RECOGNITION OF OBJECTS ON OPTICAL IMAGES IN MEDICAL DIAGNOSTICS USING FUZZY NEURAL NETWORK NEFCLASS

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***Abstract**: In the article the application of fuzzy neural network NefClass with Gaussian and triangular membership functions to pattern recognition of objects on medical images obtained by colposcopy. The characteristics of each group of diseases of cervix uterus are analyzed. Using the values of features by the color model RGB the class of the input sample is determined. Received samples are processed using fuzzy neural network RBF and a class of sample is determined. A comparative analysis of the recognition results using the fuzzy network with obtained results of crisp RBF neural network is performed.*

***Keywords**: medical images, pattern recognition, fuzzy neural network*

Introduction

An important application sphere of pattern recognition systems is the problem of classification of optical medical images and diagnostics in medicine. Especially it relates to state recognition of human organs tissue and early detection of possible cancer. One of such tasks is cervix epithelium state analysis and diagnostics using optical images obtained with colposcope (a method of survey of a mucous membrane of part of a neck of a uterus in the conditions of additional lighting and optical increase with the help of a colposcope) [1]. As a result of carrying out a colposcopy by the doctor the increased pictures of images with preliminary splitting into classes of diseases are provided. The problem of classification cervix epithelium state using images obtained with colposcope was considered in [1,2] where for its solution was suggested the application of crisp neural networks Back propagation, neural networks with radial basis functions (RBFNN) and cascade RBFNN and their efficiency investigated. The goal of this paper is the investigation of fuzzy neural network NEFClass for recognition of state of cervix epithelium in medical diagnostics and comparison of its efficiency with conventional RBF network.

Problem Statement

The problem of classification represents a problem of referring a sample to one of sets (classes). The medical problem in this case consists in classification of of obtained medical images using special medical tools: computer tomography, magneto-resonance tomography, colposcope etc.

In medical images values of the color model RGB represent components of input vector and based on this information it's needed to define, which class it should be referred to. The classifier thus refers object to one of classes according to a certain splitting of N-dimensional space which is called as input space, and dimension of this space is a number of vector components.

Preparation of basic data. For creation of classes it is necessary to define, what parameters influence on classification results. Thus there can be such problems:

1. If the number of parameters isn't enough, there can be a situation when the same set of basic data corresponds to the examples which belong to different classes. Then it is impossible to train a neural network, and the system will not correctly work.
2. Basic data have to be surely consistent. For the solution of this problem it is necessary to increase dimension of features space (quantity of input vector components). But at increasing in dimension of feature space there can be a situation when the number of examples can become insufficient for training of a network, and instead of generalization, FNN simply remembers examples from the training selection and isn't able to operate correctly.

For the solution of cervix epithelium state analysis and diagnostics problem using optical images the NefClass network with Gaussian membership function was suggested.

Architecture and training algorithm of FNN Nefclass

The NEFClass model is used for definition of a class or category of the received input sample (so-called patterns). Patterns are feature vectors $X = (x_1, x_2, \dots, x_n) \in R^n$ of a certain object, and a class is, respectively, some set $in\ R^n$. We assume that crossing of two different classes is empty. A feature of a pattern (sample) is represented by a fuzzy set, and classification is defined by a set of linguistic rules. For each input feature x_i there are q_i fuzzy sets described by membership functions (MF) $\mu_1^i, \dots, \mu_{q_i}^i$.

Also there is a rules base which contains *k* fuzzy linguistic rules, such as $R_1, \dots, R_k$. Fuzzy rules which describe data, have the following form [3]:

if x_1 is μ_1 and x_2 is μ_2 and … and x_n is μ_n ,

then the sample $(x_1, x_2, \dots, x_n)$ belongs to a class *i*,

where $\mu_1, \dots, \mu_n$ are fuzzy sets.

The main task of NEFClass is the definition of these rules, and also a type of membership functions for fuzzy sets.

The rules base represents function approximation (which it is unknown): $\phi(x)\colon R^n \rightarrow \{0,1\}^m$ and describes a classification task, such that $c_i = 1, c_j = 0\ (j = \overline{1,m},\ \forall j \neq i)$, if x belongs to a class C_i, where $\phi(x) = (C_1, \ldots, C_m)$. Fuzzy sets and linguistic rules which perform such approximation define resultant NEFClass system. The NEFClass system is presented in figure 1, which classifies input samples with two features and two separate classes, using five linguistic rules.

