NerveNet: Convolutional Neural Network Architectures for Medical Image Segmentation

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1 Introduction

1.1 Background

Advances in medical imaging is aiding in the identification of nerve structures in patients' X-ray images. Accurately identifying the appropriate nerve structures is imperative to proceeding with pain management catheters. We explore ultrasound images of the neck and attempt to segment out nerve structures from a large online dataset.

1.2 Convolutional Neural Networks

We used Convolutional Neural Networks for the task of segmenting nerve structures. In computer vision research, CNNs are used extensively for image classification and have been used to build the ImageNet database [1] which contains over 20 million classified images for training. However, for our image segmentation task, we constructed networks for regression as opposed to classification.

We followed a technique led by researchers at the University of California, Berkeley to transform CNNs designed for classification tasks into *fully convolutional networks* [2] that were able to segment medical images.

Architecture	Conv. Layers	Learning Rate
U-Net [3]	18	1.0×10^{-5}
FCN-AlexNet [4]	7	1.0×10^{-3}
FCN-VGG16 [5]	16	1.0×10^{-4}
FCN-LeNet5 [6]	4	1.0×10^{-3}

Table 1. The various Convolutional Network architectures used.

All CNNs were implemented using Keras [7], a python machine learning library.

2 Experimentation

2.1 Training

Each CNN was trained using stochastic gradient descent with momentum 0.9 and a specified learning rate (see the table above). We used *Cross Validation* after each epoch with 10% of the training data set aside. Each CNN was trained for 50 epochs on a batch size of 20 images.

The training loss was measured by the *Sørenson-Dice Coefficient*, commonly used in statistics to measure the similarity between two samples of data. In this experiment, the Dice Coefficient recorded the similarity in Run-length encoding between the network's prediction on the validation data and the desired segmented image.

2.2 Results

U-Net was the only CNN used in this experiment that was specifically engineered for sementic segmentation. Each of the other three networks were modified classification networks for segmentation.

Architecture	Dice Coeff.
U-Net	0.57
FCN-AlexNet	0.55
FCN-VGG16	0.37
FCN-LeNet5	0.53

Table 2. The best scores achieved by each CNN over 50 epochs as measured by the Dice Coefficient.

U-Net, FCN-AlexNet and FCN-LeNet5 all had scores within a tight range,, however FCN-VGG16 performed far worse.

2.3 Conclusion

Based on our results in **Table 2**, the covariance between the number convolutional layers and the Dice Coefficient is -0.1438. This does not suggest that a deeper CNN would yield accurate segmentation of nerve structures.

References

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