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DEVELOPMENT OF ALGORITHMS FOR INTELLIGENT ANALYSIS OF ECHOCARDIOGRAPHIC DATA

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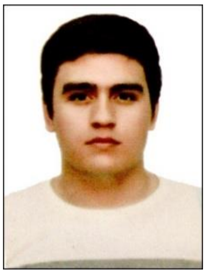

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Abstract: Intelligent processing of echocardiogram images for the identification of signs, their classification and automatic diagnostics is one of the most important tasks of modern medicine. As a result, much research is being done in this area today. The practice of diagnosing a disease based on echocardiographic images or videos is still being explored. This article creates an echocardiogram image database based on articles published in scientific journals and scientific results, based on which HCM and DCM diseases are classified.

Keywords: cardiomyopathy, echocardiogram, deep learning, CNN.

Introduction.

Cardiomyopathy is a disease associated with primary myocardial damage, which includes systemic and functional changes in the heart muscle in the absence of cardiovascular diseases, arterial hypertension, acquired and congenital heart defects.

Hypertrophic cardiomyopathy (HCM) is a thickening of the heart muscle and, as a result, a violation of the pumping function of the heart. Dilated cardiomyopathy (DCM) is a condition in which the heart's main blood vessel, the left ventricle, dilates, preventing the heart from fully pumping blood.

Today, cardiomyopathy is diagnosed in the following ways:

• Blood test;
• X-ray of the chest;
• Electrocardiogram (ECG or ECG);
• Holter monitors;
• Echocardiogram (Echo);
• Stress tests.

The most popular among them is the echocardiogram method. Since it is very difficult to make a diagnosis based on the ECG, often with this disease, the ECG changes are different or can give electrical signals, for example, the heart of a healthy person, which is completely asymptomatic. Because blood work, stress testing, and the use of Holter monitors are time-consuming, echocardiography remains the best method.

Currently, there are two roles for AI in cardiovascular imaging. One is the automation of tasks performed by humans, such as image segmentation, measurement of cardiac structural and functional parameters. The other is the discovery of clinically important insights. Most reported applications were focused on the automation of tasks. Moreover, algorithms that can obtain cardiac measurements are also being reported. In the next stage, AI can be expected to expand and enrich existing knowledge. With the continual evolution of technology, cardiologists should become well versed in this new knowledge of AI and be able to harness it as a tool. AI can be incorporated into everyday clinical practice and become a valuable aid for many healthcare professionals dealing with cardiovascular diseases.

By automating or semi-automating echocardiograms, it is possible to increase the accuracy of diagnostics and improve the quality of medical care. This is why so much research is being done in this area today. In particular, a lot of research is being done on the segmentation of the heart region in order to create a three-dimensional model of it in order to determine its various parameters. Since an echocardiogram is composed of images and videos, we can see in this analysis that the use of deep learning methods is more efficient than machine learning methods. Because CNN systems are adapted to work with images and have shown the highest results among artificial intelligence systems. and video analysis uses a combination of CNN and LSTM. There have been many studies on using the new type of GAN CNNs to highlight parts of the heart and reduce noise in the image, and good results have been achieved. However, fully automated systems that detect diseases rather than simply separating heart parameters have a number of advantages, and the need for such systems has been growing in recent years. Therefore, a number of studies are being carried out in this area.

Another major classification problem is the lack of a database and the size of existing ones. Most echocardiograms are so large that they require a lot of memory to train. among the open access databases to date only EchoNet consists of low resolution videos (112x112) but is not classified by disease, only EF, ELV, EFV values are given. The video also shows only images of the AP4 heart.

It is known that there are 4 types of echocardiogram, PLAX, AP4, AP2.

