Deep Tissue Characterization: Applications in Intravascular Ultrasound

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Abstract. This paper presents a deep learning architecture to segment plaque from human artery's IVUS image and characterize tissue into fibrotic mask, calcified mask, necrotic mask, lipidic mask. Tissues are heterogenous and colocated. Each tissue backscatter signal diffrently giving a non unique patterns in IVUS image which makes it difficult for clinicians to segment the plaque into its constituents. Our algorithm will assist clinicians to identify such heterogeneous tissues and assess plaque vulnerability. An encoder-decoder architecture is used to achieve this in a fully convolutional fashion.

Keywords: IVUS, Tissue Characterization, Machine Learning, Fully Convolutional neural networks, Deep Learning, plaque Segmentation

1 Introduction

Plaque is made up of fat, cholesterol, calcium, and other substances found in the blood. Over time, plaque hardens and narrows arteries. This limits the flow of oxygen-rich blood to organs and other parts of your body. Plaque deposition in the human arteries can lead to disease called as Atherosclerosis. There are different Atherosclerosis-Related Diseases like Coronary Heart Disease, Carotid Artery Disease, Peripheral Artery Disease, Chronic Kidney Disease. There are two imaging modalities, Intravascular Ultrasound and Computed tomography angiography used by clinicians to infer about atherosclerotic plaques composition. Intravascular Ultrasound (IVUS) is a predominant imaging modality in interventional cardiology. It provides real-time cross-sectional images of arteries. These images are used by clinicians to characterize tissue into fibrotic mask,calcified mask,necrotic maps,lipidic mask, plaque mask. Coronary Artery Disease (CAD) is the single largest killer in the western world, causing an estimated 1 in every 5 deaths [2].Therefore, early detection and quantification of plaques is of high interest. However, interpreting and detecting the plaques requires substantial experience. It can take several hours for the physicians to do manual plaque segmentation for a single CTA dataset also these plaques are heterogeneous in nature and constitute fibrous tissue, lipid deposits and calcifications. Each of these tissues backscatter ultrasonic pulses and are associated with a characteristic intensity in B-mode IVUS image. However, clinicians are challenged when colocated heterogeneous tissue backscatter mixed signals appearing as non-unique

intensity patterns in B-mode IVUS image. Tissue characterization algorithms have been developed to assist clinicians to identify such heterogeneous tissues and assess plaque vulnerability.

We have developed fully convolutional neural network to characterize tissue into its four constituents: fibrotic mask, calcified mask, necrotic mask, lipidic mask.

Prior Art: In literature different methods has been used to segment plaque. Authors in [8] in in order to perform near real time plaque segmentation of IVUS, built a classifier by assembling weak classifiers using boosting schemes. Classifier learn texture patterns of the plaque using local binary patterns. Authors in their work [7] used despeckle filtering and snakes for segmenting the atherosclerotic carotid plaque from ultrasound images.In the work [1] authors performed both Automatic segmentation and plaque characterization in atherosclerotic carotid artery MR images. MR images were segmented using model-based segmentation and fuzzy clustering to detect the vessel wall, lumen and lipid core boundaries. In [10] Machine learning techniques like Random Forests and RuleFit were used to predict high coronary artery calcification (CAC) measured by computed tomography. Authors in [5] built a model for automatic detection of plaques with severe stenosis in coronary vessels of CT angiography. They used using a nearest neighbor classification approach to segregate Lumen and vessel wall. To Detect Coronary Artery Stenosis from Multi-Detector CT imaging Authors in [11] trained the model where decision function is learned by a support vector machine (SVM). Vessel Intensity and geometric features were used by authors In [3] train a random forest (RF) classifier with four decisions (no plaque, three plaque types(calcified, soft, and mixed)) to predict coronary artery stenosis in CTA. Segmentation of the carotid plaques in 3-D ultrasound images was done using method which combines image intensity with structure information in both initialization and a level-set evolution process in [4]. These models were able to in segmenting plaque but were not able to characterize plaque accurately into its four constituents.

