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CONVOLUTIONAL NEURAL NETWORKS FOR EARLY COMPUTER DIAGNOSIS OF CHILD DYSPLASIA

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Abstract. *The problem in ultrasound diagnostics hip dysplasia is the lack of experience of the doctor in case of incorrect orientation of the hip joint and ultrasound head. The aim of this study was to evaluate the ability of the convolutional neural network (CNN) to classify and recognize ultrasound imaging of the hip joint obtained at the correct and incorrect position of the ultrasound sensor head in the computer diagnosis of pediatric dysplasia. CNN's such as GoogleNet, SqueezeNet, and AlexNet were selected for the study. The most optimal for the task is the use of CNN GoogleNet showed. In this CNN used transfer learning. At the same time, fine-tuning of the network and additional training on the database of 97 standards of ultrasonic images of the hip joint were applied. Image type RGB 32 bit, 210 × 300 pixels are used. Fine-tuning has been performed the lower layers of the structure CNN, in which 5 classes are allocated, respectively 4 classes of hip dysplasia types according to the Graf, and the Type ERROR ultrasound image, where position of the ultrasound sensor head and of the hip joint in ultrasound diagnostics are incorrect orientation. It was found that the authenticity of training and testing is the highest for the GoogleNet network: when classified in the training group accuracy is up to 100%, when classified in the test group accuracy – 84.5%.*

Keywords: convolutional neural networks, computer diagnosis, ultrasound image child dysplasia

KONWOLUCYJNE SIECI NEURONOWE DO WCZESNEJ DIAGNOSTYKI KOMPUTEROWEJ DYSPLAZJI U DZIECI

Streszczenie*. Problemem w diagnostyce ultrasonograficznej dysplazji stawu biodrowego jest brak doświadczenia lekarzy w zakresie nieprawidłowej orientacji stawu biodrowego i głowicy ultrasonograficznej. Celem tego badania była ocena zdolności konwolucyjnej sieci neuronowej (CNN) do klasyfikowania i rozpoznawania obrazów ultrasonograficznych stawu biodrowego uzyskanych przy prawidłowym i nieprawidłowym położeniu głowicy ultrasonograficznej we wspomaganej komputerowo diagnostyce dysplazji dziecięcej. Do badania wybrano sieci CNN, takie jak GoogleNet, SqueezeNet i AlexNet. Wykazano, że najbardziej optymalne dla tego zadania jest użycie CNN GoogleNet. Jednocześnie w CNN zastosowano metodologię uczenia transferowego. Zastosowano precyzyjne dostrojenie sieci i dodatkowe szkolenie na podstawie 97 próbek obrazów ultrasonograficznych stawu biodrowego, typ obrazu RGB 32 bity, 210 × 300 pikseli. Przeprowadzono dostrajanie dolnych warstw struktury CNN, w której zidentyfikowano 5 klas, odpowiednio 4 klasy typów dysplazji stawu biodrowego według Grafa oraz obraz ultrasonograficzny typu ERROR, w którym pozycja głowicy ultrasonograficznej i stawu biodrowego w diagnostyce ultrasonograficznej mają nieprawidłową orientację. Stwierdzono, że niezawodność szkolenia i testowania jest najwyższa dla sieci GoogleNet: podczas klasyfikacji w grupie szkoleniowej dokładność wynosi do 100%, podczas klasyfikacji w grupie testowej dokładność wynosi 84,5%.*

Słowa kluczowe: konwolucyjne sieci neuronowe, diagnostyka komputerowa, obrazowanie ultrasonograficzne dysplazji dziecięcej

Introduction

Statistics of hip joint disease are widespread in almost all countries of the world (2–3%), but there are significant ethnic features of its distribution. For example, the incidence of congenital malformations of the hip joint in newborns in the Scandinavian countries reaches 4%, in Germany -2%, in the USA it is higher among the white population than in African Americans, and is 1–2% [1]. Hip dysplasia is a disease characterized by underdevelopment during embryogenesis of all elements involved in the formation of the joint: ligaments, cartilage, bone surfaces, muscles, nerve and vascular structures. Diagnosis of this disease is quite difficult, so in cases of late detection and late treatment of hip dysplasia in children develop severe irreversible morphological and functional changes in the affected limb. It is possible to diagnose malformations of the hip joint in newborns and young children on the basis of the re sults of clinical and ultrasound or X-ray examin ation. However, the radiation load of X-ray examination does not allow to use this method of examination of the hip joints in children under three months. In addition, the radiograph does not show non-ossified structures – elements of the femoral head, the roof of the acetabulum, which make up the majority of these anatomical formations in children of the first year of life. The use of the method of artificial contrast of the joint is quite difficult and dangerous for the child. Today, the ultrasound method of examination of the hip joints is actively developing. Ultrasound (US) in modern medicine is a fairly common method of diagnosis and provides diagnosis of local abnormalities and malformations of the human body degenerative and dystrophic diseases of the ligaments. Therefore, ultrasound is beginning to be actively used to detect developmental hip dysplasia. Ultrasound assessment of the hip joint has the advantage over X-ray examination in that it, along with the image of the hip bone, also reflects cartilaginous structures, and covers the femoral head with the cartilage of the acetabulum. Another advantage of ultrasound diagnosis is that it can be done repeatedly, studying the development of hip dysplasia over time. The main methods of ultrasound assessment of the hip joint are the methods of Graf, Rosendahl, Harcke and Morin, Terjesen, Dahlstrom [8, 10–12, 17–19, 22]. However, they have a low reliability of diagnosis, because the result of diagnosis mainly depends on the qualifications of the doctor, because the study may be incorrect visualization of anatomical landmarks of the hip joint, diagnosed in the wrong position of the child, that is when the ultrasound sensor deviates from the standard position perpendicular to the body. The cartilaginous lip (limbus) is clearly visualized only if the sensor surface is perpendicular to the body. When fixing the ultrasound sensor with an inclination to the hip joint, the image of the limbus becomes blurred due to the effect of anisotropy. Failure to comply with the criteria of the standard ultrasound cut and, accordingly, the oblique direction of the ultrasound beam relative to the hip joint distortion of the image of the joint and make its assessment incorrectly [2, 17]. This makes it impossible to properly measure the angular performance. In addition, a fairly large error is made by visually determining the angles on the noisy speckle noise of the ultrasound image. Thus, the source of errors in determining the condition of the hip joint there is a lack of training of ultrasound specialists working in practical health care institutions, ignorance and misunderstanding that any, even minimal deviation from conventional research technology leads to projective distortion of the image on the sonogram, and therefore to the wrong conclusion. Therefore, one of the main ways to increase the reliability of the study of the hip joints is to create a new method and hardware and software for secondary processing of ultrasound images based on computer technology. The aim of this study was to evaluate the ability of the convolutional neural network (CNN) to recognize and classify ultrasound imaging of the hip joint as the correct or incorrect at position of the ultrasound sensor head in the computer diagnosis of pediatric dysplasia.

