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# ANALYSIS OF EVALUATION PROBLEMS OF THE RISK SITUATION OF PATIENTS SUFFERING FROM ISCHEMIC HEART DISEASE

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**Abstract**

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The ischemic heart disease represents a very common health issue which, thanks to its seriousness, impacts a big part of the population and is the cause of about one third of all death cases in the Czech Republic. For the analysis itself, data from medicinal practice of one of the authors of the article have been used and this study is a follow up of his PhD thesis. Concretely it was a set of patients which were being rehabilitated after a heart stroke; the results of the medical examination of these patients create 26 parameters. This data has been obtained in the course of the patients' treatment.
In the first phase of generating the classification model, the parameters that didn't have a detrimental effect on the assessment of health condition of the patients have been removed from the data set and have been kept in the category of additional parameters. For the classification itself, an approach from artificial intelligence – applying a neural network - has been chosen. For the recording and transformation of the entering data a special application has been made. The classification and analysis of the data is performed on an experimental model of the self-learning of a neural network.
The conclusions that arise from the initial analysis of this issue and the partial solution can be generalized and when using an appropriate software application they could even be used in medical practice. To do a complex analysis of the influence of all 26 parameters on the overall state of health of the patients is very difficult. A decision-making model appears to be a good solution. Last but not least, the proposed solution has to be verified on a bigger sample of patients afflicted by the ischemic heart disease.

patient, heart stroke, attribute, mortality, ischemic heart disease, self-learning neural network, expert, risk of heart death

The ischemic heart disease, which can lead all the way to a heart-attack, is currently the most common cause of death in the Czech Republic. During the last decades, patients' mortality has been significantly lessened – in relation with new medical treatments – down to about 7% in the parameter of "acute mortality". A further decrease of mortality could be achieved not only by improving the medical treatments but also by a more accurate interpretation of the data describing the actual state of the patients.

To judge the risk for patients suffering from the ischemic heart disease, artificial intelligence models are used – the multi-level and self-learning neural network. The process of self-learning has in this case a key position regarding the identification of the clusters that define the particular groups of patients. This way it is not only possible to identify the patient's group with regard to the risk degree of the patient but also to identify the process of the change. The correctness of the achieved classification may be assessed through an expert analysis by a medicine professional – a doctor, or by comparison with a different method. What seems more suitable here is the comparison with methods of cluster analysis.

## MATERIAL AND METHODS

A data set with information about 151 patients who were treated after a heart attack at the Internal Cardiologic Clinic of the Brno Faculty Hospital in the years 2003–2008, has been made available for the model proposal. Data were collected by dr. Milan Sepši, Ph.D., the co-author of this article and were used in his Ph.D. thesis (Sepši, 2008). For using the neural network it was necessary to modify the data set so that it contained only numeric data and to remove incomplete records. After the necessary adjustments a data set with records from 141 patients with 26 parameters representing 26-dimensional vectors in the entry space was prepared. Via the neural network this space will be transformed into the output space, represented by the neurons of the network.

The list of parameters that characterize each patient is shown in Fig. 1. Because of the size of the file a median and standard deviation has been introduced with each parameter.

The abbreviations used in the chart have the following meanings:

**OA HLP** – presence of hyperlipoproteinemy as a risk factor in the personal anamnesis of the patient.
**OA HT** – presence of hypertension as a risk factor in the personal anamnesis of the patient.
**OA DM** – presence of diabetes as a risk factor in the personal anamnesis of the patient.
**SKG revascularization** – says if the patient has been revascularized (completely, partially or not at all).
**SKG number of arteries** – how many heart arteries have been affected by atherosclerosis.
**EF stratification** – eject fraction of the left ventricle.
**QRS at IM** – the width of the QRS complex on EKG in the moment of heart attack.
**TF at IM** – the pulse frequency at the moment of heart attack.
**DC and AC** – deceleration capacity and acceleration capacity.
**TO** – "turbulence onset" (one of the parameters of the turbulence in heart rhythm).
**TS** – "turbulence slope" (one of the parameters of the turbulence in heart rhythm).
**HRT RES** – the turbulence of heart rhythm in total.
**HOLTER KES** – number of the ventricular extra-systoles in 24 hours.
**HRV VFL, LFreq, HFreq, mena NN, SDNN, SDANN, ASDNN, RMSSD** – parameters of variability of the heart frequency.

A part of the data set is formed by already dead patients, because the target of this study is to assess the risk of death of the patients. This information is needed for evaluation of the classification groups when teaching the neural network by the teacher and for self-learning of identifying the group of patients that are in risk.

