APPLICATION OF NEURAL NETWORK IN MEDICAL DIAGNOSTICS

S. Kajan, D. Pernecký, J.Goga

Institute of Robotics and Cybernetics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava, Slovak Republic

Abstract

The aim of this paper is to study suitability of artificial neural networks (ANN) in medical diagnostics. This work also deals with the problem of collecting clinical data and creating databases of diseases, required for use in a training process of ANN. Applying created neural models in medical practice, we were not only verifying functionality, but we were also testing various parameters, structures and training algorithms used in designing process. In a complex comparison of our results, obtained by multilayer perceptron networks (MLP), we were trying to objectively assess the appropriateness of the ANN by solving classification problems in this area.

1 Introduction

Diagnostics of diseases is broad and challenging area. Its task is to detect a disease that patient with the symptoms have. This process is very complicated, because not all disease's symptoms are specific to only one disease and often the symptoms are overlapping. Errors caused by human factor are not rare in this process. To eliminate human error, in modern medicine, different technologies are used nowadays. Some of them are clinical decision support systems. These are interactive computer programs that assist the doctors at diagnostic the patient's diseases. Using information about a patient's condition in the mathematical model the probable diagnosis can be determined. These mathematical models are based on statistical distributions, regression models and artificial intelligence [1-4].

An artificial neural network a part of artificial intelligence, with its ability to approximate any nonlinear transformation is a good tool for approximation and classification problems [10, 12, 15, 16].

The aim of this work is to study the suitability of using the artificial neural networks in medicine to diagnostic diseases. This work is trying to test various parameters and network structure for their suitability in a particular purpose. We also want to explore their successful percentage rate in the classification for each disease in our test set. To solve these problems, we will use multilayer perceptron networks that are able to correctly classify non-linear separable patterns, where sets of the input data required for diagnostics definitely are.

2 Medical diagnostics using neural networks

The artificial neural networks (ANNs) have distinct advantages over statistical classification methods. The ANNs are suitable in cases, where traditional classification methods fail, because of noisy or incomplete data. Neural networks also benefit in multivariable classification problems with a high correlation degree. The diagnosis of diseases is a good example of such complex classification problems. By correct application of artificial neural networks in this area, in order to obtain the interdependence of symptoms and proper diagnosis, this dependence can be generalized [1, 6, 11].

Based on this generalized model, we can then classify input patterns representing various symptoms of diseases. However in the application process it is not necessary to specify algorithm, or otherwise identify the disease. The application needs only input patterns. The whole diagnostic process of diseases in medical practice is shown in the following flowchart (Fig. 1).