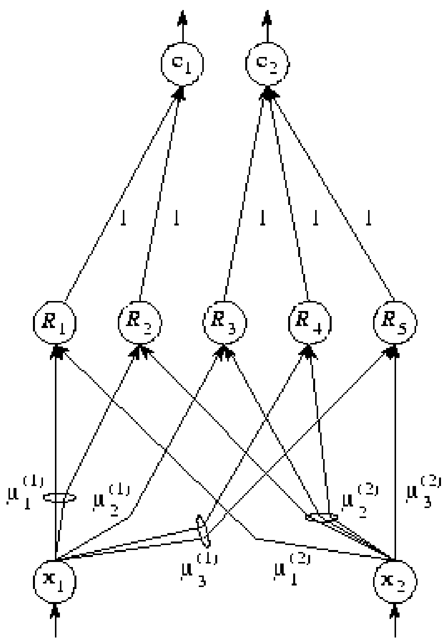

Figure 1. Architecture of FNN Nefclass

Apparently from Figure1 the NEFClass system has three-layer architecture. The first layer is a layer of input neurons which contain the input samples. Activation of neuron of this layer doesn't change input value. The hidden layer contains fuzzy rules, and the third layer consists of output neurons of each class.

Training algorithm of rules base. Let's consider NEFClass system with n input neurons $x_2, \ldots x_1, x_n$, $k \leq k_{max}$ rules neurons and m output neurons $C_1, C_2, \ldots, C_m$. The training set of samples is $L = \{(p_1, t_1), \ldots, (p_s, t_s)\}$, its each element consists of an output sample $p \in R^n$ and a desirable sample $t \in \{0,1\}^m$. The initial algorithm consists of two stages.

Generation of rules base. The purpose of the first stage is creation of k of rules neurons of NEFClass system. Stage stepsare the following.

Choose a sample (pattern) *(p, t)* from L

For each input neuron of $x_i \in U_1$ find such membership function $\mu_{j_i}^{(p)}$, which satisfies the following condition: $\mu_{j_i}^{(p)} = \max_{j_i=\overline{1,q_i}}\{\mu_{j_i}(p_i)\}$, where $x_i = p_i$.

If the number of rule nodes k is less than k_max also and the node of the rule R, such that $W(x_1, R) = \mu_{j_1}, \ldots, W(x_n, R) = \mu_{j_n}$, doesn't exist then create such node and connect it to the output node C_i, if $t_i = 1$.

If still there are not-processed samples in L and k≤k max, then go to step 1, otherwise stop.

Gradient algorithm of training fuzzy sets. At this stage training of membership functions of fuzzy sets is performed. The training algorithm with the teacher of NEFClass system has to adapt its fuzzy sets. Let the training criterion be:

$$e(W) = \sum_{i=1}^{M} (t_i - NET_i(W))^2 \to \min, \quad (1)$$

where t_i – desirable output value of a neural network;

$NET_i(W)$ is the actual value of the i-th output of a neural network for a weight matrix $W = [W^I, W^O]$. $W^I = W(x,R) = \mu_j(x)$, $W^O = W(R,C)$.

Criterion of $e(W)$ is an mean squared error of approximation .

Let function of activation for neurons of the hidden layer (neurons of rules) be

$$O_R = \prod_{i=1}^{n} \mu_{j_i}^{(i)}(x_i), \;\; j = 1, \dots, q_i,$$

where $\mu_{j_i}^{(i)}$ – membership function which has the form:

$$\mu_{j_i}^{(i)}(x) = e^{-\frac{\left(x-a_{j_i}\right)^2}{b_{j_i}{}^2}}$$

and activation function of output neuron layer is:

$$NET_c = \max_{R \in U_2} W(R,C) O_R$$

Training of NEFClass system. The NEFClass system can be constructed on partial knowledge of samples. The user has to define quantity of initial fuzzy sets for each of object feature, and set value k_{max}- the maximum number of nodes rules which can be created in the hidden layer. Membership functions of Gauss and gradient algorithm of training of fuzzy sets are used for training.

Consider the gradient learning algorithm of FNN NEFClass [3].

Let $W(n)$ - be the current value of the weights matrix. The algorithm has the following form:

$$W(n+1) = W(n) - \gamma_{n+1} \nabla_w e(W(n)) , \quad (2)$$

where γ_n - the step size at *n* -th iteration;

$\nabla_w e(W(n))$ - gradient (direction), which reduces the criterion (1).

