PARSE CHALLENGE 2022: PULMONARY ARTERIES SEGMENTATION USING SWIN U-NET TRANSFORMER(SWIN UNETR) AND U-NET

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ABSTRACT

In this paper, we describe a deep neural network architecture based on Swin UNETR and U-Net for segmenting the pulmonary arteries from CT scans. The final segmentation masks were created using an ensemble of six models, three based on Swin UNETR and three based on 3D U-net with residual units. Using this strategy, our group scored 84.36 \% on the multi-level dice. We conducted additional investigation and separated the task into three major subtasks: Task 1: Use the default hyperparameters for plain UNET segmentation and experiment with the patch size, a key hyperparameter for UNET segmentation models. Task 2: Develop a lung segmentation model that distinguishes between the major pulmonary artery and the branches in order to precisely assess the model’s performance. Task 3: Examining the mask by extracting small patches near the branches and large patches around the major pulmonary artery.

The code of our work is available on the following link:
https://github.com/akansh12/parse2022

Index Terms— Pulmonary artery, Segmentation, SWIN UNETR, UNET

1. INTRODUCTION

An important biomarker for predicting and diagnosing hypertension is the modified main pulmonary arteries (PA), which is typically found in patients with pulmonary hypertension (PH) and has a diameter that is significantly bigger than that of a normal person. A broadening of the PA in chronic obstructive pulmonary disease (COPD) is linked to higher exacerbation risk and lower survival rates. Blockage of one of the pulmonary arteries, mostly caused by blood clots, causes Pulmonary Embolism (PE). Therefore the early diagnosis of these pulmonary diseases, assessing the risk, and planning treatment for the patients at the early stage is required. Recently, advances in cardiac imaging have been accepted as good tools to help clinicians with early diagnosis and advanced planning in surgery. For the evaluation of many Pulmonary Vascular Diseases (PVD), the morphological examination of the Pulmonary Artery (PA) is crucial. However, even for specialists, the diagnosis procedure frequently takes a long time due to the enormous size and complexity of various imaging modalities; the pulmonary arteries must therefore be correctly and effectively segmented out. Angiography offers insights into the blood flow and conditions of the vascular tree. Three-dimensional volumetric angiography information can be obtained using magnetic resonance (MRA), ultrasound, or x-ray-based technologies like computed tomography (CT). Currently, it is standard procedure to evaluate coronary and pulmonary artery diseases with computed tomography angiography (CTA) as it provides high-resolution 3D imaging as non-invasiveness. Various undermentioned reasons account for the difficulty of the pulmonary artery segmentation:

- The boundaries between the artery and background are often highly fuzzy. Also, Inside the lungs, we have arteries, veins, and airways that look very similar to each other. So, Making models that only learn to segment Arteries and ignore others will be a challenge.
- The tubular structure of the coronary artery is extremely complex: the cross-section area changes gradually along the artery, and there exist a large number of bifurcations.
- The appearance and geometry of the Pulmonary artery may vary considerably from one patient to another. i.e. one such reason is the buildup of the plaque or calcification inside the artery wall may further cause the variability from one patient to another.
- Finally, the image acquisition process may further introduce inherent image noise and artifacts, making the segmentation even more challenging. Also, data scarcity in the field of medical imaging has always been a bit of a challenge.
- Creating a model that is more explainable, consumes less memory, and requires less inference time so that it can be deployed in real-time clinical applications.

The focus of our work is the accurate segmentation of the coronary artery in 3D pulmonary computed tomography angiography (CCTA) volumes. The segmentation of pulmonary artery structures benefits the quantification of its morphological changes for diagnosis of pulmonary hypertension with the task of maximizing the dice coefficient.
2. LITERATURE SURVEY

