Supervised Proposal
ECE:5995 Applied Machine Learning
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Significance:

Medical image segmentation is an important feature of modern medicine. In the past doctors have had to manually recognize different areas of an image, but with machine learning technology the processing could be done from them. This has a big impact on diagnosing heart disease, which causes millions of deaths every year. By training to identify important heart structures, like the ventricles and atrium, doctors can make faster diagnoses and save more lives.

Phase 1:

Background:

When it comes to heart segmentation, FCNs and U-Nets are the default architecture for segmentation [Chen et al. 2020]. These networks work better than normal CNNs as the image does not need to be previously broken into patches before prediction. U-Nets specifically allow for skip connections between encoder and decoder, to help recover special context.

One issue with machine learning segmentation is that it sometimes produces improbable results. This could mean holes, voids, or other inaccuracies with predictions. This can be solved by embedding prior knowledge in the network, thanks to the consistency of the human body.

Solution:

The solution to the problem will be to implement a 2D U-Net with a prior-based loss function. Data provided by the Automated Cardiac Diagnosis Challenge (ACDC) [Jodoin et al. 2017] will be used for training ventricle segmentation. The data is provided as 3D scans of patients, along with corresponding 3D ground truths. Each 3D scan will be separated into 2D slices to be trained on. A 2D U-Net architecture will be used for the network. Not only were similar architectures used for the winner the ACDC in 2017 [Isensee 2017] as well as a report written by students at the University of California San Diego in 2018 [Seo et al. 2018], there are many resources online for implementing them. It also reduces the complexity of the loss function. The loss function will be implemented using a general outline described in a paper by El Jurdi et al. 2021. The loss function will attempt to include the prior of the ventricle shape.

Timeline:

Week 1: ● Implement base U-Net. ● Analyze ground truth data to start creation of loss function.
Week 2: ● Conclude implementing base U-Net. ● Defining loss function.
Week 3: ● Code loss function. ● Implement loss function into U-Net.
Week 4: ● Train model. ● Prepare for presentation.

Anticipated Challenges:

The main anticipated challenge is designing and coding the loss function. Defining the forward and backward propagation of the function will be difficult, so I plan to use as many of the pre-built Pytorch libraries and methods as possible.

<u>Phase 2:</u>

Background:

Another method for segmentation is using adversarial training. Instead of generating an image from nothing, the generator is instead a segmenter of an image. Then the discriminator must tell the difference between a natural ground truth and one from the generation [Chen et al. 2020].

Solution:

We will again be using the ACDC data separated into 2D slices for training. The generator will use a simple 2D U-Net architecture like in phase 1, although shallower. The discriminator will be a simple CNN that will predict it either being real or fake. They will then be trained in parallel using the GAN architecture.

Timeline:

Week 1: ● Implement base U-Net/CNN. ● Additional data preparation (decreasing data used from phase 1).
Week 2: ● Training/tuning network.
Week 3: ● Training/tuning network (cont).

Anticipated Challenges:

The main anticipated challenge is the tuning of the network. GAN architecture is known for being finicky and taking time to tune. This is why the majority of time is dedicated to this.

References:

Chen, C. et al., 2020. Deep Learning for Cardiac Image Segmentation: A Review. *Frontiers in Cardiovascular Medicine*, 7, pp.1-20.

El Jurdi, R., Petitjean, C., Honeine, P., Cheplygina, V. and Abdallah, F., 2021. High-level prior-based loss functions for medical image segmentation: A survey. *Computer Vision and Image Understanding*, 210, pp.9-15.

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Seo, B., Mariano, D., Beckfield, J., Madenur, V. and Hu, Y., 2018. *Cardiac MRI Image Segmentation for Left Ventricle and Right Ventricle using Deep Learning*, California: University of California San Diego.