For identification of the patient we use an identifier that contains a letter signing the patient's gender (m – masculine, f – feminine) and serial number within the data set. For creating the model, data from 107 patients have been used, and for testing the model, data from 34 patients have been used.

Assessment of the influence of all parameters on the actual health condition of the patient after a heart attack can be managed by a model of self-learning neural network or a multi-level neural network taught by a teacher.

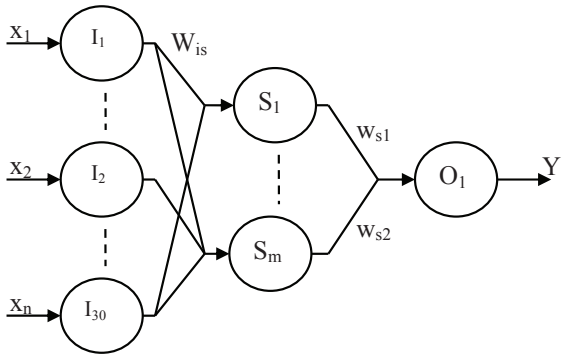
By self-learning the group of patients can be divided into a required number of classification subsets. There are usually two subsets – satisfactory and risk state, or three groups – good, satisfactory and risk state. By self-learning of the network with a number of outputs corresponding with the number of groups their representatives will be determined and by further self-learning with the outputs structured on a plane – on Kohonen's map (Kohonnen, 2001) – the visual depiction will also be created.

I: *The list of parameters*

| No. | Parameter | Median | Standard Deviation | No. | Parameter | Median | Standard Deviation |
|---|---|---|---|---|---|---|---|
| 1 | Gender | 0.752 | 0.432 | 14 | HRT T0 | -3.544 | 6.186 |
| 2 | Year of birth | 40.220 | 12.674 | 15 | HRT TS | 11.601 | 15.103 |
| 3 | OA HLP | 1.482 | 0.500 | 16 | HRT RES | 1.759 | 0.335 |
| 4 | OA HT | 1.447 | 0.497 | 17 | Holter KES | 1.319 | 0.645 |
| 5 | OA DM | 1.738 | 0.440 | 18 | Holter NSKT | 1.894 | 0.308 |
| 6 | SKG revaskular. | 1.695 | 0.789 | 19 | HRV VLF | 25.044 | 9.487 |
| 7 | SKG number of arteries | 1.794 | 0.879 | 20 | HRV LFreq | 14.800 | 6.500 |
| 8 | EF stratification | 45.709 | 12.053 | 21 | HRV HFreq | 9.563 | 4.014 |
| 9 | QRS at IM | 1.426 | 0.852 | 22 | HRV Mean NN | 873.794 | 139.367 |
| 10 | TF at IM | 75.468 | 18.954 | 23 | HRV SDNN | 120.241 | 39.808 |
| 11 | EFV positiv | -0.043 | 0.234 | 24 | HRV SDANN | 107.206 | 36.686 |
| 12 | DC | 4.759 | 3.053 | 25 | HRV ASDNN | 44.993 | 15.741 |
| 13 | AC | -5.340 | 3.423 | 26 | HRV RMSSD | 25.411 | 10.238 |

For classification into 2 subsets by means of the multi-layer neural network, a group of the deceased patients will be representing the group of patients in worse health condition and the group of living patients will be representing the group of patients in better health. The rest of the available data will be used for testing of the model's function. The practical use of the neural network models works on the assumption of two function regimes: teaching and computing, or more precisely the work regime of the classification of the patient.

The scheme of the model with a 3-level neural network and one output can be seen in Fig 1. The number of layers cannot be exactly established, but in majority of practical applications a 3-level architecture is accurate enough. In fact this network is modeling the function of *n* variables. The inputs of the neural network accept the values of variables and the outcome gives us the value of a realized function, which is dependent on the computing function of individual neurons and on the weight that connect the outputs of neurons with the inputs of the neurons of the next layer.




1: *Scheme of the 3-level neural network*

The weight in the process of learning are most commonly set by the algorithm of Back Propagation Errors. The entering values of the scales are usually random numbers from the interval (0; 1). In the process of learning the weight are set so that the value of the Error Function is minimized.

$$CH = \frac{1}{2}\sum_{k}^{Kin}(y_k - y_{0k})^2 , \tag{1}$$

where $y_k$ is the real value of the outcome and $y_k^0$ the required value of the outcome of the neural network at the $k^{th}$ combination of inputs $X^k = (x_1^k, x_2^k, x_3^k, \ldots, x_n^k)$.

