Proposed Pipeline for CT Image Lung Segmentation with a U-Net and an Optimized Back-Projection Filter

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Abstract

Segmentation of medical images is an extremely common task typically performed using various image processing techniques which can be tedious or time-intensive. The U-Net architecture has consistently proven to be highly capable of performing automated medical image segmentation. I present a U-Net implementation for the segmentation of mouse lungs in micro-CT images. Within the network, I explore the possibility of creating a back-projection filter that is specially optimized to improve the segmentation process. The segmentation process could minimize any unnecessary image losses from suboptimal back projection filration. Due to a lack of implementation mastery in TensorFlow, example filters were not successfully trained. Further work should be done to improve the TensorFlow implementation of the back Projection operation to explore the possibility of optimizing specialized back projection filters.

1 Introduction

The analysis of medical images is critical in preclinical and clinical realms. Proper diagnosis, experimental understanding, and analysis of various medical phenoma require well-annotated, accurate medical images. One image processing task that is very common in medical research is segmentation. Based on a hypothesized idea that an additional optimizable layer prior to our Classification unet could lead to interesting and important improvements in projection-domain segmentation, I will set forth my approaches and findings.

2 Related work

The ability to identify or mask specific structures can be crucial in areas such as tumor detection or radiomics [6]. Harnessing the benefits of deep-learning-based automated segmentation could open the door to more efficient means of diagnosis and treatment of a variety of medical conditions.

Deep learning approaches to segmentation offer promising benefits such as automation and possibly improved feature detection. Efforts to harness the potential of deep learning in the area of segmentation could be bolstered by additional layers of optimization in conjunction with a proven network architecture such as a U-Net. A similar approach to including optimizing physical layers has been shown by researchers at Duke with their novel illumination-optimizable microscope [1].

Furthermore, the approach of optimizing the back projection filter within a reconstruction pipeline corresponds well with the longstanding understanding of the effect of filtered back projection and the ability to alter the noise-level and blurriness of reconstructed CT or PET images by altering the projection filter [4]

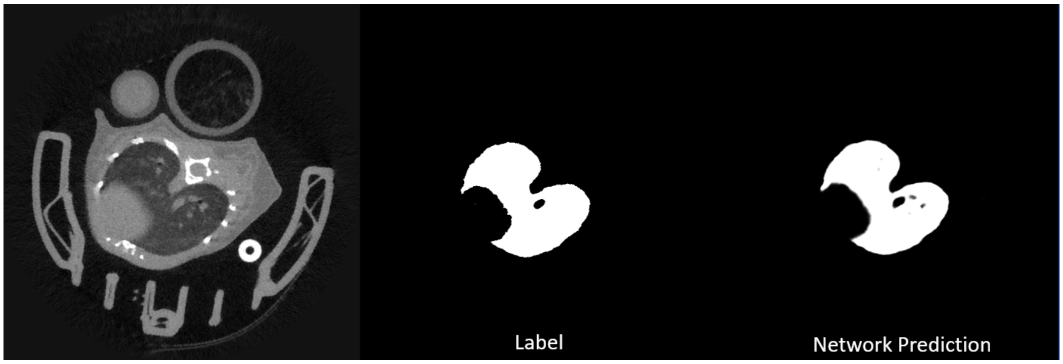

Figure 1: This is an example of an image-label pair comprising my dataset. Material vials, a cradle, and other miscellaneous objects are present that must also be correctly classified. The network prediction on the right is the output from the simple model first trained using only the clean input images.

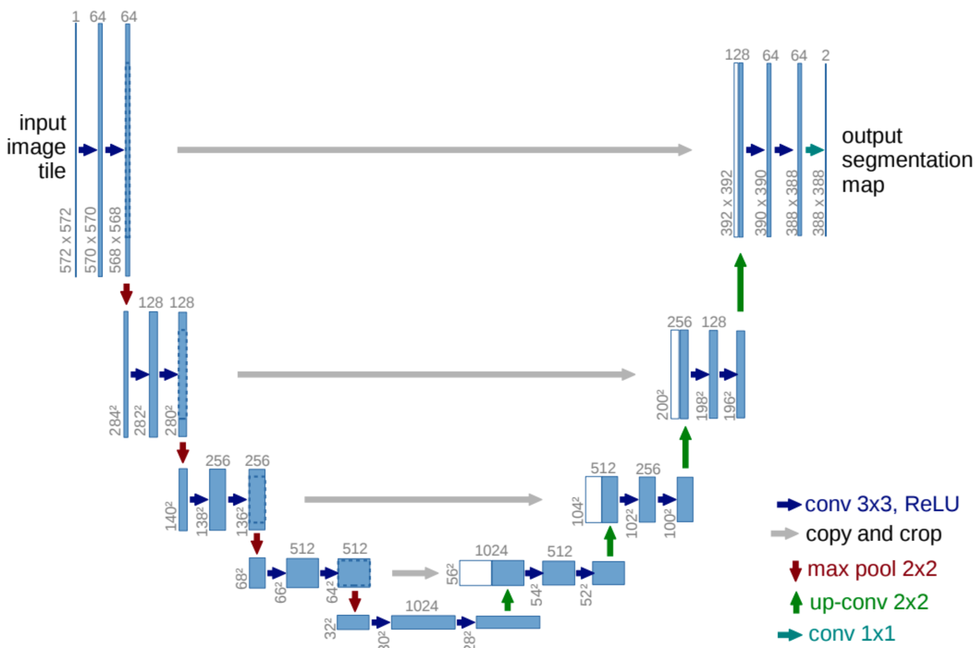

Figure 2: Basic U-Net architecture diagram.([3])

3 Methods

The dataset for this work was provided by members of the Duke Center for In vivo Microscopy (CIVM) asdf(webpage, alternative address). They provided the expertly annotated dataset. Out of the rather large dataset, 19,152 image-label pairs were extracted for use in this experimentation.