1. Ways of CNN structure reconstruction

The method of studying the condition of the hip joints on the basis of analysis of ultrasound images and classification of hip dysplasia on their basis involves the following steps:

1. Pre-processing computer of ultrasound image of the hip joint.
2. Recognition and classification of ultrasound images of the hip joint when the obtained at the correct or incorrect position of the ultrasound sensor head in the computer diagnosis of pediatric dysplasia.
3. Identification of angles in the coronal plane of the hip joint.
4. Classification of hip dysplasia according to the results of the obtained angular indicators by the Graf's method.

The algorithm can be implemented both software and hardware [3–6]. In this study we will consider in detail the main part of this approach, namely the implementation of testing and rejection of correct ultrasound images of the hip joint, which provides a significant increase in the reliability of its diagnosis as a whole. To solve this problem, we use such a powerful tool as CNN, the task of which is to assign the input image to a certain class. The widespread use of neural networks is made possible by the large number of ready-made solutions for learning deep neural networks, including the use of modern multi-core processors, computing accelerators, and computing clusters with distributed memory. Structure CNN contain several layers, such as Convolution layers, ReLU layers, Pooling layers, and Fully connected (FC) layers. The structure CNN scheme for the tasks of the classification of ultrasound images of hip dysplasia is shown in Fig. 1. The CNN architecture may vary depending on the types and number of layers included. The types and number of layers depend on the specific application of the CNN or the data it works with. Based on the analysis, it was found that the MATLAB software platform is the best option for such studies. MATLAB – Deep Learning Toolbox ™ provides a basis for the development and implementation of deep neural networks. The connection of the layers in the convolutional neural network in script MATLAB® for the tasks of classification of ultrasound images of hip dysplasia can be performed as follows:

```
layers = [imageInputLayer([210 300 1])
convolution2dLayer(5,20)
reluLayer
maxPooling2dLayer(2,'Stride',2)
fullyConnectedLayer(10)
softmaxLayer
classificationLayer];
```

After defining the layers of CNN, it is necessary to specify training options using the ‘trainingOptions’ function. For example, options = trainingOptions ('sgdm'); Then, CNN is trained in the training sample using the ‘trainNetwork’ function. Training data, layers, and variants become input to the training function. Example, convnet = trainNetwork(data, layers, options);

To perform the classification of ultrasound images of the hip joints with a size of 210 × 300 pixels by the Graf's method, experimental studies were performed using such CNN's as GoogLeNet [21], SqueezeNet [9], and AlexNet [16]. The CNN's data were chosen not by chance, as they won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in different years.

CNNs underwent a process of training on a sample of 97 ultrasound images, divided into classes by the method of Graf [2]: Type I; Type IIa, Type IIb; Type III, IV; and Type EROR. Type EROR includes ultrasound images of the hip joints, in which the cartilaginous lip (limbus) is indistinctly visualized in the case of tilting the position of the sensor surface to the body. In case of ultrasound sensor tilt:

- to the back – the contours of the lower edge of the iliac bone and the acetabulum become blurred, the thickness of the epicartilage increases;
- to the front – a more pronounced bony roof of the acetabulum, the outer bony protrusion becomes pointed;
- down – the lower edge of the iliac bone is not clearly visualized;
- to the top – the bone-cartilage border or its atypical form does not get to an ultrasonic cut, thus only back departments of an acetabulum are visualized.