As a computing function of the neurons the sigmoidal function is used most commonly

$$y(x) = \frac{1}{1+e^{-x}} . \tag{2}$$

Or the linear function

$$y(x) = kx. \tag{3}$$

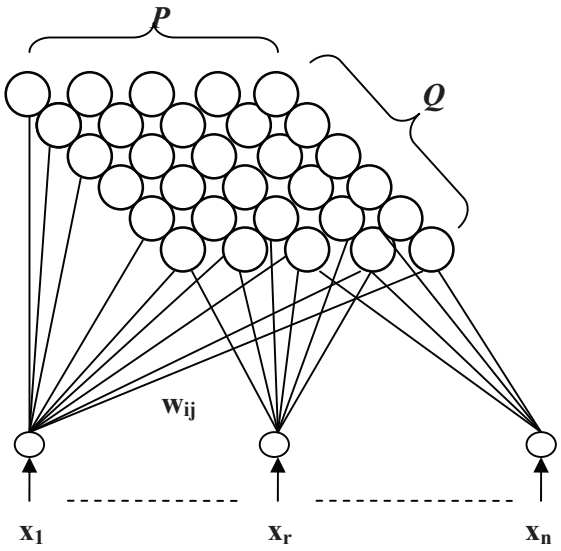
For classification of the patients via the multi-level neural network the sigmoidal function will be used (2). The number of inputs of the network is set by the number of parameters assessing the health condition of the patient. The number of outputs is set by the number of realized functions. The number of neurons in the hidden layer is established by the equation

$$m = \max(N_{in}, N_{out}), \tag{4}$$

where $N_{in}$ is number of inputs and $N_{out}$ number of outputs and is optimized when fine-tuning the model, if needed.

For a classification into two groups only one binary output with values "0" and "1" is needed. In the case of a classification into three groups, two outputs with binary values will be needed. Combinations of outputs (1, 1), (0,0) and (0,1) will represent the required classification. Combination (1, 0) of the outputs won't be utilized. A more detailed description of the issue of using the multi-level network is analyzed in the monograph (Konečný, Trenz, 2009) or (Konečný, Matiášová, Rábová, 2005).

The self-learning neural network scheme is shown on Fig. 2.




2: *The self-learning neural network scheme*

The entering neurons, analogous to the multi-layer neural network, only repeat the input vector coordinates. The output of every input vector is connected via the weight wij with the input of every output neuron. The output neurons can be assembled in a variety of ways, and in the case of a planar lay-out, they are commonly called Kohonenn's maps. When resolving the patients classification task we will use the matrix alignment, with dimensions of P x Q.

The weight entering the output neuron with the coordinate's m, n create an output neuron Wmn.

The number of output neuron sis usually equal to the number of elements with input (positron) vectors X, so that every input can be displayed with an independent output. The coordinates of input vectors are parameters of elements, the display of which is executed by the neural network.

The learning algorithm brings into effect the principle of closeness. This means that the elements that are mutually close in the entrance area must also be near in the output display. The objected represented by the vectors A, B are close to each other if |A–B| is small. In the case of self-learning, every input vector Xk activates the output neuron with the Wm vector, for which the following holds:

$$|X^k - W^m| \leq |X - W^r|, \forall r, r \neq m.$$

The neuron with the Wm vector is called the champion and its vector is rectified so that it comes close to the Xk vector. The new value of the champion neuron will be

$$\overline{W} = W^m + \alpha|X - W^m|,$$

where α is the learning coefficient. Its value, in the process of learning, decreases with the number of learning epochs. The emendation of neighboring neurons is done simultaneously with the emendation of the champion neuron. The size of the learning coefficient of neighboring neurons β decreases with the distance from the champion neuron, and with the number of learning epochs. Weight emendation at all the input neuron sis reckoned one learning epoch. The learning process is described in detail in the monograph (Konečný, Trenz, 2009).

For the classification of patients the self-learning of the neural network will be used in the model with two, three output neurons or with the outputs assembled in the shape of a two-dimensional field. The models with two or three outputs will contribute with the requested classification into two or three subsets with a list of their elements. The output neuron Wm is a point position vector, which the represented point set is closest to. We can easily verify that the point with the position vector Wm is the crux of the X-points set with a unit mass. (see Konečný, Trenz, 2009).

