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Solving problem of early diagnosis on basis of framework neurons

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Abstract. The program's structure for analyzing optic nerve images is based on methods and algorithms for quantitative assessment of pathological changes in the vascular system of the retina. Scale changes, shifts, twists, angular changes, and partial stability of other neural networks have been shown to be achieved.

1 Introduction

Mathematical methods for solving medical and biological problems have been developing for more than a hundred years. Scientists have proposed many ways to test the products of hypotheses and conclusions. In the 1960s, analytical methods were developed, and many publications were published. The common feature that unites them is the availability of precise decision-making algorithms. "Diagnostic algorithm includes a set of rules that determine the procedure for processing medical information to make a diagnosis" [1].

Although the most popular methods are still actively used in theoretical biology and medicine, they are not widely used in clinical practice. This is because the methods used to process group data are rarely applied to individual objects and, secondly, due to the specific nature of medical and biological data. Solutions to medical and biological problems depend on a wide range of factors. Therefore, although it is possible to create output rules that relate the conditions of the problem to the solution, the method usually works best only in the group of objects under study. Of course, a universal algorithm cannot be created, and when a method is used for a group of similar objects, the algorithm must almost always be completely redesigned.

Long-term studies with various precise algorithms have shown that precise methods can easily solve unclear medical problems but are more practical in the specific tasks of diagnosis, prediction, and decision-making [2].

The unclear tasks of medicine and biology have been the ideal platform for applying neural network technologies. In this field, there is the most striking practical success of neuro-communication methods.

The greatest interest in health care is the systems for disease diagnosis and differential

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diagnosis. However, various data can be used to make decisions: anamnesis, clinical examination, laboratory test results, and complex functional methods. The list of medical fields, which began with the use of new technologies, is very wide and continues to grow.

One of the fastest-growing areas is the use of neural networks in cardiology. In Italy, a very interesting system of experts has been developed to diagnose and treat hypertension [3, 4]. The system includes three neural network modules, in which the responses of the previous module provide input information for others.

A distinctive feature of the system is the ability of the user (physician) to transmit his experience to the neural network. To do this, the program's developers have created a special block, which displays a daily blood pressure schedule on a computer screen and offers the doctor to enter into the computer the scheme and dose of antihypertensive drugs. The entered example is placed in the database. At any time, neural networks can be "taught" with new examples.

[5] presented a method for the detection of atherosclerotic plaques in the arteries. To do this, a neural network is used that interprets the fluorescent spectra obtained in the study of tissues with the help of a laser. Similarly, the diagnosis of peripheral vascular disease is made [6,7], for example, forms of arteritis [8].

Several studies on using neural networks to diagnose myocardial infarction are being conducted [9, 10]. The author provides information on the sensitivity of the neural network test (77.7%) and specificity (97.2%). In addition, the study [11] identified the diagnostic value of clinical parameters in diagnosing myocardial infarction using the neural network.

Neurotransmission analysis of acoustic signals allows diagnosing cardiac valve murmurs [12] and assessing the systolic and diastolic phases of heart contraction with preliminary diagnosis [13].

Computer analysis of images has become a key tool in medical diagnostic systems, significantly increasing the quality of diagnostics. Information technology is most actively used in ophthalmology and cardiology. The research is aimed at analyzing images of the vessels of the fundus. In both cases, the images of the blood vessels contain important diagnostic information. Based on the study of blood vessels, the doctor not only concludes the organ's condition and diagnoses general systemic diseases such as diabetes, polycythemia, anemia, and hypertension [1, 1, 15].

In [16], all these types of pathology were considered in the aggregate and diagnosed based on the results of complex studies. However, the development of methods of summative analysis and their implementation in an algorithmic way is limited to selecting a single type of pathology, as it is considered an excessive task.

2 Problem statement

For example, m objects are presented as a selective table. Each object belongs to a class. When using this study option, it is necessary to determine which class the new object belongs to.

In the first step of the algorithm, the number k, which represents the number, *is* determined. If k= 1, the algorithm loses its essence and classifies the current object into the class to which the nearest object belongs. The algorithm can incorrectly solve the classification problem even with a very large value.

The second step identifies the current object *(neighbors are searched)*.

In this algorithm, if the value of the symbols consists of real numbers, the proximity of objects is determined based on Euclidean metrics

$$D_E = \sqrt{\sum_i^n (x_i - y_i)^2},$$

where ***n*** is the number of characters.

If the value of the symbols is in binary form, the Heming metric is used, and the difference function between the objects is as follows:

$$D_X(x, y) = \begin{cases} 0, & x = y, \\ 1, & x \neq y. \end{cases}$$

When using the obscure classification algorithm, the normalization process is performed on the values of the symbols. Many methods and algorithms of normalization can be observed. As a widely used normalization algorithm, we can give the formula for the minimum normalization:

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)},$$

where $\min(X)$ and $\max(X)$ are the minimum and maximum values of the symbol X.

