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Deep learning methods for detection of carotid artery wall

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Abstract: Carotid artery is the main artery located in human neck. Its main role is to deliver blood to the neck and face muscles as well as, most importantly, to the brain. Carotid artery stenosis is one of many fatal carotid artery diseases involving carotid artery. Development of stenosis on artery wall can cause brain stroke if plaque breaks. Convolutional neural networks (CNNs) proved to be successful in object classification on images as well as object detection on same images. In the field of segmentation of clinical images, U-Net and SegNet architectures proved to have good performances. The aim of this paper was to use CNN to detect carotid artery wall in order to separate artery tissue from stenosis. Automatic segmentation of carotid artery wall was done via SegNet CNN and was compared with modified U-Net based deep convolutional network. Proposed model was evaluated on the images of real patients which were acquired through ultrasound. Experimental results show that this model outperforms models of other deep neural networks.

Keywords: Carotid artery, deep neural networks, U-Net, segmentation, medical images, stenosis, SegNet

1. introduction

Carotid artery is one of the main arteries located in human neck. Its main role is to deliver blood to the neck and face muscles as well as, most importantly, to the brain. Human body has two carotid arteries located in either side of neck. Both arteries have bifurcations. One of the bifurcated arteries, inner carotid artery, has the main role to deliver blood to the brain, while other, exterior carotid artery delivers blood to face and neck [1]. As well as other arteries, carotid arteries can succumb to a number of fatal diseases including carotid artery vasculitis, stroke, stenosis, aneurysms, atherosclerosis etc. The main resemblance of these diseases is their high mortality rate. Thus, great efforts are made to recognize these problems, solve them and even predict their development [1].

Main reasons for high mortality rate of carotid artery diseases is their detection and recognition by clinicians. Even though it is relatively easy detect aneurysms on carotid artery through ultrasound or X-ray, the problem occurs when doctors try to recognize plaque formation, to separate it from the artery wall and to recognize which type of plaque has formed (figure 1).

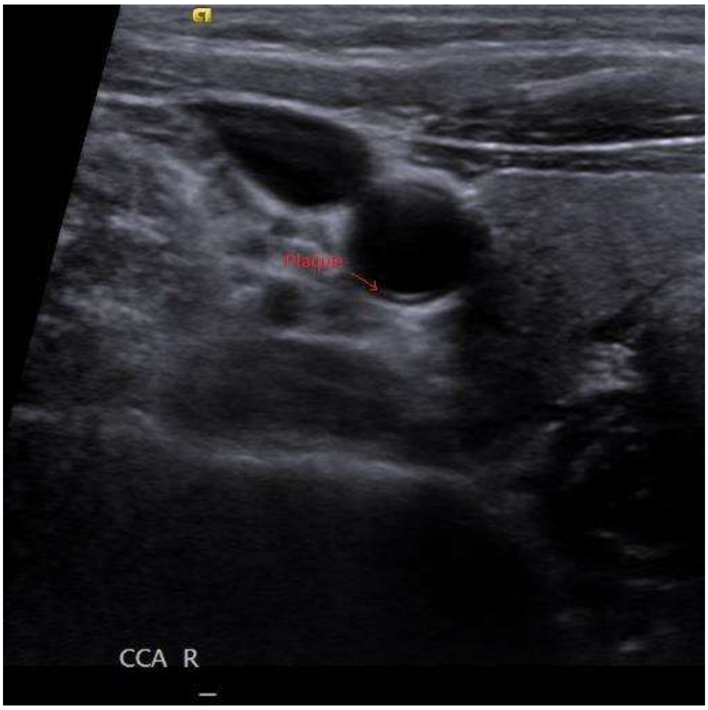

Figure 1. *Transversal cross section of carotid artery and plaque*

With development of technology in medicine, clinicians tried to describe diseases in simpler ways [2-4], while, with the development of neural networks, many attempts to automate the process of disease detection have occurred. As of the start of 21th sanctuary many attempts on automatic characterisation of plaque on blood vessel walls were attempted [5-9] with the previous steps of lumen and wall detection.
In this paper, attempt on automatic carotid wall detection was made as pre-step for plaque detection on carotid artery walls as well as their characterisation. This segmentation was applied on lungs of real clinical patients using SegNet based CNN and was compared with U-Net model. Models were evaluated on a set of ultrasound images with the resolution 512x512. Segmentation results were evaluated in the terms of dice coefficient. Experimental results show that SegNet model outperforms other models.

2. Methodology

In this study, the U-Net [10] and SegNet [11] architectures have been applied on a set of ultrasound images of carotid arteries. Images were separated into two sets, coloured images and black-white (BW) images (figure 2).

Figure 2. Different images from the dataset, coloured (left) and BW (right)

In order to use CNN models, segmented images had to be acquired for validation set. Manual segmentation was done in open source image editing software. Result of the manual segmentation is shown on figure 3.