1. At each iteration, we first train (adjust) the input weight *W*, which depend on the parameters *a* and *b* (see the expression 5.14)

$$a_{ji}(n+1) = a_{ji}(n) - \gamma_{n+1} \frac{\partial e(W)}{\partial a_{ji}} , \quad (3)$$

$$b_{ji}(n+1) = b_{ji}(n) - \gamma'_{n+1} \frac{\partial e(W)}{\partial b_{ji}} , \quad (4)$$

where γ'_{n+1} - step size for parameter *b*.

$$\frac{\partial e(W)}{\partial a_{ji}} = -2\sum_{k=1}^{M}\big(\big(t_k - NET_k(w)\big)\cdot W(R,C)\big)\cdot O_R \cdot \frac{(x-a_{ji})}{b_{ji}^2}, \tag{5}$$

$$\frac{\partial e(W)}{\partial b_{ji}} = -2\sum_{k=1}^{M}\big(\big(t_k - NET_k(w)\big)\cdot W(R,C)\big)\cdot O_R \cdot \frac{(x-a_{ji})^2}{b_{ji}^3}. \tag{6}$$

2. We find (train) output weight:

$$\frac{\partial e(W^O)}{\partial W(R,C_k)} = -\big(t_k - NET_k(W^O)\big)\cdot O_R, \tag{7}$$

$$W_k^O(n+1) = W_k^O(n) - \gamma''_{n+1}\frac{\partial e(W^O)}{\partial W(R,C_k)}. \tag{8}$$

3. $n := n+1$ and go to the next iteration.

Stages of recognition process and experimental investigations

Let's consider stages of recognition process.

1. *Work with data*. Construct a database of examples, characteristic for this task. Split all data set into two sets: training and test in the following ratio:
   - training 50%, test 50%;
   - training 60%, test 40%;
   - training 70%, test 30%;
   - training 80%, test 20%;
   - training 90%, test 10%;
2. *Preliminary processing*. Choose system of features, characteristic for this task, and transform data appropriately that is to be fed into network inputs. As a result it is desirable to receive linearly separated space of a set of samples. As input data for medical images of benign processes, are used namely:
   - inflammatory processes in the form of branching of vessels;
   - cervical erosion;
   - traumatic deformation;
   - large cervical ectropion.
   - small cervical ectropion.

Each of these diseases is presented by a number of features which is to be classified by a neural network and are shown in the figures 2-6.

3. *Designing, training and assessment* of a network work quality. At this stage the number of rules, quantity of fuzzy sets and percentage ratio of training and testing samples are determined.
4. *Choosing algorithm* of a network training. As a training algorithm the gradient method was used. At this stage it is necessary to specify the accuracy, the steps size for all variables and a number of iterations.
5. *Application and diagnosing*. At the last stage we receive result of application of the neural NefClass network to a problem of medical diagnostics. We observe splitting images into RGB to

the color scheme and a class to which the sample initially belonged. Also we obtain the result of recognition – a class to which the sample after training of a neural network belongs. The amount of misclassifications and an average error on sample are determined. Sample size is 70 elements.

