharing raw ECG data. Each client C_i has its dataset D_i and trains the model locally.

1) Initialization: Initialize the stacked CNN model architecture: Begin by defining the architecture of the stacked CNN model, where W and b are the outputs needed. Distribute the initial model to all participating nodes: Share the initial model parameters (W and b) with each node to start the FL process.

2) Local Model Training:

- Train the local model on ECG datasets: Each node independently optimizes its local model by minimizing the loss function ($\mathcal{L}$) using FL techniques:
$$\min_{W,b} \mathcal{L}(W, b, X_{local}, Y_{local}) \tag{8}$$
where X_{local}, and Y_{local} are the local ECG dataset and corresponding labels, respectively.
- Utilize backpropagation and optimization algorithms: Update the model parameters using backpropagation and optimization by using stochastic gradient descent (SGD) algorithms:
$$W_{new}, b_{new} = \text{SGD}(\nabla\mathcal{L}, W, b). \tag{9}$$

3) Model Aggregation:

- Use weighted averaging for importance: Employ weighted averaging to give more significance to clients:
$$\text{Weighted Average } = \frac{\sum_i w_i \cdot M_i}{\sum_i w_i} \tag{10}$$
where M_i represents the model parameters from node i and w_i is the weight assigned to node i.

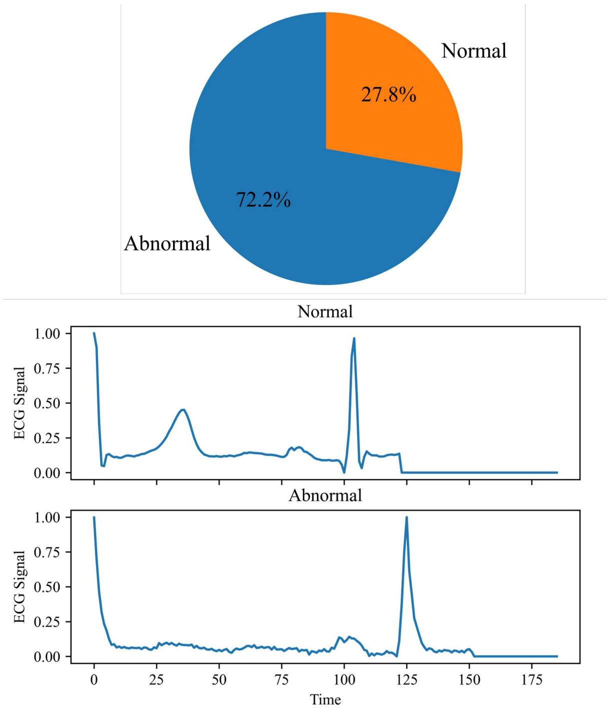

Fig. 2. Data visualization.

- Aggregate locally trained models: Combine the locally trained models (W_{new} and b_{new}) from all nodes to obtain a global model:

$$W_{global}, b_{global} = \text{Average}(W_{i,new}, b_{i,new}) \tag{11}$$

4) Communication and Iterative Process: In the proposed iterative process, the global model parameters (W_{global} and b_{global}) are communicated to all participating nodes, initiating local training and subsequent model aggregation. This iterative cycle repeats for a predefined number of iterations, progressively improving the global model. Convergence is monitored throughout the process by assessing changes in the loss function and performance metrics. The training concludes either upon achieving convergence or after a set number of iterations, ensuring an effective and optimized FL system.

III. System Setup

A. Data Collection and Preprocessing

The PTB diagnostic ECG database [7] comprises 14,552 binary-classified ECG signal samples from Physionet's PTB diagnostic database. Recorded at 125Hz, each sample represents the heart's electrical activity. Fig. 2 visualizes the data. Preprocessing ensures uniformity, involving handling missing values, normalizing amplitudes, and aligning signals. The dataset is split for training and testing, with measures like data augmentation and addressing class imbalances implemented.

