Decentralized Federated Learning for Privacy-Preserving Cardiac Image Analysis

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ABSTRACT - Heart-related problems are the number one killer in today's world, so it is necessary to have early screening methods with imaging systems like X-ray, MRI, and CT. Medical data is very confidential and is subject to privacy laws that limit its use outside hospitals. Therefore, it would be difficult to build efficient machine learning algorithms based on centralized data sources.

Federated Learning technology allows for a collaborative effort between different parties to perform machine learning-based analyses in the field of cardiology in a confidential manner. A scenario involving multiple clients is constructed by splitting the data into several parts, with each part treated as a separate client. The clients train independently and upload their results to a central server.

The federated learning paradigm works successfully in this scenario, and data confidentiality was maintained. Real implementation is not carried out; however, the theoretical idea was proven efficiently.

Keywords: Federated Learning (FL), Privacy-Preserving Machine Learning, Cardiac Image Analysis, Medical Imaging, Distributed Learning Systems, Simulated Multi-Client Architecture, Model Aggregation (FedAvg), Healthcare AI, Deep Learning, Client-Server Architecture, Data Privacy in Healthcare, Collaborative Learning Systems

I. INTRODUCTION

The mortality rate caused by cardiovascular diseases is high, and hence early detection of these diseases using techniques like x-rays, MRI, and CT scans is very crucial. With the development of artificial intelligence, the process of analysing these medical images has been greatly enhanced. Training AI models requires a vast amount of data, but since the healthcare sector involves sensitive medical data that is regulated by stringent laws on privacy, data transfer between healthcare institutions poses major challenges.

Centralized machine learning techniques have proven inefficient because they require data transfer and collection in one location. This poses security risks and violates privacy laws. Decentralized learning should therefore be adopted to solve this problem.

In this project, Federated Learning will be used to facilitate collaborative training while ensuring data privacy. The system will be set up such that there are multiple clients, each containing a portion of the dataset. In the proposed system, clients are simulated by partitioning the data into multiple segments, each segment serving as an individual client.

A. Motivation

The driving force behind this research work is to find a solution to the problem of a trade-off between data privacy and efficiency in medical AI-based applications.

Centralized traditional techniques pose threats to the privacy of sensitive information in patients' data, whereas the training of a model using small-scale locally available data fails to generate an efficient model because of its narrow scope. This study intends to solve both these issues by employing federated learning.

B. Problem Definition

In the traditional AI system used in medicine, it is impossible for hospitals to exchange patient data, as it is governed by strict privacy guidelines. As a result, there is less training data, which adversely affects the efficiency of the model.

What is needed is a system that:

- Supports cooperation among several data sources
- Protects the privacy of the data involved
- Enhances the accuracy of the model without using centralized data

C. Existing System

The current models employ centralized machine learning methods for cardiac image analysis. The data collected from various sources is stored in a single server for learning.

Although this makes the model more accurate, it comes with certain limitations, such as:

- Increased possibility of data leakage
- Privacy policy violations
- Restricted contribution by parties reluctant to share their data
- Relying heavily on one single method

Therefore, the existing methods lack an efficient combination of effectiveness and security.

D. Proposed System

The federated learning-based system uses a multi-client system in simulation form. Here, data will be separated into several sets, with each set forming an individual client.

The operation performed by each client is:

- Training the model on their own data
- Sharing model weight updates to the server

On the other hand, what is done by the server is:

- Combining all the updates received
- Generating a better global model

This process is continuously repeated through various training rounds to create a global model that learns together from different clients without revealing raw data.

Here, it shows how federated learning can offer an effective way of analysing medical images privately and efficiently.

II. LITERATURE SURVEY

Recently, the trend towards privacy preservation and collaboration in machine learning has gained much momentum, especially in the health care industry. In traditional artificial intelligence algorithms in the health care industry, centralized data storage is usually used, which causes many concerns about privacy, security, and compliance issues. With the introduction of Federated Learning, a new direction emerges for training machine learning algorithms without violating any privacy issues. With advancements in deep learning and distributed computing methods, along with healthcare artificial intelligence, it is possible to build scalable solutions to analyze medical images securely. This paper highlights some recent studies conducted in this field, with an emphasis on heart disease diagnosis using medical images.

S.No	Year	Author	Title	Methodology
1	2024	A. Pennisi et al	Decentralized Learning for TB and Melanoma	Developed a distributed model for both IID and Non-IID data.
2	2023	Hwang et al	FL with Proximal Regularization for EHR and Skin Lesions	Integrating federated learning with proximal optimization to enhance EHR analysis accuracy.
3	2022	Muthukrishnan et al	MammoDL for Breast PD and Complexity Detection	Deep learning-based system using federated learning for precise breast density estimation.
4	2022	Luo and Wu	FedSLD for Medical Image Classification	Employing federated learning with MNIST and CIFAR-10 datasets.
5	2022	Jiang et al	Semi-supervised Federated Learning for CT and	Combining FL and semi-supervised techniques to manage large-scale image data.