6. The results of classification after training at training and test samples are presented in the table1.
7.

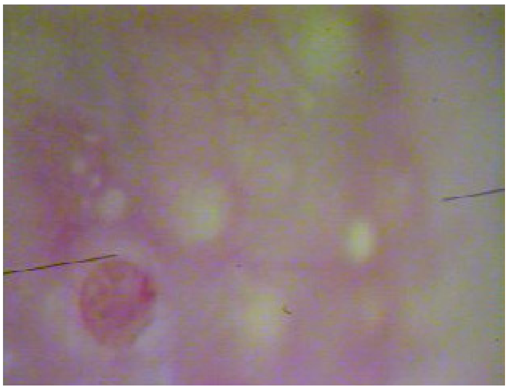

Figure 2. Inflammatory processes

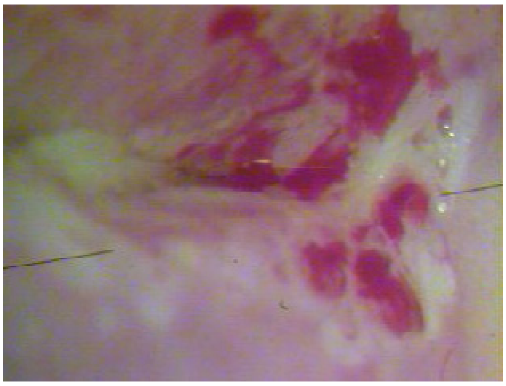

Figure 3. Cervical erosion

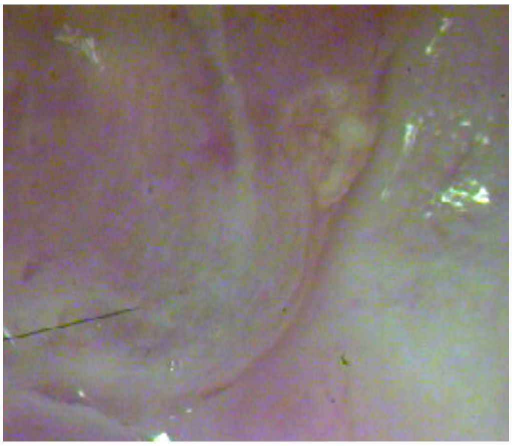

Figure 4. Traumatic deformation

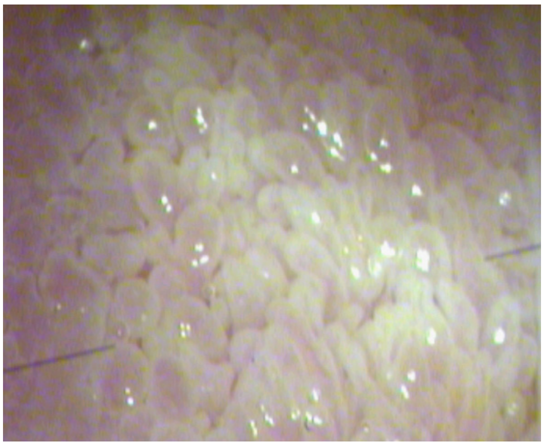

Figure 5. Large cervical ectropion

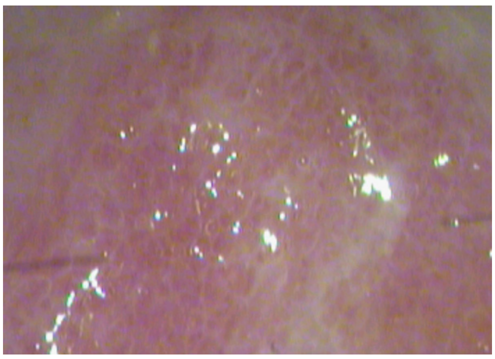

Figure 6. Small cervical ectropion

Table 1. Performance results of NEFClass.

# of sets	Number of patterns in training/ test samples	Ratio training/test sample %	misclassified patterns training	misclassified patterns testing	MSE training	MSE testing	% Misclassification
3	35-35	50-50	13	16	0,559	0,588	45.12%
	42-28	60-40	17	12	0,588	0,551	42.1%
	49-21	70-30	20	9	0,570	0,549	42.85%
	56-14	80-20	23	6	0,562	0,540	42.857%
	63-7	90-10	25	4	0,551	0,562	57.14%
6	35-35	50-50	2	9	0,1697	0,336	25.71%
	42-28	60-40	2	9	0,1699	0,330	32.14%
	49-21	70-30	3	6	0,167	0,306	28.57%
	56-14	80-20	2	2	0,1495	0,254	14.28%
	63-7	90-10	2	0	0,154	0,197	0%
7	35-35	50-50	2	9	0,116	0,314	25.71%
	42-28	60-40	4	8	0,118	0,341	28.57%
	49-21	70-30	3	8	0,108	0,407	38.09%
	56-14	80-20	3	3	0,109	0,335	21.42%
	63-7	90-10	2	2	0,127	0,263	28.5%
11	35-35	50-50	3	11	0,091	0,440	31.42%
	42-28	60-40	1	7	0,055	0,466	25%
	49-21	70-30	1	8	0,0434	0,550	38.09%
	56-14	80-20	2	4	0,054	0,377	28.57%
	63-7	90-10	1	1	0,064	0,221	14.28%

Figures 7, 8, 9 and 10 shows the dependence of ratio training/testing samples on the mean squared error and misclassification % (MAPE) for different number of fuzzy sets for each variable (feature) .