In the calculation or rather testing regime we can classify new inputs which were not part of the learning process. In the model where outputs have been assembled in a two-dimensional field, the self-learning algorithm ensures that the principle of distance between the output neurons'vectors holds, but without identifying the sub-sets. The pertinence of the outputs to individual sets can be established on the basis of the distance between the output vector Wk and the individual representatives' vectors. The pertinence to the MK set is given by the closest representative.

From a practical viewpoint this model is more suitable because it offers information about the distance of the tested object not only from the representative of the set, but also from the neighboring sets, which enables us to assess the risk of transferring to another set with a change of parameters.

Bearing in mind that the parameter values appear in different metrics, the variability of parameter values can influence the models' quality to a great extent. For the purpose of data adjustment, standardization, normalization and transformation into a given interval appear as suitable solutions.

Standardization is a linear transformation of parameter values in such a way that the resulting data have a set mid-value (usually zero) and a standard deviation (usually one).

By transforming the interval, the parameter data from the interval <Min, Max>, where Min is the minimum value and Max the maximum value of the parameter, are transformed into a selected interval (usually <–1, 1>).

By means of normalization the input vectors are transformed in such a way that their absolute value is identical (usually equal to one). The points defined by the input vectors are subsequently placed on the surface of a sphere with a radius equal to the selected absolute value of the transformed vectors.

The normalization eliminates the distance caused by the absolute value of the vectors; the transformation into the interval enlarges the small deviations, and scales down the large ones. The deviations are transformed proportionally to the size of the intervals.

Standardization appears to be the most useful tool for the utilized neuron models.

## RESULTS AND DISCUSSION

### Implementation of the multi-layer neural network model

For creation of this model it is necessary to have the learning file objects divided into the required number of classification groups. Bearing in mind that all the patients have suffered a heart attack and the influence of other factors on patients' mortality is, in a cross-section of all the patients, approximately the same; we will assume that the difference in mortality in individual groups is due to the ischemic heart illness. One part of the dead patients is represented by the group:

$$M_{zem} = [\text{m10, m21, m22, m23, m24, m25, m29, m31, f34, m74, f78, m87, m91, m100, m101, f108, m111, f113, m117, m128, m139, m148}] \quad (6)$$

and it will be used for the neural network learning. The requested neural network output value for this subset (22 units altogether) will be "0".

Subsequently, the dead patients form the group:

$$P_{zem} = [\text{m116, f106, f33, m112, f80, f36, m65, f144, m61, nm37, m149, m103, f123, f98, m26}]. \quad (7)$$

They are grouped into the testing file and the group "0" classification is expected. The test-group

doesn't influence the learning process of the neural network.

The group of living patients, whose distance from a representative (the set's centre of gravity) of dead patients is around the standard deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{j}\left(d_j - \bar{d}\right)^2}\ , \tag{8}$$

where $N$ is the number of dead patients, $\bar{d}_j$ – the distance of the $j$-th patient from the representative, $\bar{d}_j$ – the mid-value of the distance of the dead patients from the representative, and will also be used for verifying the model's function. Around the standard deviation σ = 27,72 are patients of the set

$M_{TA}$ = [f47, m58, f67, f69, m102, m134, m136, m143, m147]. (9)

The second part of the testing file will be formed by randomly generated set of living patients

$M_{TB}$ = [m82, m48, m18, m62, m38, m64, m14, m9, f84, f2]. (10)

In sets $M_{TA}$ and $M_{TB}$ made up of living patients we expect a classification with output „1".

The rest of the patients (a total of eighty-five) form the group

$M_{ziv}$ = [m1, m3, m4, m6, f7, m8, f11, f12, m13, m15, m16, f17, m19, m20, m27, m28, m30, m32, f39, m40, m41, m42, f43, f44, m45, m46, m49, m50, m51, f52, f53, f54, m55, f56, m57, m60, m66, m68, m71, m73, m75, f77, m79, m81, f83, m85, f86, m89, m90, f92, m93, m94, m95, m96, m97, m99, m105, m107, m109, m110, m114, m115, m118, m119, m120, m121, m122, m124, m125, m126, m127, m129, m130, m131, f132, m133, f135, f138, m140, f141, m142, m145, m146, m150, m151] (11)

made up of living patients with an acceptable state of health. The requested output of the neural network for these patients will have the value of "1".