S.No	Year	Author	Title	Methodology
			Dermoscopy	
6	2022	Shiri et al	Decentralized FL Transformer for PET/CT Segmentation	Integrating transformer architectures for low-error segmentation and multi-centre data collaboration.
7	2021	Dayan et al	Federated Learning for Predicting Future Oxygen Requirements	Utilized X-ray data for forecasting oxygen needs in patients.
8	2021	Stripelis et al	Federated Learning for Age Prediction Using MRI Images"	Demonstrating decentralized MRI-based modelling with privacy retention.
9	2020	Roth et al	Federated Learning for Breast Density Classification	Focused on privacy-preserving classification using federated learning techniques.

III. METHODOLOGY

A. Dataset Collection

The data set used in the experiment contains the openly available cardiac imaging data that can be classified. The reason for the use of the data set in such a manner is that it would be impossible to obtain access to the real hospitals' datasets due to privacy reasons. In order to ensure realism of experiments, each subset of the data set is considered as one separate client (or hospital).

B. Data Preprocessing

Data preprocessing is carried out locally on each client machine to ensure uniformity in model training. The preprocessing pipeline consists of normalizing the images, resizing the images to a common size (for example, 224x224), and basic data augmentation like rotation and flipping. The labels are encoded as numerical values to be used for classification tasks.

C. Model Selection

The CNN is used to classify cardiac images since it is proficient at learning spatial features from images. The CNN architecture is set up in such a way that it can learn useful features from the input images and perform classification operations. In each round, the clients train the model using their own dataset and send only the model parameters to the central server, which combines the updates using FedAvg to improve the global model.

D. Backend Development

The backend code is built on top of Python and uses federated learning libraries, such as Flower Federated Learning Library. Also, backend APIs are integrated (using libraries like FastAPI) to enable communication between the frontend and backend applications.The backend uses a modular architecture that helps simulate client-server communications within a single framework environment.

E. Frontend Development

The front-end has been developed using Angular, which includes HTML, CSS, and TypeScript programming languages in a modular approach to ensure scalability and maintainability. Real-time visualization of metrics related to federated learning such as client performance, training loss, and model updates is provided by the frontend. The front end interacts with back-end APIs to fetch dynamic data and present it to users in real-time.

F. Federated Learning Integration

Federated Learning is used in the system to facilitate decentralized learning. The global model is distributed among the clients, who perform learning in a private database using this model. The clients send the updated parameters to the central server that combines them by employing the FedAvg method to improve the global model. This process takes place repeatedly in several iterations.

G. Deployment

This approach is done using an environment that features several virtual clients on one computer. This makes the testing process simpler since there is no need to carry out a real test involving a distributed network.

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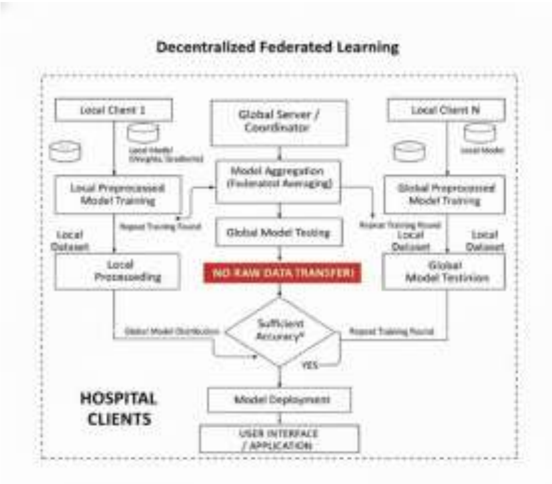
IV. SYSTEM DESIGN

A. Dataflow Diagram

Fig. 1 describes the process flow in a federated decentralized learning framework. In this process, the individual clients train their models based on their own datasets and pass on the trained model's weights to the central server. The server then uses the FedAvg algorithm to generate the global model, which is again sent back to the clients for further training. The entire process is performed for several iterations without any transfer of data. Once the desired level of accuracy is achieved, the final global model is evaluated and deployed.

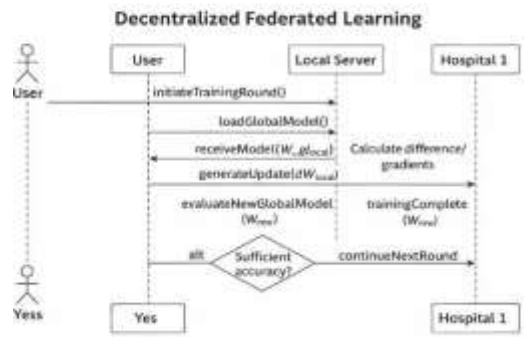


[Fig. 1: Dataflow Diagram]

B. Sequence Diagram

Fig. 2 below shows the relationship between the user, the local server, and the client (hospital). The cycle begins when the user starts a training session. The local server first loads the global model and distributes it to the client. The client trains the model using its data set, calculates gradients/weights, and sends these to the server.

