Deep Diagnostics: Applying Convolutional Neural Networks for Vessels Defects Detection

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Abstract. Coronary angiography is considered to be a safe tool for the evaluation of coronary artery disease and perform in approximately 12 million patients each year worldwide. [1] In most cases, angiograms are manually analyzed by a cardiologist. Actually, there are no clinical practice algorithms which could improve and automate this work. Neural networks show high efficiency in tasks of image analysis and they can be used for the analysis of angiograms and facilitate diagnostics. We have developed an algorithm based on Convolutional Neural Network and Neural Network U-Net [2] for vessels segmentation and defects detection such as stenosis. For our research we used anonymized angiography data obtained from one of the city’s hospitals and augmented them to improve learning efficiency. U-Net usage provided high quality segmentation and the combination of our algorithm with an ensemble of classifiers shows a good accuracy in the task of ischemia evaluation on test data. Subsequently, this approach can be served as a basis for the creation of an analytical system that could speed up the diagnosis of cardiovascular diseases and greatly facilitate the work of a specialist.

Keywords: Myocardial Ischemia, Angiography, Convolutional Neural Networks (CNNs), U-Net

1 Introduction

At present day, Coronary angiography is a widely used method for blood vessels defects’ detection as well as magnetic resonance imaging (MRI). In this method, contrast substance is injected into coronary arteries during the x-ray video recording process. Arteries are clearly visible on the video and a video fragment can be divided into images of blood vessels for the following analysis. The relevance of this method results in increasing the amount of data to be analyzed by a specialist. But now in many Russian Hospitals there are no artificial intelligence based systems which can provide some detailed analysis of angiography images.

There are two types of vessel’s defects that prevent normal blood flow - stenosis and ischemia. Stenosis can be determined on angiography images as the areas of abnormal narrowing. Ischemia, in contrast, is the broadening areas on vessels. Both these pathologies are visible on images (see fig.1).
Fig. 1: Coronary angiography images. These images are manually analyzed by a cardiologist to detect vessels’ defects such as stenosis or ischemia. Ischemia occurs due to atherosclerotic plaques and it prevent normal blood flow which leads to myocardial infarction. On images this defect can be recognized as black dots on the vessels. Segmentation of these images allows us keep necessary properties of vessels and provide precise image classification by peoples with pathology and without it.

In 2012, the class of neural models called Convolutional Neural Networks (CNN) showed impressive results in image recognition at the ImageNet contest [3]. Another great success of CNN is developing the neural network U-Net for precise Image segmentation with a few training samples. [2] This architecture has achieved good result on the ISBI challenge for segmentation of neuronal structures. These advances imply the possibility of using CNN in the task of angiography images’ segmentation and for the following classification by CNN for ischemia diagnostics.

In this paper, we investigate the task of blood vessel defects’ detection by angiography images. The data for this task were obtained in one of the city hospitals and then it was segmented by U-Net. After that, CNN extracted the features of segmented images for the classification.

The remaining of this work is organized as follows: In Section 2 we briefly review U-Net architecture. In Section 3 we describe the data set and the training process. In Section 4 results of our approach were demonstrated. And, finally, in section 5, we make some conclusions and discuss further research directions.
2 Segmentation

For Cardiovascular blood vessels segmentation we used neural network U-Net (presented in [2]). The network architecture is illustrated in Figure 2. It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions, each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution (up-convolution) that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers. For our investigations we used U-Net implementation from [4]

Fig. 2: U-Net architecture. U-Net consists of a downsampling and an upsampling block. The first half of the network follows a typical CNN architecture, with stacked convolutional layers of stride two and Rectified Linear Unit (ReLU) activations. The second part of the architecture upsamples the input feature map symmetrically to the downsampling path.
3 Experiments

Fig. 3: Model Pipeline. Angiography images were segmented by U-Net and then classified by an ensemble of three classifiers: ResNet-50, VGG-16 and Gradient Boosting on extracted features.

3.1 Dataset and Pre-processing

For our research we obtained the anonymized data from one of the city hospitals. The training set consists of 276 labeled coronary angiography images which are usually used for diagnostic process. The resulting data set was split into training and test sets comprised of 220 and 56 samples, respectively. The data were pre-processed as follows: firstly we used black-white conversion for normalized images. Secondly, we used Histogram equalization for better segmentation. In this method dark areas become darker and the light areas become lighter. Because of big image’s size we separate each image into patches of a smaller size.

3.2 Metrics

As the metric for classifier we used sensitivity and specificity. It is standard metrics for many diagnostics tasks. Sensitivity (or recall) characterize the probability to give right diagnoses of a sick patient. It equals:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity describes the probability to give wrong diagnosis of a healthy patient. It equals:

$$Specificity = \frac{TN}{TN + FP}$$

3.3 Classification

After segmentation we classify images on two classes: by patients with ischemia and without it. For classification an ensemble of 3 classifiers was used: The first
branch is the VGG-16 binary classifier, the second is the ResNet-50 classifier
and the third branch is Gradient Boosting classifier on feature vectors extracted
from segmented images. The whole classification pipeline demonstrated on fig.3.

4 Results

| Model                        | Sensitivity | Specificity |
|------------------------------|-------------|-------------|
| XGBoost on feature vectors   | 67.13%      | 74.82%      |
| Vgg-16                       | 70.58%      | 73.61%      |
| ResNet-50                    | 75.29%      | 72.97%      |
| Ensemble                     | 70.47%      | 69.93%      |

Table 1: Classification results.

For segmentation with U-Net we obtained 91% of segmentation accuracy.
We examined the results of all the classifiers separately and also calculated the
weighted mean for sensitivity and specificity. The results of different classifiers
applications demonstrated in table 1. The ResNet-50 binary classifier shows the
best result along other classifiers. It demonstrated 70.19% of sensitivity and
69.82% of specificity. Weighted mean of all classifiers equals 70.47% of sensitivity
and 69.93% of specificity.

Fig. 4: Segmentation results. First row: The original images of blood vessels
from our test set. Second row: U-Net segmentation. All images have 584 × 565
resolution.
5 Conclusions

Convolutional neural network ResNet-50 demonstrated good results on the test set in the ischemia classification task and U-Net provided high quality segmentation. Solution of cardiovascular defects’ detection task will point to the possible efficiency in other medicine image analysis problems. But several challenging tasks in the area of diagnostics such as detecting the same defect at all heart projections and precise defects allocation still remains unsolved. Further, neural networks can be used for solving these tasks and for developing a robust automatic diagnostic system.

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