For teacher-based learning as well as self-taught learning a file of 107 patients with 26 standard parameters and with a standard deviation σ = 1 and a median of the i-*th* parameter $\bar{x}_i = 0$. The reason for the transformation is the weight equalization of all the parameters, due to the fact that setting the differentiated weights is very difficult. Nonetheless, in the case of practical usage, the implementation of the parameter weight and a subsequent re-learning of the model will be possible. The basic advantage of using the neural networks is precisely the simple possibility of changing their function without adjusting the programmes by means of a simple re-learning with completed data.

For the model with a multi-layer neural network we have selected the configuration:

- input and output layer of 26 neurons,
- output layer of 1 neuron,
- sigmoidal neuron calculation function according to the relation. (2)

The neural network learning was ended on having reached the value of the error function $CH = 10^{-4}$

II: *Testing results of a multi-layer neural network*

| Identifier | Re-learning | Unfinished learning | Requested value | Identifier | Unfinished learning | Re-learning | Requested value |
|---|---|---|---|---|---|---|---|
| f47 | 1.00 | 0.99 | 1 | m116 | **1.00** | **1.00** | 0 |
| m58 | 1.00 | 0.98 | 1 | f106 | 0.04 | 0.01 | 0 |
| f67 | 0.98 | 0.84 | 1 | f33 | 0.02 | 0.00 | 0 |
| f69 | 0.58 | 0.53 | 1 | m112 | **1.00** | **1.00** | 0 |
| m102 | 1.00 | 0.92 | 1 | f80 | 0.13 | 0.11 | 0 |
| m134 | 1.00 | 0.99 | 1 | f36 | **0.87** | **1.00** | 0 |
| m136 | 1.00 | 0.99 | 1 | m65 | **1.00** | **1.00** | 0 |
| m143 | 0.98 | 0.80 | 1 | f144 | **1.00** | **1.00** | 0 |
| m147 | 1.00 | 0.92 | 1 | m61 | **1.00** | **1.00** | 0 |
| m82 | 1.00 | 1.00 | 1 | m37 | 0.17 | 0.06 | 0 |
| m48 | 1.00 | 1.00 | 1 | m149 | 0.33 | 0.02 | 0 |
| m18 | 1.00 | 1.00 | 1 | m103 | **1.00** | **1.00** | 0 |
| m62 | 1.00 | 1.00 | 1 | f123 | **0.86** | **0.86** | 0 |
| m38 | 0.59 | 0.66 | 1 | f98 | **0.78** | **0.96** | 0 |
| m64 | 1.00 | 1.00 | 1 | m26 | **0.54** | **0.52** | 0 |
| m14 | 0.02 | **0.45** | 1 | | | | |
| m9 | 1.00 | 0.99 | 1 | | | | |
| f84 | 0.89 | 0.76 | 1 | | | | |
| f2 | 1.00 | 0.98 | 1 | | | | |

in the case of *re-learning* and $CH = 0.5$ in the case of *unfinished learning*.

The results of the testing with highlighting the erroneous results are listed in Tab II. We can see from the table that the regimes of re-learning or unfinished learning do not influence the quality of classification. Leaving out one case (m14), the classification of living patients is correct. The overall majority of mortalities is classified erroneously. Out of the total of 15, only 4 mortalities are classified correctly. This is clearly caused by the fact that the neural network learning is performed with a small sub-group (twenty-two) of non-living patients, as opposed to the sub-group of living patients (eighty-five).

Considering the fact that it is not possible to set aside also a group of patients along with the "convenient" and "risk" groups, the learning with the teacher cannot facilitate the creation of a three-sub-group classification model.

## Realization of a self-learning neural network

The problem with dividing the learning group into several sub-groups is resolved using a self-learning neural network. The same set of patients will be used for this model as for the multi-layer neural network. This means that the self-learning will be done with sets (6) and (11), but without defining the output. For the self-learning the sets of living and dead patients are not marked in any way.

As we have said, standardization appears to be the most suitable method for the parameter value transformation, because it represents the linear transformation balancing the variability of divergences among individual parameters. The constant values are not important for the model and can be left out. However, important parameters can appear as such as well, only due to the employed metrics. Leaving out important parameters is unwanted, and therefore it is suitable to – by means of the standardization of parameters – level their impact on the model's function.

The question of the optional introduction of the scales that would reflect the importance of the parameters will need to be, like with the previous model, resolved in the course of the model's practical usage.

The self-learning neural network offers two models which differ in the number of outputs. One model with the number of outputs equal to the number of subsets will be used for establishing the representatives of the classifying subsets, and according to the distance of the entry objects, for carrying out their classification. This model is decisive for the classification of the entry set elements.

