DOI: https://doi.org/10.15407/pmach2024.02.054

UDC 004.8

INCREASING THE ACCURACY OF DETERMINING THE CARDIOTHORACIC RATIO WITH THE HELP OF AN ENSEMBLE OF NEURAL NETWORKS

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The cardiothoracic ratio is one of the main screening tools for heart health. Cardiothoracic ratio is usually measured manually by a cardiologist or radiologist. In the era of neural networks, which are currently developing very rapidly, we can help doctors automate and improve this process. The use of deep learning for image segmentation has proven itself as a tool that can significantly accelerate and improve the process of medical automation. In this paper, a comparative analysis of the use of several neural networks for the segmentation of the lungs and heart on X-ray images was carried out for further improvement of the automatic calculation of the cardiothoracic ratio. Using a sample of 10 test images, manual cardiothoracic ratio measurements and 7 automatic measurement options were performed. The average accuracy of the measurement of the cardiothoracic ratio of the best of the two neural networks is 93.80%, and the method that used the ensemble of networks obtained a result of 97.15%, with the help of the ensemble of neural networks it was possible to improve the ratio determination by 3.35%. The obtained results indicate that thanks to the use of an ensemble of neural networks, it was possible to improve the result of automatic measurement, and also testify to the effectiveness and prospects of using this method in the medical field.

Keywords: *machine learning, neural networks, deep learning, image segmentation, medical image analysis.*

Introduction

The cardiothoracic ratio is the ratio between the largest transverse size of the heart and the largest transverse size of the chest measured on a chest X-ray [1]. The threshold value in calculating the ratio is 0.5. Normal values are in the range from 0.42 to 0.50, they should not be presented as a percentage, but as a ratio. A value above 0.5 should be considered an enlargement of the heart. However, this statement is not always true and may increase the number of false-positive results, especially among obese or elderly people [2]. The maximum transverse size of the heart on an X-ray is mainly composed of the diameter of the left ventricle and the right atrium, but this value can be affected by many factors, not only the dilatation or hypertrophy of the heart, but also the dilatation of the other chambers of the heart and the aorta, as well as the position of the person during the X-ray, their breathing. An increase in the cardiothoracic ratio can help in the early detection of cardiomegaly. Which, in turn, is an important sign that can indicate various heart diseases, such as coronary heart disease, heart failure, myocardial hypertrophy. Also, with the help of the ratio, it is possible to assess the cardiac function, and determine how it pumps blood. The cardiothoracic ratio can be used not only at the stage of diagnosis, in the process of monitoring treatment, in the treatment of such diseases as myocardial hypertrophy or heart failure, its value can be used to track the effectiveness of therapy and changes in the heart size. Thus, the cardiothoracic ratio is definitely a significant factor that helps to identify various heart diseases, as well as being useful in monitoring the patient's health.

Physiology and value of the cardiothoracic ratio

To determine the cardiothoracic ratio, data from various imaging methods, such as computed tomography, magnetic resonance imaging, radiography, and ultrasound, are used. The choice of the data determination method depends on various factors, the general condition of the patient, the clinical task, and the degree of radiation. Radiography has limited detail, when using magnetic resonance imaging it is possible to get more detailed images, in turn, computer tomography can provide a quick and good image of the heart and chest.

Two main parameters are used to determine the cardiothoracic ratio:

– The transverse size of the heart is the largest size of the heart in the transverse direction. Most often, this parameter is better obtained on chest X-ray images or on computer tomography sections;

– Transverse chest size is the largest size of the chest in the transverse direction. It can usually be measured at the same level as the heart diameter.

In Fig. 1 you can see the necessary transverse dimensions for calculating the cardiothoracic index.

The formula for calculating the cardiothoracic ratio looks like this:

$$CTR = \frac{D_h}{D_c}, \quad (1)$$

where CTR is the cardiothoracic ratio; D_h is the transverse dimension of the heart; D_c is the transverse chest size.