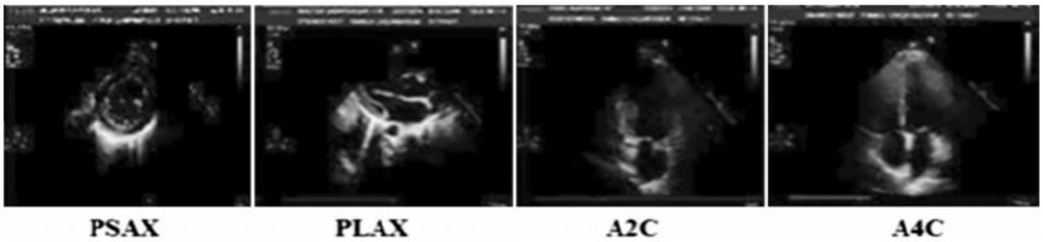

Figure 1. 4 different types of echocardiogram

Currently, using short-axis view the left ventricle is divided in 4 LV wall segments: anterior and posterior septum and posterior and lateral wall. Segments are visualized at mitral and papillary level, whereas the possible extension to the apex is visualized by 4 chamber view. Classical LV hypertrophy cut-off suggestive of HCM in the general adult population is 15 mm. Usually the pattern of LV hypertrophy is asymmetrical, with the anterior septum involved in the majority of cases being also the site of the maximal LV hypertrophy in most patients. In almost 40% of patients, LV hypertrophy involves two segments, whereas the concentric pattern or hypertrophy confined to the apex are particularly uncommon in Western countries (1% each). Recently, it has been demonstrated that mutations in the alpha-cardiac actin gene can express apical HCM or LV non compaction or septal defects. Nevertheless, LV non compaction has to be differentiated from the apical form of HCM.

Hypertrophy preferentially involves the interventricular septum in the basal LV segments, but often extends into the lateral wall, posterior septum and LV apex. Although HCM is typically characterised by asymmetric septal hypertrophy (ASH), almost any myocardial segment may be involved.

The following two-dimensional (2D) echocardiographic criteria are used to aid diagnosis:

1. Unexplained maximal wall thickness >15 mm in any myocardial segment, or
2. Septal/posterior wall thickness ratio >1.3 in normotensive patients, or
3. Septal/posterior wall thickness ratio >1.5 in hypertensive patients.

Results.

In this study, we used videos posted on websites to create a database. First of all, we collected videos with echocardiograms of HCM and DCM from trusted sites. Since most of these videos were educational, they contained a lot of additional material that did not include an echocardiogram that provided information about these two diseases. Therefore, we cut out the time intervals described on the echocardiogram from these videos, which we did in 2-5 seconds. We have also removed all unnecessary characters, notes, and patient information from the cut video clip. Then we split the video fragment into frames. We reduced the size of the selected frame to 112x112. It is worth noting that in the process of removing noise from the cropped video frame, we tried to crop the image of the heart in the video in the form of a square. This is because resizing the rectangular image will affect the quality of the data. This effect may not affect CNN performance in normal images, but it is very important for UZI images because when you turn a rectangular image into a square, the walls of the heart, the shape of the ventricles, and the size of the heart image also change. However, they are the most important factor in making a diagnosis.

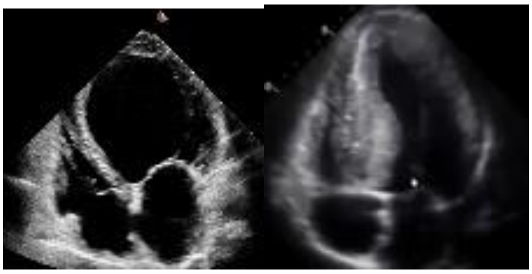

Figure 2. Echocardiogram images

This created a database of 15,000 images. We divided the resulting database into 2 parts, for training and testing. We divided them by a ratio of 9:1. We did this process manually, not automatically. Because when this is done automatically, frames belonging to the same video are more likely to end up in both folders, resulting in a misjudgment of network bandwidth, i.e., classification accuracy will be higher, but the network will overfit. Detailed information about the distribution of images in the database is presented in Table 1.