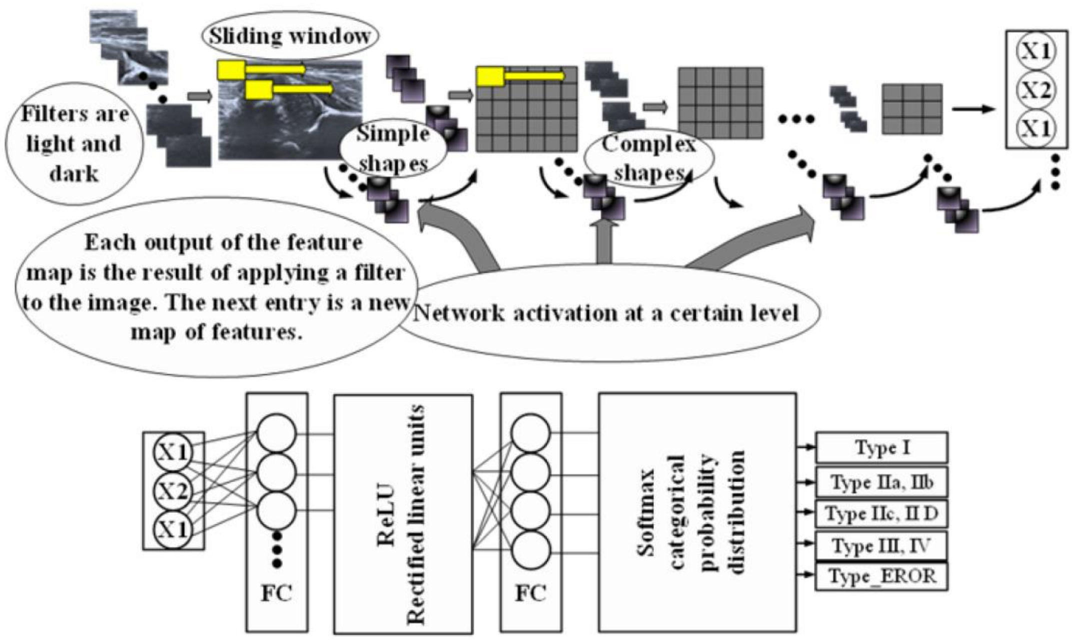
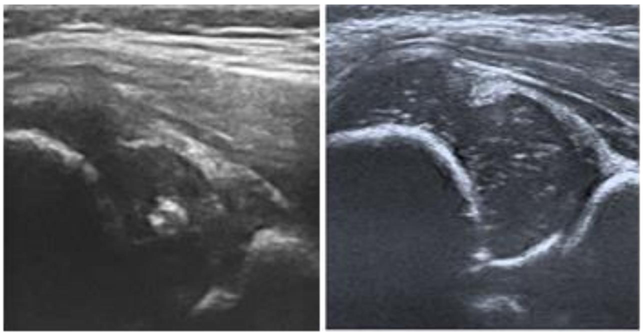


Fig. 1. Detailing of the structure of CNN for the tasks of classification of ultrasound images of hip dysplasia according to the Graf

As a result of the conducted researches the work of CNN used was compared. In Fig. 2 shows the image of the hip joint at the wrong (Fig. 2a) and correct position of the ultrasonic sensor head (Fig. 2b). A sample of 97 ultrasound images is usually insufficient, but for this task can be considered representative. The study presents as an example of GoogLeNet CNN configuration and training, but the same studies were done on SqueezeNet and AlexNet CNN. Due to the large amount of material epy studys, SqueezeNet and AlexNet are not considered in the article, but their final parameters are compared.



a) b)

Fig. 2. Image of the hip joint: a) the image of the hip joint in the case of the inclined position of the ultrasound sensor head to the rear (incorrect position of the ultrasonic head sensor); b) the image of the hip joint at the correct position of the sensor of the ultrasonic head

2. Fine-tuning and learning of CNN on the example of GoogLeNet

GoogLeNet is a convolutional neutron network that not only shows high accuracy, but also requires relatively low computing power of the PC [21]. It was used to identify abnormalities on chest radiographs. In addition, the network has shown itself well in the task of recognizing breast cancer, which shows its effectiveness in working with medical images [23]. In this study used transfer learning CNN [24], that is, this approach involves the use of CNN GoogLeNet, which earlier was trained on one data, and then reconfigured the network and learning to solve the problems of classification of ultrasound images of hip dysplasia.

It is called fine-tuning of the network while retraining took place on the database of 97 benchmark datasets of the trained sample of ultrasonic images of the hip joint were applied. CNN GoogLeNet has the structure shown in Fig. 4, 5. CNN contains 144 layers (input and output layers) and its at structure fine-tuning for the classification of hip dysplasia images. On her you can view the structure and settings of Convolution, ReLU, MaxPooling, and Inception blocks. In Fig. 3 shows the result of fine-tuning the lower layers of the GoogLeNet CNN structure, in which 5 classes are allocated, respectively (4 classes of hip dysplasia types according to the method Graf, and the Type ERROR class described above).

Fragments of the GoogLeNet CNN structure and Convolution, ReLU, MaxPooling, and Inception settings (input layers and output layers) are shown in Fig. 4 and 5, respectively.

3. Training of CNN GoogLeNet

A benchmark datasets of ultrasound images of the hip joints has been prepared for the CNN training. For this purpose, we used the library of images of the hip joints, which was provided by National Pirogov Memorial Medical University. Ultrasound images of hip dysplasia were selected for the experiments and divided into 5 classes: Type I; Type IIa, IIb; Type IIc, II D; Type III, IV; by Graf, and Type_ERROR. Quantitative indicators of the base of benchmark datasets for training and testing are presented in table 1.