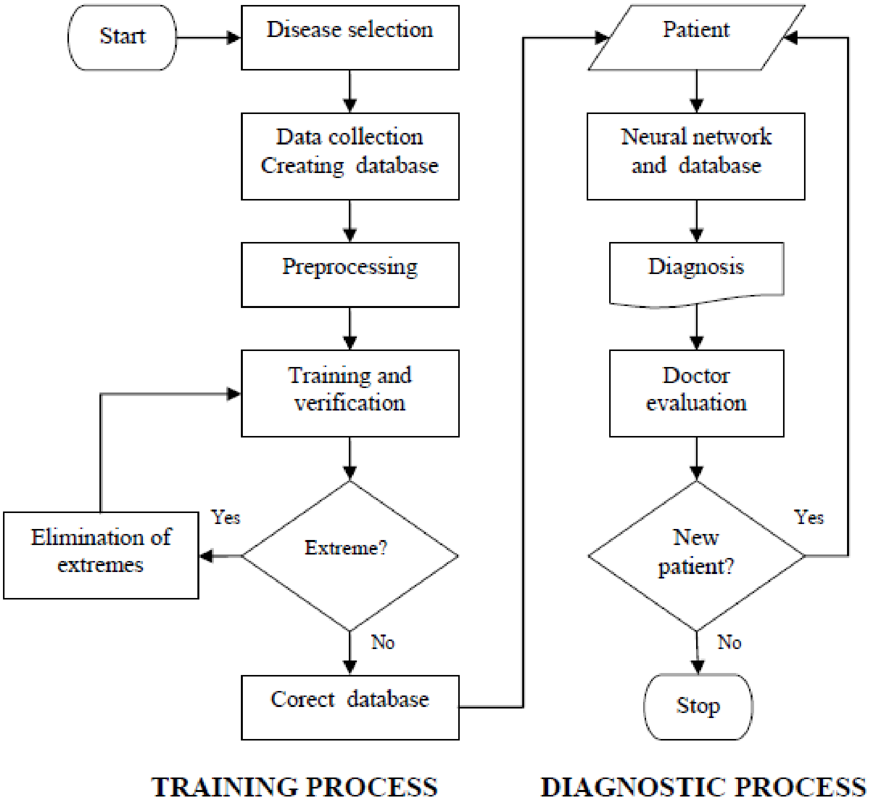

Figure 1: The flowchart for process of diagnostic diseases in medical practice

The whole diseases diagnostic process can be divided into training and diagnostic part. In general the training process begins with the choice of target diseases for which the classification problem will be related to. After appropriate choice of disease, it is necessary to determine the specific parameters, symptoms and laboratory results which in detail describe character of this disease. In the following step, based on these data, it is created a database that must be validated and extreme values out of range must be discarded. The neural network is trained using this database and afterwards results obtained in this process are verified. If the results of the trained neural network are correct, then the neural model can be used in medical practice. With this step the diagnostic process begins. The patient's data are processed by the neural network, which determines the probable diagnosis. This result is then validated by the attending physician. The final diagnosis is result of physician's decision, who based on his own experiences evaluates all aspects of the disease and the result of neural network classification.

2.1 Creating of databases

In creating process of database for neural network training it is needed that this data describe the clinical status of the patient properly. The data which represents unnecessary or inaccurate information about the patient's diagnosis should not be used. The selection process of suitable characteristic data is doctor's task. Most often these data are basic information about the patient's health state, results of biochemical analyzes, symptoms and other information that helps determine the correct diagnosis. All these data of one patient which were collected and evaluated represent one input pattern of neural network. The ability of generalization of the found dependence between symptoms and diagnosis heavily depends on the input patterns used in the training process. The database should therefore contain a sufficient amount of reliable patterns which characterize the diagnosis. This will enable in the training process of the neural network to approximate the hidden dependence in the data set and to use this knowledge to generalize in patient's diagnostic cases, even for cases which are not in the training data. The database structure has a form of table or matrix containing information about health status of patients and their diagnosis.

2.2 Structure of MLP network for diseases classification

For the medical diagnostic the most often applied ANNs are the multi-layer perceptron networks. The basic idea of the medical diagnostic with use of the MLP and with its structure is displayed in Figure 2. Logical sigmoid function (logsig) was used in the hidden and the output layer of the network. Network inputs in the database were represented as normalized medical parameters in a range of (0, 1), based on this data MLP realized classification into classes. Every network output had a value in range of (0, 1) representing a group membership rate. The number of hidden neurons was set experimentally. The choice with too little hidden neurons, caused a deficient approximation of searched relation. If number of hidden neurons was too large, then the neural network approximated the searched relation in training data very exactly and thereby the network loosed ability to generalize.

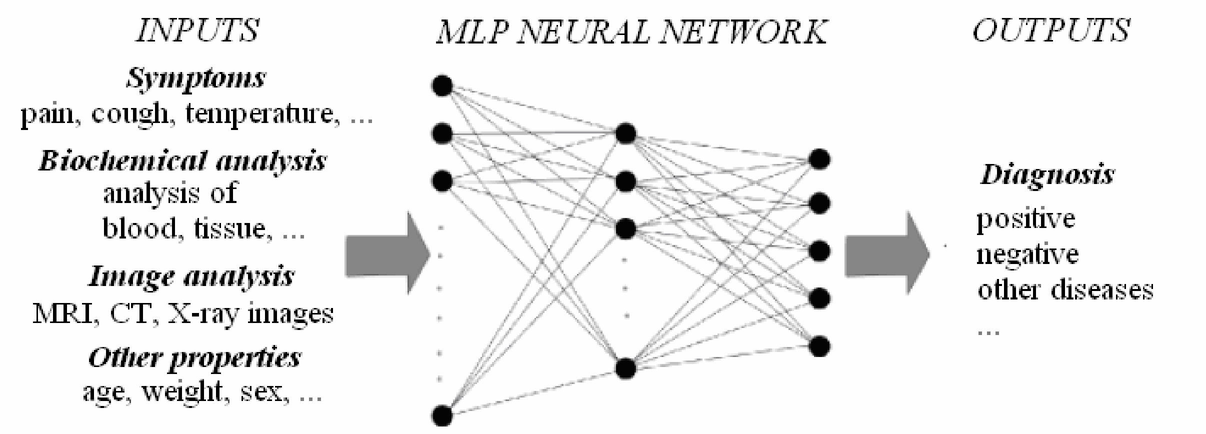

Figure 2: Medical diagnostic using MLP neural network

Normalized data of patient's diagnosis from the database were applied for training the MLP neural network. The data of patient's diagnosis were normalized to range (0, 1). For correct training of the neural network it is necessary to suitably divide the data into training, testing and validation data, so that each group (diagnosis) should have equal representation.

