Project Title: Federated Learning of Medical Image Reconstruction

Team Members:
- Joshua Sheldon (jsheldon2022@my.fit.edu)
- Izzy MacDonald (imacdonald2022@my.fit.edu)
- Tanuj Kancharla (tkancharla2022@my.fit.edu)
- Yash Jani (yjani2023@my.fit.edu)

Faculty Advisor: Dr. Debasis Mitra (dmitra@fit.edu)

Client: Dr. Debasis Mitra, Florida Institute of Technology

Date(s) of Meeting(s):
- January 22, 2025 @ 4:00 P.M.

Goal and Motivation: "Single photon emission computed tomography (SPECT) is a nuclear imaging technique using gamma rays" (University of Utah). A SPECT scan is begun by injecting a patient with a gamma ray emitting pharmaceutical (a tracer). The patient then lies down on a table in a scanning room equipped with a gamma camera, which uses a collimator instead of a lens and creates images by detecting radioactivity instead of light. These images are monochromatic images, where brightness in any given pixel of the image is determined by the tracer detection count at that position on the collimator's surface.

The gamma camera is rotated around the patient, capturing projections of a portion of the patient's body at different angles, creating a unique type of image called a sinogram, "where the horizontal axis represents the count location on the detector [gamma camera], and the vertical axis corresponds to the angular position of the detector" (Philippe P. Bruyant, PhD).

These sinograms are then reconstructed, traditionally using analytic and iterative algorithms, to create a medical image easily interpretable by medical professionals. However, these algorithms are slow. The "Tomographic Medical Image Reconstruction using Deep Learning" project attempts to develop a machine learning model that can perform the exact reconstruction much quicker than traditional methods. The project aims to train this model on synthetically generated data.

However, the accuracy of the project's model is limited by the lack of variety in the training data and the exclusive use of synthetic data. This project aims to improve the accuracy of this existing machine learning model by addressing both concerns.

Approach: We intend to improve the accuracy of the existing machine learning model through two approaches. Additionally, two parties are involved in the implementation of our approach:

- **Learning Managers** - Individuals, likely involved with this project or the client's lab, who are working to develop this machine learning model through traditional and federated learning.
- **Medical Professionals** - Individuals who are conducting SPECT scans and are willing to use gathered data to contribute to the machine learning model.

Our first approach to improving accuracy is augmenting the size and quality of the existing synthetic dataset by generating more data. While augmented with a robust data pipeline consisting of affine transformations and other strategies, the current dataset is derived from data from a relatively low number of unique simulated human body images. Additionally, the current dataset does not include images from patients with infractions or ailments in the heart and other organs. We want to improve and use the machine learning pipeline from the previous project to continue training the existing model with new, more diverse data. This machine learning pipeline is both improved and used by the learning managers.

Machine Learning Pipeline
- Learning managers can use the data generation pipeline to generate synthetic, realistic human body images and simulated sinograms of that body.
- Learning managers can specify for the data generation pipeline to include anomalies like heart infractions in the generated data.
- Learning managers can supply generated data to train a machine learning model reconstructing medical images from sinograms.
- Learning managers can apply this machine learning model to reconstruct medical images from sinograms.

Our second approach to improving accuracy is developing an application set that enables the model to be trained with federated learning. Federated learning is a machine learning technique that allows a model to be trained using data from third-party contributors without those contributors ever having to share the raw data.

This technique is realized through two different applications: an orchestrator application, which facilitates the learning, and a contributor application, which allows the use of relevant data to contribute to the learning.

The orchestrator application connects with a set of contributor applications, and distributes an initial machine learning model to them (in our case, this model will be the one developed by the "Tomographic Medical Image Reconstruction using Deep Learning" project). The contributor applications use local data to train this model, and then send their models back to the orchestrator application. The orchestrator application averages the parameters of all of these separate models, creating a new initial machine learning model, which is again distributed to the contributor applications, restarting the cycle.

In our project, the learning managers would run and manage the orchestrator application. The medical professionals would run and use the contributor applications to train the machine learning model using medical data from their institutions.

This would allow medical institutions to contribute to the model with real data without violating patient privacy regulations. We hope introducing real training data will raise the model's accuracy to a level unattainable with synthetic data.

Orchestrator Application

- Learning managers can interact with the federated learning orchestrator application through a user interface.
- Learning managers can supply an initial model for federated learning or randomly initialize one if no training has been done.
- Learning managers can define trusted contributors to the federated learning.
- Learning managers can see which contributors have new data for training.
- Learning managers can start a round of training and select which contributors will participate (likely educated by which contributors have new data for training).
- Learning managers can send an initial model to all contributors in the training round.
- Learning managers can receive trained models from contributors.
- Learning managers can combine the contributor’s models to create a new initial model.

Contributor Application

- Medical professionals can connect to a federated learning orchestrator application.
- Medical professionals can submit training data to the application (which notifies the orchestrator application).
- Medical professionals can agree to participate in training rounds initiated by the orchestrator application.
- Medical professionals can receive initial models from the orchestrator application.
- Medical professionals can allow the contributor application to train the initial model distributed by the orchestrator application using submitted training data.
- Medical professionals can allow the contributor application to send their trained model back to the orchestrator application.