In this section we review two most recent approaches one [9] where Random forest were employed for learning of tissue specific ultrasonic backscattering statistical physics and signal confidence primal from labeled data for predicting heterogeneous tissue composition in plaques. Other is [6] where A structured learning technique was proposed by author to detect all coronary arterial lesions with stenosis greater than 25 %. The proposed machine learning algorithm consists of two stages: (1) two independent base decisions indicating the existence of lesions in each arterial segment and (b) the final decision made by combining the base decisions. One of the base decisions is the support vector machine (SVM) based learning algorithm, which divides each artery into small volume patches and integrates several quantitative geometric and shape features for arterial lesions in each small volume patch by SVM algorithm. The other base decision is the formula-based analytic method. The final decision in the first stage applies SVM-based decision fusion to combine the two base decisions in the

second stage. Method performed with high sensitivity (93%), specificity (95%), and accuracy (94%), with receiver operator characteristic area under the curve of 0.94. The proposed algorithm shows promising results in the automated detection of obstructive and non obstructive lesions from CTA.

2 Methodology

Fully Convolutional Neural networks

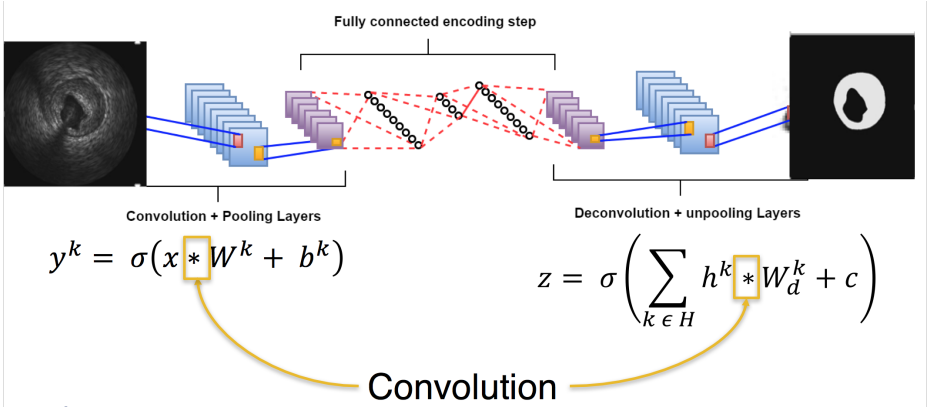


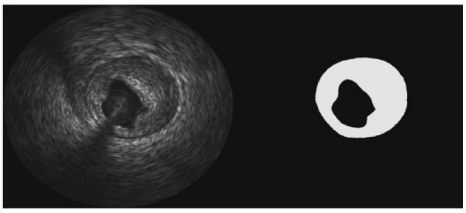
Fig. 1: - Illustration of Fully convolutional neural network

Convolutional Neural Networks are very similar to ordinary Neural Networks. They are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g. SVM/Softmax) on the last layer.

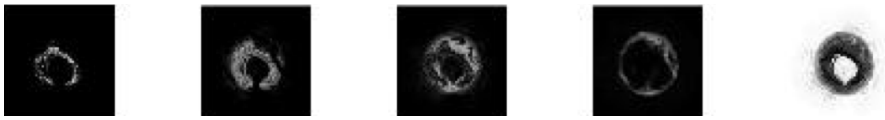
A simple ConvNet is a sequence of layers, and every layer of a ConvNet transforms one volume of activations to another through a differentiable function. We use three main types of layers to build ConvNet architectures: Convolutional Layer, reLU and Pooling Layer. We stacked these layers to form a full 3 level Encoder-Decoder ConvNet architecture for our problem.

3 Data Description

Our dataset comprises IVUS images of 25 patients with 6 marked labels i.e. plaque mask, confidence map, calcified mask, fibrotic mask, lipidic mask and necrotic mask. In total, our dataset has 1802 images. We assigned data of 19 patients to training set and rest to test set by randomly generated permutation of numbers,



(a) IVUS image and plaque label



(b) Label from left : Calcified, Fibrotic, Lipidic and Necrotic label

Fig. 2: IVUS and labeled data

thus assigning 76% of data in training set. We applied rotation augmentation to our training data with 10 degree rotation to multiply the samples for training. Each image in the dataset is of 512 x 512 dimension. For the problem of plaque segmentation and confidence map we downscaled the image to 256 x 256 and for Tissue characterization problem we reduced it to 128 x 128 to meet the memory availability of GPU for our networks. fig:2 shows the IVUS image and 6 labeled data for corresponding IVUS image.