Figure 7. MSE for 3 sets

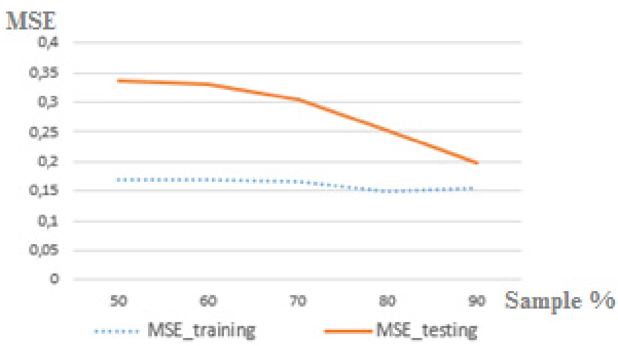

Figure 8. MSE for 6 sets

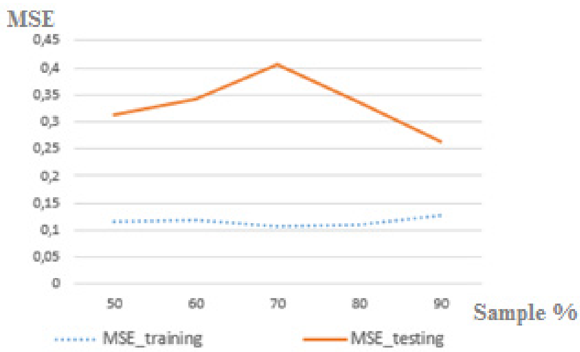

Figure 9. MSE for 7 sets

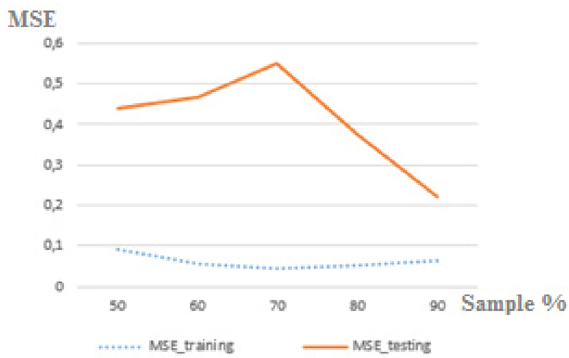

Figure 10. MSE for 11 sets

The next step in experiments was calculating of results change due to variation of the rules number. For each number of fuzzy sets (3, 6, 7, and 11) training/test sample ratio was used. It should be noted there is a number of rules, after which there is no change in the classification of samples and in the mean square error. The results are shown in Table 2.

Table 2. Results of the neural network with change of the rules number

	3	6			7			11		
rule	for all rules	7	15	50	7	12	50	7	15	50
Sample %	90-10	90-10	90-10	90-10	80-20	80-20	80-20	70-30	70-30	70-30
mismatch training	23	23	3	2	15	5	3	13	3	1
mismatch testing	4	3	0	0	7	6	3	14	9	8
MSE training	0,550	0,426	0,163	0,154	0,335	0,170	0,1090	0,363	0,1647	0,0434
MSE testing	0,536	0,344	0,214	0,197	0,492	0,442	0,335	0,664	0,556	0,550
% Misclassification	57.142%	42.85%	0%	0%	50%	42.85%	21.42%	66.6%	42.85%	38.09%

Figures 11, 12, 13 and 14 show the dependence of rules number on classification accuracy (%).

