Senior Design Plan Spring 2025

1. Topological Medical Imaging using Deep Learning
2. Names and email addresses of team members (CSE members first--this is a plan for the CSE contribution)

Asher Burrell, aburrell2022@my.fit.edu
Christopher Hinton, chinton2022@my.fit.edu
Thomas (Ty) Mercer, tmercer2022@my.fit.edu

3. Faculty advisor: name and email address

Dr. Mitra, dmitra@fit.edu

4. Client: name and affiliation

Dr. Mitra, Florida Tech

5. Meeting(s) with the Client for developing this Plan:

   1/20/2025

6. Goal and motivation: Discuss the overall goal (help make the intended users "happier") and motivation (why are the intended users not too "happy"? limitations/pains of current systems)

Topographic medical image reconstruction using deep learning. Right now, medical image reconstruction with iterative statistical algorithms takes about 30 seconds. Using deep learning inferencing with our project would reduce this time to milliseconds, allowing massive amounts of data to be generated in a small amount of time. Additionally, our project includes synthetic data generation, allowing us to get good results without training on real data (effectively zero-shot learning), and our system can provide easy access to synthetic data.

7. Approach (key features of the system): Discuss at least three key features/functionalities that your system provides for the users to help achieve the overall goal.
   (what features does your system have that can help make the intended users "happier"?)

(at least one paragraph for each feature, more specific less vague) [e.g. Similar to app descriptions at Google Play, **NOT** the underlying tools]

- The user can generate synthetic SPECT data using the system. This data will be realistic and will strongly resemble real human data. It will be captured in a physics simulation using a realistic human torso and callimeter. This controlled environment will allow all of the data collection to be as accurate as possible.
- The user can reconstruct a 3D model of human organs using a pre-trained neural network. The neural network will be trained on our synthetic SPECT data, which will be of interest to researchers. However, a user who is only interested in an accurate SPECT image reconstruction need not worry about the training and can simply provide the data to be reconstructed. This reconstructed data will automatically be saved to the user's computer, so there will be no need to hunt for it later.
- The user can view, resize, and rotate the reconstructed 3D model to identify potential heart defects. The output from the neural network will be an accurate representation of the real reconstructed data. As such, any heart defects that would be present in a traditional reconstruction will also be apparent in the AI reconstruction.

8. Algorithms and tools (libraries/api/frameworks/languages) for the key features: Discuss how and which algorithms and tools are used to achieve the features

- SPECT data generation uses upgraded extended cardiac-torso (XCAT) software internally referred to as XCAT+ and a GATE simulation. An XCAT human body phantom is filled in with statistical tracer data using the XCAT+ software, and is used as input for the GATE simulation to generate synthetic SPECT data.
- We will use a convolutional neural network (CNN) for image reconstruction. The use of zero-shot learning with this neural network is the primary novel feature of this project.
- Viewing, resizing, and reconstructing the reconstructed image is a function of Fiji (a publicly available image viewing software), which we are incorporating into our project.

9. Novel features: Discuss which features/functionalities are novel and why.

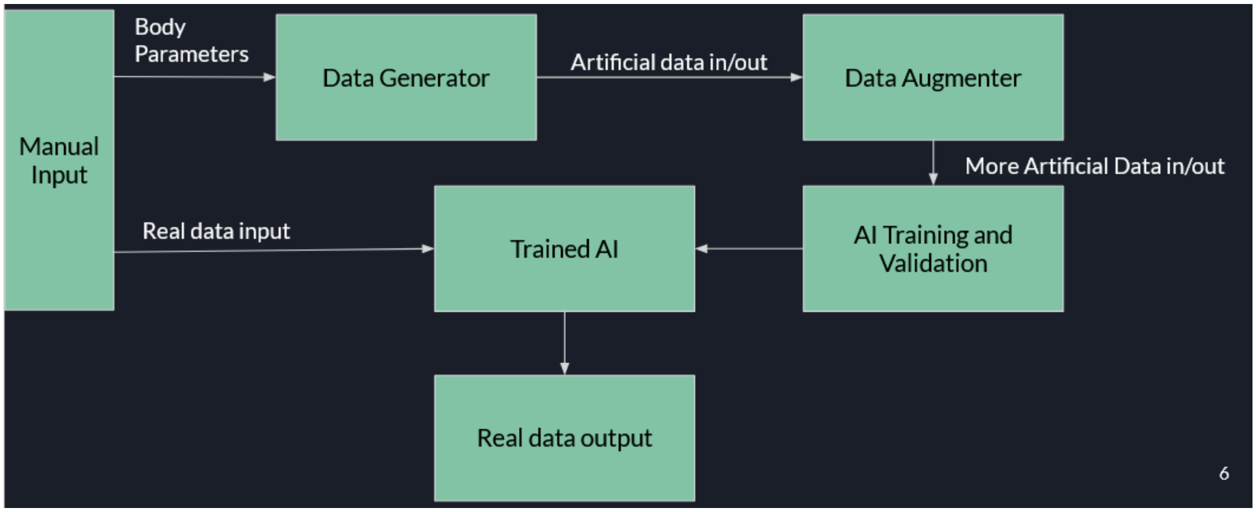
To the best of our knowledge, no one has ever done a 3D medical image reconstruction by training a neural network without real data.
The user can view the reconstructed image in milliseconds, whereas it would take upwards of 30 seconds using traditional reconstruction methods.

10. Technical Challenges: Discuss three main technical challenges for this semester (for example, "we plan to find the shortest path from A to B, but don't know which algorithm to use.")

