

ARTIFICIAL NEURAL NETWORKS IN MEDICAL DIAGNOSIS

Abstract. Artificial neural networks are finding many uses in the medical diagnosis application. The article examines cases of retinopathy in type 2 diabetes. Data are symptoms of disease. The multilayer perceptron networks (MLP) is used as a classifier to distinguish between a sick and a healthy person. The results of applying artificial neural networks for diagnose retinopathy based on selected symptoms show the network's ability to recognize to recognize diseases corresponding to human symptoms. Various parameters, structures and learning algorithms of neural networks were tested in the modeling process.

Keywords: artificial neural networks, medical diagnosis, multilayer perceptron with back-propagation training, diabetic retinopathy, function of activity.

Introduction. The task of diagnosis is to identify a disease that a patient has with certain symptoms. 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. 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 [1-3].

An artificial neural network a part of artificial intelligence provide a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. Most applications of artificial neural networks to medicine are classification problems; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes [1].

Medical Diagnosis using Artificial Neural Networks is currently a very active research area in medicine. This is primarily because the solution is not restricted to linear form. Neural Networks are ideal in recognizing diseases because there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognize the disease is not needed [14].

In supervised learning, the network is trained by providing it with input and output patterns. During this phase, the neural network is able to adjust the connection weights to match its output with the actual output in an iterative process until a desirable result is reached.

The whole diseases diagnostic process can be divided into training and diagnostic part. For each 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.

The aim of this work is to study the suitability of using artificial neural networks in medicine for the diagnosis of diabetic retinopathy. This is one of the most severe complications of diabetes mellitus, affecting the vessels of the retina of the eyeball. It is observed in 90% of patients with diabetes mellitus. This work attempts to test various parameters and network structure for their suitability for recognizing this disease. To solve these problems, we will use multilayer perceptron networks that are capable of correctly classifying nonlinear separable input data sets required for diagnostics.

Main part. Each artificial neural network is a set of simple elements - neurons that are connected in some way. The particular form of executable network data conversion due not only characteristics of neurons that make up its structure but also its architectural features such as topology interneuron links directions and methods of information transfer between neurons and learning tools[4, 5].

Multilayer neural networks of direct distribution are nonlinear systems that enable better qualified than conventional statistical methods. Multilayer perceptron (MLP) has a plurality of input nodes that provide the input layer with one or more hidden layers of neurons and output layers. Each neuron of MLP which learns based on back propagation algorithm has nonlinear smooth activation function often use nonlinear logistic sigmoid function type or hyperbolic tangent [4, 6].

It is important to highlight that a neural network may have many hidden layers or none, as the number of neurons in each layer may vary. However, the input and output layers have the same number of neurons as the number of neural inputs/ outputs, respectively.

The network learning process includes setting values weights and bias of network to optimize network performance. Setting performance for networks with direct propagation is determined by the mean squared function (mse) between the outputs of the network (a) and targeted outputs (t) and defined by the formula [4]:

$$F = \text{mse} = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2 \quad (1)$$

After training and testing neural network the network object can be used to calculate the answer for any input value.

For the diagnosis of diseases, a typical neural network with direct feedback is proposed. Such a network allows signals to travel one-way only; from source to destination; there is no feedback. The hidden neurons are able to learn the pattern in data during the training phase and mapping the relationship between input and output pairs. Each neuron in the hidden layer uses a transfer function to process data it receives from input layer and then transfers the processed information to the output neurons for further processing using a transfer function in each neuron.

Experimental Results. The network must be trained using a suitable database. The database is a table (or matrix) of data concerning patients for whom the diagnosis (positive or negative) is already known. Each row of the matrix refers to one patient. The string consists of 10 elements that represent medical data. A separate matrix - column vector represents the result (diagnosis). The term “medical data” indicates age (years), duration of diabetes, glycated hemoglobin, Body mass index (weight in kg/(height in m)², low-density lipoprotein concentration in the blood (mmol / l), high-density lipoprotein concentration in the blood, blood triglyceride concentration (mmol / l), blood glucose, diastolic blood pressure (mm Hg). All these indications are presented in table 1.

