Federated Learning of Medical Image Reconstruction

Software Design Document

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1.0 INTRODUCTION

1.1 Purpose

This software design document describes the architecture and system design of the "Federated Learning of Medical Image Reconstruction" project, including both user-facing and backend software.

1.2 Background and Objectives

"Single photon emission computed tomography (SPECT) is a nuclear imaging technique using gamma rays" [1]. 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" [2].

These sinograms are then reconstructed, traditionally using analytic and iterative algorithms [2], to create a medical image easily interpretable by medical professionals (henceforth referred to as a "reconstruction"). However, these algorithms are slow. The "Tomographic Medical Image Reconstruction using Deep Learning" project (henceforth referred to as "year 1 project") attempts to develop a machine learning (ML) model that can perform the reconstruction much quicker than traditional methods. The year 1 project trains this model exclusively on synthetically generated data, due to the lack of availability of and privacy concerns surrounding real data. Additionally, due to the lack of information regarding the statistical distribution of tracer concentration in other organs, the year 1 project's data consists exclusively of sinograms and reconstructions of the human heart and liver.

The accuracy of the year 1 project's model is limited by (1) the quality of the synthetic data and (2) the exclusive use of synthetic data. Federated Learning of Medical Image Reconstruction (henceforth referred to as "year 2 project") aims to improve the accuracy of this existing ML model by addressing both concerns.

1.3 Definitions and Acronyms

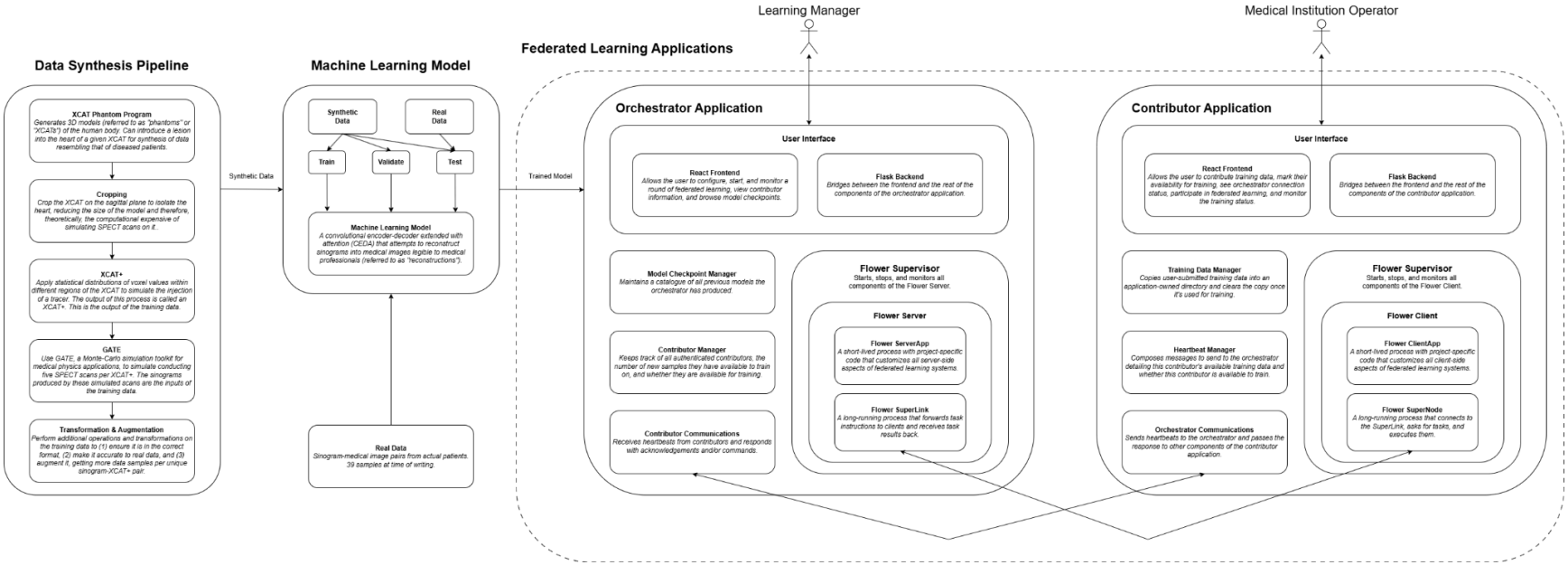
1.3.1 Acronyms

Acronym	Term
SPECT	Single photon emission computed tomography
ML	Machine learning
BP-shift-FP	Backproject-shift-forwardproject
FL	Federated learning

1.3.2 Definitions

Term	Definition
Tracer	A gamma ray emitting pharmaceutical used in nuclear imaging to capture tomographic images.
Sinogram	An image consisting of multiple projections of the subject at different angles.
Reconstruction	A tomographic image, reconstructed from a sinogram. Typically used by medical professionals.
Year 1 project	Tomographic Medical Image Reconstruction using Deep Learning, a senior design project from 2024-2025. Working in tandem with the project this document belongs to.
Year 2 project	Federated Learning of Medical Image Reconstruction, the project this document belongs to.
Phantom	A digital stand-in for the human body for the sake of imaging [3].

