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CORONARY ARTERY STENOSIS DETECTION BASED ON DEEP LEARNING MODELS

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Abstract
Nowadays, cardiovascular diseases are the most common threat to human health, and coronary artery disease is a particularly serious disease. Coronary angiography is used to detect coronary artery disease. However, the high cost and complexity of analyzing its results have led to the need to automate the process of diagnosis of coronary artery stenosis.
In this work, we considered popular models of deep learning-based stenosis detection. The models varied in their underlying neural network architecture and were pre-trained on publicly available data. The data consist of video sequences clinically obtained by invasive coronary angiography and labeled into separate frames for each video containing coronary artery stenosis with a resolution of (512x512) pixels. The paper presents a comparative analysis of the models based on the main performance indicators: average accuracy (mAP), image processing time, and the number of model parameters. The Faster R-CNN and EfficientDet D4 models showed the best performance. Compared to other models, they are characterized by relatively low parameter weights, high detection accuracy, and high image processing speed. The comparative analysis showed that the results of this study are superior to or comparable to those of other researchers.
Keywords: deep learning; coronary artery stenosis; neural network; X-ray coronary angiography
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ВЫЯВЛЕНИЕ СТЕНОЗА КОРОНАРНЫХ АРТЕРИЙ НА ОСНОВЕ МОДЕЛЕЙ ГЛУБОКОГО ОБУЧЕНИЯ

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Аннотация
В настоящее время сердечно-сосудистые заболевания являются наиболее распространенной угрозой для здоровья человека, а ишемическая болезнь сердца является особенно серьезным заболеванием. Коронарная ангиография используется для выявления ишемической болезни сердца. Однако высокая стоимость и сложность анализа ее результатов привели к необходимости автоматизации процесса диагностики стеноза коронарных артерий.
В данной работе мы рассмотрели популярные модели обнаружения стеноза на основе глубокого обучения. Модели различались по своей базовой архитектуре нейронной сети и были предварительно обучены на общедоступных данных. Данные состоят из видеопоследовательностей, полученных клинически с помощью инвазивной коронарной ангиографии и размеченных в отдельные кадры для каждого видео, содержащего стеноз коронарных артерий, с разрешением (512x512) пикселей. В статье представлен сравнительный анализ моделей на основе основных показателей производительности: средней точности (mAP), времени обработки изображения и количества параметров модели. Наилучшую производительность показали модели Faster R-CNN и EfficientDet D4. По сравнению с другими моделями они характеризуются относительно низкими весами

параметров, высокой точностью обнаружения и высокой скоростью обработки изображений. Сравнительный анализ показал, что результаты данного исследования превосходят или сопоставимы с результатами других исследователей.
Ключевые слова: глубокое обучение; стеноз коронарных артерий; нейронная сеть; рентгеновская коронарография
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INTRODUCTION

Cardiovascular diseases are the cause of almost 30% of deaths [1]. Current clinical practice uses medical pictures acquired using a variety of diagnostic techniques to determine the existence and severity of coronary heart disease [2, 3]. Nowadays, the competence and expertise of the specialists play a major role in the accuracy and dependability of coronary angiography interpretation. It is anticipated that automating the identification and categorization of coronary artery vascular lesions will simplify the work of medical practitioners by reducing the probability of misinterpretation and speeding up selecting the best course of action.

The use of computer diagnostic systems play an important role in cardiology in detecting arterial anomalies, since this process is time-consuming, and the number of clinical specialists is limited. Today, research in the field of automation of processing large volumes of medical data has advanced significantly due to the introduction of deep learning methods.

The purpose of this research is to use deep learning detectors to create a model for stenosis detection in individuals with coronary artery vascular lesions [4, 5]. A result the work, models were identified that provide the level of coronary artery stenosis detection accuracy detection comparable to that achieved by other researchers of the problem [6].

MATERIALS AND METHODS

When working with X-ray video sequences to detect stenosis, it is necessary to filter all the videos and keep only the images with visible arterial structure. The classification process is performed based on these candidate images using an object-oriented framework or image classification task. In image classification, the probabilities of the image class labels are calculated. In the field of medical imaging, object-based classification is reduced to locating the lesions and classifying them. In contrast, in object localization and classification, a bounding box is drawn around the objects of interest in the image and a class label is assigned to them.

