# Algorithm For Detecting Eye Diseases Using Convolutional Neural Network


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***Abstract*—Currently, a convolutional neural network and its modifications are algorithms for finding the best objects in terms of accuracy and speed. Therefore, in the diagnosis of eye diseases, a network of neurons was used, based on the principles of neocognitron and supplemented by training on the inverse error distribution algorithm. The article proposes a fully connected neural network with several architectures and several hidden layers, consisting of nonlinear neurons in each layer.**



***Index Terms*—Convolutional neural network, perceptron, inverse error distribution algorithm, neuron weight.**


## I. Introduction

Since 2012, neural networks have been ranked first in the popular international logo recognition competition ImageNet. The main reason for the success of the convolutional neural network was the concept of shared weights. Despite their large size, these networks have fewer configurable parameters compared to their ancestor, the neocognitron. Neocognitron-like variants of a flat neural network. There is a mosaic convolutional neural network in which there is a partial rejection of associated weights, but the learning algorithm remains the same and is based on the inverse distribution of errors [1-2]. Convolutional neural network consists of different types of layers: (convolutional) layers, downsampling layers, and a "normal" neural network - percepton layers. The first two types of layers (convolutional, downsampling) are interleaved to form an unwanted symbol vector for the multilayer perceptron [3-4].

The network gets its name from the operation described later. Convolutional networks are a successful break between biologically similar networks and simple multilayer perceptrons. Today, with their help, the best results in image recognition are achieved. The neural network is the core technology of deep learning. [5-6].

## II. Convolutional neural network structure

Convolutional neural network can be trained faster by running the sequential machine faster and by purely parallelizing the cortical process on each map, as well as the reverse cortex of the distribution of errors over the network.[3-5].

Model of neuron $NET = \sum_{i=1}^{n} w_i * x_i + w_0,$

here$w_i$ i-weight of neuron;

$x_i$-neuron output;

$w_0$ auxiliary parameter, offset;

$n$number of synaptic connections included in the neuron.

Determining the network topology is a task that needs to be solved based on research data and personal experience. [6].

Following steps influence the choice of the topology:

definition of the problem to be solved by the neural network (classification, forecast, modification);

to identify the constraints on the problem (speed, accuracy of the answer);

to identify the incoming (type : image, sound, size: 100x100, 30x30, format: RGB, gray levels) and outgoing (number of classes) data.

The problem that needs to be solved using a neural network is to classify images into particular fundus images. The network's limitations are the response speed - no more than 1 second and the recognition accuracy of at least 70 $\%$ .

Input data consists of color JPEG images. If the size is too large, the computational complexity increases, accordingly, the restrictions on the response speed are violated, and in this case the problem of determining the size is solved by the selection method. If a very small size is obtained, the network may not be able to distinguish important facial features. Each image is divided into 3 channels: red, blue and green channels. The input data of each precise pixel value is normalized to a range of 0 to 1 using the following formula [7]:

$$f(p, \min, \max) = \frac{p-\min}{\max - \min},$$

here $f$ normalization function;

$p$ value of the transparent color of the pixel from 0 to 255;

*min* minimal value of the pixel 0;

*max* maximal value of the pixel 255.

A map layer consists of a set of maps (also known as character maps, in real life these are simple matrices), each map has a synaptic core (different sources call it differently: scan kernel or filter) [8].

Size of all cards in the convolutional layer is the same and is calculated using the formula [7]:

$$(w, h) = (mW - kW + 1, mH - kH + 1),$$

here *(w, h)* calculated size of the convolutional map;

*mW* weight of the previous map;

*mH* height of the previous map;

*kW* weight of the core;

*kH* height of the core.

Performs a scrolling operation according to the following formula used in image processing. [7-8]:

$$(f * g)[m, n] = \sum_{k,l} f[m-k, n-l] * g[k, l],$$

here $f$ specified image matrix;

$g$ convolution kernel.

In the process of scanning the map of the previous layer with the core of the sublayer (filter), the scanned core does not intersect, unlike the layer of the layer. Typically, each card will have a 2x2 core, which will allow you to shrink the previous cards in the stack layer by 2x. All character cards are divided into cells of 2x2 elements, from which the maximum value is selected [6-7].

Typically, the RelU activation function is used at the subselection level. Additional operation (or MaxPooling - choose the maximum)

The layer can be expressed by the following formula [7]:

$$x^l = f(a^l * subsample(x^{l-1}) + b^l),$$

here $x^l$-layer output;

$f()$ activation function;

$a^l, b^l$layer displacement coefficients;

Subsample ()operation of selecting the local maximum value.

Fully glued layer

The last type of layer is a simple multi-layer perceptron layer. The purpose of the layer is to classify a complex nonlinear function that improves the quality of recognition by optimizing it.

## III. Identification of fundus vascular objects using deep neural networks

Using artificial neural networks to solve image recognition problems requires preliminary training.