The second model will perform the display of the entering subjects (patients) represented by the entry vectors, onto a plane with a configuration that accepts the principle of distance. Their classification is performed according to the distance of the representatives' vectors from the output neurons, and for an easy orientation, a colorful distinction of the sub-sets.

For a two-set classification, a model with an entry-layer containing twenty-six entry neurons (parameters characterizing the patient) and one hundred and seven output neurons which are assembled in a field measuring 10 × 11 neurons. This number of output neurons ensures that one output neuron is reserved for every element of the classified set (a total of 107).

The classification itself is performed based on two representatives, which have been established via the self-learning of the two output neurons. The coordinates of the vectors of these two output neurons create representatives of the sets

$$M_k = \lfloor X_i; |X_i - R_k| < |X_i - R_j|, \forall j, j = 1, 2, \ldots \rfloor.$$

This relationship will also be used for classifying the output field neurons, only instead of the $X_i$ vector, we need to use the $W_{ij}$ neuron vector.

Display and classification of (107) patients into two subsets $[M_{ziv} \cup M_{\check{z}em}]$ – viz (11) and (6) after the learning of the neural network is listed in Fig. 3a. The neurons displaying individual elements of the sets contain the corresponding identifier. The representatives *r1* and *r2* have moreover a clearer border. The tested elements are in a circle in whose bottom part is the identifier of the tested element.

According to this model, the input elements are divided into the following classificatory subsets.

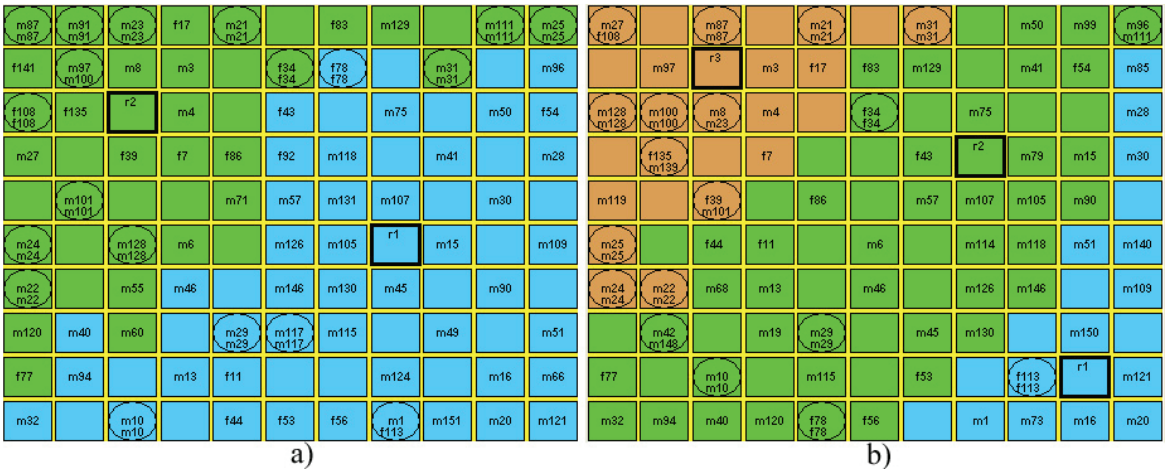
$M_{r1}$ = [m1, m6, m13, m15, m16, m19, m20, m28, m29, m30, m32, m40, m41, f43, f44, m45, m46, m49, m50, m51, f52, f53, f54, f56, m57, m66, m73, m75, m79, m81, m85, m89, m90, f92, m93, m96, m99, m105, m107, m109, m110,f113, m114, m115, m117, m118, m121, m122, m124, m126, m130, m131, m140, m142, m145, m146, m150, m151]

blue with the representative *r1 a*

$M_{r2}$ = [m3, m4, f7, m8, m10, f11, f12, f17, m21, m22, m23, m24, m25, m27, m31, f34,f39, m42, m55, m60, m68, m71, m74, f77, f78, f83, f86, m87, m91, m94, m95, m97, m100, m101, f108, m111, m119, m120, m125, m127, m128, m129, f132, m133, f135, f138, m139, f141, m148]

green with the representative *r2*.

It is evident that the classification isn't identical with the classification prescribed for a multi-layer neural network, nonetheless it provides much more information. According to the principle of distance, the near elements of the set are displayed by means of near outputs, and in the case of very near elements they share the same output neuron. The greater the distance from the representative of one set, the more the element moves further from the characteristics of the representative. The presence of the element in the border region of the sets calls for a certain cautiousness in the sense of its evaluation.