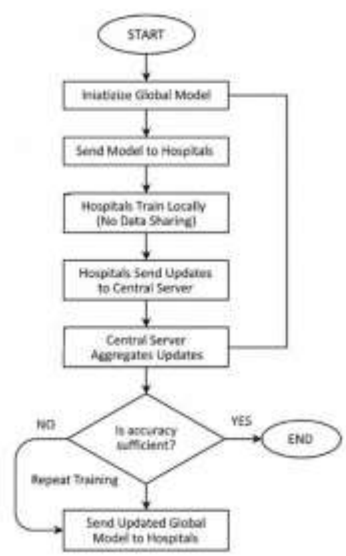
The server combines the calculated gradients to generate a new global model and evaluates its efficiency. Based on the accuracy achieved, the cycle either moves on to the next training session or stops



[Fig. 2:Sequence Diagram]

C. Workflow Diagram

Fig. 3 shows the process flow in federated learning. In the first step, the global model is created and then distributed to the client-side, wherein each participant independently trains the model locally without sharing any raw data. The clients send the results back to the server-side, which collects and integrates them for better performance of the model.

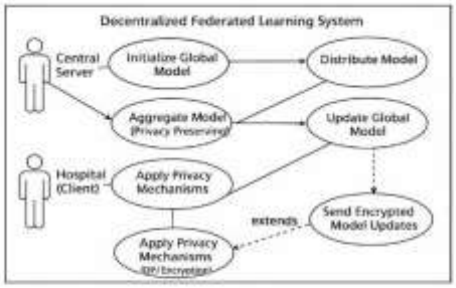


[Fig. 3:Workflow Diagram]

D. Use Case Diagram

Fig. 4 is the schematic of the decentralized federated learning architecture. In this structure, the central server first trains the global model, and then this is sent out to the clients, who locally train their models and apply methods to keep their learning private.

Next, the trained models are returned to the server for aggregation and improvement of the global model.



[Fig. 4:Usecase Diagram]

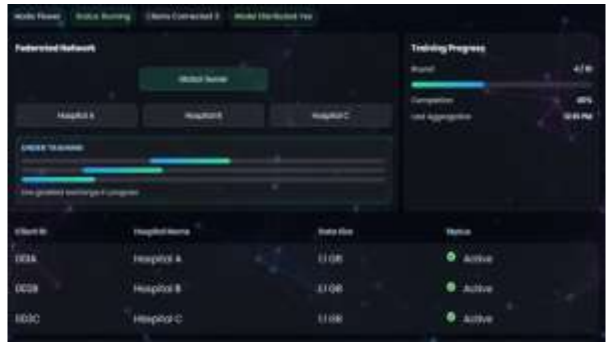
V. TESTING AND RESULTS

A. Testing

- Functional Testing: Validates whether the interactions between the client and the server, model training, and aggregation procedures are implemented correctly.
- Unit Testing: Tests various parts of the code separately, which includes the code for processing, training, aggregating the weights (FedAvg), and API functions.
- Integration Testing: Ensures the smooth functioning of integration between the Angular frontend, backend APIs, and federated learning algorithms.
- UI Testing: Analyzes whether the UI is capable of displaying the training metrics (loss, accuracy, etc.) for clients and the overall model.
- Data Validation Testing: Checks whether datasets used for training are correctly processed and prepared.
- Model Performance Evaluation: Determines accuracy and loss of client and global models at each training round.
- Performance Testing: Tests the performance of the system based on training time and communication costs.

B. Results

As shown in Fig. 5, the dashboard interface of federated learning. The figure illustrates the global server as well as the clients involved. The training progress is shown in real time, showing the number of training rounds as well as the percentage of training that has been completed. Information regarding each client, including ID and dataset size, is provided.



[Fig. 5: Application Interface]

Fig. 6 shows a closer look at the performance of the client. The diagram includes data on the client's loss, accuracy, and time to train, along with the performance details of each round and its training status.

[Fig. 6: Pause-and-Ask AI Feature]

Fig. 7: Training Results. The main indicators displayed in the dashboard include accuracy, loss, average score, and training epochs. Global trends in accuracy and loss over the epochs can also be observed on this dashboard.

[Fig. 7: Pause-and-Ask AI Interaction]

VI. CONCLUSION

The development of the federated learning system applied to cardiac image processing represents an innovative step toward privacy-preserving health care AI. The suggested solution addresses the shortcomings of classical centralization strategies, in which private medical information needs to be shared to be used for training. In particular, federated learning allows for cooperative training while keeping all medical data on the side of clients.

Client-server communication using federated learning represents an effective coordination strategy between individual learning and final model construction. The implementation of a simulated environment with several clients clearly shows all steps involved: client-side training, server-side model updating, and performance tracking. Overall, the research presents federated learning technology application for improvement of model performance.

Future modifications of the system could include its actual deployment in a distributed environment with appropriate communication security features and further advances in privacy protection. Improvements in terms of architecture and performance of federated models are expected.

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