Simplified neural network training process can be summarized as follows. The data available in the database allows you to train the neural network by comparing the input data with the available data. Weight is adjusted every time you workout [9,10].

Suppose there is some unknown recognition function$g : X \to Y$, argument, $x_n \in X$ , an image, represented as the length of a vector$n, y \in Y$- classes are given. The training scheme is a set of values of this function, namely $D = \{(x_0, y_0), (x_1, y_1), ...(x_m, y_m)\}$.Function for solving training problems $gD$function that approximates all of its defining properties, including values not includedto find $h : X \to Y$, [11].

Application of the artificial neural network learning algorithm involves solving the search optimization problem in the space of weights. There are stochastic and mass training methods. In the stochastic learning mode, the neural network inputs are linked to individual examples from the training scheme. The network weights are updated after each instance. In mass training, training samples are updated to the weights of the entire network, after which the neural network is prepared for input. The network weight error will be collected for subsequent updates.

The classic measure of the measurement error is the sum of the root mean square errors. [7-12]:

$$E_n^p = \frac{1}{2} E_{rr}^2 = \frac{1}{2} \sum_j^M (x_j - d_j)^2 \to \min,$$

here $M$ - number of neurons in the output layer, j is the number of output neurons, $x_j$- actual value of the output signal of the neuron, $d_j$expected value.

To reduce the squared error of training the neural network, we use the gradient drop method by calculating the frequency product for each weight. We have the following relationship[7-10]:

$$\frac{E_n^p}{w_i} = (x_j - d_j) \times \frac{\partial(x_j - d_j)}{\partial w_i} = (x_j - d_j) \times$$
$$\times \frac{\partial}{\partial w_i} g(Y - g(\sum_{j=0}^n w_j x_j)) - (x_j - d_j) \times g'(in) \times x_j,$$

$$\frac{\partial E_n^p}{\partial w_i} = x_{n-1}^j \cdot \frac{\partial E_n^p}{\partial y_n^i},$$

$$\frac{\partial E_n^p}{\partial y_n^i} = g'(x_n^j) \cdot \frac{\partial E_n^p}{\partial x_n^i},$$

here $g'$activation function

$$\frac{\partial E_n^p}{\partial y_n^i} = x_n^i - d_n^i,$$

$x_{n-1}^j$-$j$- layer (n-1)- neuron output, $y_n^i$ -$(n-1)$-scalar product of all outputs of the layer neurons and the corresponding weights. The gradient descent algorithm ensures that the error propagates to the next layer and

$$\frac{\partial E_{n-1}^p}{\partial x_{n-1}^i} = \sum_i w_n^{ik} \cdot \frac{\partial E_n^p}{\partial y_n^i},$$

if you want to decrease$E_n^p$, the weight is updated as follows

$$w_i \leftarrow w_i + \alpha \times (x_n^j - d_n^j) \times g'(in) \times x_i,$$

here $\alpha$ degree of study.

If $E_{rr} = (x_n^j - d_n^j)$If the error is positive, the network output is very small and therefore the weights increase for positive inputs and decrease for negative inputs. If the error is negative, the opposite is true. This error, obtained in the calculation of the gradient, can be considered as noise that affects the correction of the weights and can be useful for exercise.

Mathematically, the gradient is a partial loss product for each learned parameter, and the update of one parameter is formed as follows [7]:

$$w_i := w_i - \alpha * \frac{\partial L}{\partial w_n},$$

here-L loss function.

Gradient of the loss function relative to the parameters is computed using a small portion of the training dataset applied to the parameter updates. This technique is also called mini-batch gradient descent, often also called stochastic gradient descent, and the mini-batch size is also a hyperparameter[8].

## IV. Comparative analysis of image object recognition programs based on convolutional neural networks

Lateral view images of the ophthalmic vessel were obtained from the open data collection site kaggle.com [12-14]. Images from this dataset were distributed as follows (Table 1).

1-Table

Distribution of images used in experiments

| | NORMAL | CNV | DRUSEN |
|---|---|---|---|
| Total number of images | 8616 | 26315 | 37205 |
| Number of read images | 242 | 242 | 242 |
| Number of tested images | 8858 | 26557 | 37447 |

Based on this data set, the results of the analysis of various structures were obtained (Table 2).

2-Table

Training Accuracy in Convolutional Neural Networks with Different Structures

| № | Convolutional neural network structure | Training Accuracy (good range 0.003 to 0.001) |
|---|---|---|
| 1 | 7 Conv (2x2) pool(2x2) | 0.725 |
| 2 | 10 Conv (5x5) pool (2x2)<br>4 Conv (3x3) pool (2x2) | 0.95 |
| 3 | 8 Conv(4x4) pool (2x2)<br>6 Conv(3x3) pool (2x2) | 0.53 |
| 4 | 20 Conv (5x5) pool (2x2)<br>30 Conv (3x3) pool(2x2) | 0.78 |
| 5 | 40Conv (4x4) pool (2x2) | 0.91 |
| 6 | 40Conv (5x5) pool (2x2) | 0.80 |

Also important is the structure that needs to be built for convolutional neural networks. The result of the accuracy obtained from the training process determines whether a model has been created for the image data. According to the importance of sharpness, the correct classification of the image is assessed. Untrained information enables image recognition [12-14].