3 Case study

3.1 Medical data for diseases classification

In this work we used data of several diseases, for example breast cancer, cardiac arrhythmia, dermatological disease and Parkinson's disease. These data were obtained from an online database from University in Wisconsin [18].

The first used dataset was breast cancer disease. The creators of the database are Dr. William H. Wolberg, W. Nick Street and Olvi L. Mangasarian from University in Wisconsin [17]. The database contains 30 characteristic parameters obtained by calculation and measurement from characteristic of breast tissue collected from patient. In database are 569 samples, where 357 samples are benign type and 212 samples are malignant type of cancer.

The second used dataset was cardiac arrhythmia disease. The database for this disease was created in year 1997 by authors Altay Guvenir, Burak Acar, and Haldun Muderrisoglu in university Bilkent in Turkey [8]. Database contains measured data acquired using electrocardiogram from 452 patients. From the measured data were 279 chosen as characteristic parameters. Data were associated to 16 groups by diagnosis. Some of the diseases included a few samples, so we reduced the number of groups in to 10.

The third used dataset was created by Little Max from University in Oxforde in year 2007 from audio recordings of speech of 23 people suffering of Parkinson's disease [13]. By processed audio recordings of each sample there were generated 23 characteristic properties, where these properties represent spectral properties of each audio record. Together in the database are 195 samples of 31 people.

In last database are samples of six dermatological diseases. Together in the database are 366 samples with 34 characteristic parameters. Parameters representing different patterns were obtained from histopathological characteristics of removed skin samples and basic information about the patient's situation. Authors of database are Nilsel Ilter from Gazi University and Altay Guvenir from university Bilkent in Turkey [9].

3.2 Training and verification of neural models

Training and testing of neural models for several diseases was realized in program environment Matlab using the Neural toolbox [5].

The available data of each disease were divided into training (60%) and testing (40%) data. The testing dataset were divided in equal proportion to the testing and the validating part.

One hidden layer was selected in our network structure. The number of neurons in hidden layer was adjusted to 25 neurons, fixed for all datasets. By this we ensured an independence of obtained results in term of several diseases comparison.

In order to generalize the obtained results, we used for verification statistical validation method. For classification problems we chose Cross Validation method [16]. By dividing dataset to 10 parts at the same rate in terms of distribution of classified groups, we have created independent sets. Combining these individual data components, we have created 10 different data blocks, which were assigned for training, testing and validation. For each data block five training experiments of neural network were realized. For statistical evaluation we therefore had 50 neural models. Various modified training algorithms were used, the back-propagation of errors with adaptive learn rate and momentum parameter, conjugate gradient method and Levenberg-Marquardt method [5].

The created neural models were compared in term of average and maximum successful percentage rate. In the training process of neural network we were observing the error function behavior, which is defined as mean square error (MSE),

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(y_{target} - y_{net}\right)^2 \qquad (1)$$

where y_{target} represents submitted data samples, y_{net} is for neural network outputs and N is number of samples.

Achieved results of neural model were compared with classification method of linear discriminate analysis (LDA) [2]. For the most successful neural models, we also evaluated the specific error of patterns classified into different subgroups in form of contingency table (confusion matrix) [7].

Obtained results for breast cancer

The neural network has been trained for breast cancer disease. The best results were obtained for neural model with the Levenberg-Marquardt learning algorithm. In figure 3 training process of neural network is shown. Comparison of obtained successful percentage rate of classification methods is in Table 1. The comparison shows that there is no big difference in the classification using neural networks and discriminate analysis. The average and maximum of successful percentage rate in classification for the same testing set are comparable.

