Detecting Volumetric Medical Image Features for Radiotherapy

Dong Joo Rhee, Tucker Netherton, Constance Owens

UT MD Anderson Cancer Center, Radiation Physics Dept.

November 2018

1 Introduction

Recently, methods of computer aided detection have greatly influenced the medical imaging community. Tasks using convolutional neural networks have allowed for the detection of pneumonia, retinal disease, spinal metastases, and many other applications[1–3]. These models were either built from the ground up, or inspired and retrained from various models that competed in ImageNet challenges (e.g. VGG[4], Inception[5], Resnet[6], RCNN[7]) to classify two dimensional images into various categories.

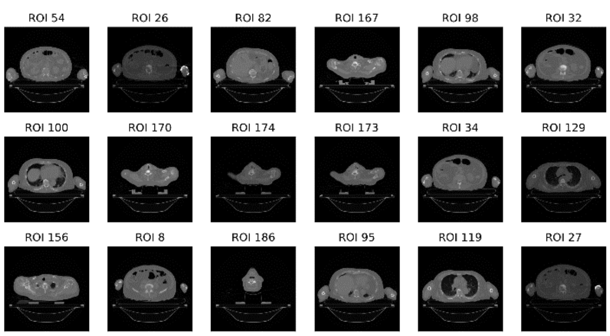

Figure 1. Various slices from a patient's CT

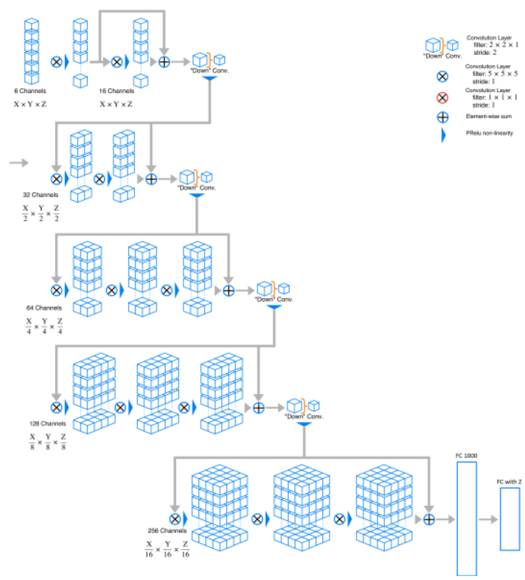

Figure 2. V-NET architecture, modified for our purposes

Medical images from CT (computed tomography) are composed of collections of "slices" that build a three dimensional image volume (Fig 1). These scans give anatomical information about a patient; each volumetric pixel reports on the electron density measured in that region. Our research group provides automated services for the segmentation of normal tissue structures in these images as well as detection of features (such as cancer or abnormal anatomy) using deep learning.

We are currently in need of a three dimensional deep-learning architecture to classify the presence of three-dimensional features.

2 Methods

Currently, the standard in our field is to hand annotate every organ's presence. We hope to predict the presence of organs in CT images to automate aspects of the radiotherapy workflow.

To do this we propose to modify the VNET[8] architecture, made available through (https://github.com/MiguelMonteiro/VNet-Tensorflow). By using half of this architecture (before the up-sampling occurs), and adding fully connected layers, we plan to train this network to perform medical image classification tasks (Fig 2). At each layer, we will implement batch-normalization.

We plan to demonstrate the usefulness of this unique architecture by performing three separate tasks related to radiotherapy: 1) bone metastases detection, 2) normal anatomy classification, and 3) head and neck HPV status prediction.

We will optimize image-preprocessing steps and the following hyper-parameters: normalization, learning rate, number of fully-connect units, and number of fully-layers.

3 Dataset

The following CT images have been collected for training, validation, and testing.

1) 800 CTs x N_{slices} x 512_{pixels} x 512_{pixels}, labeled as diseased or not diseased vertebral bodies

2) 1,557 CTs x 20_{slices} x 512_{pixels} x 512_{pixels}, labeled as having an organ of interest or not

3) 511 CTs x N_{slices} x 512_{pixels} x 512_{pixels}, labeled as HPV+ or HPV-

We will use an NVIDIA DGX1 with 4 V100 Tesla GPUs for training.

4 Expected Outcomes

We can compare the resulting models to results from similar two dimensional architectures. Making these three dimensional architectures will allow for volumetric features to be seen by our model and we hypothesize that it will improve the accuracy of the above classification tasks.

References

[1] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, M.P. Lungren, and A.Y. Ng, (2017).

[2] J. Cornebise, P.A. Keane, and O. Ronneberger, Nat. Med. (n.d.).

[3] J. Chmelik, R. Jakubicek, P. Walek, J. Jan, P. Ourednicek, L. Lambert, E. Amadori, and G. Gavelli, Med. Image Anal. (2018).

[4] A. Krizhevsky, I. Sutskever, and G.E. Hinton, (n.d.).

[5] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, (2015).

[6] K. He, X. Zhang, S. Ren, and J. Sun, (n.d.).

[7] K. He, G. Gkioxari, P. Dollár, and R. Girshick, (2017).

[8] F. Milletari, N. Navab, and S.-A. Ahmadi, (2016).