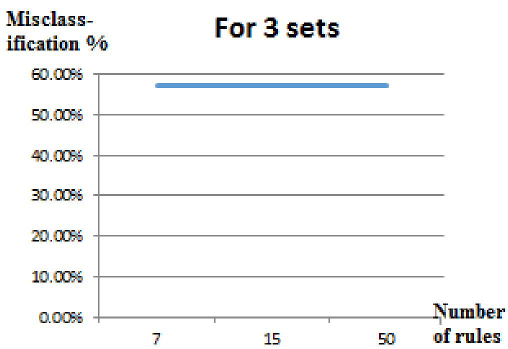

Figure 11. Misclassification for 3 sets

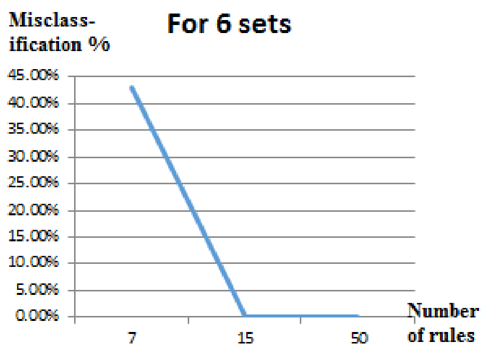

Figure 12. Misclassification for 6 sets

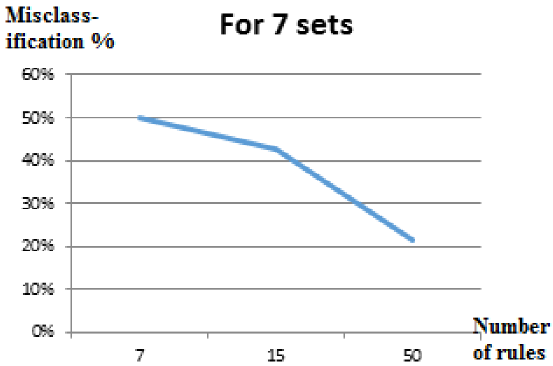

Figure 13. Misclassification for 7 sets

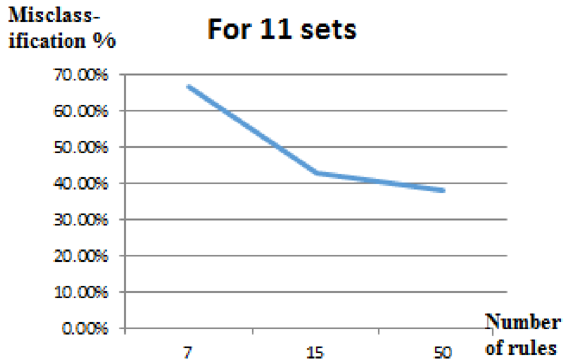

Figure 14. Misclassification for 11 sets

Compare the work of fuzzy neural network NefClass with the work of the neural network RBF. The results of RBF are shown in Table 3.

Table 3. Results of RBF network.

	50-50	60-40	70-30	80-20	90-10
number of coincidences	20	16	17	10	6
number of non coincidences	15	12	3	4	1
% Misclassification	42.9%	42.9%	19%	28.6%	14.3%

Figure 15 shows a comparison of misclassification error(%) of the fuzzy neural network NefClass with a non-fuzzy neural network RBF.

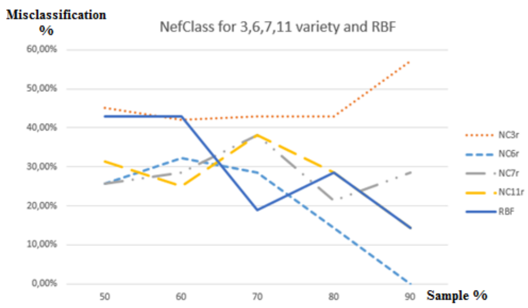

Figure 15. Comparison of NefClass with RBFN

Presented curves indicate that the fuzzy neural network NefClass shows the better results than non-fuzzy RBF network.

Conclusion

1. The problem of recognition of objects on medical images in medical diagnostics is considered. The investigations were performed on the cervix uterus images obtained using colposcope. 70 images were selected which contained 5 classifications of diseases .
2. Fuzzy neural network NefClass and non fuzzy neural network RBF were used for classification. Experiments were carried out on training / test samples in the ratios: 50/50, 60/40, 70/30, 80/20 and

90/10. In process of experiment with NefClass number of fuzzy sets varied 3, 6, 7 and 11, the number of rules – 50, for each sample the value of MSE (training and testing) was calculated. The best result was obtained for samples ratio 90-10, which in the case of 6 sets were correctly classified all the patterns, with 11 sets 6 patterns were correctly classified, 1 was classified incorrectly. The worst results were with 3 and 7 sets.

3. While changing the number of rules it was found that there exists an optimal number of rules after which the recognition error of the sample does not change, and the time spent on experiments, only grows.
4. The experiments with non-fuzzy RBF neural network had shown the best result was obtained for training/test sample ratio 90-10, with an error of classification 14.3%. The results of the fuzzy neural network proved to be much better than the RBFN. Additionally, for NefClass FNN it is possible to change the number of fuzzy sets and the number of rules

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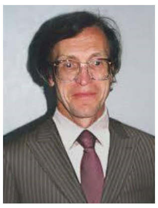

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