4 Implementation and Analysis

This section describes implementation and results.

4.1 Plaque Segmentation

We used fully convolutional neural network in 3 level encoder-decoder structure for plaque feature extraction and image reconstruction. Fig:3 illustrates the representation of our network. Encoder block for feature extraction constitutes of Convolutional layer, batch normalization layer, ReLU layer and pooling layer while each decoder block for reconstruction constitutes of unpool layer, concat layer, 2 convolutional layers , batch normalization and ReLU layers. We used L2 loss (least square errors) in the network. We have used batch size of 25 and 120 epochs in our network. We then used dice and jaccard similarity on the results of our network to compare with ground truth.

fig:4 shows the ground truth image of segmented plaque and image constructed by our network.

fig:5 shows the plot between sensitivity vs specificity from which we obtained threshold of 0.5. We got accuracy of .983 , dice similarity of .803 and jaccard similarity of .691 on threshold value of 0.5 obtained from ROC curve between ground truth and image constructed by network. Due to high number of true

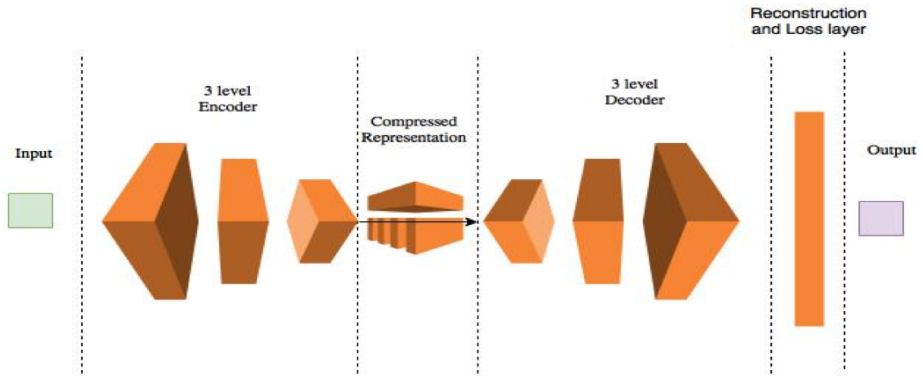


Fig. 3: - 3 level Encoder-Decoder fully convolutional neural network

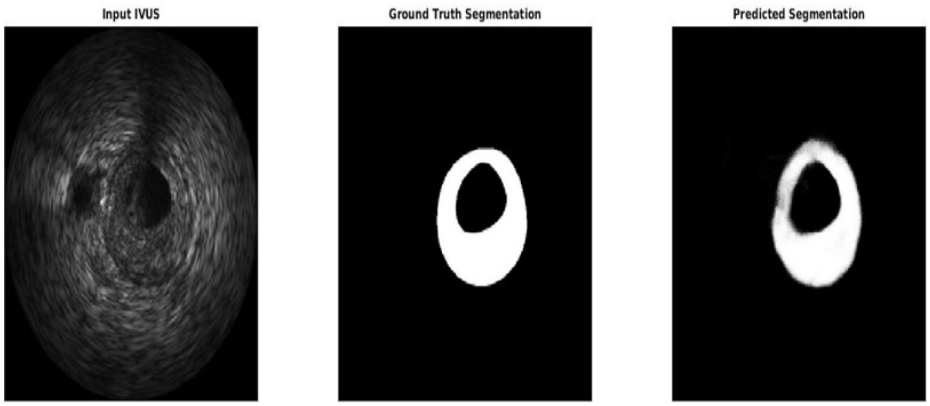


Fig. 4: - Ground truth and segmented plaque

