Privacy-Preserving Federated Learning for In-home Monitoring of Elderly Using Wearable Biometric Sensors

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Abstract

The increasing elderly population creates a growing need for personalized health care and home monitoring solutions. Although wearable devices have emerged as a promising tool for continuous health monitoring and safeguarding the well-being of the elderly, the use of data collected by wearable biometric sensors raises serious privacy concerns. To overcome these problems, in this study, we explore a specific solution based on the principles of Privacy-Preserving Federated Learning (PPFL) applied to each monitored individual. PPFL does not require centralized collection of sensitive data for a strict privacy-by-design strategy to avoid the disclosure of sensitive data at all phases (training, testing, actual use) of its lifecycle. To test the feasibility of the approach and estimate the computational resources required for each participant in the monitoring campaign, we applied the PPFL approach to detect and classify arrhythmias in a simulated group of elderly individuals monitored through wearable electrocardiographic (ECG) devices. The tested system, while preserving the privacy of each local model, was able to effectively classify heartbeat types. We have used the Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) arrhythmia benchmark dataset to test our proposed model. The classifier thus trained achieved 96.17% and 96.14% accuracy in arrhythmia detection using clean and noisy data, respectively.

Keywords

Privacy-Preserving, Federated Learning, Elderly, ECG, In-home Monitoring

1. Introduction

Population aging is a significant and unprecedented phenomenon of the 21st century. The increasing likelihood that people will live to old age, although not always in excellent health, and the rising proportion of elderly people in the population, are trends that affect the entire world. Reduced fertility and increased survival, often caused by demographic change, also contribute to amplifying the effects of global aging.

Italy is leading global aging: 23.3% of the population is 65 or older, and 7.5% is 80 or older [1]; life expectancy in 2015-20 is among the highest in the world, both at birth (83.3 years) and at the age of 65 (21.1 years), with current very low levels of fertility (1.24 children per women in 2020). This implies a significant economic impact on the public and personal finances of various sectors of society.

Age-It is a research program, funded by the National Recovery and Resilience Plan (PNRR), that aims to generate a quantum leap by making Italy a leading scientific hub in research and an innovative laboratory for the aging process.

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In this perspective, Age-It aims to contribute to defining the gold standard in terms of socioeconomic, biomedical, policy, and technological solutions for an inclusive aging society, helping Italy to become a reference point for other societies, including those outside Europe, that are aging rapidly [2].

Wearable and invasive sensors are pointed out by studies include smartwatches, smart clothing, activity monitoring, fall detection devices, and others. Sensors can be used for blood oxygen saturation, heart rate monitoring, heart rate variability, pulse rate variability, blood pressure, indoor positioning, physical activity tracking, and real-time monitoring of vital signs. Diseases like cardiovascular diseases, respiratory diseases, sleep disorders, Parkinson's disease, seizures, and osteoporosis can be monitored.

Within Age-It, our research group, based in Bari, Italy, has the main goal of supporting physicians, from an IT and technology perspective, to perform home monitoring, tele-monitoring, and health analytics on the data collected through these activities. The monitored subjects are over-65 autonomous or caregiver-assisted, at risk of falling, not necessarily suffering from chronic diseases or in the acute or post-acute phase. The research team aims to develop an effective approach to help the elderly prevent from unattended emergencies. This strategy aims to provide peace of mind to caregivers and relatives, enabling the elderly to live freely and safely for as long as possible. Home monitoring of the elderly involves sensors to capture biometric data for processing and decision-making by preserving data privacy regulations.

2. Motivation and background

Modern healthcare systems can collect enormous amounts of medical data, and data-driven machine learning (ML) has appeared as a practical method for developing precise and reliable statistical models from this data. The main reason existing medical data and Machine Learning techniques are not widely adopted in Italy is because data is often not available in digital formats (e.g., it is handwritten, on paper) or, if digitalized, it is stored in data silos and access to it is restricted due to privacy concerns [3]. For example, training an AI-based tumor detector requires a large amount of data encompassing the full spectrum of anatomies, pathologies, and input data types. Data like this is hard to obtain because health data is extremely sensitive, and its usage is tightly regulated [4]. Even if data anonymization could bypass these limitations, it is now well understood that removing metadata such as patient name or date of birth is often not enough to preserve privacy [5]. Also, the fact that it takes a lot of time, effort, and money to gather, curate, and keep a high-quality data set is another reason data sharing is not routinely done in the healthcare industry.