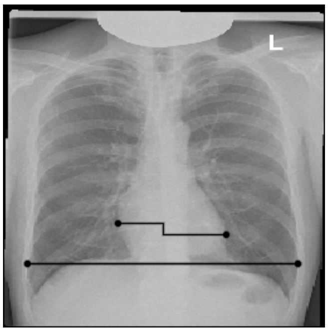

Fig. 1. Visualization of transverse dimensions

Using deep learning in medicine

The application of deep learning in the medical field nowadays has made it possible to improve the accuracy of diagnosis and make the work of doctors easier. The main aspects of the application of this technology are beyond the scope of this paper, so its advantages in the field of image processing will be presented:

– Deep learning is often used to automate the process of analyzing medical images obtained by radiography, magnetic resonance imaging, and computed tomography. Thanks to its analysis, it is possible to automatically determine pathologies, the stages of the disease;

– The use of computer vision in combination with deep learning helps classify various abnormalities in medical images, such as cysts, tumors, and others [3].

Returning to the task of determining the cardiothoracic ratio using deep learning, several key advantages of its application in the field of medical diagnostics and assessment of cardiovascular health can be highlighted:

1. Calculation accuracy. Models that are trained on huge amounts of data are able to provide the best results in calculating the cardiothoracic ratio because they have knowledge about the differences in the chest tissue and the heart of different people.

2. Process automation and diagnosis time reduction. Determining the cardiothoracic ratio using a computer can speed up the processing time of large volumes of data. When a medical institution needs to determine the ratio for a large number of people, it will take a long time for the doctor to perform this work manually.

3. Adaptation and personalized approach. Factors such as gender, age, genetics and health can be taken into account for a personalized approach to matching personal characteristics with machine learning algorithms.

Neural networks training

To create a successful deep learning model, one of the most important stages is the selection of suitable data for training. Depending on the success of this process, the performance of this model and its accuracy are determined. For the given task – segmentation of the lungs and heart, it is necessary to correctly select the data, the obtained set should represent various forms of the heart and lungs, and take into account various differences in anatomy among patients. It is necessary to collect data so that they can contain information with different characteristics, such as gender, age, state of health, so that the model can be generalized for different groups of patients. It is also important to obtain high-quality and artifact-free data.

To train various models, a database of images obtained from a publicly available source was collected [4]. The source included X-rays and masks with annotated lungs. 132 images were selected, after which the heart class was drawn on the existing lung masks. The training sample consisted of 122 images, and the test sample consisted of 10. At the next stage of image preparation, each mask was a set of 3 classes – the class of background, lungs, and heart. The PNG format was selected for the entire dataset, with both snapshots and masks having the same extension. Data augmentation was not reproduced.

Two neural networks were chosen to perform the segmentation task – Mobilenet_Unet and Mobilenet_Segnet, which are modifications of the MobileNet network. The U-Net modification was chosen due to the fact that it is effective for segmentation tasks, including organ segmentation in medical images. Also, an important feature is efficiency when used with small amounts of data [5]. The SegNet modification was chosen due to the fact that it provides good performance with competitive output time and the most efficient use of memory [6]. The Adam optimizer was also used for training. This method is simple to implement and computationally efficient. The results show that Adam works well in practice and compares favorably with other stochastic optimization methods [7].

The training process of one network consisted of 30 epochs. 50 Mobilenet_Segnet and 50 Mobilenet_Unet networks were trained, resulting in 100 neural networks, each making 10 predictions for the test images. In Fig. 2 shows an example of one of the training images.

The Mean Intersection over Union (Mean IoU) was used to measure segmentation accuracy. This metric is a variation of the Jaccard index, which is a well-known measure of similarity between two sets [8]. This coefficient is a metric that is considered one of the common metrics for evaluating segmentation quality. First, the Jaccard index is determined

$$IoU_i = \frac{TP_i}{TP_i + FP_i + FN_i},$$

where IoU_i is the intersection over union; TP_i is the true positive results; FP_i is the false positive results; FN_i is the false negative results.