Machine learning classifiers are used for artery segmentation using predefined image features and various algorithms. Deep CNN methods extract features automatically, and we studied papers on vessel and airway segmentation from lungs CT/CTA. [8] talks about 2-D orthogonal cross-hair filters for artery segmentation, offering improved speed, lower memory footprint, and network complexity compared to 3-D filters. The filters utilize 3D context information at a reduced computational burden while maintaining comparable accuracy. The authors also generate a synthetic dataset using a computational angiogenesis model for transfer learning. [6] uses an algorithm which consists of scale-space particle segmentation, 3-D CNN classification, and graph cuts optimization for vessel segmentation with 94% accuracy, outperforming other CNN architectures and Random Forest. The paper also explores the use of tree-structured LSTM for modeling underlying tree structures in NLP tasks. [5] proposes a tree-structured ConvGRU model for learning the coronary artery’s anatomical structure. By considering local spatial correlations in input data, the model is better suited for image analysis. [9] uses the method that extracts lung parenchyma with Unet++ and then uses nnUnet to extract pulmonary veins within the parenchyma. This eliminates interference from extracellular tissues and improves accuracy with an "AND" operation on the original image and segmentation results. The paper [7] presents an automated system to differentiate pulmonary arteries and veins on chest CT without contrast agents. The system uses CNN to identify extrapulmonary arteries and veins and applies a computational differential geometry method to detect high-density tubular structures as intrapulmonary vessels. The algorithm achieves a 98% sensitivity in labeling pulmonary artery and vein branches compared to a human expert. [4] demonstrates a 2.5D segmentation network applied from three orthogonal axes, which presents a robust and fully automated pulmonary vessel segmentation result with lower network complexity and memory usage compared to 3D networks. The introduction of the slice radius convolves the central slice’s nearby information, and multi-planar fusion enhances the presentation of intrand inter-slice features by achieving a DICE score of 0.9272 and a precision of 0.9310. Inspired by all these papers we proposed our approach.

3. DATA DESCRIPTION

The dataset is provided by PARSE 2022 Grand Challenge[10]. The dataset contains 200 3D volumes provided in compressed NIFTI (.nii.gz) format and with refined pulmonary labels. These CTPA (Contrast Enhanced CT Pulmonary Angiography) are obtained from Harbin Medical University, Harbin, China. CTPA is a medical diagnostic test that employs computed tomography (CT) angiography to obtain an image of the pulmonary arteries. During the test, dye (normally Iodine contrast) will be injected into a vein that travels to pulmonary arteries. This dye makes the arteries appear bright and white on the scan pictures. The size of the CT volumes ranges from 512x512x228 to 512x512x376. Pixel sizes are between 0.50mm/pixel and 0.95mm/pixel. Slice thickness is 1mm/pixel. The annotations are: 0 is referred to as Background and 1 as Pulmonary artery in voxel-level segmentation. Out of these 200 3D volumes, 100 volumes are provided as a Training Dataset which consists of an image and respective label volume. 30 volumes for validation cases and 70 volumes for test cases.

4. METHODOLOGY

To perform segmentation of Pulmonary Arteries, we experimented with different encoder-decoder deep neural network architectures. We boiled down these architectures to two class models that were finally used to make predictions in this challenge’s validation and test phase. These two categories of models are 3D UNet with residual units[1] and Swin U-Net Transformer(Swin UNETR)[2, 3]. Our final predictions are made using a weighted ensemble of six models, out of which three are based on 3D UNet with residual units, and the other three are Swin UNETR trained in a different fashion in respect to each other. Details of architecture and training methods will be described later part of this section.

4.1. Pre-processing and Data Augmentation

The CTA images were transformed and pre-processed for optimal results before passing them into the model. The Hounsfield unit(HU) of all the CT scans is clipped between -1000 HU to 1000 HU, and then these values were scaled to the range of 0 to 1. After performing clipping and scaling operations, extra slices containing no information were removed. Following this, the most important pre-processing step was to convert the CT scan volume into smaller 3D volume patches. As discussed in the data description section, the input(CT scans) size ranges from 512x512x228 to 512x512x376, which cannot be passed entirely to 3D convolution because of high computational cost. Hence each CT scan volume is divided into smaller 3D cubes of patches. For U-Net based model, we experimented with different patch sizes of 96x96x96, 128x128x128, and 160x160x160. For the model, Swin UNETR, we stuck to the size of 96x96x96 because of computational cost.

Furthermore, to increase the total number of data points and to increase the robustness of the trained model augmentation technique like random flipping of volume along a different axis, random rotation within -30 to 30 degrees, and random intensity shift with a small offset of 10HU were performed.
4.2. Model Architecture

In total, six models were used to make a prediction, out of which three were U-Net based, and three were based on Swin UNETR. The model architecture of the 3D U-Net model had 16, 32, 64, 128, and 256 channels in subsequent layers with a stride of 2x2x2. The number of residual units was equal to 2, and the output layer had two channels, one representing the background and the other representing the Pulmonary Arteries. While training different U-Net-based models, we experimented with different patch sizes, augmentation techniques, and learning rates. Swin UNETR, the input size was set to 96x96x96, with input channels and output channels equal to 1 and 2, respectively. The feature size was set to 48. Similar to U-Net, three selected Swin UNETR used for prediction were trained with different learning rate, loss, and augmentation techniques.