## CONCLUSION

This article discusses the construction of a classification system based on the diagnostic features of the vessels of the fundus and the optic nerve head area. The main difficulty in the practical application of the system lies in the fact that when a doctor diagnoses a system for training, it is important to classify the fundus as a whole, even if one image of the fundus contains vessels with pathological changes in normal or early stages. pathological development. Consequently, there will also be streaks in the choice of the curriculum, which are deliberately distributed among the classes.

In a conventional multilayer network, the detection process slows down significantly due to the large number of connections between neurons, that is, synapses. A way to reduce the number of links and allow you to find one character across the entire image area.

## References


[1] Zagidullin B.I., Nagaev I.A., Zagidullin N.Sh., Zagidullin Sh.Z. A neural network model for the diagnosis of myocardial infarction. // Russian Journal of Cardiology. 2012; (6): 51-54.

[2] Andrisevic N., Ejaz Kh., Rios-Gutierrez F., Alba R., Nordehn G., Burns Sh. / Detection of Heart Murmurs Using Wavelet Analysis and Artificial Neural Networks // Journal of biomechanical engineering VL-127, 2005/12/01, 899-904, DOI 10.1115/1.2049327

[3] Higuchi K., Sato K, Makuuchi H., Furuse A., Takamoto S., Takeda H.// Automated diagnosis of heart disease in patients with heart murmurs: Application of a neural network technique// Journal of medical engineering technology 2006/03/01, SP - 61-68 pp, EP - 8 , VL - 30, DOI: 10.1080/03091900500131110

[4] Cujic D, Golubovic S, Bojic-Trbojevic Z, Ilic N, Baricevic I, Nedic O. Differential diagnosis of liver diseases using serum biomarkers. J BUON. 2010 Jan-Mar;15(1):141-146. PMID: 20414942.

[5] B. B. Vincent Lyon. Differential diagnosis of diseases of the liver. // Ann Intern Med.1935; Volume 9, Issue 3. Page: 258-263doi:10.7326/0003-4819-9-3-258

[6] Zevallos Maldonado C, Ruiz Lopez MJ, Gonzalez Valverde FM, Alarcon Soldevilla F, Pastor Quirante F, Garcia Medina V. Hallazgos ecograficos asociados al cancer de vesicular biliar. // Cir Esp. 2014;92:348355

[7] Durstewitz D., Koppe G., Meyer-Lindenberg A. Deep neural networks in psychiatry // Molecular Psychiatry - 2019, SP - 1583 EP - 1598 VL - 24, SN - 1476-5578, DO - 10.1038/s41380-019-0365-9

[8] Lalonde M., Gagnon L., and Boucher M.-C., Automatic visual quality assessment in optical fundus images / // Proceedings of Vision Interface (V I2001), pp. 259-264. Ottawa, Canada, June 7-9, 2001.

[9] Muxamediyeva D.K. Methods for solving the problem of the biological population in the two-case // IOP Conf. Series: Journal of Physics: Conf. Series 1210 (2019) 012101 doi:10.1088/1742-6596/1210/1/012101.

[10] R. Estrada, M. J. Allingham, P. S. Mettu, S. W. Cousins, C. Tomasi and S. Farsiu, "Retinal Artery-Vein Classification via Topology Estimation," in IEEE Transactions on Medical Imaging, vol. 34, no. 12, pp. 2518-2534, Dec. 2015, doi: 10.1109/TMI.2015.2443117.

[11] Farmonov SH.R, Bekmuratov T.F, Muhamedieva D.T. About the dodges plans of the continuous selective control // International Conference on Information Science and Communications Technologies, ICISCT 2020, 2020, 9351415. 4-6 november. DOI: 10.1109/ICISCT50599.2020.9351415

[12] Mirzayan K., Dilnoz M., Barno S. (2021) The Problem of Classifying and Managing Risk Situations in Poorly Formed Processes. // In: Aliev R.A., Yusupbekov N.R., Kacprzyk J., Pedrycz W., Sadikoglu F.M. (eds) 11th World Conference Intelligent System for Industrial Automation (WCIS-2020). WCIS 2020. Advances in Intelligent Systems and Computing, vol 1323. Springer, Cham. Pp 280-286. https://doi.org/10.1007/978-3-030-68004-6-36

[13] Mukhamedieva D T 2020 Journal of Physics: Conference Series1546(1) 012091

[14] Muhamediyeva D., Sotvoldiyev D., Mirzaraxmedova S., Fozilova M. Approaches to handwriting recognition // International Conference on Information Science and Communications Technologies, ICISCT 2020, 2020, 9351505. 4-6 november. DOI: 10.1109/ICISCT50599.2020.9351505