3: *Display of classification into two subsets (a) and three subsets (b)*

The classification itself does not speak about the contents proper of the subsets. The semantic contents must be set according to several elements or characteristics of the representatives. In the given case, we use the display of the subset of deceased patients for the subsets' evaluation. From the figure we can see that the r2 – green set contains many more mortalities. From this we can judge that this group of patients is exposed to greater risk than the r1 set. Based on the performed classification, or rather on the vectors of the representatives and the deceased patients' parameters vectors, we can establish the following classification of deceased patients

$$Z_{R1} = [\text{m29, f113, m117}],$$

$Z_{R2}$ = [m10, m21, m22, m23, m24, m25, m31, f34, m74, f78, m87, m91, m100, m101, f108, m111, m128, m139, m148]

and mortality $K_{mor}$ as a ratio of the number of deceased from the *ri* set to the overall number of elements in this set.

$$K_{mor}(r1) = \frac{N(Z_{R1})}{N(M_{r1})} = \frac{3}{58} = 0.052,$$

$$K_{mor}(r2) = \frac{N(Z_{R2})}{N(M_{r2})} = \frac{19}{49} = 0.39$$

The $M_{r2}$ has a greater mortality and therefore we can judge that this group of patients is exposed to greater risk than the $M_{r1}$ group.

The results of the classifying model self-learning neural network are partially listed in Fig. 3a and fully in chart III. In the classification of later-deceased patients, four patients are incorrectly classified. In the case of patients near the r2 set representative ($M_{TA}$ set), most of the elements are correctly classified in the r2 set. The testing $M_{TB}$ set originated in a random selection and thus contains elements of both classification sets.

III: *Results of the two-set self-learning test*

| Testing set $M_{TB}$ | | Testing set $M_{TA}$ | | Testing set $P_{zem}$ | |
|---|---|---|---|---|---|
| **Identifier** | **Set** | **Identifier** | **Set** | **Identifier** | **Set** |
| m82 | r1 | f47 | r1 | m116 | R2 |
| m48 | r1 | m58 | r2 | f106 | R2 |
| m18 | r2 | f67 | r2 | f33 | R2 |
| m62 | r1 | f69 | r2 | m112 | **R1** |
| m38 | r2 | m102 | r2 | f80 | R2 |
| m64 | r2 | m134 | r1 | f36 | R2 |
| m14 | r2 | m136 | r1 | m65 | **R1** |
| m9 | r1 | m143 | r2 | f144 | R2 |
| f84 | r1 | m147 | r1 | m61 | **R1** |
| f2 | r2 | | | m37 | R1 |
| | | | | m149 | R2 |
| | | | | m103 | **R1** |
| | | | | f123 | R2 |
| | | | | f98 | R2 |
| | | | | m26 | R2 |

For the medicinal practice it is useful to classify patients into three subsets. In the case of employing self-learning this does not actually present a problem. It is possible to establish, like in the preceding case, three representatives and, by means of a subsequent self-learning, to perform an output neuron display onto a plane (11 × 10). The resulting input display – same sets [$M_{ziv} \cup M_{zem}$] like in the previous case, is listed in fig.3b. Individual classifying sets contain, after learning, the following elements:

$M_{r1}$ = [m1, m16, m20, m28, m30, m49, m51, m66, m73, m85, m109, f113, m121, m122, m124, m140, m142, m150, m151],

$Z_{r1}$ = [f113],

$M_{r2}$ = [m6, m10, f11, m13, m15, m19, m29, m32, f34, m40, m41, m42, f43, f44, m45, m46, m50, f52, f53, f54, m55, f56, m57, m60, m68, m71, m75, f77, f78, m79, m81, f83, f86, m89, m90, f92, m93, m94, m95, m96, m99, m105, m107, m110, m111, m114, m115, m117, m118, m120, m125, m126, m127, m129, m130, m131, m133, f138, m145, m146, m148],

$Z_{r2}$ = [m10, m29, f34, f78, m111, m117, m148],

$M_{r3}$ = [m21, m22, m23, m24, m25, m31, m74, m87, m91, m100, m101, f108, m128, m139],

$Z_{r3}$ = [m3, m4, f7, m8, f12, f17, m21, m22, m23, m24, m25, m27, m31, f39, m74, m87, m91, m97, m100, m101, f108, m119, m128, f132, f135, m139, f141].