To overcome these types of limitations, in 2016 Google developed a Federated Learning (FL) approach which protects the privacy of data owners (e.g., the hospitals) by training ML models on data sets distributed across multiple sites. To train these models, participants only exchange gradients rather than raw data. A central aggregator is responsible for combining these gradients and distributing the updated results back to participants. As further studies indicated that private data can still be obtained from gradients, new schemes and strategies have been proposed, based on secure multiparty computation and differential privacy techniques.

These solutions are often computationally or communication costly or limit the number of participants, which reduces their applicability in practical scenarios, especially when the workload and complexity of these methods exceed the available processing capacity, making them difficult to use [7]. More recently, software frameworks have been developed by highly active communities and adopted by hospitals for clinical research in scenarios including Internet of Things (IoT) sensors and mobile health monitoring. Encouraged by these results, we decided to verify the feasibility and scalability of a testbed system in which a small number of home-monitored elderly people participate in a long-term monitoring campaign with two main goals:

- For the community of participants: to develop a set of "toy ML models" periodically (re)trained on the vital signs of the participants to retrospectively test the predicting power of the available digital biomarkers vs. specific health conditions.
- For each single participant: to develop a personalized profile for each participant, to better understand how long-term variations of vital signs correlate to the health status of that individual.

It is worth noting that this type of research, very relevant for the physicians coordinating the

Age-It project, is greatly simplified by the adoption of the PPFL technique. With this approach, each participant is the only owner and manager of his health data. A richly federated data set is available to the Project for retrospective analyses and clinical research, with no need for a central repository collecting sensitive data.

To evaluate the proposed testbed system, in this paper, we describe a system in which 10 simulated participants' local models with electrocardiogram (ECG) data to use the PPFL model is trained to classify patients' arrhythmias.

3. Related work

Using Internet of Things (IoT) sensors and safety measures, a practical and privacy-preserving system for Alzheimer's disease (AD) is developed by [16]. In particular, the system solely gathers user audio via IoT devices commonly used in the smart home environment and uses topic-based linguistic features to enhance detection accuracy to achieve successful AD detection. The experimental results show that the system achieves an accuracy of 81.9% and a low time overhead of 0.7 s after being assessed on 1010 AD detection trials from 99 health and AD users.

The study by [17] focused on wearable sensor monitoring for mental healthcare. Data was collected with smart bands for stress-level monitoring in different events with federated learning to monitor mental health from elderly heart activity. The study achieved encouraging results for using federated learning in IoT-based wearable biomedical monitoring systems by preserving the privacy of the data.

The study by [18] pointed out that mobile devices and recent breakthroughs in machine learning have enabled an emerging class of new AI-powered health systems for applications like Alzheimer's Disease monitoring. The study presented the first end-to-end system that integrates multi-modal sensors and federated learning algorithms for detecting multidimensional AD digital biomarkers in natural living environments.

The study [19], designed an end-to-end connected smart in-home monitoring system (FEEL) for elderly people for activity monitoring and location estimation, fall detection, and medical recommendations for unusual health conditions. A customized wearable band for collecting data like body temperature, blood oxygen saturation, blood pressure, heart rate, and motion-related parameters in a continuous manner is used.

Adaptive federated learning [20], proposes a technique to obtain personalized models for local clients. The study uses a weighted personalized federated transfer learning algorithm via batch normalization for healthcare, to experiment on five medical datasets. The proposed local model learning method with federated learning achieved reliable results relative to similar studies.

Cloud-edge-based federated learning framework [21], for in-home health monitoring achieves data privacy protection by keeping user data locally for in-home health monitoring using a generative convolutional autoencoder. It learns a shared global model in the cloud from multiple homes at the network edges.

Support for diagnostic and treatment procedures is another typical application area. As an illustration, the diagnosis of mental health issues currently heavily relies on the doctor's subjective assessment based on interactions with patients and the results of patient health surveys [22]. The study presented a federated depression detection approach in this area. Participants in the evaluations were given smartphones to track their keyboard usage during sessions, which took place in a hospital setting.

A fall detection algorithm combining Federated Learning and Extreme Learning Machine is implemented in [23]. Online extreme learning can use a small amount of misclassified user data to update the parameters so that its performance is improved for individual users. Then, Federated Learning is applied to share data information among different users without involving user privacy. In this way, the generalizability of the fall detection algorithm is improved, and the performance of the proposed algorithm is analyzed by experiments.

