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COMPARATIVE STUDY OF MODERN NEURAL NETWORK ARCHITECTURES FOR MEDICAL IMAGE SEGMENTATION PROBLEMS

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Abstract. *Computer Vision is the area of Machine Learning that is responsible for machine perception of visual information. Image segmentation is a subfield of Computer Vision that solves the task of dividing a digital image into segments by their class label. One of the main problems in the subfield is the scarcity of data and the restoration of spatial information for the classified image. This article is a brief survey of current Biomedical Image Segmentation approaches, specifically Convolutional Neural Networks architectures and the morphological transformation for data augmentation.*

Key words*: computer vision, biomedical image segmentation, convolutional neural networks, data augmentation.*

МЕДИЦИНАЛЫҚ КЕСКІНДЕРДІ СЕГМЕНТТЕУ МІНДЕТТЕРІНЕ АРНАЛҒАН ЗАМАНАУИ НЕЙРОНДЫҚ ЖЕЛІ АРХИТЕКТУРАЛАРДЫҢ САЛЫСТЫРМАЛЫ ЗЕРТТЕУІ

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Аңдатпа. *Компьютерлік көру – визуалды ақпаратты машиналық қабылдауға жауап беретін машиналық оқыту саласы. Кескін сегментациясы – сандық кескінді сынып белгісі бойынша сегменттерге бөлу мәселесін шешетін компьютерлік көру саласы. Бұл саладағы негізгі проблемалардың бірі – деректердің жетіспеушілігі және жіктелген кескін үшін кеңістіктік ақпаратты қалпына келтіруі болып табылады. Аталған мақала биомедициналық кескіндерді сегментациялаудың заманауи тәсілдеріне, атап айтқанда конволюциялық нейрондық желілердің архитектурасына және деректерді көбейту үшін морфологиялық түрлендіруіне қысқаша шолу жасайды.*

Түйінді сөздер: *компьютерлік көру, медициналық кескіндерді сегментациялау, конволюциялық нейрондық желілер, деректерді аугментациялау.*

СРАВНИТЕЛЬНОЕ ИССЛЕДОВАНИЕ СОВРЕМЕННЫХ НЕЙРОСЕТЕВЫХ АРХИТЕКТУР ДЛЯ ЗАДАЧ СЕГМЕНТИРОВАНИЯ МЕДИЦИНСКИХ ИЗОБРАЖЕНИЙ

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Аннотация. *Компьютерное зрение – это область машинного обучения, которая отвечает за машинное восприятие визуальной информации. Сегментация изображения – это сфера компьютерного зрения, которая решает задачу разделения цифрового изображения на сегменты по их метке класса. Одной из основных проблем в данной сфере является нехватка данных и восстановление пространственной информации для классифицированного изображения. Эта статья представляет собой краткий* *обзор современных подходов к сегментации биомедицинских изображений, в частности архитектур сверточных нейронных сетей и морфологического преобразования для аугментации данных.*

Ключевые слова: *компьютерное зрение, сегментация медицинских изображений, сверточные нейронные сети, аугментация данных.*

Introduction

Image segmentation is the process of dividing digital images into several segments. The purpose of segmentation is to simplify and modify the representation of an image so that it is easier to analyze. Image segmentation is commonly used to highlight objects and boundaries in images. More specifically, image segmentation is the process of assigning labels to each pixel in an image such that pixels with the same labels have common visual characteristics.

The result of image segmentation is many segments that together cover the entire image or many contours extracted from the image. All pixels in a segment are similar in some characteristic or computed property, such as color, brightness, or texture. Adjacent segments differ significantly in this characteristic.

In this article, we reviewed and compared articles on image segmentation in different areas. We touched upon the topics of Fully Convolutional Network, Convolutional Neural Network, and Fuzzy Logic in image segmentation.

Review

There is a problem in Deep Learning that relates to the lack of quality data. Moreover, it greatly affects the Computer Vision area because, typically, CV architectures need a lot of data to learn and generalize well. Furthermore, there is not much existing data to train deep architectures in the Biomedical tasks for Computer Vision. The Convolutional Neural Network called U-Net [1], which got the name from its U-shaped architecture, as shown in Figure 1, addresses this problem for the task of Biomedical Image Processing. The proposed solution uses the encoder-decoder approach but in a slightly modified way. It showed great results on Image Segmentation tasks, and it is also very quick: for an image with a resolution of 512x512 pixels, the processing time was less or equal to second in most cases with a recent GPU.