In solving the problem of diagnosis, in some cases, the degree of importance of the characteristics of the object - the weight is also important. This level of significance of the marks can be determined by experts or based on a given standard table (training sample).
follows:

$$D_E = \sqrt{\sum_i^n Z_i (x_i - y_i)^2},$$

as coefficient Z_i significance *of the* i -sign is calculated accordingly.

A set of real numbers $X = \{x_1, x_2, .., x_m\} \subset R$ and k be real numbers $s_1, s_2, .., s_k$ in ascending order: For the set

$$s_1 < s_2, < .. < s_k$$

X, the $A_1, A_2, .., A_k$ obscurity can be done using the triangular function.

$$\mu(x, b; a) = \max\left[\min\left(1, \frac{x-a}{b-a}\right), 0\right].$$

3 Results and Discussion

The results are obtained using the following obscure clustering algorithm.

1. The number k defuzzification parameter, the l= 0, and the centers of the clusters are given initial values. Then the deflection components of the functions and functions of obscure relativity are calculated.

2. The iteration index is multiplied, $l \rightarrow l + 1$ i.e., we calculate cluster centers, obscure affiliation functions, defuzzification components, and functions.

Step 3. $d=\sum_{i=1}^{k}\left|\mu_i^{(l)}-\mu_i^{(l-1)}\right|$ what do we calculate? If d> δ, we return to step 2; otherwise, we go to step 4.

Step 4. Data storage and finishing.

Unclear logic is "*Soft Computing*", which allows you to use expert knowledge in the form of linguistic ideas. The obscure model, based on combining obscure logic with evolutionary algorithms, gives a whole new quality. In such vague models, it is possible to use knowledge of natural languages.

In general, the vague classification model is described using the conclusions of vague rules as follows [4, 17]

$$\bigcup_{p=1}^{k_j}\left(\bigcap_{i=1}^{n} x_i = a_{i,jp},\, w_{jp} \text{ by weight}\right) \rightarrow y_j = f_j(x_1, x_2, ..., x_n)\cdot$$

Here $a_{i,jp}$ is a linguistic term x_i that evaluates the variable of the jp line.

w_{jp} - *jp* is the weight coefficient of the rule.

At present, there are three main areas of recognition:

1. Neuron-type recognition;
2. Comparison of images with the standard;
3. Recognize the image by characteristic points (in this case, the method of obtaining characteristic points can differ).

Typically, distinguishing the characteristic points in an image involves the following basic steps:

1. Obtaining a normalized gray image;
2. Search for areas of study;
3. Identify the edges of the studied areas (Sobel, Laplace, Kani's methods, etc.);
4. Convert the viewed area to a monochrome image;
5. Analysis of the obtained monochrome and gray images in the field of study.

Detection of objects in the fundus vessels of the eye using deep neural networks.

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

The simplified neural network learning process can be described as follows. The data available in the database allows the study of the neural network by comparing the input data with the available data. Weights are adjusted for each gal training [18; 19].

Let there be some unknown recognizing function $g: X \rightarrow Y$, and let the argument $n, y \in Y$ be an image $n, y \in Y$ -class expressed as a vector length. The learning model takes the form of a set of values of this function; that is, the solution of the learning problem is to find the values that are not included in the $D=\{(\mathrm{x}_0,\mathrm{y}_0),(\mathrm{x}_1,\mathrm{y}_1),...(\mathrm{x}_m,\mathrm{y}_m)\}.$, including *g* function *D,* the function that approximates the whole definition $h: X \rightarrow Y$.

The use of an artificial neural network training algorithm involves solving the problem of searching for space optimization. There are stochastic and mass learning methods. Introducing a neuron type in a stochastic learning mode is associated with individual examples from the learning pattern. After each example, the network weights are updated. In mass teaching, the study examples update the weights of an entire network, after which the neural network is prepared for insertion. The network weight error is cumulative for subsequent updates.

The classical standard for measuring errors is the sum of the root mean square errors.

$$E_n^p = \frac{1}{2} E_{rr}^2 = \frac{1}{2} \sum\nolimits_j^M (x_j - d_j)^2 \rightarrow \min, \qquad (1)$$

where M is the number of neurons in the output layer, j is the number of output neurons, x_j is the actual value of the output signal of the neuron, and d_j the expected value is.

Mathematically, the gradient is a partial product of the loss for each parameter to be mastered, and the update of one parameter is formed as follows [18-21]:

$$w_i := w_i - \alpha * \frac{\partial L}{\partial w_n}, \qquad (2)$$

where L is the loss function.

The gradient of the loss function concerning the parameters is calculated using a small part of the training data that is applied to the parametric updates. This method is also called mini-batch gradient descent, often called stochastic gradient descent, and the mini-batch size is also a hyperparameter [21, 22].