A study [24] designed an FL framework for ECG monitoring, which can effectively classify various arrhythmias. Furthermore, the authors incorporated an explainable artificial intelligence-based module on top of the classifier to ensure the interpretability of the classification results, thereby enabling clinical practitioners to better understand the prediction results.

A study conducted an experiment on the arrhythmia database MIT-BIH [25] showed that FL can generate a global disease diagnosis model through multiparty collaboration, and it reduces the probability of reconstructing patient medical data while ensuring high precision heart disease diagnosis.

A federated learning mechanism-based, privacy-preserving online diagnosis system was put into effect [26]. In general, it is also used in privacy-preserving medical interventions like medical imaging and diagnosis. Li et al. [27] focus on practical FL systems for brain tumor segmentation by using the BraTS dataset and the usage and advantages of FL were further demonstrated.

Also, [28] proposed an architecture that can diagnose the type of skin disease by conducting experiments using Dermatoscopy images to test and validate the model's classification accuracy and adaptability.

In recent years, this new learning paradigm has been successfully adopted to address the concern of data governance in training ML models. This is the case of MELLODY, an Innovative Medicines Initiative (IMI)-led consortium. Its primary goal is to develop a multi-task FL framework to improve the predictive performance and chemical applicability of drug discovery-based models [13].

Substra is an open-source implementation of federated learning for healthcare and biomedical applications. It is well-known for maintaining various tools, libraries, and models that are widely used by the tech community and developers [6]. FedML [13] is also an open-source library that supports three computing paradigms: on-device training for edge devices, distributed computing, and single-machine simulation. The framework addresses key concerns about privacy-preserving FL such as security, privacy, efficiency, weak supervision, and fairness.

Despite numerous FL-based system improvements in privacy preservation, there are still issues that reduce the effectiveness of healthcare services. As previously indicated, the literature does not adequately address the data scarcity and varied elderly user behavior. Moreover, little existing works have attempted to develop an FL-enabled system for old age homes using low computational power biometric sensors.

4. Our proposal PPFL system

4.1 Proposed architecture

According to the "Age-It Project" scenario, our in-home elderly health monitoring system includes sensors to measure blood pressure, heart rate, blood glucose, oxygen saturation, sleep monitoring, temperature, ECG, and others. These sensors are often included in wearable devices powerful enough to collect health data, process it, and send it to a local unit in charge to permanently store the streams coming from all sensors and perform the computations needed for the PPFL approach. The logic structure of the proposed system, represented in Figure 1, includes:

1. **In-home monitoring devices:** devices such as sensors, cameras, wearable devices, and smart appliances are placed in the elderly person's home to collect data on activities of daily living, vital signs, and other relevant information. These components can also be used for data preprocessing, time-series analysis, image processing, and feature extraction.
2. **Global model:** this part coordinates the federated learning process. It manages model updates, aggregation, and distribution. It contains three elements, the first one is a machine-learning model used for in-home monitoring. It is designed to process the extracted features and make predictions or classifications. The second has the role of aggregating model updates from all clients to build a global model that improves over time. The third is the updating unit, in charge of sending back new model parameters after aggregation, so that local clients can further train their models and ensure continuous improvement.
3. **Alerts and User Interfaces:** alerts are generated and sent to caregivers or healthcare providers if any concerns are detected. Also, caregivers, family members, or healthcare professionals can access user-friendly interfaces or dashboards to monitor the elderly person's well-being and receive real-time alerts.

The proposed framework shown in Figure 1 aims to achieve minimized communication overhead, minimized training time, and accurate health monitoring and prediction through federated learning by preserving sensitive elderly health information.