Novel Features/Functionalities: To the best of our knowledge, training a machine learning model to reconstruct medical images from SPECT scans, using synthetic data **with artificially introduced heart infractions**, has never been done before.

The second branch of our approach, applying federated learning in a medical context, is not novel, having been realized by projects such as MELLODDY. This aspect of our approach is largely focused on using proven techniques in a new problem space.

Algorithms and Tools: We will use all the tools introduced in the "Tomographic Medical Image Reconstruction using Deep Learning" project, including Python, the XCAT Phantom program, OpenGATE, PyTorch, and Fiji (a distribution of ImageJ).

- Python - The language used to run the entire pipeline.
- XCAT Phantom program - Creates full-body images of the human body (referred to as XCAT phantoms).
- OpenGATE - A physics simulator that we use to simulate the output of conducting a SPECT scan on an XCAT phantom.
- PyTorch - Allows us to train and use machine learning models.
- Fiji - Allows us to view medical images, like those reconstructed by our machine learning model.

Additionally, we'll be using a new set of tools to accomplish the federated learning branch of our project. This will invariably include tools for federated learning, user interface (either through a web app or a traditional GUI), networking, authentication, orchestration logic, and more. However, we hope to use established tools, libraries, and frameworks as much as possible. In particular, we are looking at using Flower, Substra, PySyft, or OpenFL as our federated learning framework.

Technical Challenges:

- The existing machine learning pipeline established by the previous project is deeply complex and consists of various highly specialized tools. We will need to become experts on this existing project, including the tools it uses. This will be particularly difficult as half of our team is entirely new to biomedical imaging and machine learning.
- Splitting our efforts between learning, using, and improving the existing machine learning pipeline and developing a new set of software applications for the federated learning portion of the project will require immense time, effort, and dedication from all our team members.
- No one on our team has real-world experience with federated learning, which is one of the key focuses of our project.

Milestone 1 (February 24):

- Compare and select technical tools for federated learning, user interface, networking, authentication, and orchestration logic.
- Provide small ("hello world") demo(s) to evaluate the tools for federated learning, user interface, networking, authentication, and orchestration logic.
- Resolve technical challenges:
    - Coordinate with members of "Tomographic Medical Image Reconstruction using Deep Learning" to familiarize ourselves with the existing machine learning pipeline and the tools that enable it.
    - Designate members of the team to have ownership over specific components of the machine learning pipeline and of the federated learning software.

    - Research federated learning by reading relevant literature, watching lectures from industry titans, and exploring projects that implement it.
- Compare and select collaboration tools for software development, documents/presentations, communication, task calendar
- Create Requirement Document
- Create Design Document
- Create Test Plan

Milestone 2 (March 26):

- Implement, test, and demo the Orchestrator Application features:
    - “Learning managers can interact with the federated learning orchestrator application through a user interface.”
    - “Learning managers can supply an initial model for federated learning or randomly initialize one if no training has already been done.”
- Implement, test, and demo the Contributor Application features:
    - “Medical professionals can connect to a federated learning orchestrator application.”
    - “Medical professionals can submit training data to the application (which notifies the orchestrator application).”
- Implement, test, and demo the Machine Learning Pipeline feature: “Learning managers can use the data generation pipeline to generate synthetic, realistic human body images and simulated sinograms of that body.”
- Assist the “Tomographic Medical Image Reconstruction using Deep Learning” team in dataset augmentation and testing the neural network on real medical data.

Milestone 3 (April 21):

- Implement, test, and demo the Orchestrator Application features:
    - “Learning managers can define trusted contributors to the federated learning.”
    - “Learning managers can see which contributors have new data for training.”
    - “Learning managers can start a round of training and select which contributors will participate in it (likely educated by which contributors have new data for training).”
- Implement, test, and demo the Machine Learning Pipeline features:
    - “Learning managers can supply generated data to train a machine learning model which reconstructs medical images from sinograms.”
    - “Learning managers can apply this machine learning model to reconstruct medical images from sinograms.”
- Assist the “Tomographic Medical Image Reconstruction using Deep Learning” team in dataset augmentation and finalizing the parameters and testing for the neural network.

Task Matrix for Milestone 1:

Task	Joshua	Izzy	Tanuj	Yash
Compare and Select Technical Tools	Federated Learning & Networking	User Interface	Authentication	Orchestration Logic
Provide Demos	Federated Learning & Networking	User Interface	Authentication	Orchestration Logic
Familiarize with Existing Pipeline	25%	25%	25%	25%
Research Federated Learning	70%	10%	10%	10%
Select Collaboration Tools	25%	25%	25%	25%
Create Requirement Document	10%	10%	40%	40%
Create Design Document	70%	10%	10%	10%
Create Test Plan	10%	40%	10%	40%

Approval from Faculty Advisor
I have discussed this with the team and approved this project plan. I will evaluate the progress and assign a grade for each of the three milestones.

Signature: ____ Date: ________________