4.3. Further investigation

We conducted additional research and separated the task into four major subtasks:

- Task 1: Use the default hyperparameters for plain UNET segmentation and experiment with the patch size, a key hyperparameter for UNET segmentation models.
- Task 2: Develop a lung segmentation model that distinguishes between the major pulmonary artery and the branches in order to precisely assess the model’s performance.
- Task 3: Examining the mask by extracting small patches near the branches and large patches around the major pulmonary artery.

4.4. Training and Evaluation

The training set for the PARSE challenge 2022 had in total of 100 CTA scans. We created a local validation set consisting of 10 CTA scans to train the model. Hence model was trained on 90 CTA images and validated on the remaining images. The training was performed using the ADAM optimizer with the loss function set as the sum of cross-entropy loss and Dice Loss. Using this configuration, both U-Net and Swin UNETR based were trained, and three of each category were chosen. Finally, the weighted sum of predictions from each model was performed in the evaluation step. The calculations of weights and final prediction are explained in equations 1, 2, and 3.

Let D be a 1x6 matrix with each entry as a dice score from the corresponding model. So

\[ D \in \mathbb{R}^{6x1} \]

where Di represents the dice score of model i on the local validation set. Then ensembling weights, W is defined as in equation 1.

\[ W = (1/\sum D_i) \times D \quad (1) \]

This W was later used to make a weighted segmentation prediction, as explained in equations 2 and 3. Let Pfinal be the final prediction, and Pi represents the segmentation result from model i, then,

\[ P_{final} = f(\sum W_i \times P_i) \quad (2) \]

where f(x) is a thresholding function performed on all matrix elements and is defined in equation 3.

\[ f(x) = \begin{cases} 0 & x \leq 0.5 \\ 1 & 0.5 \leq x \end{cases} \quad (3) \]

Table 1. Dice score of selected models on local validation set.

| Model       | Patch Size   | Description                                                                 | Dice Score |
|-------------|--------------|-----------------------------------------------------------------------------|------------|
| Unet_1      | 128x128x128  | U-Net model with no augmentations.                                           | 84.30      |
| Unet_2      | 160x160x160  | U-Net model with bigger patch size but with no augmentations.                | 85.50      |
| Unet_3      | 160x160x160  | U-Net model with bigger patch size but with augmentations.                  | 85.52      |
| Swin_UnetTr_1 | 96x96x96  | Swin UNETR based architecture with augmentations, Learning rate = 1e-4     | 86.55      |
| Swin_UnetTr_2 | 96x96x96  | Swin UNETR based architecture with augmentations, Learning rate = 1e-5      | 86.75      |
| Swin_UnetTr_3 | 96x96x96  | Swin UNETR based architecture with augmentations, Learning rate = 1e-5      | 86.87      |

5. RESULTS AND DISCUSSION

Table 1 describes the different models used for final prediction and their corresponding Dice score on the local validation set.
In our experiments, we found that Swin UNETR gave a better dice score than U-Net based model. However, this difference is very small, with 1 percent of the dice score. Upon making multiple submissions to the validation phase, we found out that the Swin UNETR-based model performed better in segmenting Arteries’ branches while the U-Net model performed better in detecting the main Artery. Hence, to capture the benefit of both models, we performed ensembling to capture the main artery and branches better. For the U-Net model, the size of the input patch cube was one of the critical hyperparameters. One of the plausible explanations for this is that a larger patch size helps in better context and improved training. To carefully detect the branches and model needs more context. Because of the high computational cost, we cannot increase the input patch size from 96x96x96 for the Swin UNETR model. We also experimented with Post-processing techniques like the largest Connected Component Analysis (CCA). However, CCA was not used in the final pipeline as we concluded from our experiments that after applying CCA to the final prediction, the average dice score of the main artery increases, while for branches, the average dice score decreases. But the PARSE challenge used the Multi-level Dice Similarity Coefficient score, which is the weighted sum of the average dice score of branches and main artery with more weight given to branches. So reducing branch dice score after applying CCA was hurtful to our raking on the leaderboard. Finally, Figure 1, shows a 2 dimensional(2D) plot of one of the local validation set example. These 2D plots are generated by summation of the slices in corresponding, axial, sagittal or coronal, planes.

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