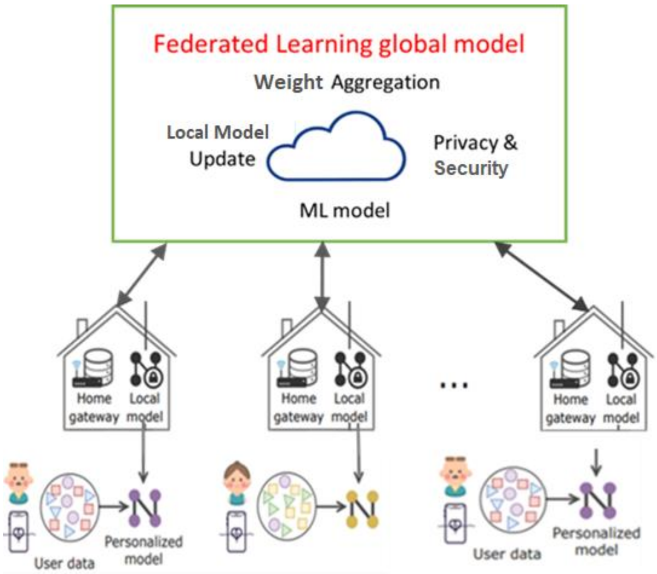


Figure 1: Proposed architecture for in-home health monitoring for elderly people

In this preliminary study, we use a single computer to simulate the central/aggregator model and local model. Simulated local models were used to participate in the federated training process orchestrated by the central server. As a global model aggregation strategy, we select the most widely used aggregation strategies in, Federated Averaging (FedAvg). Our proposed federated learning model process is shown in algorithm 1. For this study, we use this algorithm to classify possible arrhythmia.

A Multi-Layer Perceptron (MLP) (i.e., a feedforward neural network characterized by multiple layers of interconnected neurons) has been adopted in our simulation [30] to train both the local and global model. In more detail, two-layer MLP with Relu activation for the middle layer and SoftMax for the output layer were used.

The global model Gs creates an MLP model with predefined hyper-parameters and a Keras auto-tuner. After creating the MLP, Gs waits for the clients' request. When clients request Gs, it sends the MLP model weights to train on the client data. When the training is done, the client sends back the model's trained weights to the global server. When the desired number of clients send their weights and are received by Gs, it aggregates the weights of all the clients and averages the weights to train the global model and update.

Algorithm 1: Training process of Proposed method

Input: Data from in-home sensor nodes D1, D2, . . ., Dn

Output: Trained aggregated and updated model

1. Global Server Gs constructs the initial Global MLP
2. Gs waits for requests from the local model Li. If a request is received, Gs sends the MLP to the Li
3. Li receives the MLP, train it on its local data Di, and sends trained weights to Gs
4. Gs wait for all Li to send back their local trained MLP.
5. if weights are received from all Li, then
6. F(w) =aggregate (Weights)
7. Gs constructs a classifier based on the average weight
8. Gs sends weight to Li

9. Li set (w) as weight of MLP and makes predictions.
10. Repeat until maximum round reached

4.2 Experimental setup

The proposed model was simulated on a local machine with an intel core i5-4300M CPU, and 8GB RAM. We simulated 10 client nodes with the batching technique to divide the dataset between the local models, the client was trained with 80% of the data and tested using 20%. Furthermore, each client used a fixed batch size of 32, was trained for 100 epochs and used a learning rate of 0.01.

4.3 MIT-BIH dataset

We used the MIT-BIH arrhythmia dataset [29], which is 48 half-hour ECG recording excerpts from 47 people who were being collected by the BIH arrhythmia laboratory between 1975 and 1979. There are 109,446 samples in the collection and 4,000 24-hour ambulatory ECG recordings were taken from a mix of 60% inpatients and 40% outpatients. The dataset contains 5 types of heartbeat and arrhythmias these are:

- **Normal beat (N):** Class of normal sinus rhythm beats that present regular and healthy heartbeat.
- **Ventricular ectopic beat(V):** These are abnormal heartbeats originating in the ventricles and occurring earlier than expected.
- **Fusion beats (F):** Result of the simultaneous activation of the ventricles via two pathways: the normal conduction pathway and an aberrant pathway.
- **Supraventricular ectopic beat (S):** Heartbeats that occur earlier than expected and originate from the atria or the atrioventricular node.
- **Unknown beat (U):** This class contains other unknown and non-annotated heartbeat signals.

The classes in this dataset are not balanced and the distribution is highly dispersed, which can lead to issues like overfitting. Therefore, we employed the Synthetic Minority Over-sampling Technique (SMOTE) to up-sample non-normal samples to balance the class distribution. This up sampling is done for only the training portion of the dataset.