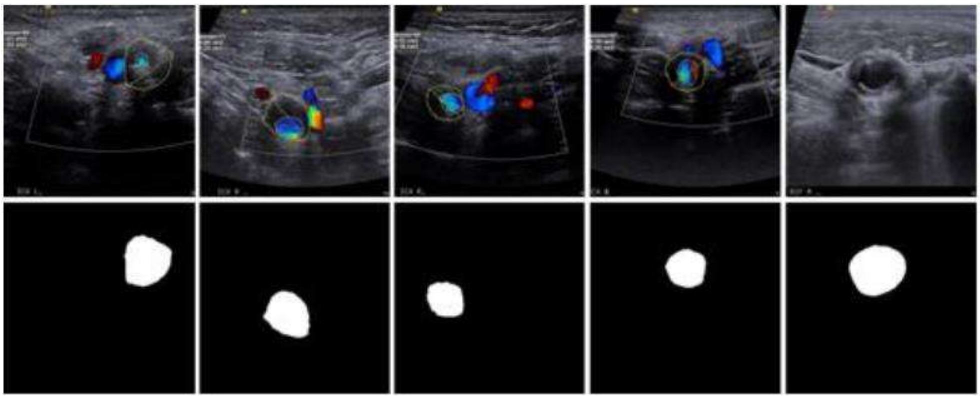

Figure 3. Manually segmented images from the dataset

Modified U-Net based CNN and baseline SegNet architectures were used on the dataset. U-Net architecture used in this study was modified from the aspect of depth. An additional block was added to encoder and decoder figure 4 as it was shown in Arsic et al. 2019 [12].

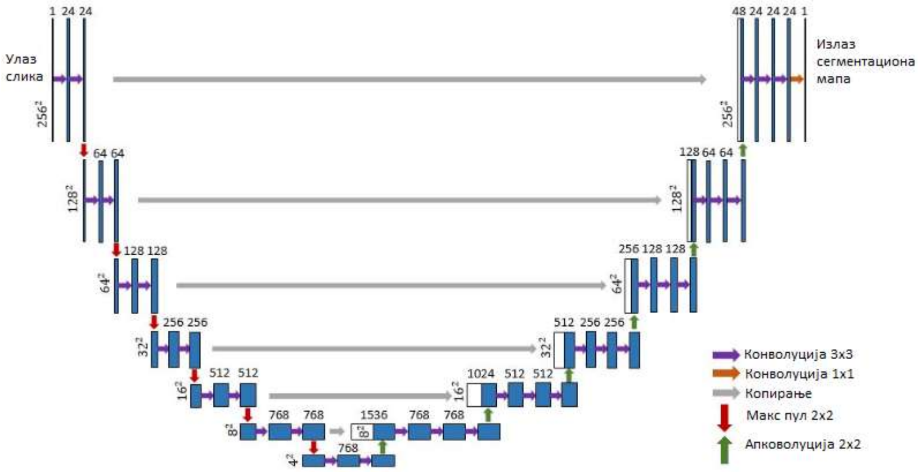

Figure 4. Modified U-Net architecture

Figure 4 shows that every encoder block has two convolutional layers with filter 3x3 which are followed by 2x2 max pull layer and that every decoder block has 2x2 upconvolution layer and a skip connection followed by three 1x1 convolutional layers with sigmoid activation function. All convolution layers are arranged so that height and width of output image is the same as it was on input. Additional difference between baseline and presented U-Net architecture is that modified architecture uses serial normalization after each convolution layer which proved to give better results [13]. Models were trained with a combination of binary crosentropy and dice coefficient.

3. Results and Discussion

In this paper, task of binary classification of segmented images was taken in consideration. Results have been evaluated using dice coefficient (F1 score) on two separated sets (colour and BW). U-Net model achieved F1 score of 0.91 and 0.93 on BW and coloured images respectively while SegNet achieved 0.92 and 0.94. While scores are not very different, SegNet has achieved slightly better results. This is a result of the fact that modified U-Net uses twice as much training parameters compared to SegNet thus getting slightly worse results in the process.

Figure 5 shows a comparison of original and SegNet segmented images.

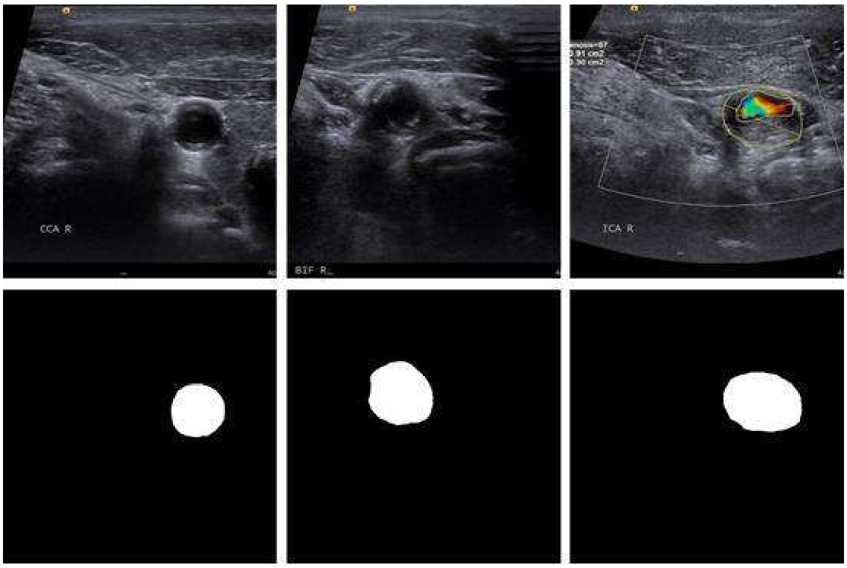

Figure 5. Results of SegNet architecture

As it can be seen in figure 5, SegNet architecture has smoot edges compared to manually segmented images shown on figure 3.

5. Conclusion

This study has shown the use of deep learning methods for detection of carotid artery wall. Set task of was achieved with SegNet neural network with the dice coefficient of 0.92 for BW and 0.94 for coloured images.
Future work will include lumen detection as well as plaque characterization.

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