The U-Net is built upon a Fully Convolutional Network architecture [2]. The main idea is to add upsampling operators to the network's right side (decoder), which mirrors its left side (encoder). The distinctive feature of all Fully Convolutional Networks is skip-connections. They are used to keep the spatial information of an image and transfer it to the upsampling convolutions.

The encoder part comprises typical 3x3 convolutional layers. Each of these is followed by ReLU and 2x2 max pooling for downsampling. Then, in the decoder part, each feature map is upsampled by 2x2 up-convolution and concatenated with a corresponding cropped feature map from the encoder part (skip connection), convolved by two 3x3 convolutions with each convolution followed by ReLU. A 1x1 convolution follows the final layer for mapping the resulting feature map to the number of segmentation classes.

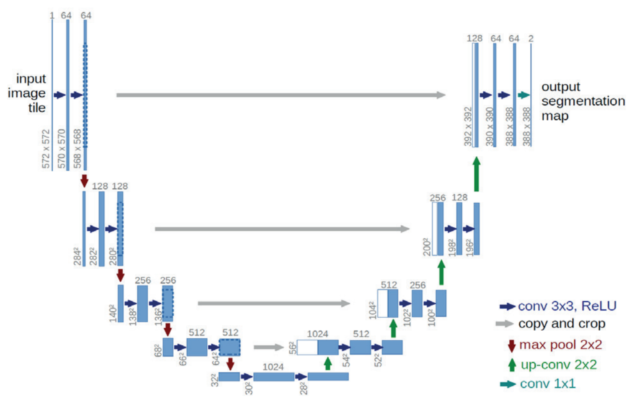

Figure 1. The U-Net architecture, example for 32x32 image

For efficient computing, the architecture favors the large input tiles over the large-sized batches; hence the batch size is set to a single image. Data augmentation is an important step in the training of U-Net. The random elastic deformations, shifts, and rotation of images showed great results in tasks with very few annotated examples. Also, the dropout layers of the encoder part of the network perform an additional data augmentation.

U-Net with its Fully Convolutional Architecture in combination with the efficient training and data augmentation approaches showed great results on Biomedical Segmentation tasks.

Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	0.9203	0.7756

Table 1. Segmentation results (IOU) on the ISBI cell tracking challenge 2015

The second article in this review is "Medical Image Segmentation Algorithm Based on Optimized Convolutional Neural Network-Adaptive Dropout Depth Calculation". Authors: Feng-Ping An et al., [3].

In this article, authors tried to solve some image segmentation problems. To solve the problem of network structure flexibility in a deep learning model, they optimized the convolutional neural network model by adding cross-layer connections in a traditional convolutional neural network. At the same time, authors add the adaptive dropout model, to enhance the generalizability of the dropout method to reduce the deep learning model.

Here is the basic steps corresponding the idea in this article:

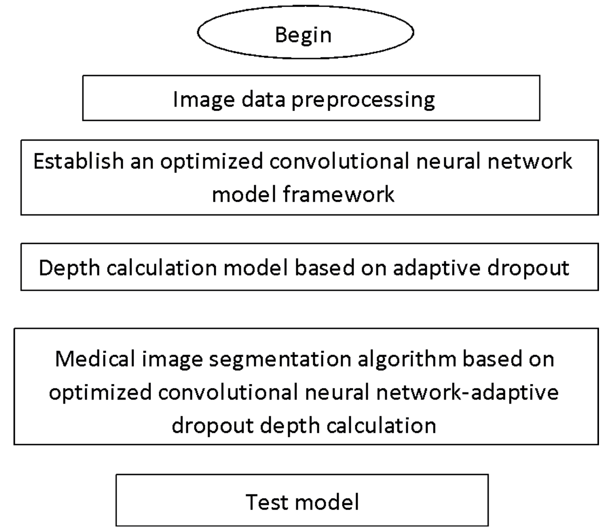

Figure 2. Basic idea of medical image segmentation algorithm based on optimized convolutional neural network-adaptive dropout depth calculation

1. First, medical image data was preprocessed such as denoising, adding, and expanding.
2. Then authors used the convolutional neural network model by adding cross-layer connections in traditional convolutional neural networks, which they established, to make a image segmentation
3. Moreover, they added an adaptive dropout model to the convolutional neural network model by adding a cross-layer connection. According to the hidden layer position, an adaptive distribution function is designed to set the activation probability of each layer of neurons; it further improves the generalizability of the dropout model.