Today, CNN is an artificial intelligence algorithm that performs image manipulation, classification, cropping and cropping tasks with the highest results. In particular, CNN networks are widely used in telemedicine when analyzing graphic data, including UZI, MRI, MSKT. The most commonly used layers in CNN are input layer, convolution layer, batch normalization layer, RELU layer, fully connected, Softmax, output layer.

In this study, the CNN network was divided into 16 layers using input layer, convolution layer, batch normalization layer, RELU layer, fully connected, Softmax, output layer. For this, special Python 3.0 libraries were used. The parameters of these layers are shown in the table below.

Table 1. Parameters of layers

N	Layer	Parameteres
1	Input	(112, 112, 3)
2	Convolution	Fs-(4,4), Fn-74, S-(2,2), P-(0,0)
3	Batch Normalization	
4	ReLu	
5	Convolution	Fs-(3,3), Fn-4, S-(1,1), P-(same)
6	Batch Normalization	
7	ReLu	
8	Convolution	Fs-(2,2), Fn-16, S-(2,2), P-(0,0)
9	Batch Normalization	
10	ReLu	
11	Convolution	Fs-(3,3), Fn-8, S-(2,2), P-(0,0)
12	Batch Normalization	
13	ReLu	
14	Convolution	Fs-(2,2), Fn-2, S-(1,1), P-(same)
15	Batch Normalization	
16	ReLu	
17	Convolution	Fs-(2,2), Fn-16, S-(2,2), P-(0,0)
18	Batch Normalization	
19	ReLu	
20	Fully Connected	2
21	Softmax	
22	Classifation	2

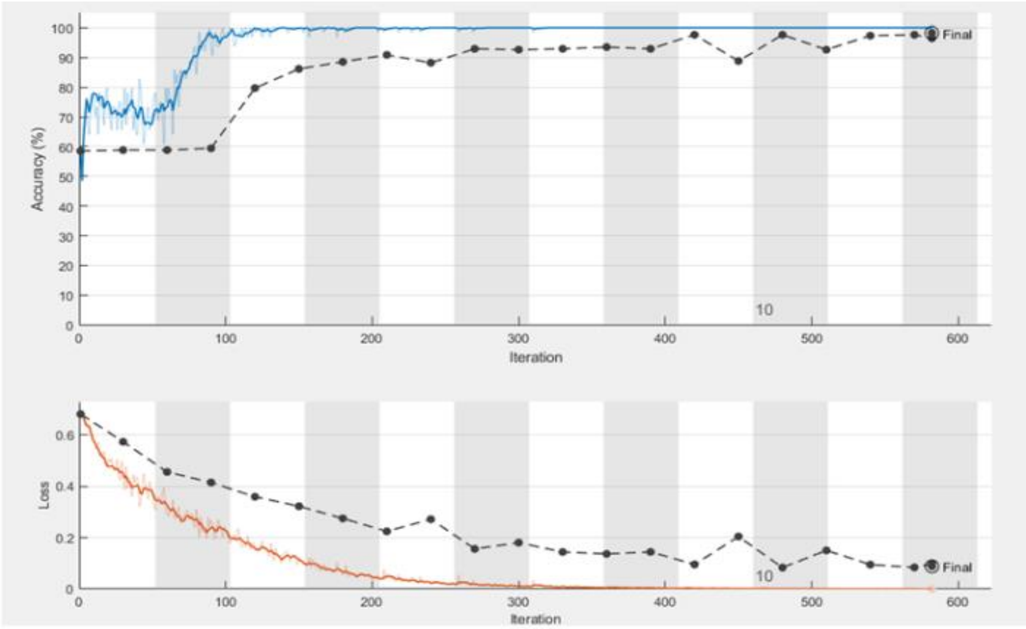

Figure 3. Network learning process

When we trained the network, the classification accuracy of the network reached 98.2%. We then created a configuration matrix to calculate other network parameters. Figure 4 shows the confusion matrix. Using a confusion matrix, we determined sensitivity, specificity, and F1 scores.