For more complex classification, a patch-based method can be used, where each patch in the image is assigned a class. In this strategy, each patch is considered as a labeled object. First, a keyframe detection mechanism is used to select images, highlighting the most degraded coronary artery. Then, for each keyframe, deep learning-based stenosis classification is performed using a pre-trained deep model on the ImageNet dataset. In cases where access to labeled images is limited, a patch-based method has been proposed to improve the accuracy of frame labeling. It in-volves classifying a separate region of the image, rather than the entire image. Thus, several patches of a given size (e.g., 16x16 pixels) are created in a full-size image, which increases the number of training images.

The stenosis identification problem has been approached in several ways, such as by employing deep convolutional neural networks (CNNs) to automatically extract features from images [7]. Stenosis-DetNet, a neural network that chooses candidate frames from unprocessed X-ray angiography movies, was introduced by the authors of Ref. [8]. The neural network then uses previous knowledge of coronary artery displacement and image attributes to optimize the bounding boxes of candidate objects that contain stenotic areas.

Danilov et al. investigated eight CNN architectures for object detection to find single stenotic lesions. These architectures include single-stage detector (SSD), Faster-RCNN, and deep convolutional networks with region-based detection R-FCN, as well as deep convolutional neural networks MobileNet-v2, ResNet50, RFCN ResNet101, Inception-v4, and NASNet. The RFCN configuration ResNet101 has shown the trade-off between accuracy and speed, which at present is optimal [9]. Moon et al. proposed a two-stage approach for automated stenosis recognition in coronary angiography [10].

In this work, artery stenosis sites were identified using popular deep learning detectors, including SSD (Single Shot Detector) [11], R-FCN [12], Faster-RCNN [13], RetinaNet [14], and EfficientDet [15]. One of the most effective single-stage object detection algorithms for identifying relatively small objects is RetinaNet. RetinaNet's architecture is divided into four primary components, each with a distinct function:

1) The primary neural network used to extract information from the input image is called Backbone. This variable portion of the network may be based on neural networks for classification, such as ResNet, VGG, EfficientNet, etc.

2) The Feature Pyramid Net (FPN) is a pyramid-shaped convolutional neural network that combines feature mappings from the network's upper and lower tiers.

3) The Classification Subnet solves the classification problem by retrieving data about object classes from FPN.

4) The Regression Subnet solves the regression problem by retrieving data about the locations of objects in an image from FPN.

The ResNet50 neural network serves as the backbone of the RetinaNet architecture, as seen in Figure 1. An output answer regarding an object's class and location within the image is generated by each of these subnets.

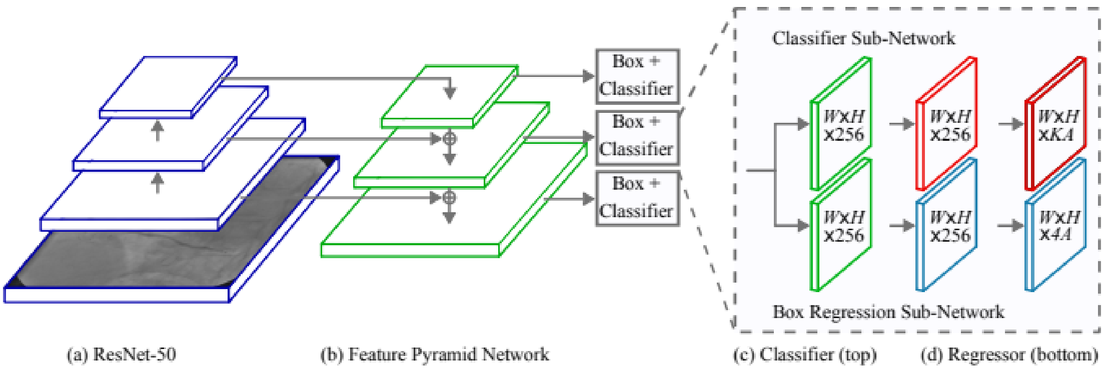

Fig. 1. RetinaNet neural network architecture [11]:
a) ResNet; b) FPN c) classifier subnet(top) d) Regressor subnet (bottom)
Рис. 1. Архитектура нейронной сети RetinaNet [11]:
a) ResNet; b) FPN; c) подсеть классификатора (вверху); d) подсеть регрессора (внизу)

The feature pyramid network FPN is the core component of this model [16]. In convolutional neural networks, this network serves as a general design for building feature pyramids. To construct the pyramid, a layer is determined for each stage, and the output of the last layer from each stage is used as a support set for the next one.