Mean IoU is calculated as the average IoU value across all classes

$$Mean\ IoU = \frac{1}{n}\sum_{i=1}^{n} IoU_i, \qquad (2)$$

where n is the the number of classes.

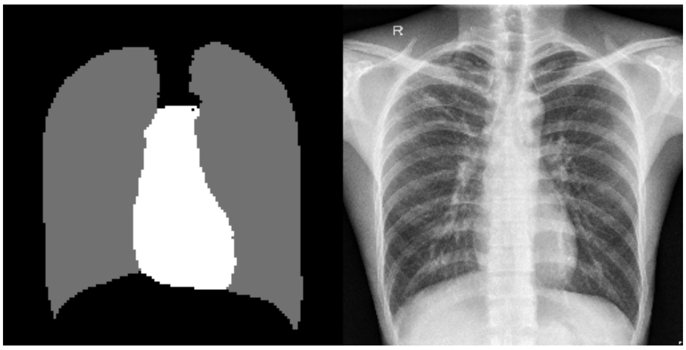

Fig. 2. An example of a picture and its mask

Application of ensemble of neural networks

The main idea of improving the accuracy of image segmentation is to use an ensemble of neural networks. It exactly involves the use of several neural networks, which in our case are Mobilenet_Segnet and Mobilenet_Unet. In order to study the effect of different number of neural networks on the result of segmentation accuracy and the result of improving the accuracy of automatic cardiothoracic ratio measurement, it is proposed to create 5 options of network ensembles, namely:

1. Consists of 10 networks Mobilenet_Segnet;
2. Consists of 10 networks Mobilenet_Unet;
3. Consists of 50 networks Mobilenet_Segnet;
4. Consists of 50 networks Mobilenet_Unet;
5. Consists of 50 networks Mobilenet_Segnet + 50 networks Mobilenet_Unet.

The algorithm takes identical images predicted by neural networks and compares them according to the specified threshold, after which it saves the original image as the result of its work. It is worth noting that the prediction image is a grayscale image and consists of 3 colors and has the following values – 0, 122 and 255. First, we define a threshold and adjust the output image

$$M = \frac{n}{2},$$

where M is the threshold; n is the number of input images.

$$R(x, y) = 0, \quad \forall (x, y),$$

where $R(x, y)$ is the pixel value at position (x, y) in the resulting image R.

For each pixel in position (x, y) the counter for each color is configured

$$count(c) = 0, \quad \forall c \in C,$$

where C is the set of valid pixel values {0, 122, 255}; *count* (c) is the number of color repetitions c in position (x, y).

After that, it is needed to calculate each color in the position (x, y)

$$count(I_i(x, y)) = count(I_i(x, y)) + 1, \quad \forall i \in \{1, ..., n\},$$

where I_i is the input image where $i \in \{1, 2, \ldots, n\}$; $I_i(x, y)$ is the pixel value at position (x, y) in the image I_i.

Definition of the end pixel for the source image at position (x, y)

$$R(x, y) = c, \text{ where } count(c) \geq M \text{ and } c \in C.$$

Thus, the final image has the following form:

$$R(x,y)=\begin{cases}0, & \text{if } count(0)\geq M\\ 122, & \text{if } count(122)\geq M\\ 255, & \text{if } count(255)\geq M\end{cases},$$

where

$$count(c)=\sum_{i=1}^{n}\delta(I_i(x,y)=c).$$

In Table 1, it is possible to see the accuracy determined by formula (2) for the predictions of trained networks, as well as the accuracy for ensembles of neural networks.

In Fig. 3, it is possible to see a visual example of the neural network ensemble algorithm. The mask on the left is surrounded by a white square and is the result of the algorithm, while the six masks on the right are predictions of the neural networks on the basis of which the original mask is created

Analyzing the results obtained in Table 1, it is possible to conclude that out of 100 trained networks, one Mobilenet_Unet network gave a result of 91.54%. At the same time, the use of an ensemble of 10 Mobilenet_Unet networks made it possible to obtain 91.68% accuracy, which is 0.14% better than the independent result.