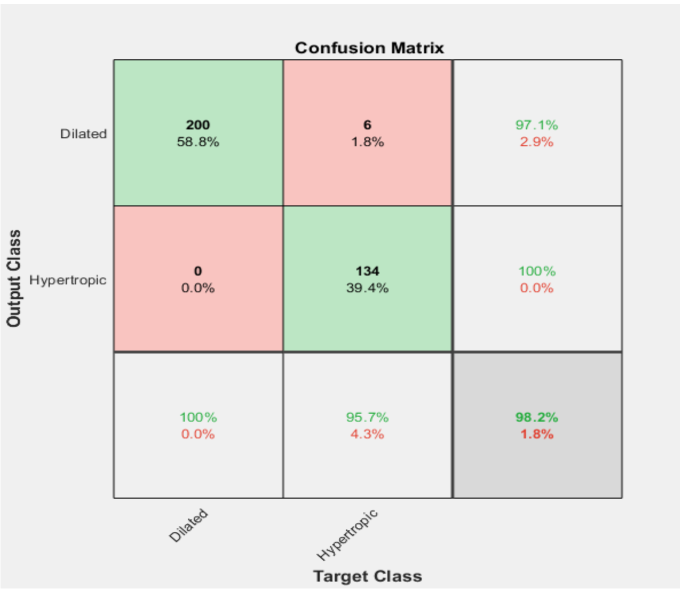

Figure 4. Confusion matrix

For this we used the following formulas:

1. $Sensitivity \ = \frac{TP}{TP+FN}$;
2. $Specifity \ = \frac{TN}{TN+FP}$;
3. $Precision \ = \frac{TP}{TP+FP}$;
4. $F1 - score \ = \frac{2*Precision*Sensitivy}{Precision+Sensitivy}$;

5. $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$

The results obtained are presented in table 2.

Table 2. Values of statistical parameters estimating network accuracy

	Dilated	Hypertropic
Specifity	95,7	100
Sensitivity	100	95,7
Precision	97,1	100
F1-score	98.5	97.8
Accuracy	98.2	98.2

Although the number of DCM images in the database is almost 2.5 times the number of HCM images, we can see that the network sensitivity and F1 score are very close to distinguish between these two classes.

Echocardiogram images are more abstract and incomprehensible, which requires many years of experience and in-depth knowledge from a specialist. In many cases, there are cases of misdiagnosis and death due to lack of skills. Thus, the automation of echocardiographic analysis through the use of artificial intelligence systems in this process increases the accuracy of diagnosis, saves the lives of patients and allows timely and accurate diagnosis of the disease. Many programs developed to date have made semi-automated echocardiography possible. Solving the problem of automatic classification of cardiomyopathy based on ultrasound images is a very complex issue, and today there are more than 14 types of cardiomyopathy. But the most common type in the population is HCM, a life-threatening disease. For this reason, algorithms have been developed to detect this type of cardiomyopathy early or distinguish it from other types of cardiomyopathy.

Conclusion

In this study, a database of echocardiogram images was created based on videos collected from reliable sources on the Internet, and HCM and DCM diseases were classified on this basis. At the same time, the classification accuracy reached 98.2%.

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РАЗРАБОТКА АЛГОРИТМОВ ИНТЕЛЛЕКТУАЛЬНОГО АНАЛИЗА ЭХОКАРДИОГРАФИЧЕСКИХ ДАННЫХ

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Аннотация: Интеллектуальная обработка изображений эхокардиограммы для выделения признаков, их классификации и автоматической диагностики - одна из важнейших задач современной медицины. В результате сегодня в этой области проводится много исследований. Практика диагностики заболевания на основе эхокардиографических изображений или видео все еще изучается. В этой статье создается база данных изображений эхокардиограммы на основе статей, опубликованных в научных журналах, и научных результатов, на основании которых классифицируются заболевания HCM и DCM.

Ключевые слова: кардиомиопатия, эхокардиограмма, углубленное обучение, CNN.