Feature pyramid networks (FPNs) have several advantages over deep feature maps. First, object localization is a challenge for deep feature maps since minor changes in the deep feature map result in large localization errors when compared to the input image. Second, deep feature maps are disadvantageous for small objects. FPNs solve the problem in object localization by using multilevel feature pyramids and the spatial resolution strategy of FPNs, which involves integrating features from various scales, improves the ability of FPNs to accurately classify object categories. The RetinaNet model uses a focal loss function [17], which considers the imbalance between positive and negative samples as well as easy and difficult samples, greatly improving the quality of the bounding regions. To process many generated boxes and eliminate the class imbalance between the background and stenosis in the work, we use the values of its parameters $\alpha = 0.25$ and $\gamma = 2$ for the focal loss function, at which it achieves the best performance:

$$FL(pt) = \alpha t\,(1 - pt)\gamma \log(pt) \qquad (1)$$

Also, to solve the problem, we used the EfficientDet deep learning-based detection model, in which the pre-trained EfficientNet neural network is used as a backbone and the bidirectional neural network of the feature pyramid BiFPN (Feature Pyramid Network) [15,16] is used as a feature extractor. This model keeps the balance between prediction speed and accuracy. Figure 2 shows the architecture of the EfficientDet model.

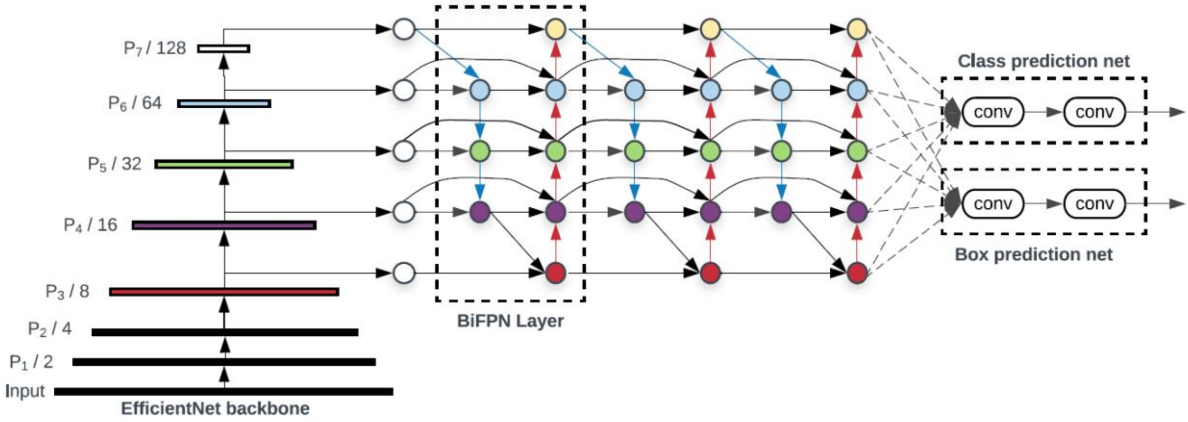

Fig. 2. EfficientDet architecture [13]
Рис. 2. Архитектура EfficientDet [13]

RESULTS

A dataset of X-ray pictures from 438 patients who had coronary angiography and had been diagnosed with coronary artery disease was used in this investigation [18]. Annotated into individual frames for each video recording showing coronary artery stenosis, the data comprised 9378 clinically obtained video sequences from invasive coronary angiography in DICOM format. In all, 1593 image sequences with 512x512 pixel resolution were annotated.