As can be seen from the table, fifteen images were selected from each class for teaching and 3 for testing. During the construction of the base of benchmark datasets, 97 ultrasound images of hip joints 210 × 300 pixels, RGB image type, color depth 32 bits were prepared. The process of learning CNN is shown in Fig. 6.

Before learning, the learning parameters were set, which are shown in the MATLAB script snippet:

```
miniBatchSize=10;
numImages=numel(train.Files);
maxEpochs=30;
lr=0.0004;
opts = trainingOptions ('sgdm', ...
'InitialLearnRate',lr,...
'LearnRateSchedule','piecewise', ...
'LearnRateDropFactor',0.2, ...
'LearnRateDropPeriod',6, ...
'MaxEpochs',maxEpochs, ...
'MiniBatchSize',miniBatchSize, ...
'Plots','training-progress');
net=trainNetwork(train,lgraph_2,opts);
% save('trainedNetIn.mat','net')
% save('test.mat','test')
```

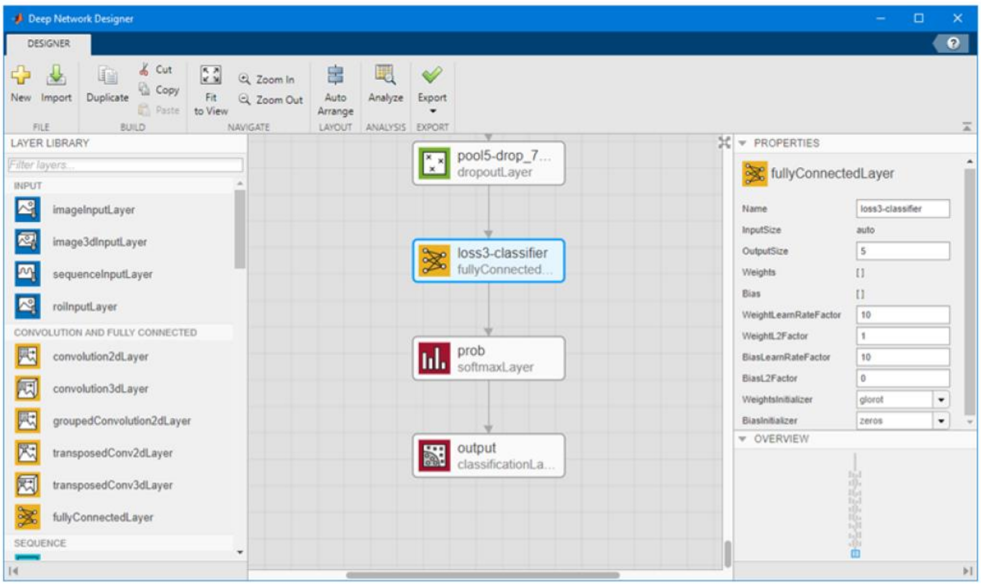


Fig. 3. Fragments of the lower layers of the GoogLeNet CNN structure and the results of fine-tuning

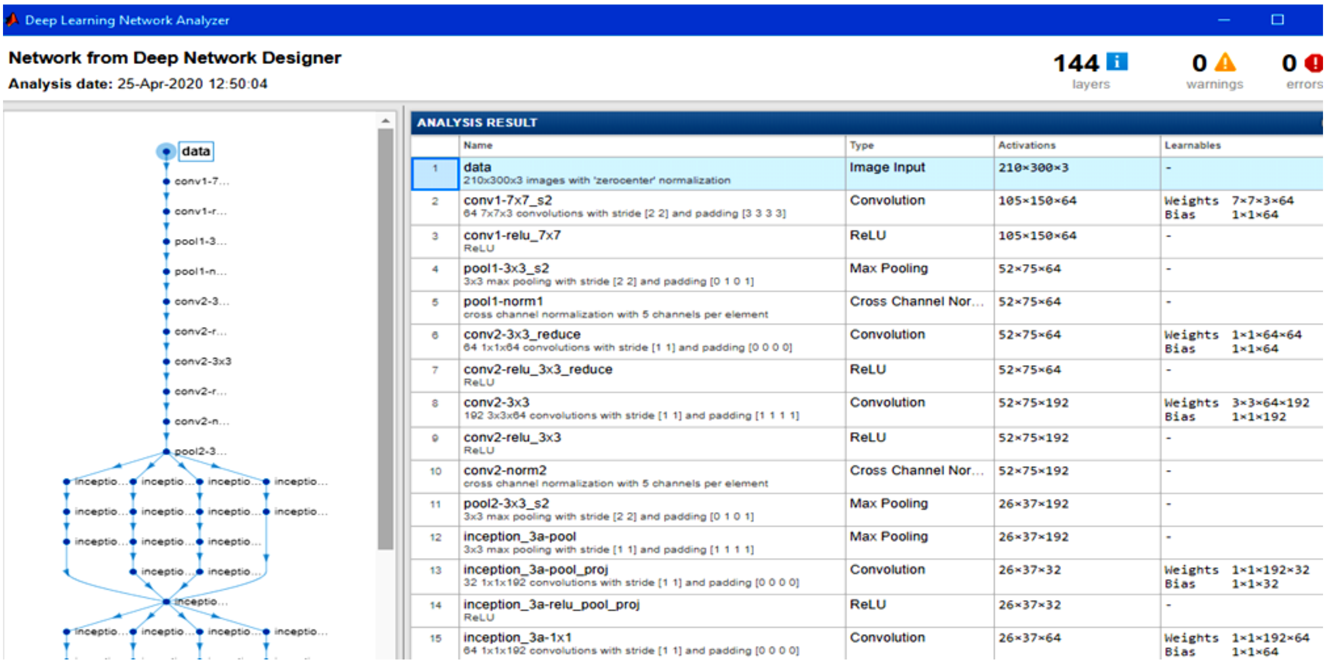


Fig. 4. Fragments of the GoogLeNet CNN structure and Convolution, ReLU, MaxPooling settings (input layers)