The public teaching of stochastic learning has some advantages:

* In most cases, public learning is much faster;
* can be used to track changes;
* often helps to get better acquainted.

If 500 reading samples consist of 10 identical sets of 50 examples, the average gradient per thousand examples will give the same result by calculating the gradient based on fifty examples. Thus, before the renewal of the weights of the nervous system of public education, the same value is recorded 10 times. Stochastic learning represents an entire period as 10 iterations (periods). In practice, examples are rarely found in the study sample, but there are still clusters of very similar examples [23, 24].

Nonlinear networks often have many local minimums at different depths. The training task is to study the network in one of the minimums. The burden of public education is at an all-time low. In stochastic studies, the noise generated during weight correction is likely to cause the network to jump from one local minimum to another, possibly deeper [24].

The architecture of complex neural networks, including the cascade of fully-connected layers (FL) and the stacked convolutional and pooling layers, which are usually followed by several fully connected layers (FLs), is a step-by-step process of local perception. The filters (W matrices) work with the entire area of perception, which means that they can process data with a large area of the original image, that is, to replicate the pixel space. The output layer of a composite network consists of a map of characters: each element of the output layer is composed by applying a known filter (kernel) and then acting as a final part-field (receptive field) with the input layer under the influence of a nonlinear activation function.

To process images using integrated neural networks, it is necessary to solve the following problems [26]:

i To determine the size of the input layer;
ii The size of the output layer;
iii Number of layers in the frame;
iv Dimensions of compacted layers;
v Number of sub-discretion layers;
vi Dimensions of sub-discretizing layers.

It is possible to use it after creating and teaching the architecture of a complex neural

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network. Constructing a classifier using a complex neural network, a properly distributed neural network, begins with the first complex layer.

Conv (32x3x3) pool 2x2 Conv (64x3x3) pool 2x2 Conv (64x3x3) pool 2x2 Dropout 0.25 SoftMax has been developed for the diagnosis of eye diseases based on the image of the lateral vein. In this case, 32 3x3 filtering is performed, which is reduced by a 2x2 pool. 2 times 64 3x3 filtering is performed, 2x2 pool is shortened. With the help of Dropout 0.25, 0.25 important neurons are released [27-30]. With the help of the SoftMax activation function for eye diseases, the division into 3 classes is carried out. Based on the eye's lateral image, the program's functional structure was developed (Fig. 1).

The data set of the lateral view of the eye vessel was taken from the open data set site kaggle.com. The images from this data set were distributed as follows.

Table 1. Distribution of images used in experiments.

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

Based on this data set, analyses of the results in different structures were obtained.

Table 2. Accuracy of training in neural networks with different structures.

№	Structural neural network structure	Learning accuracy (good range from 0.003 to .001)
1	7 Conv (2x2) pool (2x2)	0.725
2	Conv (5x5) pool (3x3) pool (2x2)	0.95
3	8 Conv (4x4) pool (2x2) 6 Conv (3x3) pool (2x2)	0.53
4	20 Conv (5x5) pool (2x2) 30 Conv (3x3) pool (2x2)	0.78
5	40Conv (4x4) pool (2x2)	0.91
6	40Conv (5x5) pool (2x2)	0.80

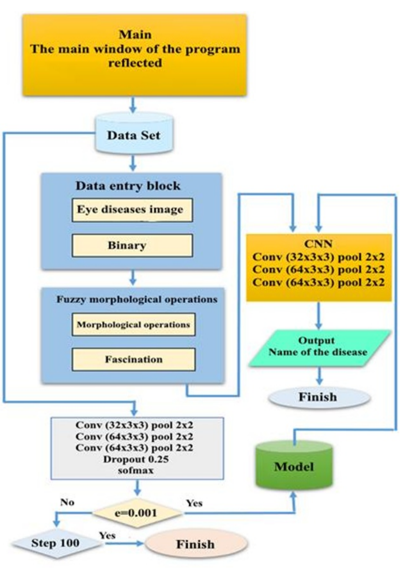

Fig. 1. Functional structure of program

The structure that needs to be built for the wrapped neural network is also important.

The accuracy result obtained during training determines whether a model has been generated for the given images.

4 Conclusions

This article discusses constructing a classification system based on the diagnostic features of the optic nerve and optic disc vessels. The main difficulty in using the system in practice is that when a doctor diagnoses the system for training, the vessels that have undergone pathological changes in the eyeball's image are normal or in the early stages of pathological development. Therefore, some veins are allocated to specific classes by mistake in selecting education.

The DL proposed a fully connected deep neural network with several architectures and latent layers but consisted of insignificant neurons in each layer.

In a simple multilayer network, the detection process is significantly slowed down due to the large number of connections between neurons, i.e., synapses. A method has been proposed to reduce the number of connections and allow a single character to be found across the entire image area through a packet network.

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