Table 1. Accuracy results of neural networks

Option name	Mobilenet_Segnet	Mobilenet_Unet
Maximum	90.45	91.54
Minimum	84.19	84.13
Average	87.76	88.32
Algorithm for 10 networks	90.65	91.68
Algorithm for 50 networks	89.89	91.16
Algorithm for 100 (all) networks	91.31	91.31

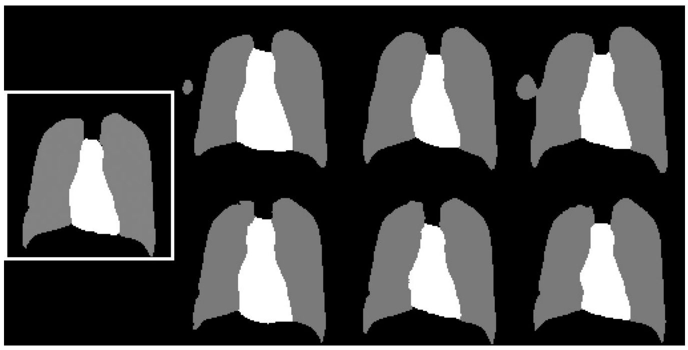

Fig. 3. An example of the operation of the ensemble algorithm

Determination of the cardiothoracic ratio

After successfully obtaining prediction images, the next step is to calculate the accuracy of the automatic cardiothoracic ratio measurement. Table 2 presents the results obtained using formula (1). Tables 2 and 3 show the results for all 10 test images, the following abbreviations will be used in these tables – M_Seg:

M_Seg – Mobilenet_Segnet;

M_Unet – Mobilenet_Unet;

10 M_Seg – ensemble of 10 Mobilenet_Segnet net;

50 M_Seg – ensemble of 50 Mobilenet_Segnet networks;

50 M_Unet – ensemble of 50 Mobilenet_Unet networks;

100 M_Seg + M_Unet – ensemble of 50 Mobilenet_Segnet networks and 50 Mobilenet_Unet networks.

Table 2. Values of manual and automatic measurements of cardiothoracic ratio

Option name	Test image number									
	1	2	3	4	5	6	7	8	9	10
Manual	0.46	0.42	0.41	0.43	0.39	0.39	0.49	0.42	0.47	0.40
M_Seg	0.53	0.44	0.40	0.41	0.42	0.44	0.47	0.43	0.43	0.41
M_Unet	0.51	0.46	0.41	0.41	0.47	0.42	0.47	0.46	0.49	0.47
10 M_Seg	0.52	0.42	0.38	0.40	0.42	0.39	0.45	0.41	0.44	0.40
10 M_Unet	0.51	0.43	0.41	0.44	0.42	0.41	0.49	0.42	0.45	0.41
50 M_Seg	0.47	0.42	0.38	0.40	0.41	0.39	0.46	0.42	0.43	0.40
50 M_Unet	0.50	0.44	0.39	0.44	0.42	0.39	0.49	0.42	0.45	0.41
100 M_Seg + M_Unet	0.50	0.42	0.41	0.42	0.42	0.39	0.46	0.42	0.45	0.40

The accuracy of the automatic measurement was calculated according to the following formula:

$$Acc = \left(1 - \left|\frac{a-q}{q}\right|\right) \cdot 100,$$

where a is the manual measurement; q is the automatic measurement.

Table 3. Accuracy of automatic measurement of cardiothoracic ratio

Option name	Test image number									
	1	2	3	4	5	6	7	8	9	10
M_Seg	86.79	95.45	97.50	95.12	92.85	88.63	95.74	97.67	90.69	97.56
M_Unet	90.19	91.30	100.00	95.12	82.97	92.85	95.74	91.30	95.91	85.10
10 M_Seg	88.46	100.00	92.10	92.50	92.85	100.00	91.11	97.56	93.18	100.00
10 M_Unet	90.10	97.67	100.00	97.72	92.85	95.12	100.00	100.00	95.55	97.56
50 M_Seg	97.87	100.00	92.10	92.50	95.12	100.00	93.47	100.00	90.69	100.00
50 M_Unet	92.00	95.45	94.87	97.72	92.85	100.00	100.00	100.00	95.55	97.56
100 M_Seg + M_Unet	92.00	100.00	100.00	97.61	92.85	100.00	93.47	100.00	95.55	100.00