The model's performance is assessed in this research using the following metrics: mAP (mean average precision), precision, recall, and F1-score. The average accuracy of the recall metric value between 0 and 1 is calculated, the detection accuracy increases with the mAP value. The percentage of accurate predictions is determined by the precision metric. The number of all positive cases is shown by the recall metric.

$$mAP = \frac{1}{|classes|} \sum_{[0.5,\ldots,0.95]} \frac{TP(c)}{TP(c) + FP(c)}, \qquad (2)$$

where $TP(c)$ is the number of correct predictions of class c made by the model, $FP(c)$ is the number of erroneous predictions of class c made by the model, and *classes* is the number of classes (the number of analyzed video files). In order to evaluate (2), the model's prediction accuracy was first evaluated at a 50% threshold, meaning that the areas of the forecast and the true marking are assumed to overlap by at least 50%. In contrast to a false positive event $FP(c)$, this corresponds to a true positive indicator $TP(c)$. The mAP expression (2) is then computed by averaging all the accuracy values obtained for a specific threshold, increasing the threshold in increments of 0.05 to a value of 0.95.

Our computational experiments were conducted using popular neural network models of object detection SSD, R-FCN, Faster R-CNN, RetinaNet, and EfficientDet. The models were trained on a training set of images with the following parameters: the input image size was (512x512) pixels, batch_size=8, learning_rate=0.0025, epochs number=200. During the training, data augmentation methods were also used to improve the quality and increase the size of the dataset. A total of 8300 grayscale images with a size of (512x512) pixels were selected, of which 80% were used for training, 10% for validation, and 10% for testing. The dataset sizes thus achieved were obtained by generating additional modified versions in brightness and contrast from the original frames to exclude model overfitting. Also, the early stopping procedure was used to reduce the risk of overfitting. The trained models were then tested on the test set using mean average precision (mAP) expression (2).

All tests were performed using the Tensorflow environment and the Python 3.8 programming language. The results of the comparative analysis of the obtained results are summarized in Table 1.

Table 1

Results of the comparative analysis of the performance indicators of stenosis detection models

Таблица 1

Результаты сравнительного анализа показателей эффективности моделей выявления стеноза

Model	**mAP, %**	**F1-score, %**	**Params, M**	**Time, ms**
SSD Inception V2	53	74	4.2	36
SSD ResNet-101	61	77	4.2	42
R-FCN Inception V2	68	81	5.43	78
R-FCN ResNet-101	81	85	5.43	107
Faster R-CNN Inception V2	73	86	25.6	110
Faster R-CNN ResNet-101	89.23	90,2	25.6	117
RetinaNet (ResNet50_FPN)	87	88	44	126
RetinaNet (ResNet101_FPN)	90	91.4	44	132
EffivientDet-D0 (512x512)	90.64	90.25	3.9	117
EfficientDet-D4 (720x720)	95.8	98.22	20.7	124

DISCUSSION

The study of employing the most potent and sophisticated deep learning-based detectors to identify coronary artery stenosis is presented in this publication: SSD (Inception V2, ResNet-101), R-FCN (Inception V2, ResNet-101), Faster-RCNN (ResNet-101, Inception V2), RetinaNet, EfficientDet-D0, and EfficientDet-D4. The highest prediction speed is possessed by the SSD Inception V2 model, which has a value of the indicator (2) on the test sample equal to 53%, the prediction rate is 36 frames per millisecond.

With a mAP value of 81% and a prediction speed of 107 ms, the R-FCN model, which uses the Inception V2 residual neural network as the foundation model, offers a decent compromise between accuracy and speed. The model with the best accuracy/prediction time ratio is the Faster-RCNN ResNet-101(50 proposals). The Faster-RCNN ResNet-101 model's mAP prediction accuracy was 88.23%, and its prediction speed was 117 ms. All tests were performed using the Tensorflow environment and the Python 3.8 programming language.