The deduced mortalities are: h

$$K_{mor}(r1) = \frac{1}{19} = 0.053,$$

$$K_{mor}(r2) = \frac{7}{61} = 0.115,$$

$$K_{mor}(r3) = \frac{14}{27} = 0.52,$$

which means, that the risk set is the *r3* set, the better set is *r2*, and *r1* represents the group of patients with comparably best health.

The test results of the test done with the same elements like in the previous models are listed in chart IV.

Patients in the $P_{zem}$ set are classified mostly in *r2* and *r3* sets, which can be considered correct. The *m103* patient, like in the previous model, is grouped in the *r1* set. Such a situation cannot be ruled out, due to the fact that patients treated with the ischemic heart disease are not exempt from other serious death causing illnesses.

Compared with self-learning and two-set classification, this model is somewhat stricter, considering the reduced patient placement into the *r1* set.

IV: *Results of self-learning test in three subsets*

| Test group $M_{TB}$ | | Test group $M_{TA}$ | | Test group $P_{zem}$ | |
|---|---|---|---|---|---|
| **Identifier** | **Group** | **Identifier** | **Group** | **Identifier** | **Group** |
| m82 | r2 | f47 | r2 | m116 | R3 |
| m48 | r1 | m58 | r2 | F106 | R3 |
| m18 | r2 | f67 | r3 | F33 | R3 |
| m62 | r2 | f69 | r3 | m112 | R2 |
| m38 | r2 | m102 | r2 | F80 | R3 |
| m64 | r2 | m134 | r2 | F36 | R3 |
| m14 | r2 | m136 | r2 | m65 | R2 |
| m9 | r2 | m143 | r3 | F144 | R3 |
| f84 | r2 | m147 | r2 | m61 | R2 |
| f2 | r2 | | | m37 | R2 |
| | | | | m149 | R3 |
| | | | | m103 | **R1** |
| | | | | F123 | R3 |
| | | | | F98 | R3 |
| | | | | m26 | R3 |

## CONCLUSION

The hereby presented patient set classification results imply that the most suitable model is a self-learning neural network which classifies sets of treated patients into two or three subsets. In both cases there is a clear-cut subset of higher-risk patients who have a significantly higher mortality rate. Bearing in mind that a two-subset classification is quite simplistic, a three-subset classification model appears to be more suitable.

A disadvantage is the relatively high number of decision-making parameters, many of which are difficult to reach. For this reason a subsequent detailed analysis of the parameters used will be necessary, one in which the parameters' importance, i.e., their weight in terms of their importance for assessing the ischemic heart disease patients' risks.

The listed models show another possible and advantageous application of artificial intelligence methods. A timely and successful treatment brings fruit not only to the patient, but also a competition advantage to the hospital and treatment facilities.

## SUMMARY

In the article the problem of identifying health risk of ischemic heart disease patients has been discussed. The goal was to find a simple method which would enable to easily distinguish the present state, using the data available.

In the first problem-solving phase a multi-layer neural network model was set up, with the aim of classifying patients' states, by means of a learning classification suggested by an expert. In the course

of the testing the results were not satisfactory, however, due to the small number of classified patients of the higher-risk group.

In the following phase a self-learning neural network model was set up. A two- and three-set classification version was tested. Based on the neural network output assessment, the three-set classification version was chosen as the adequate one; the one to be further improved and later to be used in practice.

The attained results were satisfactorily assessed by an expert. In the case that this model is tested on a wider population spectrum and that the adequacy of the approach is verified, we may consider its practical usage in medicinal practice. The approach was also compared with the options of the cluster analysis (k-means) with no great difference the conclusion of the employed model was confirmed.

## REFERENCES

KOHONNEN, T., 2001: Self-Organizing Maps. 3rd edition Springer-Verlag Berlin. ISBN 3-540-67921-9.

KONEČNÝ, V., MATIÁŠOVÁ, A., RÁBOVÁ, I., 2005: Učení n-vrstvé neuronové sítě. Acta Universitatis Agriculturae et Silviculturae Mendeliane Brunensis. sv. LIII, č. 6, s. 75–84. ISSN 1211-8516.

KONEČNÝ, V., TRENZ, O., 2009: Rozhodování s podporou umělé inteligence. Folia Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, roč. II, 2009, č.8, ISSN 1803-2109, ISBN 978-80-7375-344-3.

SEPŠI, M., 2008: Srovnání stratifikačních postupů k určení rizika náhlé srdeční smrti u nemocných po infarktu myokardu. Disertační práce k získání vědecké hodnosti Ph.D., Interní kardiologická klinika Masarykovy univerzity v Brně.

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