B. Experimental System Setup

Table I highlights key parameters and considerations for setting up a healthcare-focused FL system using a stacked CNN architecture. It covers aspects like Xavier initialization, learning rate, batch size, training iterations, aggregation weighting, regularization, and optimization algorithm (SGD with momentum). Monitoring and logging support analysis and debugging in the FL process.

TABLE I
System Setup

Parameters	Initialization
Model Initialization	Default parameters
Batch Size	32
Learning Rate	0.001
Training Iterations	100
Aggregation Weighting	Proportional
Regularization	L2 (0.01)
Optimization Algorithm	SGD (momentum = 0.9)
Neural Network	Xavier initialization

C. Evaluation Metrics

In the evaluation of the proposed FL system for ECG signal classification, a robust set of classification metrics is employed to assess the model's efficacy in accurately classifying electrocardiographic patterns:

- Accuracy: $ACC = \frac{TP + TN}{TP + TN + FP + FN}$
- Precision: $P = \frac{TP}{TP + FP}$
- Recall: $R = \frac{TP}{TP + FN}$
- F1 Score: $F1 = \frac{2 \times P \times R}{P + R}$

where, TP represents instances correctly classified as positive, while TN denotes instances correctly classified as negative. Conversely, FP accounts for instances incorrectly identified as positive, and FN encompasses instances incorrectly identified as negative.

IV. Experimental Results

A. Training Process

The presented figures illustrate the intricacies of the training process for our proposed ECG signal classification model on both the local and server sides. These visual representations provide valuable insights into the convergence and performance dynamics during the training phase.

In Fig. 3, the server-side training process is depicted, offering insights into how federated learning influences model development. The figure mirrors the structure of the local side, presenting the progression of the model during training iterations on the left. The accuracy visualization on the right provides a parallel view of accuracy trends during server-side training. Comparing patterns and accuracy trends between local and server sides informs the effectiveness of federated learning in harmonizing model performance across decentralized datasets, contributing to crucial insights for strategy refinement and collaborative model optimization.

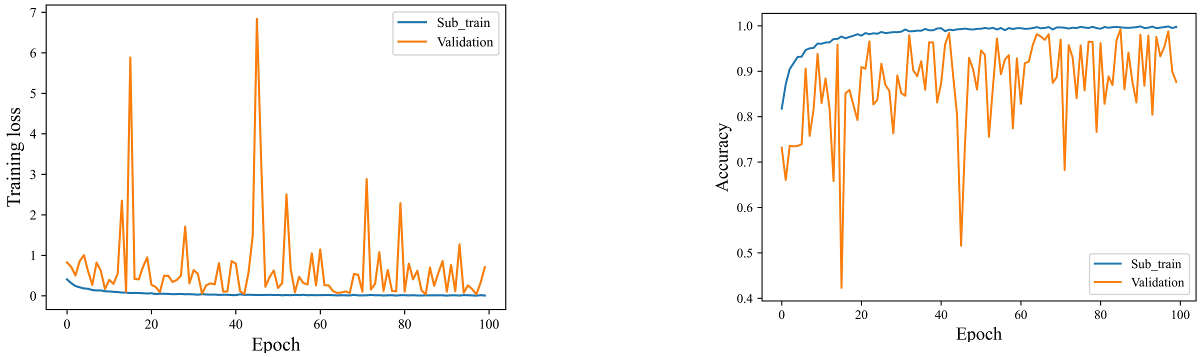

Fig. 3. Training process on server side.