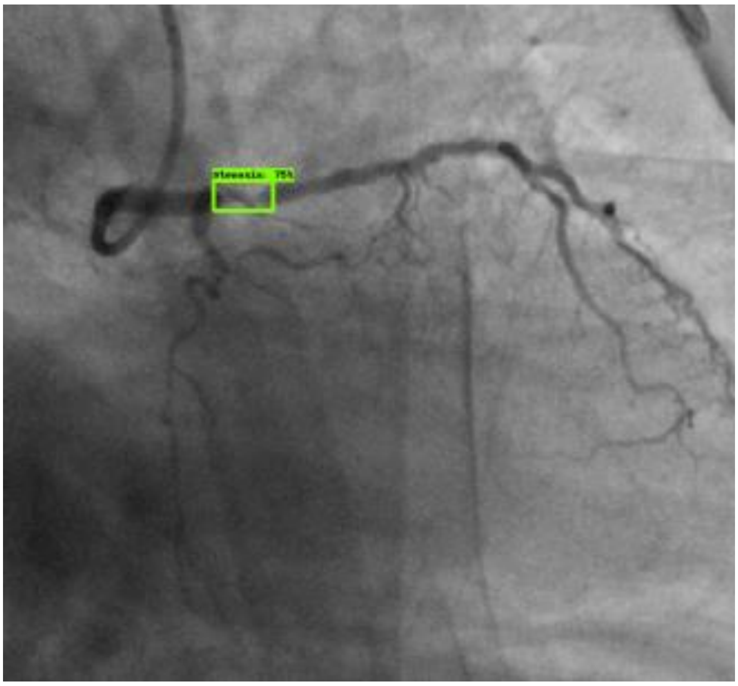

Fig. 3. Result of the EfficientDet D4 model
Рис. 3. Результат модели EfficientDet D4

The RetinaNet model, which was pre-trained on the COCO dataset, was employed in this study [19, 20]. It has a rather high accuracy rate of mAP=90%, but the average image processing speed of 132 ms is not high enough for real-time operation. In addition, its dimensionality also requires a large amount of memory, because of which it cannot be used as a first-choice detection model. The EfficientDet model was also pre-trained in TensorFlow on the MSCOCO images. Two variants were chosen from among the potential EfficientDet specifications: D0(512x512) and D4(720 × 720) [21]. With an accuracy rate of mAP=95.8% and an image processing speed of 124 fps, the EfficientDet D4 model outperformed other networks including R-FCN and Faster R-CNN. The ResNet101 model is the best model for RetinaNet, EfficientDet, Faster RCNN, and R-FCN. The feature extractor architecture selection is less critical for the SSD model.

With a balanced ratio of high accuracy, detection speed, and a relatively low weight of their parameters, the Faster R-CNN and EfficientDet D4 detection models – which use the ResNet101 neural network as a base model – are the best detectors for identifying coronary artery stenosis, according to the results obtained. As is evident, nevertheless, they are unable to process X-ray video sequences in real time. The SSD Inception V2 model, for instance, has this capability, but its detection accuracy is poor. In this instance, we believe that reducing the possibility of incorrect coronary artery stenosis detections – which can be quantified using the F1-score metric – should take precedence. From this point of view, the above models also showed an optimal balance of the necessary metrics, comparable or superior to the results of similar studies presented in Table 2.

Table 2

Results of comparative analysis of detection characteristics

Таблица 2

Результаты сравнительного анализа характеристик обнаружения

Publication	maP, %	F1-score, %	Prediction time, ms
[8] Stenosis-DetNet	84.22	88.1	-
[9] Faster RCNN ResNet50V1	92	-	98
[10] reccurent CNN	93.4	95.6	-

[22] RetinaNet (ResNet101_FPN)	95.78	96	-
[23] Wu	87.2	83.2	-
[24] U-Net+gbdt	87	89	-

"-" means that the data are not presented by the publication.

CONCLUSION

Neural network techniques for coronary angiography data analysis, including single-vessel lesions, are examined in this study; naturally, this does not encompass the whole range and complexity of atherosclerosis. To identify single-vessel arterial stenoses, a set of neural network detectors was trained using clinical angiographic data. It was demonstrated that the EfficientDet-D4 architecture can provide excellent localization accuracy of the stenosed area in the image (up to 95.8%); but, because of its complexity, it cannot do real-time analysis, meaning that its performance is insufficient. The accuracy and speed of coronary artery stenosis detection using deep detection methods 11 the algorithm could be improved with additional work to optimize the input data for analysis or to employ auxiliary techniques, opening the door to the development of a quick and reliable tool to support interventional cardiology.

The creation of a computer system that can simultaneously detect two or more stenoses, characterize them in detail, and help doctors make decisions would be more beneficial for clinical practice. The performance of detection models would be enhanced by the application of cutting-edge technologies to increase image processing speed and accuracy through contrast image processing, coronary artery region refinement, etc. Future research will also concentrate on these areas to generalize the suggested models to images of other patients, but real-time detection and classification of multivessel disease is a more intricate and multidimensional task. This is because X-ray angiographic images are extremely noisy, and the presence of bony structures, spinal vertebrae, catheters, and diaphragms exacerbates this issue.

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