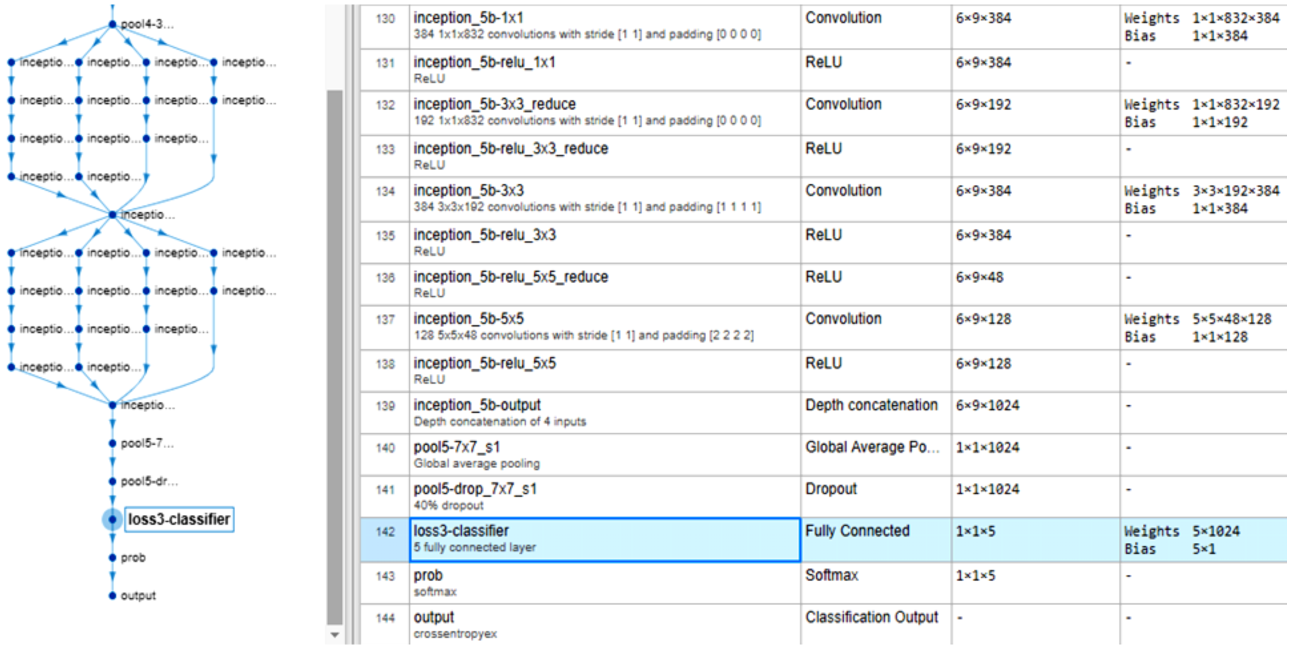
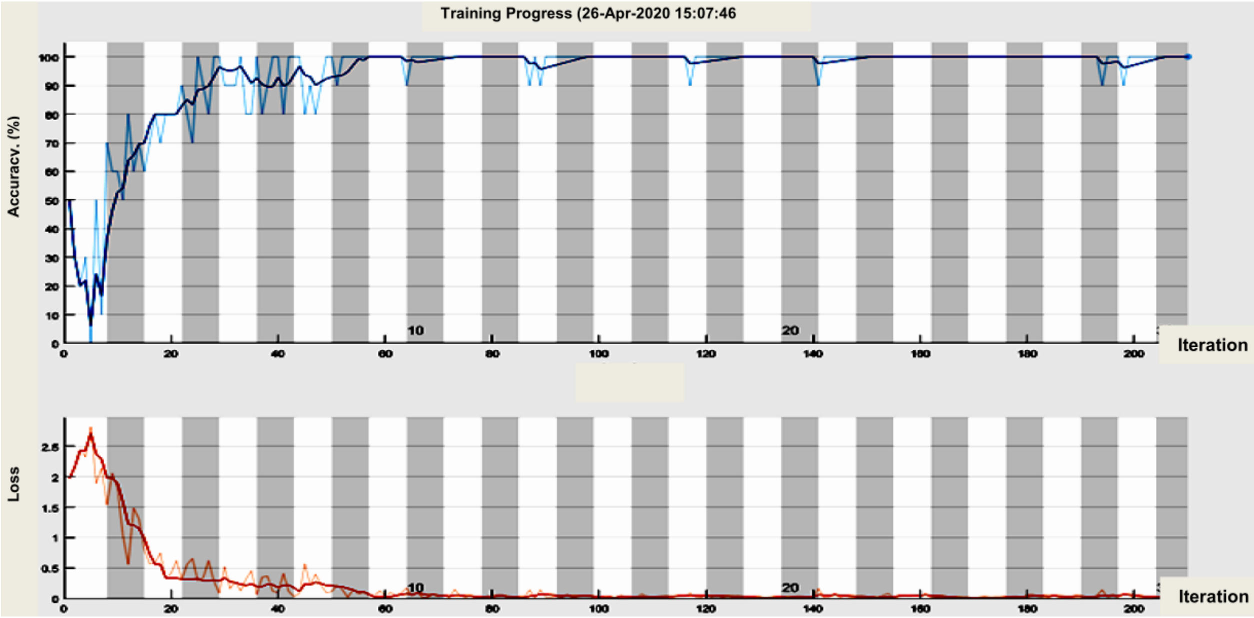