- Our system is bottlenecked by the need to generate more artificial SPECT data in order to train our AI. Despite recent advances in data augmentation, we are still having a hard time getting enough training data for an effective neural network.
- We have no idea how our AI will perform on real data. Validation on simulated data is going well so far, however, there are artifacts and imperfections in real data that are not accounted for in our simulations.
- Right now there are a couple portions of the project that only one team member is experienced with developing/using. We each need to familiarize ourselves more with different portions of the project.

11. Design: system architecture diagram
    - Data Generation Pipeline
        i. Inputs: Manually entered parameters for XCAT phantom (full-body image); Statistical data from real medical images.
        ii. Outputs: XCAT+ phantom with simulated tracer information (heart and liver image); Artificial sinogram (raw SPECT data)
    - Data Augmentation Pipeline
        i. Inputs: One pair of artificial sinogram and the corresponding XCAT+ phantom
        ii. Outputs: More pairs of artificial sinograms and the corresponding XCAT+ phantoms
    - Convolutional Neural Network
        i. Inputs: Real or artificial sinogram(s); Training and validation data consisting of real or artificial sinograms, which is divided into:
            1. Pairs of artificial sinograms (input)
            2. XCAT+ phantoms with simulated data (expected output));
        ii. Outputs: 3D image of reconstructed heart, matching the inputted sinogram(s)
    - Fiji (ImageJ)
        i. Inputs: Any binary file (XCAT+ phantom, reconstructed image, etc)
        ii. Outputs: A scrollable UI window with a visualization of that file as a 3D image

Simplified Design Diagram:



12. Evaluation

We are currently investigating potential evaluation functions for the neural network. In addition to mean squared error, which is commonly used in similar scientific applications, we are looking into newly developed scientific methods of image comparison, such as feature-based similarity index measure (FSIM) and information theoretic-based statistics similarity measure (ISSM).

For the other aspects of the project (primarily artificial data generation), we will be evaluating the functionality of the system based on the achievement of requirements listed in our requirements document.

13. Progress Summary:

Module/feature	Completion %	To do
Synthetic data generation	95%	Finish refactoring existing code for more convenient use. Use this data generation pipeline to generate data for AI training (below).

Reconstruction via CNN with Zero-Shot Learning	50%	Choose a better loss function. Generate more training data. Refine AI parameters. Continue fine-tuning the model until we achieve the best possible reconstruction. Look into utilizing AI Panther for faster training. This is our primary focus this semester.
Image viewing	90%	Tool already exists (Fiji/ImageJ); Just need to integrate it with existing methods.

14. Milestone 4 (Feb 24): itemized tasks:
    - Generate 3,000 sinograms using the model pipeline
    - Train and tune the PyTorch AED model to start reconstructing real sinograms based on the data we have currently
    - Validate the model on synthetic data through AI Panther
    - Incorporate the validation scoring method for reconstruction quality
15. Milestone 5 (Mar 26): itemized tasks:
    - Test the AI on real medical data
    - Conduct evaluation and analyze results
    - Create poster for Senior Design Showcase
16. Milestone 6 (Apr 21): itemized tasks:
    - Finish testing the CNN
    - Identify best AI parameters and keep them as our final product
    - Test/demo of the entire system
    - Conduct evaluation and analyze results
    - Create user/developer manual
    - Create demo video
17. Task matrix for Milestone 4 (teams with more than one person)

Task Matrix for Milestone 4	Asher	Chris	Ty
Generate 3000 sinograms using the model pipeline	10%	10%	80%

Train and tune the PyTorch AED model to start reconstructing real sinograms based on the data we have currently	35%	35%	30%
Validate the model on synthetic data through AI Panther	45%	45%	10%
Incorporate the validation scoring method for reconstruction quality	40%	40%	20%

Description (at least a few sentences) of each planned task for Milestone 4:

- Task 1: Generate 3,000 sinograms using the model pipeline

Currently, we have 1200 sinograms generated. We can generate 25 sinograms every 5 days, and can augment that data to get 100-200x as many in that timeframe. This rate should allow us to generate at least 800 sinograms by the milestone deadline. This rate was improved from 10 sinograms per 5 days over the break; we were able to get the script running across 3 computers as opposed to 1.

What sinograms we generate is an important consideration. We need to make sure we set the parameters correctly to fully enumerate many possible heart variations. From there, we can determine how many heart variations we can complete sinograms for.

- Task 2: Train and tune the PyTorch AED model to start reconstructing real sinograms based on the data we have currently

The training and tuning is a task that will continue until the end of the project. Recently, we were able to fix the model pipeline so that it correctly works with the new set of input data that we have generated. Also, we have begun some basic training tasks and experiments. Currently, our loss function shows a flat curve, indicating that we should experiment with reducing the training time. We will experiment with this over the course of the winter break.

- Task 3: Validate the model on synthetic data using AI Panther

Now that we have a functioning model, we will start to validate the model's reconstructions on synthetic data that we have not shown it before. We will also experiment with moving the entire codebase for the training and testing to AI Panther. If we can successfully do that, we will be able to train our model much more quickly than we are currently. Also, we will be able to remote connect to the AI Panther computer and run the training script without being on campus.

- Task 4: Incorporate the validation scoring method for reconstruction quality

Our validation method right now simply involves looking at the reconstructed image and determining whether it looks somewhat similar to the original image of the human heart. We would like to make this process more precise. Therefore, we will be experimenting with various validation scoring methods to determine exactly how far off the reconstructed image is from the original image. Completing this task would allow us to improve how we fine-tune the model.

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

Signature: DocuSigned by: Debasis Mitra ___________________________ Date: 1/20/2025 ________