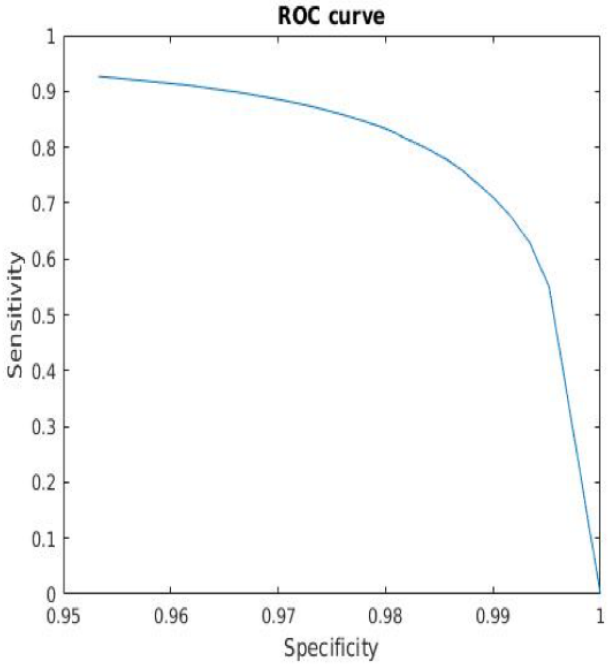


Fig. 5: - ROC curve for plaque segmentation

negatives in our data we have not plotted actual ROC curve (Sensitivity vs 1-Specificity).

4.2 Tissue characterization

For tissue characterization we used 3 level encoder-decoder fully convolutional neural network. We used 5 labeled data. The 4 labels are Calcified mask, fibrotic mask, lipidic mask and necrotic mask. The fifth label is subtraction of all these 4 labels from a white image. We have reconstructed each label at last decoder of the network. fig:5 shows the configuration of the network being used for the dataset. We have reconstructed each of the 5 labels at 3rd level of decoder. Encoder block for feature extraction constitutes of Convolutional layer, batch normalization layer, ReLU layer and pooling layer while each decoder block for reconstruction constitutes of unpool layer, concat layer, 2 convolutional layers , batch normalization and ReLU layers. At third level decoder we have used reconstruction layer (convolutional layer) for image reconstruction, Sigmoid layer and L2 loss layer for each of the five labels. We have used batch size of 25 and 120 epochs in our network. We then used dice and jaccard similarity on the results of our network to compare with ground truth.

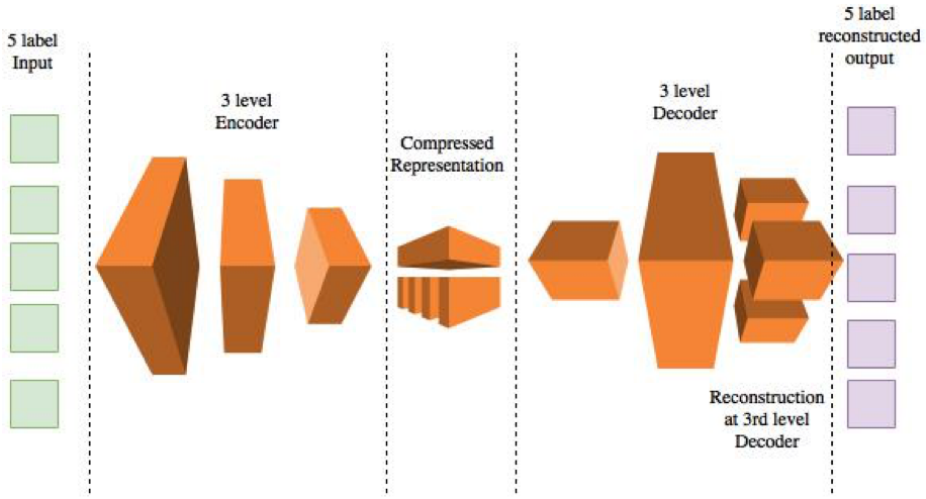
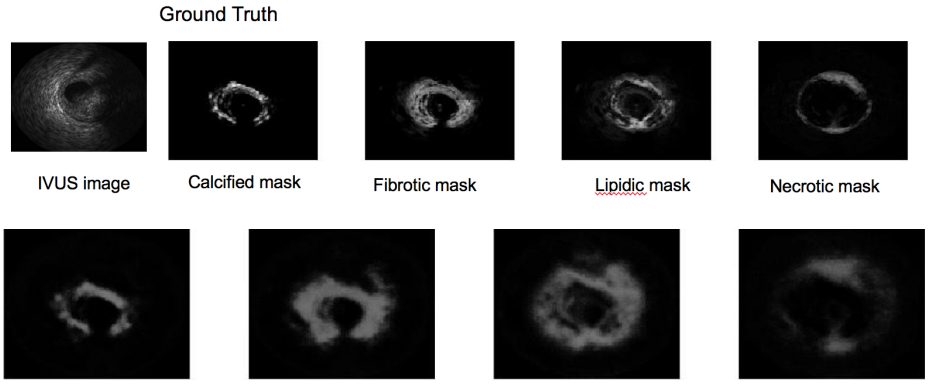