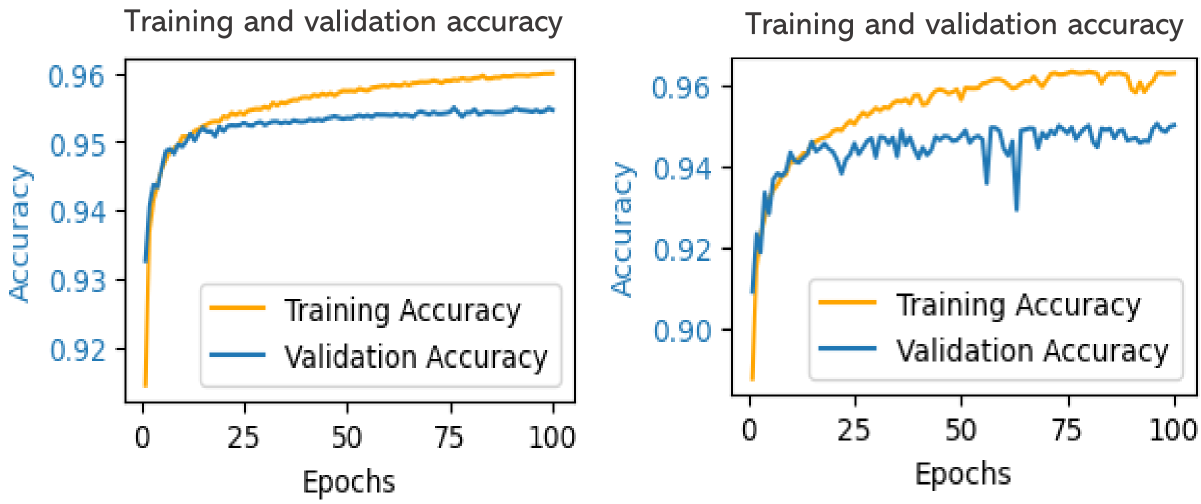
5. Results and Discussion

We tested our proposed system to evaluate its feasibility by addressing communication security for a federated learning-based model. To simulate the federated learning paradigm and secure communication of the local model to the global model, we assume that the global model has an open communication port number 8080. Also, the training and testing datasets are preloaded in each local model. For secure communication, the global model generates a self-signed certificate and key. We used Rivest-Shamir-Adleman (RSA) encryption to create public and private keys and sign certificates. Then the private key is encrypted with the AES-256 encryption technique (Advanced Encryption Standard with a 256-bit key). When using this method of security our proposed system was severely affected by the encryption and handshaking process to start communication rounds.

Another aspect we tried to address is to study the effect of noisy data, baseline wander, muscle noise, poor sensor contact noise, respiration variation, morphological changes of an elderly person or other types of noise can be a factor too. In this study, we are focused on age-related noise such as sensitive skin or electromyographic (EMG) noise, that can lead to poor sensor contact. Simulating noise related to these issues is relevant for assessing the performance of the proposed model. We simulated this noise by introducing intermittent signal disruptions or fluctuations and adding noise spikes at irregular intervals.

To measure the classification performance of the model accuracy, precision, recall, and F1-score are the four common metrics identified in the literature [31]. Accuracy measures the overall system performance across all classes in the dataset. Model accuracy is a vital performance parameter that shows the capacity of our proposed FL models to produce correct predictions on healthcare data. It is important because model accuracy reflects the ability of the models to analyze the data. Precision is the proportion of accurately anticipated observations to all predicted positive observations. Recall, on the other hand, is the proportion of accurately predicted positive observations to all of them, and F1-score is the harmonic means of accuracy and recall.