Fig. 5. Fragments of the GoogLeNet CNN structure and Convolution, ReLU, MaxPooling settings (output layers)

Table 1. Quantitative indicators of the base of benchmark datasets for training and testing

tbl = 5×2 table (The presence of benchmark datasets in the training sample)			ans = 5×2 table (Selection of probabilistic benchmark datasets from each class)		
	Label	**Count**		**Label**	**Count**
1	Type I	18	**1**	Type I	18
2	Type III, IV	18	**2**	Type III, IV	18
3	Type IIa, IIb	25	**3**	Type IIa, IIb	18
4	Type IIc, II D	18	**4**	Type IIc, II D	18
5	Type_ ERROR	18	**5**	Type_ ERROR	18



Training on single GPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:01	50.00%	1.9713	0.0004
8	50	00:00:57	100.00%	0.1120	8.0000e-05
15	100	00:01:55	100.00%	0.0255	1.6000e-05
22	150	00:02:52	100.00%	0.0267	3.2000e-06
29	200	00:03:50	100.00%	0.0057	6.4000e-07
30	210	00:04:01	100.00%	0.0260	6.4000e-07

Fig. 6. CNN GoogLeNet learning process

lr = 0.0004 – the LR (learning speed) hyperparameter can significantly affect the time required for a training model. The speed of learning determines how quickly the weight coefficients of convolutional neural networks are updated. The maximum number of epochs is 30. The minimum package size for analysis is 10. Some specific learning parameters 'LearnRateDropFactor' – 0.2, 'LearnRateDropPeriod' – 6 respectively, the rate of decline in learning speed and the rate of decline of the learning period.

The parameters listed in the table Fig.6 have the following definition:

- Mini-batch accuracy in CNN training. The accuracy of the classification of the mini-batch of training data sets, which is reported during the training of CNN, corresponds to the accuracy of the specific classification of the mini-group of data sets on a given iteration. During training using the Stochastic Gradient Descent with momentum (SGDM) optimization algorithm, the algorithm groups the complete set of data into iterations. The iteration corresponds to the calculation of network gradients for each mini-batch of data sets.
- Epoch – the algorithm of the neural network is iterative; its steps are called epochs or cycles. Epoch – one iteration in the learning process, which includes the presentation of all examples of data sets from the learning set and, possibly, to check the quality of learning on a test sample. The learning process is carried out on a training sample.
- Mini-Batch loss – trends in loss and accuracy when learning on a mini-group of data sets. If the source layer is a Classification Source Level object, then the loss is an entropy cross loss for a multiclassification task with mutually exclusive classes.
- Base Learning rate – Basic learning speed. The software multiplies the norm coefficients of the rate of learning of the layers by this value.

Convolutional neural networks through the use of a special operation – the actual convolution – allows you to simultaneously reduce the amount of information stored in memory, thereby better cope with images of higher resolution. This allows you to highlight reference features of the image, such as edges, contours or borders. At the next level of processing from these edges and faces it is possible to recognize repeating fragments of textures which can further develop into fragments of the image. In essence, each layer of the neural network uses its own transformation. If on the first layers the network operates with such concepts as "edges", "borders", etc., then the concepts "texture", "parts of objects" are used further. As a result of such processing, we can correctly classify the image of a condition of a hip joint of the child. In Fig. 7 shows the so-called tile images of the input image of the hip joint of the child, which forms the first convolutional layer conv1 CNN filters with an amount of 8 × 8, size 7 × 7 × 3.

The script of the MATLAB R2019b package for forming a tile of the state of the child's hip joint, for the first convolutional layer conv1 CNN is written below:

```
net = GoogLeNet;
im = imread(fullfile(matlabroot,'examples','nnet','60-57_300-210.jpg'));
imshow(im)
imgSize = size(im);
imgSize = imgSize(1:2);
act1 = activations(net,im,'conv1');
sz = size(act1);
act1 = reshape(act1,[sz(1) sz(2) 1 sz(3)]);
I = imtile(mat2gray(act1),'GridSize',[8 8]);
imshow(I)
```

CNN GoogLeNet on 144 layers was trained in a training sample of 97 images of hip dysplasia with learning parameters: number of epochs 30, number of iterations 210, training time 4.1 minutes, mini – batch accuracy in classification on the training group up to 100%, mini – batch loss in training on mini-group of data sets – 0.0260, basic learning speed – 6.4×10^{-7}, network weight after training 87,739 MB, table on the Fig. 6.

The personal computer on which the learning process took place had the following computing power:

- CPU: Intel (R) Core (TM) i7-4702MQ CPU @ 2.2GHz… 2.2GHz;
- RAM: 8.00 GB;
- GPU video adapter: GT 750M (GK107 graphics processor is equipped with 384 CUDA cores and operates at a frequency of 967 MHz (turbo mode is supported), and the width of the memory bus is 128 bits).