2.0 SYSTEM OVERVIEW



The year 2 project consists of three components: the data synthesis pipeline, the machine learning model, and the federated learning applications.

2.1 Data Synthesis Pipeline

The data synthesis pipeline enables the generation of entirely artificial training data for use with the machine learning model.

The pipeline begins with the creation of human body phantoms, which are digital stand-ins for human tissues [3]. This is accomplished with the XCAT phantom program by Dr. Paul Segars. “Combined with accurate models of the imaging process, the XCAT can produce realistic multimodality imaging data close to that obtained from patient studies… Through user-defined parameters, any number of different anatomies, cardiac or respiratory motions or patterns, and spatial resolutions can be simulated to perform medical imaging research” [4].

However, while the phantoms contain all organs of the human body, we are exclusively interested in the heart and the liver, for which we have tracer concentration distributions. Therefore, after generating the phantom, we crop it on the sagittal plane to isolate the heart, accepting some portions of the liver and other organs will remain in the cropped phantom.

In the above quote, “accurate models of the imaging process” are mentioned. This is because the voxel values of the phantom are only used to identify the different types of tissues in the phantom, meaning there is no data regarding tracer concentration within the phantom. However, due to previous research [5], we do have statistical distributions for tracer concentration within the heart and the liver for both healthy and diseased patients at rest and under stress. For the purposes of this project, we only synthesize data modeling patients at rest. The next step after cropping is applying these statistical distributions to the phantom using XCAT+, a program developed in part by members of the year 2 project. The phantom processed by XCAT+, for our intents, is a tomographic image, hopefully similar to those reconstructed from sinograms of real patients.

Next, we use GATE, a Monte-Carlo simulation toolkit for medical physics applications [6]. GATE allows us to simulate performing a SPECT scan on the processed phantom. We simulate five SPECT scans on each phantom, generating five sinograms and therefore five training data samples, where the input is the sinogram and the output is the tomographic image. However, with our current computational resources, it takes upwards of ten hours to generate one sinogram. While we hope to reduce this time by using AI.Panther [7], even if the time was reduced substantially, the rate of synthesis would not be sufficient to train the model within our allotted time.

The solution, therefore, is augmentation. The augmentation stage of the pipeline currently consists of two steps:

1. A Z-shift in Cartesian space, or a clockwise rotation of the sinogram and the tomographic image.

2. A step titled “backproject-shift-forwardproject” (henceforth referred to as “BP-shift-FP”), where the inverse radon transform is applied to the sinogram, both the sinogram and the tomographic image are shifted on the XY plane, and then the radon transform is applied again to the sinogram, bringing it back to its original form.

However, one consequence of the augmentation stage is that the BP-shift-FP step drastically reduces image quality. It was implemented in the year 1 project because of the lack of anatomical diversity in phantoms, meaning that without the shifting step the model would never generalize to different positions and orientations of the heart. The year 2 project hopes to eliminate this step by increasing the anatomical diversity of XCATs, and make up for the loss in augmentation factor by reducing sinogram generation time through phantom cropping and running GATE on AI.Panther.

This pipeline allows for the synthesis of training data with (theoretically) a high degree of similarity to real data. While the vast majority of this pipeline is carried over from the year 1 project, multiple steps have been added, removed, and modified to improve the quality of the data.

2.2 Machine Learning Model

The ML model is a convolutional encoder-decoder extended with attention (CEDA), modeled after prior research in performing the inverse radon transform with deep learning [8]. The model takes in sinograms and attempts to reconstruct them into tomographic images in a similar fashion to traditional iterative methods. While the train and validation sets are comprised entirely of synthetic data, the test set contains 39 samples of real data, ensuring that modifications that we make to the data synthesis pipeline and the model improve performance on real data.

2.3 Federated Learning Applications

The choice to train a model with synthetic data derives from the scarcity of real patient data, largely due to legal and privacy concerns. However, one interesting solution to this predicament is the federated learning paradigm. “Federated Learning (FL) is a machine learning technique that enables multiple entities to collaboratively learn a shared model without exchanging their local data” [9]. Federated learning accomplishes this by executing the following procedure with one orchestrator machine and one or more contributor machines:

1. The orchestrator initializes a model to train, and distributes the model to a set of contributor machines.
2. The contributor machines train this model with locally stored data.
3. The contributor machines send their respective trained models to the orchestrator.

4. The orchestrator uses an aggregation function to merge the models of the contributors into one model, which ideally benefits from the learning of each contributing model.

This paradigm has clear application in the medical field, as it can allow medical institutions to contribute to research using patient data without directly sharing data and/or accidentally violating the patient's privacy. Therefore, our objective is to build a set of applications that can apply FL to "fine-tune" our already trained ML model with real data. To assist in the implementation of this paradigm, we use the Flower federated learning framework in our applications [11].

3.0 DATA DESIGN

The input sinogram shape is 128x128x120, where 120 is the number of projections captured.

The output tomographic image shape is 128x128x128, where 128 is the number of transverse slices of the human body.

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