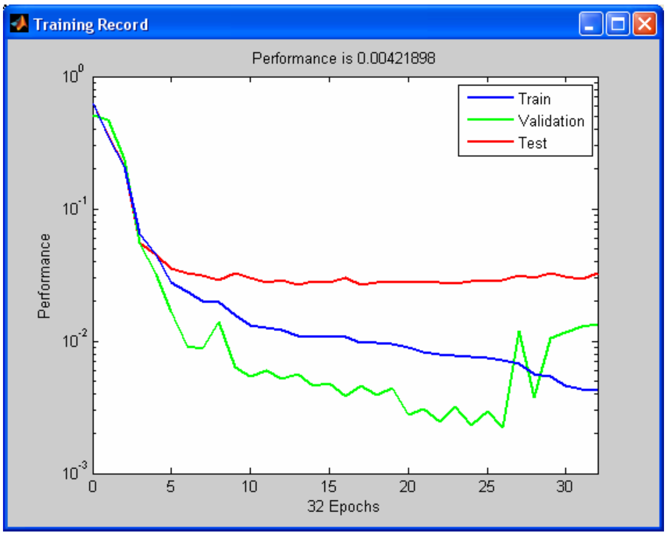

Figure 3: Training process of neural network for breast cancer data

TABLE 1: COMPARISON OF SUCCESFUL RATE FOR CLASIFICATION MODELS OF BREAST CANCER

Method	*Classification successful rate [%]*	
	Mean	*Max*
NN (trainlm)	95.89	99.1
LDA	95.01	95.23

TABLE 2: CONTINGENCY TABLE OF THE BEST NEURAL MODEL FOR BREAST CANCER

		Classification with NN model	
		benign	*malignant*
Real distribution	*benign*	355	2
	malignant	3	209

Obtained results for Parkinson's disease

The neural network has been trained for Parkinson's disease. The best results were obtained for neural model with the Levenberg-Marquardt learning algorithm. In figure 4 training process of neural network is shown. Comparison of obtained successful percentage rate of classification methods is in Table 3. The obtained classification using neural networks shows better results than compared discriminate analysis.

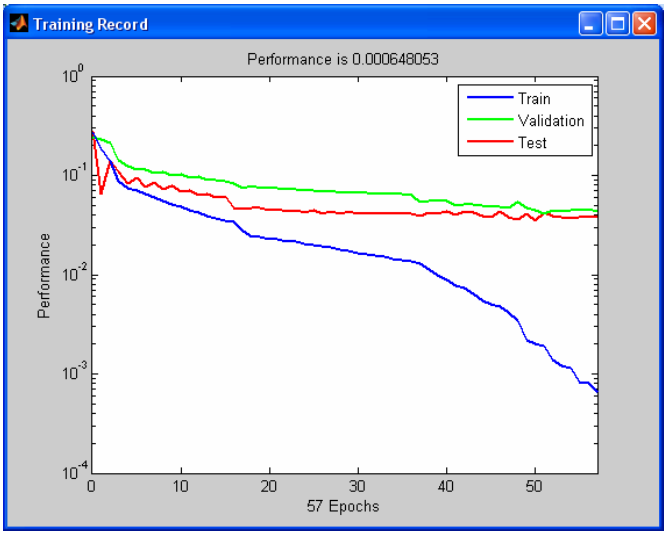

Figure 4: Training process of neural network for data of Parkinson's disease

TABLE 3: COMPARISON OF SUCCESFUL RATE FOR CLASIFICATION MODELS OF PARKINSON'S DISEASE

Method	*Classification successful rate [%]*	
	Mean	*Max*
NN (trainlm)	89.53	99.0
LDA	84.85	85.94

TABLE 4: CONTINGENCY TABLE OF THE BEST NEURAL MODEL FOR PARKINSON'S DISEASE

		Classification with NN model	
		negative	*positive*
Real distribution	*negative*	48	0
	Positive	2	145

Obtained results for dermatological diseases

The neural network has been trained for dermatological diseases. The best results were obtained for neural model with the back-propagation of errors algorithm with adaptive learn rate and momentum parameter. In figure 5 training process of neural network is shown. Comparison of obtained successful percentage rate of classification methods is in Table 5. The obtained classification using neural networks shows better results than compared discriminate analysis.