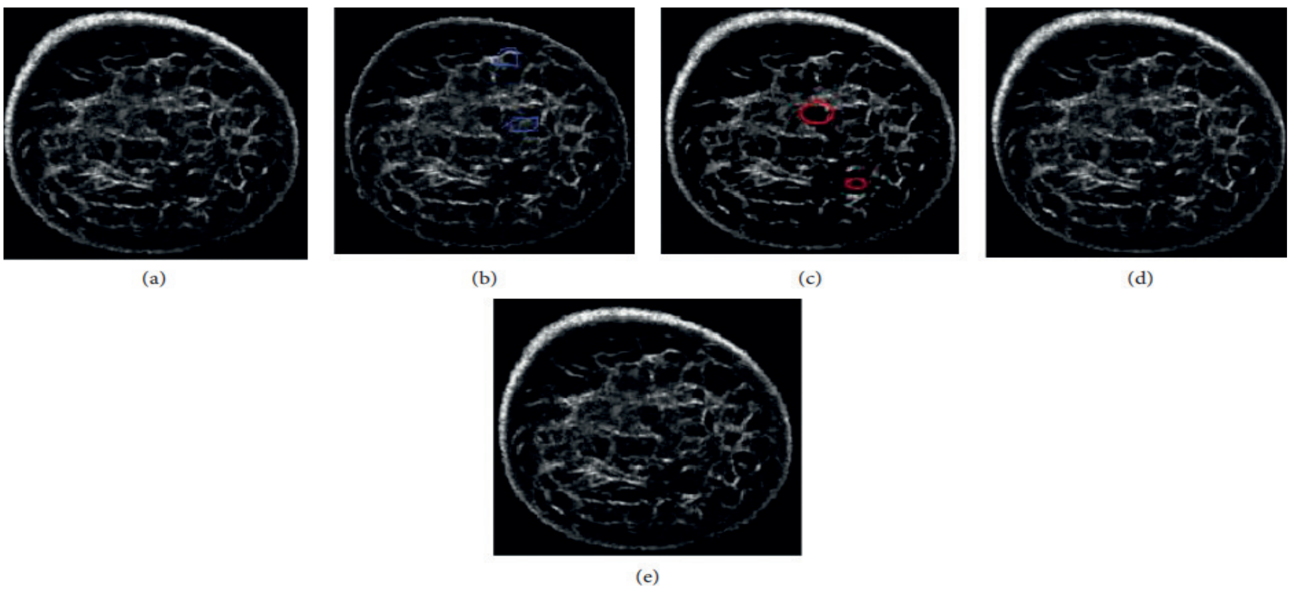

Figure 3. Partial image segmentation results

As a result, authors make comparison by Dice coefficient, Jaccard coefficient and False positive cases between traditional machine learning model (b, c), traditional convolutional neural network (d) and new an optimized convolutional neural network with adaptive dropout depth calculation (e).

Segmentation method	Dice	Jaccard	FP
b	0.8397	0.7826	0.1337
c	0.8485	0.7932	0.1191
d	0.9132	0.8557	0.0582
e	0.9904	0.9827	0.0012

Table 2. Comparison of ultrasonic tomographic image dataset segmentation results

As shown in Table 2, the new an optimized convolutional neural network with adaptive dropout depth calculation presents the better results among four of them.

The third article where authors used image segmentation in medical image data is "A Two-Step Segmentation Method for Breast Ultrasound Masses Based on Multi-Resolution Analysis".

Authors: R. RODRIGUES, et al., [4]

In this article, authors first proposed an approach by the following workflow, shown in Figure 4.