Table 4. Average accuracy of automatic measurement of cardiothoracic ratio

Option name	M_Seg	M_Unet	10 M_Seg	10 M_Unet	50 M_Seg	50 M_Unet	100 M_Seg + M_Unet
Average accuracy	93.80	92.05	94.78	96.66	96.18	96.60	97.15

The accuracy results from Table 3 provide information about each test shot. Analyzing each image separately, it is possible to understand that a complete match of accuracy occurs only in one case for independent neural networks – this is Mobilenet_Unet for image no. 3. For an ensemble of 100 neural networks, the situation is already improving, in this case there was a 100% match for 5 out of 10 images. If we calculate the average accuracy for each algorithm, we can see that the best result among independent networks is Mobilenet_Segnet with an accuracy of 93.80%, and the best ensemble algorithm consisting of 100 networks obtained a result of 97.15%, which is 3.35% better than an independent network.

Conclusions

The application of neural network ensemble methods to improve the determination of the cardiothoracic ratio presents a significant advantage and prospects for improving automation and accuracy. In consequence of this study, the following results were obtained:

1. The use of an ensemble of neural networks in one of the cases improved the accuracy of lung and heart segmentation.

2. The use of an ensemble of neural networks to improve the accuracy of the automatic measurement of the cardiothoracic ratio demonstrated its superiority over conservative methods and proved that further studies of this method can bring even better results for its comprehensive use. Thanks to an ensemble of 100 networks, the improvement rate was 3.35%.

3. Comparison of the obtained results with standard methods for determining the cardiothoracic ratio confirmed a slight deviation from the specified norms and proved the effectiveness of the automation of this process.

4. The study included the analysis of different groups of patients who differed in gender and age. The studied method demonstrated its suitability for a wide range of patients.

5. The used method allows to automate the process of measuring the cardiothoracic ratio, which improves and speeds up the assessment procedure. This is a good potential for optimizing the working time of medical professionals.

Summing up, this paper confirmed the effectiveness and reliability of using an ensemble of neural networks to determine the cardiothoracic ratio and is a promising approach for application in the field of medicine and image segmentation.

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Received 22 April 2024

Підвищення точності визначення кардіоторакального індексу за допомогою ансамблю нейронних мереж

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Кардіоторакальний індекс є одним із основних засобів скринінгу здоров'я серця. Зазвичай вимірювання кардіоторакального індексу виконується вручну лікарем-кардіологом або радіологом. В епоху нейронних мереж, які зараз дуже стрімко розвиваються, ми можемо допомогти лікарям автоматизувати й покращити цей процес. Використання глибокого навчання для сегментації зображень зарекомендувало себе як засіб, який може значно прискорити і вдосконалити процес медичної автоматизації. У даній роботі проведено порівняльний аналіз використання декількох нейронних мереж для сегментації легень і серця на рентгенівських знімках для подальшого вдосконалення автоматичного розрахунку кардіоторакального індексу. Застосовуючи вибірку із 10 тестових знімків, було проведено ручні вимірювання кардіоторакального індексу і 7 варіантів автоматичного вимірювання. Середня точність виміру кардіоторакального індексу найкращої з двох нейронних мереж дорівнює 93,80%, а за допомогою методу, який використовував ансамбль мереж, отримано результат 97,15%, тобто вдалося покращити визначення індексу на 3,35%. Отже, отримані результати вказують на те, що завдяки ансамблю нейронних мереж вдалося покращити результат автоматичного вимірювання, а також свідчать про ефективність і перспективність використання даного методу в медичній сфері.

***Ключові слова**: машинне навчання, нейронні мережі, глибоке навчання, сегментація зображення, аналіз медичного зображення.*

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