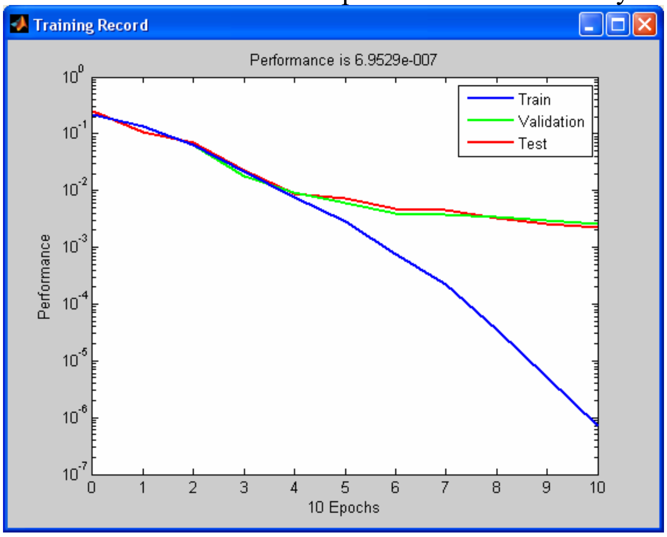

Figure 5: Training process of neural network for data of dermatological diseases

TABLE 5: COMPARISON OF SUCCESFUL RATE FOR CLASIFICATION MODELS OF DERMATOLOGICAL DISEASES

Method	*Classification successful rate [%]*	
	Mean	*Max*
NN (traingdx)	96.94	99.7
LDA	75.41	83.22

TABLE 6: CONTINGENCY TABLE OF THE BEST NEURAL MODEL FOR DERMATOLOGICAL DISEASES

		Classification with NN model					
		D1	*D2*	*D3*	*D4*	*D5*	*D6*
Real disease	*D1*	111	0	0	0	0	0
	D2	0	60	0	1	0	0
	D3	0	0	71	0	0	0
	D4	0	0	0	48	0	0
	D5	0	0	0	0	48	0
	D6	0	1	0	0	0	19

Obtained results for cardiac arrhythmia

The neural network has been trained for cardiac arrhythmia. The best results were obtained for neural model with the conjugate gradient back-propagation algorithm. In figure 6 training process of neural network is shown. Comparison of obtained successful percentage rate of classification methods is in Table 7. The obtained classification using neural networks shoes much better results than discriminate analysis.

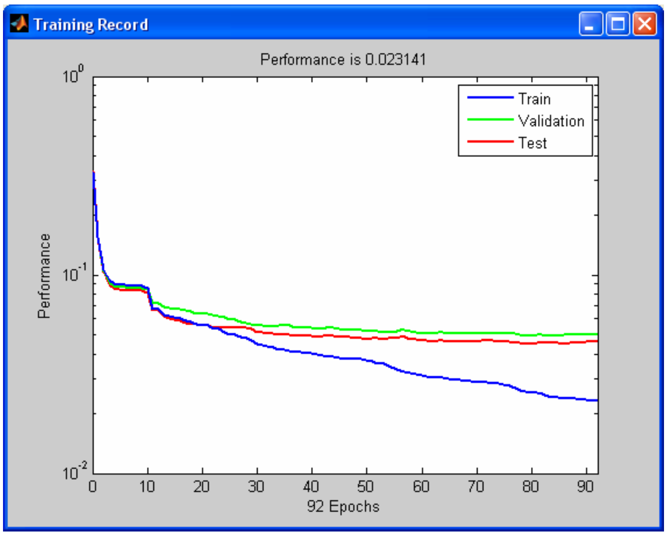

Figure 6: Training process of neural network for data of cardiac arrhythmia

TABLE 7: COMPARISON OF SUCCESFUL RATE FOR CLASIFICATION MODELS OF CARDIAC ARRHYTHMIA

Method	*Classification successful rate [%]*	
	Mean	*Max*
NN (trainscg)	72.31	79.86
LDA	28.4	33.75

TABLE 8: CONTINGENCY TABLE OF THE BEST NEURAL MODEL FOR CARDIAC ARRHYTHMIA

		Classification with NN model									
		D1	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*D10*
Real disease	*D1*	234	3	0	1	0	0	0	5	0	0
	D2	12	25	0	1	0	0	0	1	0	0
	D3	0	0	14	0	0	0	1	1	0	0
	D4	3	0	0	10	0	0	0	1	0	0
	D5	9	0	0	0	3	0	0	1	0	0
	D6	21	0	0	0	0	2	0	2	0	0
	D7	0	0	0	0	0	0	8	0	1	0
	D8	3	0	0	0	0	0	0	47	0	0
	D9	11	2	0	0	0	0	0	3	5	0
	D10	5	2	0	0	0	0	0	0	1	5

4 Conclusion

Classification using neural models revealed a very good successful percentage rate. For assessing how the results of a statistical analysis are able to generalize an independent data set Cross-validation technique has been used. Compared to linear discriminate analysis, the MLP network reached only slightly better results in a sufficient number of input data. However in classification of complex tasks and tasks with insufficient number of training patterns, the neural network reached much better results than the standard statistical model. We have verified the tested MLP networks for classification problems as suitable for use in medicine.