TABLE II
COMPARISON BETWEEN VARIOUS CLASSIFICATION MODELS

Algorithm	Platform	Classification Type	Accuracy	F1 score	Precision	Recall
Ensemble Classifier [8]	Local	Multi-label	75.2	75.2	80.8	71.6
1D-CNN [9]	Local	Multi-label	98.0	93.7	95.7	91.8
AlexNet [10]	Local	Binary	98.2	-	93.0	92.0
FL-EDEA [11]	Server	Binary	98.0	-	99.0	91.0
This work	Local	Binary	95.5	94.8	96.1	93.5
(FL-Stacked CNN)	Server	Binary	98.6	98.8	99.1	98.6

B. Testing Performance

Table II compares various systems to solve the ECG signal classification problem. Examining models without FL reveals distinctive performances in various classification tasks. The ensemble classifier achieves a balanced performance locally with an accuracy of 75.2%, emphasizing its effectiveness in diverse labeling scenarios. Similarly, the 1D-CNN excels on the local platform, boasting an impressive accuracy of 98.0% in multi-label classification. In binary classification on the local platform, AlexNet demonstrates proficiency with a notable accuracy of 98.2%. Transitioning to models enhanced by FL, this work, represented by FL-Stacked CNN, achieves commendable results. Locally, it attains an accuracy of 95.5% in binary classification, maintaining a strong F1 score, precision, and recall. On the server side, FL-Stacked CNN showcases remarkable performance, achieving an accuracy of 98.6% with outstanding F1 score, precision, and recall.

V. CONCLUSION

This study emphasizes the vital role of FL in healthcare, specifically in classifying ECG signal data while prioritizing patient privacy. We demonstrate FL's feasibility, focusing on scalability, communication efficiency, and model robustness. Achieving 98.6% accuracy with a stacked CNN in a decentralized setting highlights FL's potential to address privacy concerns in healthcare. Future research includes exploring advanced FL architectures and optimizing communication protocols for broader healthcare applicability.

REFERENCES

[1] G. D. Flora and M. K. Nayak, "A brief review of cardiovascular diseases, associated risk factors and current treatment regimes," *Current Pharmaceutical Design*, vol. 25, no. 38, pp. 4063–4084, 2019.

[2] Q. Wang, Y. W. Mao, L. Ren, Z. Li, and H. Liu, "Automatic classification of ECG data quality for each channel," *IEEE Access*, vol. 8, pp. 196 094–196 101, 2020.

[3] L. Wang, C. Zhao, M. Dong, and K. Ota, "Fetal ECG signal extraction from long-term abdominal recordings based on adaptive QRS removal and joint blind source separation," *IEEE Sensors Journal*, vol. 22, no. 21, pp. 20 718–20 729, Nov. 2022.

[4] E. Çelik and M. K. Güllü, "Comparison of federated learning strategies on ECG classification," in *2023 Innovations in Intelligent Systems and Applications Conference (ASYU)*, 2023, pp. 1–4.

[5] T. Tan, J. Wang, C. Xu, and Z. Tan, "An optimized federated learning approach with the data-sharing function to the analysis of cardiothoracic time-series signals," in *2023 45th Annual International Conference of the IEEE Engineering in Medicine Biology Society*, 2023, pp. 1–6.

[6] L. Zou, Z. Huang, X. Yu, J. Zheng, A. Liu, and M. Lei, "Automatic detection of congestive heart failure based on multiscale residual UNet++: From centralized learning to federated learning," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–13, 2023.

[7] S. Fazeli, "Heartbeat classification dataset," https://www.kaggle.com/datasets/shayanfazeli/heartbeat.

[8] Z. Sun, C. Wang, Y. Zhao, and C. Yan, "Multi-label ECG signal classification based on ensemble classifier," *IEEE Access*, vol. 8, 2020.

[9] J. Malik, O. C. Devecioglu, S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1D self-operational neural networks," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 5, pp. 1788–1801, May 2022.

[10] Z. Ahmad, A. Tabassum, L. Guan, and N. Khan, "ECG heart-beat classification using multimodal image fusion," in *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 1330–1334.

[11] R. N. Asif, A. Ditta, H. Alquhayaz, S. Abbas, M. A. Khan, T. M. Ghazal, and S.-W. Lee, "Detecting electrocardiogram arrhythmia empowered with weighted federated learning," *IEEE Access*, vol. 12, pp. 1909–1926, 2024.