4. Experimental research and comparison of modeling results

In order to select the best CNN for the task of recognition, classification and selection of correct ultrasound images of the hip joint, machine learning and testing of GoogLeNet, SqueezeNet and AlexNet CNNs were carried out. Characteristics of the considered CNN's are summarized in table 2.

As can be seen from table 2, reliability in training and testing on a sample of 97 images of hip dysplasia the highest for the GoogLeNet network: up to 100% for classification in the training group, 84.5% for classification in the test group. The main objective of this study was to classify ultrasound images hip joint on the correct (Type I; Type IIa, IIb; Type IIc, IID; Type III, IV; by Graf), and incorrect class Type_ERROR, where position of the head of ultrasound sensor in ultrasound diagnostics of the hip joint are incorrect orientation to the body. In Fig. 8 shows a histogram of the comparison of the main characteristics of CNN's SqueezeNet, GoogLeNet, AlexNet.

Table 2 and the histogram show that a number of key characteristics such as the number of layers, the weight of the network after training (MB) – CNN SqueezeNet has better performance, and the accuracy in the classification of the test group (%) approaching GoogleNet. Also, in the study of CNN AlexNet found that the number of layers – 25 is not enough to achieve accuracy in the classification of the test group at least up to 80%. In the future, it is proposed to use software and hardware of artificial intelligence, which are discussed in [13,14,15], which will help improve the proposed approach and increase the speed and reliability of diagnosing ultrasound medical images of hip dysplasia.

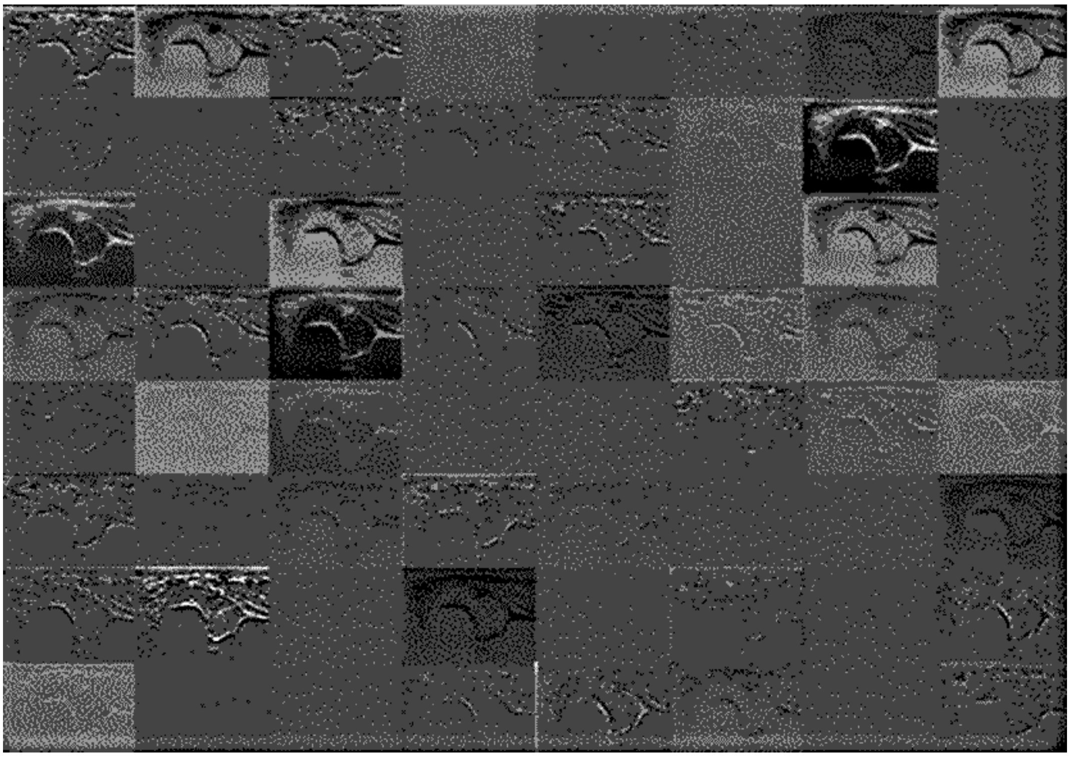


Fig. 7. Tiles of the images of the input image of the hip joint of the child, which forms the first convolutional layer conv1 CNN filters in the amount of 8 × 8, size 7 × 7 × 3

Table 2. Characteristics of CNN's SqueezeNet, GoogLeNet and AlexNet during training and testing on a sample of 97 images of hip dysplasia

	SqueezeNet	GoogLeNet	AlexNet
Number of layers	68	144	25
Number of epochs	30	30	12
Number of iterations	270	210	216
Training time (minutes)	2.16	4.7	0.46
Accuracy in the classification of the training group (%)	up to 100%	up to 100%	up to 75%
Accuracy in the classification of the test group (%)	83	84.5	62.7
Basic learning speed (coefficient)	6.4×10^{-7}	6.4×10^{-7}	8.0×10^{-5}
Network weight after training (MB)	13	87.739	68.4