References

[1] Q. K. Al-Shayea. *Artificial neural networks in medical diagnosis.* International Journal of Computer Science Issues, 2011, 8.2: 150-154.

[2] E. I. Altman, I. Edward, G. Marco, F. Varetto. *Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks* (the Italian experience). Journal of banking & finance, 1994, 18.3: 505-529.

[3] F. Amato, et al. *Artificial neural networks in medical diagnosis.* Journal of Applied Biomedicine, 2013, 11.2: 47-58. ISSN 1214-0287.

[4] W. G. Baxt. *Application of artificial neural networks to clinical medicine.* The lancet, 1995, 346.8983: 1135-1138.

[5] H. Demuth, M. Beale, M. Hagan. *Neural network toolbox.* User's guide, 2008

[6] J. J. Forsström, K. J. Dalton. *Artificial neural networks for decision support in clinical medicine.* Annals of medicine, 1995, 27.5: 509-517.

[7] J. Goga. *Využitie neurónových sietí na diagnostiku ochorení*, Bachelor thesis FEI STU in Bratislava, 2015, (in Slovak)

[8] A. H. Guvenir, et al. *A supervised machine learning algorithm for arrhythmia analysis.* In: Computers in Cardiology 1997. IEEE, 1997. s. 433-436.

[9] A. H. Guvenir, G. Demiröz; N. Ilter. *Learning differential diagnosis of erythemato-squamous diseases using voting feature intervals.* Artificial Intelligence in Medicine, 1998, 13.3: 147-165.

[10] S. Kajan. *GUI for classification using multilayer perceptron network*, Technical Computing Prague, 2009

[11] I. Y. Khan, P. H. Zope, S. R. Suralkar. *Importance of Artificial Neural Network in Medical Diagnosis disease like acute nephritis disease and heart disease.* Int. J. Eng. Sci. Innovat. Technol, 2013, 2: 21.

[12] V. Kvasnička, a kol. *Úvod do teórie neurónových sietí.* Bratislava: Iris, 1997. 285 s. ISBN 8088778301, (in Slovak)

[13] M. A. Little, et al. *Suitability of dysphonia measurements for telemonitoring of Parkinson's disease.* Biomedical Engineering, IEEE Transactions on, 2009, 56.4: 1015-1022.

[14] O. L. Mangasarian, N. W. Street, W. H. Wolberg. *Breast cancer diagnosis and prognosis via linear programming.* Operations Research, 1995, 43.4: 570-577.

[15] M. Negnevitsky, *Artificial Intelligence*. Pearson Education Limited, 2005

[16] B. D. Ripley. *Pattern recognition and neural networks.* Cambridge university press, 1996. 403 s. ISBN 0-521-46086-7.

[17] N. W. Street, W. H. Wolberg, O. L. Mangasarian. *Nuclear feature extraction for breast tumor diagnosis.* In: IS&T/SPIE's Symposium on Electronic Imaging: Science and Technology. International Society for Optics and Photonics, 1993. s. 861-870.

[18] UCI: Machine Learning Repository [online]. http://archive.ics.uci.edu/ml/

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Ing. Slavomír Kajan, PhD.:
Institute of Robotics and Cybernetics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava, Slovak Republic, Ilkovičova 3, 812 19 Bratislava, E-mail: slavomir.kajan@stuba.sk

Ing. Daniel Pernecký:
Institute of Robotics and Cybernetics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava, Slovak Republic, Ilkovičova 3, 812 19 Bratislava, E-mail: daniel.pernecky@stuba.sk

Bc. Jozef Goga:
Institute of Robotics and Cybernetics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology in Bratislava, Slovak Republic, Ilkovičova 3, 812 19 Bratislava, E-mail: xgoga@is.stuba.sk