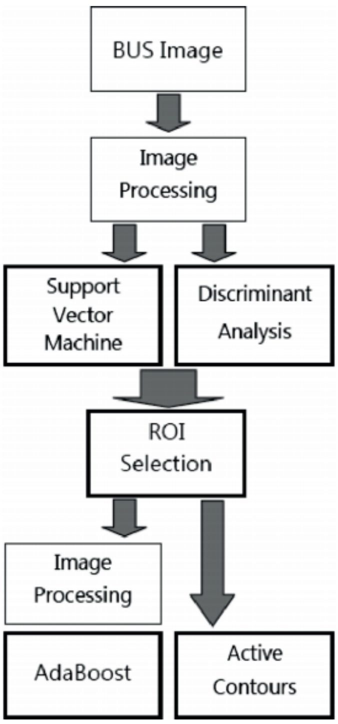

Figure 4. Global workflow for the two-stage beast mass segmentation approach

Firstly, to classify the BUS image (breast ultrasound) apply the SVM and DA classification algorithms using a pixel descriptor with five different features. As long as the original BUS image were the non-linear diffusion and the FIR filter two bandpass outputs with and two different scale-space mean curvature measures. The next stage is ROI Selection (region of interest). This stage was used to reduce the number of misclassified pixels. Moreover, initial contours that used in the subsequent segmentation steps appeared in this stage.

Further, after the ROI selection stage the author applies the AdaBoost algorithm to classify. This algorithm uses a weak classifier to establish a threshold for data dimensions according to a distribution. The goal of this algorithm is to minimize the classification error. In the author's example AdaBoost algorithm applied with 200 iterations. The output of the algorithm was submitted to the selection of the largest area object, to eliminate small non-relevant objects that might result from defragmentation of the main contour, yielding the final segmentation results.

The other path proposed by authors for making segmentation is the Segmentation refinement using active contours. This algorithm was focused on minimizing the equation energy. In comparison to the previous algorithm, this algorithm was applied with 100 iterations. Similarly, to the preceding stage, the output of the algorithm was submitted to the selection of the largest area object. The results of both algorithms are given in the Table 3.

	Initial	AdaBoost	Active contours
Accuracy	97.3%	97.7%	97.5%
Recall	68.1%	79.6%	77.8%
Precision	92.4%	89.3%	89.3%
$Dice_{coef}$(overlap)	0.690	0.824	0.813

Table 3. Segmentation performance measures

The both methods, which was used in this article, have shown the good overlap and recall results. In a direct comparison of the two segmentation refinement methods, AdaBoost improves the normalized overlap coefficient in 0.134, whereas active contours improve this measure in 0.123. Moreover, the AdaBoost algorithm shows better recall results 79.6% against the recall result of active contour algorithm 77.8%.

In the article named "CT liver tumor segmentation hybrid approach using neutrosophic sets, fast fuzzy c-means and adaptive watershed algorithm" authors A. M. Anter, et al., [5] proposed the method to make liver tumor CT image segmentation. According to this hybrid segmentation approach, the authors used several algorithms like watershed algorithms, neutrosophic sets, and fast fuzzy c-means. The main reason is that each technique has its own problems, which the others do not have.

The shortest algorithm proposed by this article:

The first is pre-processing. At this step, the image is converted to grayscale, and filters are applied to remove noises. The second is CT image transformation. Each pixel of the image will be converted to an NS domain. It means that each pixel will belong to either true or false or indeterminate subsets in the NS domain. The third step is post-processing. After converting images to the neutrosophic domain, some morphological operators are used to remove small objects and focus on disease images. The fourth step is liver parenchyma segmentation using a watershed algorithm. After that, the maximum region of interest (ROI) was selected to extract liver from abdominal CT using a connected component algorithm. The last step is tumor segmentation and extraction. At this step, fast fuzzy c-means (FFCM) algorithm is applied on segmented images to detect and segment tumors from the liver image. The proposed FFCM provides excellent results for tumor clustering and segmentation without any loss of tumor detection with high accuracy. In addition, false-positive regions that affect system performance are reduced.

Conclusion

In this overview of existing image segmentation techniques, it was found that the task of biomedical image segmentation is not yet solved completely. Still, there are advances in approaches to image segmentation that greatly improve results of said models. Studying the most effective techniques, we can highlight following approaches: a) Skip-connections and upsampling techniques help in restoring spatial information of the segmentation operations; b) Combination of morphological operations for data augmentation and at inference times greatly improves the generalization capabilities of models and help in cases of quality data scarcity.

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