Fig. 6: - 3 level Encoder-Decoder fully convolutional neural network for Tissue characterization

fig:6 shows the ground truth image of labels which are calcified mask, fibrotic mask, lipidic mask ,necrotic mask and complement of these masks. Figure shows the plot between sensitivity vs specificity for each of the 4 masks by which we obtained threshold value to compute similarity. We got accuracy of 0.9800, 0.9469, 0.9276, 0.9430 for prediction of calcified mask, fibrotic mask, lipidic mask and

necrotic mask respectively. We got dice similarity of 0.86891788, 0.67305690, 0.76629132 and 0.80084586 and jaccard similarity of 0.76887542, 0.51084661, 0.62646443 and 0.67194611 for calcified mask, fibrotic mask, lipidic mask and necrotic mask respectively.As mentioned above due to high number of true negatives in our data we have not plotted actual ROC curve (Sensitivity vs 1-Specificity).



(a) Output Label from left : Calcified, Fibrotic, Lipidic, Necrotic label

Fig. 7: IVUS and 5 labeled data

5 Conclusion

we have constructed a framework for plaque segmentation and characterizing co-localized heterogeneous tissues in ultrasonic imaging. To achieve this we have used fully convolutional neural networks in different configuration. We could attain 98.3% accuracy in plaque segmentation and in tissue characterization, we got accuracy of 0.9800, 0.9469, 0.9276, 0.9430 for prediction of calcified mask, fibrotic mask, lipidic mask and necrotic mask respectively.

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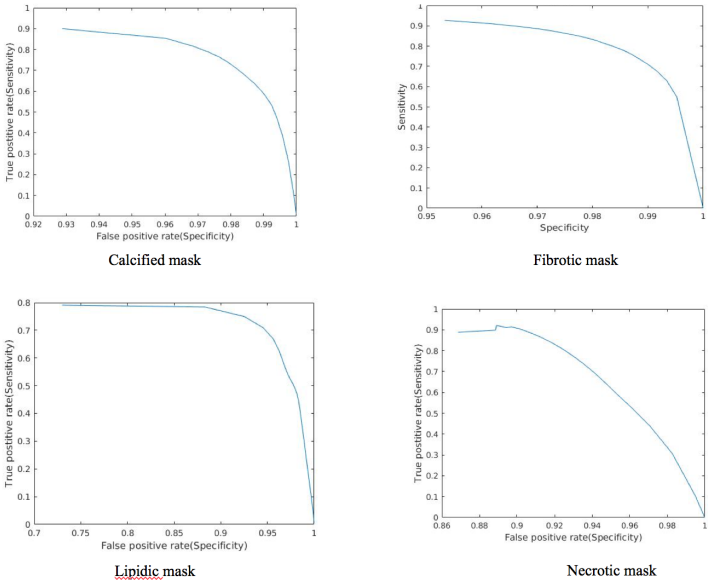

Fig. 8: - ROC curves for the tissues

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