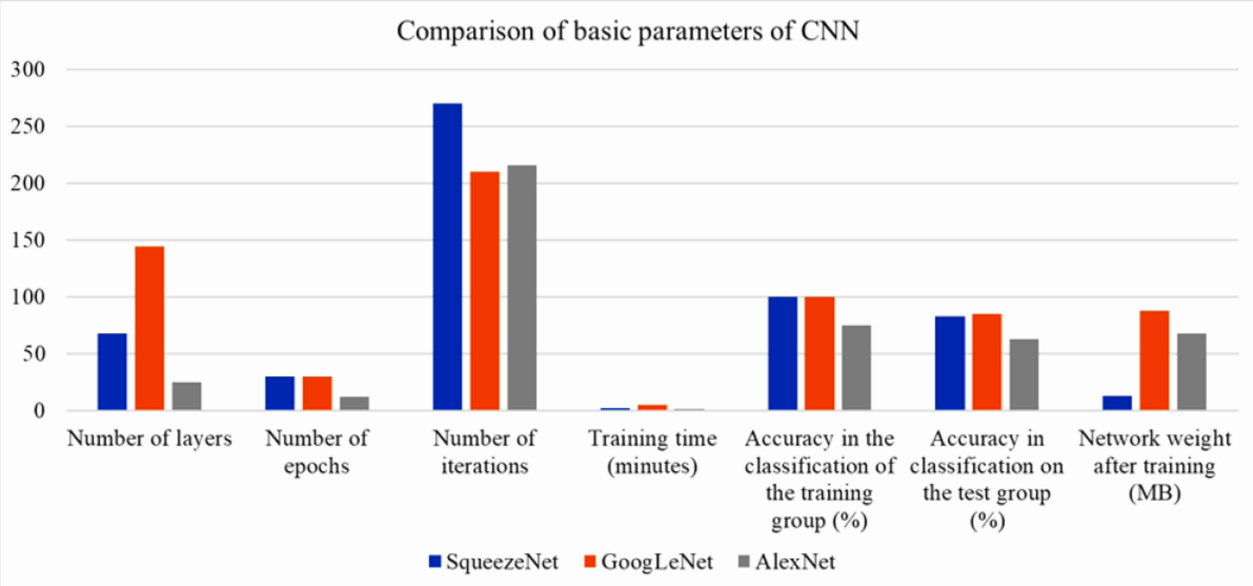


Fig. 8. Comparison of the main characteristics of CNN's SqueezeNet, GoogLeNet, AlexNet

5. Discussion

It is possible to diagnose malformations of the hip joint in newborns and young children on the basis of the re sults of clinical and ultrasound or X-ray examination. Ultrasound assessment of the hip joint has the advantage over X-ray examination in that it, along with the image of the hip bone, also reflects cartilaginous structures, and covers the femoral head with the cartilage of the acetabulum. Another advantage of ultrasound diagnosis is that it can be done repeatedly, studying the development of hip dysplasia over time. The main methods of ultrasound assessment of the hip joint are the methods of Graf, Rosendahl, Harcke and Morin, Terjesen, Dahlstrom [8,10,11,12,17,18,19,22]. However, they have a low reliability of diagnosis, because the result of diagnosis mainly depends on the qualifications of the doctor, because the study may be incorrect visualization of anatomical landmarks of the hip joint, diagnosed in the wrong position of the child, that is when the sensor deviates from the standard position perpendicular to the body. The cartilaginous lip (limbus) is clearly visualized only if the sensor surface is perpendicular to the body. When fixing the sensor with an inclination to the hip joint, the image of the limbus becomes blurred due to the effect of anisotropy. Failure to comply with the criteria of the standard cut and, accordingly, the oblique direction of the ultrasound beams relative to the hip joint distortion of the image of the joint and make its assessment incorrectly [17,2]. Thus, the problem in ultrasound diagnostics hip dysplasia is the lack of experience of the doctor in case of incorrect orientation of the hip joint and ultrasound head. Therefore, the work has taken the first step towards creating an intelligent system that will predict the class of development of hip dysplasia and will filter out ultrasound images of the hip joint with incorrect diagnostics. Similar CNN-based systems are used to recognize and classify diseases in medical images [7, 20]. In the future, it is proposed to add a computer algorithm for quantitative measurement of the angles α and β of the hip joint according to Graf's method.

6. Conclusion

The study proposes a computer method for classification of ultrasound images of hip dysplasia using Graf's classification. The positive possibilities of the convolutional neural network for the classification and recognition of images of the hip joint obtained at the correct or incorrect position of the ultrasound sensor head are shown. The ability of CNN to select correct ultrasound images of the hip joint, thereby improving the accuracy of diagnosing pediatric dysplasia, has been demonstrated. With this purpose it was conduct experimental studies on GoogLeNet, SqueezeNet, and AlexNet CNNs to select the best. The CNN's data were chosen not by chance, as they won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in different years. They were fine-tuned and trained using a database of ultrasound images of the hip joint. It was found that the reliability of training and testing on a sample of 97 images of the hip joint is the highest for the GoogLeNet network: when classified in the training group accuracy is up to 100%, when classified in the test group accuracy – 84.5%. According to the others parameters such as the number of layers, the accuracy of classification in the test group, the weight of the network after training, CNN SqueezeNet has marginally better performance. In the study of CNN AlexNet found that the number of layers of 25 is insufficient to achieve accuracy in the classification of the test group at least up to 80%.

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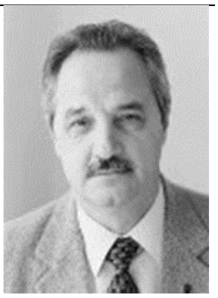

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