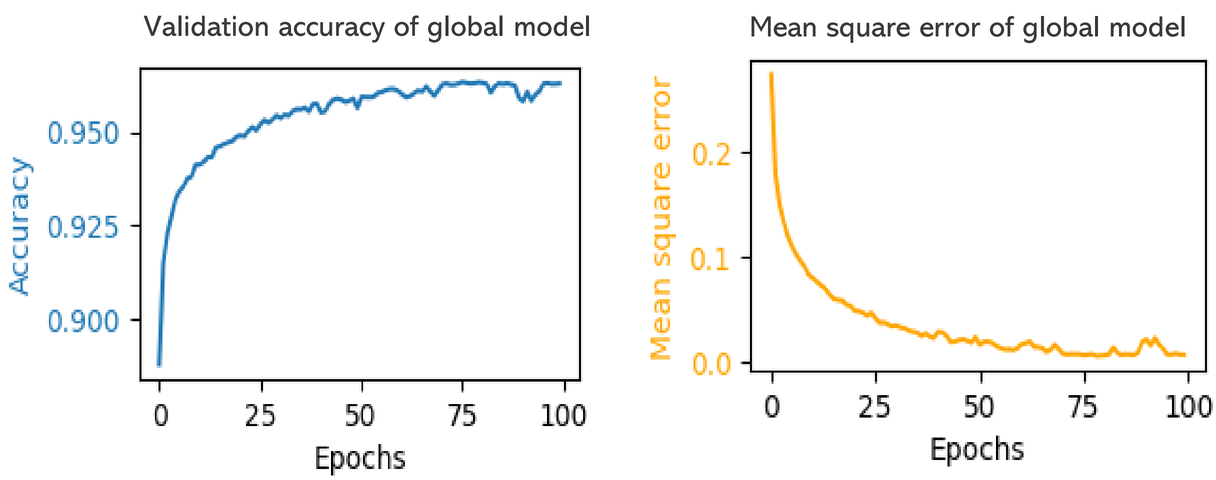
The performance plot shown in Figure 2, shows the performance of local models trained with different data portions. We trained one of the local models, Figure 2(b) with noisy data, to simulate noisy data caused by poor sensor contact for ECG collection. The result shows that model performance decreased by 0.03% relative to the local model trained with clean data. However, even in noisy data that can be collected by the biometric sensors, our proposed architecture can achieve reliable results. Also, Figure 2(a) shows the local model trained and tested with clean data.



(a) Local model trained with clean data (b) Local model trained with noisy data

Figure 2: Train and validation accuracy archived on local models.

The global model trained using the proposed model is affected by the number of iterations as shown in Figure 3. The model achieves an accuracy of 96.17%, 96% f1-score, recall of 91.6%, and a mean square error of 0.0051. The performance archived in this preliminary experiment is comparable with related studies. However, the global model aggregated with noisy local model archived test accuracy of 96.14%, 96% f1-score, recall of 91%.



(a) Validation accuracy of global model (b) Mean square error plot of global model

Figure 3: Validation accuracy and mean square error of the global models.

The main purpose of our proposed model is to use federated learning in computationally constrained low-end devices. The training and testing process for both the local and global models was done simultaneously on a specified laptop. It takes 140 minutes (about 2 and a half hours) of training time for 100 epochs.

The confusion matrix shown in Figure 5, depicts the error distribution in beat classification of the five arrhythmic labels. The diagonal light-colored score showed higher classification accuracy of the proposed model. Normal arrhythmia is classified with 97% accuracy and 80% accuracy for the fusion beat class.

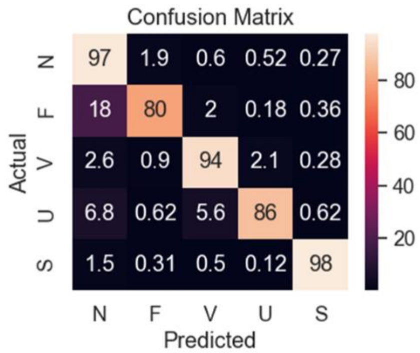


Figure 5: Confusion matrix of 5 different heartbeat signals

6. Conclusions and future work

In this study, we suggested AI-based architecture for privacy-preserving federated learning to overcome the shortcomings of deep learning application models. For predicting geriatric health status, the proposed model used the federated-based learning architecture. We have tested an ECG classification algorithm as a preliminary experiment. To denoise and classify ECG data, we used a multilayer perceptron model based on a federated architecture. In comparison to prior studies, the suggested model offered an enhanced overall performance when trained on the baseline dataset.

Hence, the proposed framework shows its potential research in the classification of clean and noisy data by achieving robust performance over the experiment. Therefore, the proposed architecture after more research can be a solution for real-world applications in elderly biometric signal monitoring and risk prediction. Even though the proposed framework is in the initial research stage it encourages participation of data owners and health professionals, with fewer privacy concerns. The model's classification results can be used to identify new potential patterns leading to heart arrhythmias.

As a future research direction, we aim to apply the proposed framework to more applicable health status monitoring system and scenarios like human activity monitoring, fall prediction, and anomaly detection in the context of in-home monitoring. Also, heterogeneous data sources present both challenges and opportunities in the context of federated learning. In addition, communication overheads, encryption latency, and multi-modal data-related machine learning techniques will be studied deeply to use the system in the existing communication infrastructures and home environment.

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