The U-Net architecture used was adapted from the TensorFlow implementation presented by Ronneberger et. al. [3] (see Figure 2).

Initial verification of our dataset and unet architecture was performed on the raw input images and labels. The purpose of this first round of testing was to establish confidence in the programmed U-Net

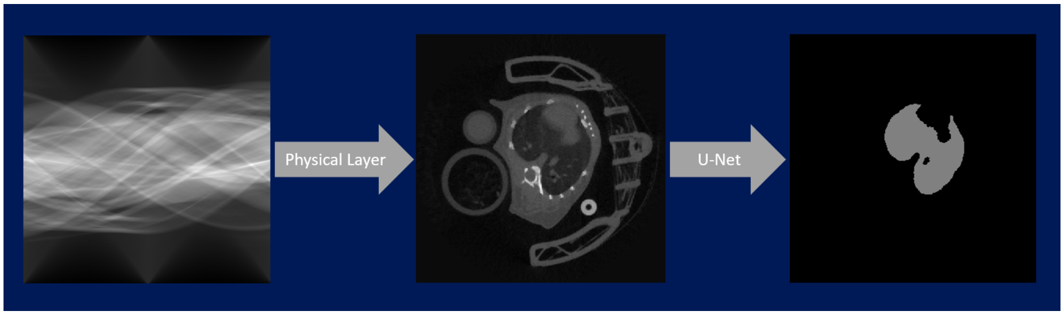

Figure 3: The proposed pipeline for the use of an optimized filtration layer within the segmentation network. Projection sinogram data would ideally be the input and a reconstructed mask would be the output.

Table 1: Network metrics after 25 epochs

Network	Validation Loss	Validation Accuracy
Basic UNet without back projection	0.0653	99.2
Full forward model with fixed filter	0.1544	97.2

implementation and the importing of the image data. Figure 1 contains a representative image-label pair along with the predicted mask from this initial model.

Following this initial verification step, I began experimenting with the prospect of including an optimizable filtered back projection layer as the new first layer of the network. I performed a simple parallel-beam forward projection simulation radon transform to the original images. This set of sinogram data became the new input to the network. The first layer became responsible for performing the filtered back projection of the incoming sinogram data. The inverse radon transform along with the projection filter convolution was implemented in TensorFlow. The filter was initialized with values of 1 to simulate fully unfiltered back projection. A sample pipeline of images going through the final proposed network can be seen in Figure 3.

The TensorFlow implementation of the back projection layer was unfortunately unable to train due to some errors relating to how TensorFlow computes gradients and stores variables during training. In order to gather at least some useful results for later comparison, a final experimental training was performed by using a fixed value for the projection filter.

4 Results

Unfortunately, due to the inability for the TensorFlow implementation of the proposed network, I was unable to gather key results for a trained network which included the optimized filter. Further work should be done to be able to quantitatively analyze the benefit to a trained filter. Basic training results for the training of the original raw data, as well as for the final experiment using a fixed filter are shown in Table 1. Qualitative results from the final experiment is shown in Figure 4.

5 Discussion

I hypothesized that including a trainable back projection layer with an optimizable filter would allow for more optimal segmentation performance given original projection data. This first layer in the netword would serve to deblur the image to the optimal level for possible improvements in network performance. By optimizing the filter, the network could learn to only filter information that is not needed for its task, while maintaining all other key information. This approach could be applied in other areas as well. The inherent removal of data that comes with any filtration process seems to imply a chance for optimization. In this specific experiment however, we wouldn't expect this optimized network to perform any better than the original clean, verification training set due to the

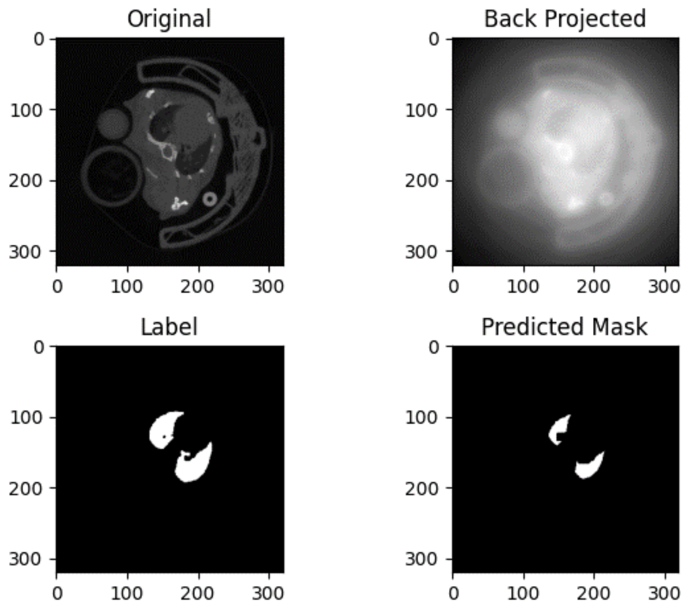

Figure 4: The results of training the full forward model with constant, non-trainable filter weights. The upper right image represents the output of the unfiltered back projection layer implemented in TensorFlow.

fact that the sinogram data was extracted directly from images which had already been reconstructed. Real improvements would come if raw projection data were gathered for testing purposes.

Acknowledgments

I would like to acknowledge Professor Roarke Horstmeyer and his teaching assistants from Course 548L within the Biomedical Engineering Program at Duke University for their efforts to teach me key principles of deep learning and how they apply to different imaging modalities.

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