To classify retinopathy, a multilayer perceptron with two neurons in the output layer is used: one indicates the presence of a disease, and the other indicates the absence.

Medical data for each patient

Variable name	Type	Minimum value and maximum value
Diagnosis result	OUTPUT	[0;1]
Age (years)	INPUT#1	[21;95]
duration of diabetes	INPUT#2	[0;50]
Man/ Woman	INPUT#3	[1/0]
glycated hemoglobin	INPUT#4	[5.0;10.0]
Body mass index (weight in kg/ (height in m) ²	INPUT#5	[20;67]
low-density lipoprotein concentration in the blood (mmol / l),	INPUT#6	[40;160]
high-density lipoprotein concentration in the blood,	INPUT#7	[40;70]
blood triglyceride concentration (mmol / l),	INPUT#8	[50;290]
blood glucose	INPUT#9	[2.0;7.9]
Diastolic blood pressure (mm Hg)	INPUT#10	[0.0;122]

700 patient records are taken for training and 110 records for testing.

For the training of MLP the algorithm of back - propagation training was first used.

The creation of a neural network is performed in the Java programming language.

Initially, we are defined six classes: *Neuron*, *Layer* (abstract) that describes the layers, *InputLayer* class that describes the input layers (class inherits attributes and methods from the *Layer* class), *HiddenLayer* class that defines the middleware (class inherits attributes and methods from the *Layer* class), *OutputLayer* class describes the output layer (class inherits attributes and methods from the *Layer* class), *NeuralNet* (the values of the neural net topology are fixed in this class)[6].

Many algorithms for the functioning and training of neural networks have been developed, and for each task it is necessary to configure the network in different ways. Therefore, researches were conducted to determine the best network parame-

ters, such as: activation functions of input and hidden neurons and determining the number of neurons in the hidden layer. Hyperbolic tangential activation function (*Hypertan*) and logistic sigmoidal activation function (*Siglog*) were used in experiments.

Parameters *MSE* (1) and *accuracy* was used for evaluate the neural network. The parameter *accuracy* is formed on the basis of the expected and real data provided by the neural network. The test results are shown in table 2:

Table 2

Results of experiments with activation functions

Experiment	Activation function	MSE training rate	Accuracy
#1	Hidden layer: <i>hypertan</i> Output layer: <i>siglog</i>	0.021919833988	0.800
#2	Hidden layer: <i>siglog</i> Output layer: <i>siglog</i>	0.0182524727261	0.825
#3	Hidden layer: <i>siglog</i> Output layer: <i>hypertan</i>	0.0258190787972	0.725
#4	Hidden layer: <i>hypertan</i> Output layer: <i>hypertan</i>	0.0291983398831	0.75

The best results were shown by the logical sigmoidal function (*Siglog*) in the hidden and output layers of the network. Nine neurons were taken from the hidden layer. The number of learning epochs was 500.

The backpropagation algorithm, like all gradient-based methods, usually presents slow convergence, especially when it falls in a zig-zag situation, when the weights are changed to almost every two iterations the same value.

Therefore, a method for finding the coefficients was developed based on the Gauss-Newton algorithm and the gradient descent algorithm.

This is the Levenberg-Marquardt algorithm. It works with a Jacobi matrix, which is a matrix of all partial derivatives with respect to each weight and bias for each data row.

In order to effectively implement the LM algorithm, it is very useful to work with matrix algebra. To address that, we defined a class called *Matrix*, including all the matrix operations, such as multiplication, inverse, and LU decomposition, among others. The Levenberg-Marquardt algorithm uses many features of the back propagation algorithm; that's why we inherit this class from back propagation.

One more difference between the back propagation and the Levenberg–Marquardt algorithm is that the weights here are updated once at an epoch, not on every data point. This is necessary because the Jacobian matrix is built using the entire dataset.

We performed many experiments to try to find the best neural network to determine if there is a threat of diabetic rhinopathy or not. The results of the experiments showed that the two algorithms show approximately the same values of the mean square error $MSE = 0,018$, and the accuracy is 80%.

Graphically, the MSE evolution over time is very fast, as can be seen in the following figure 1:

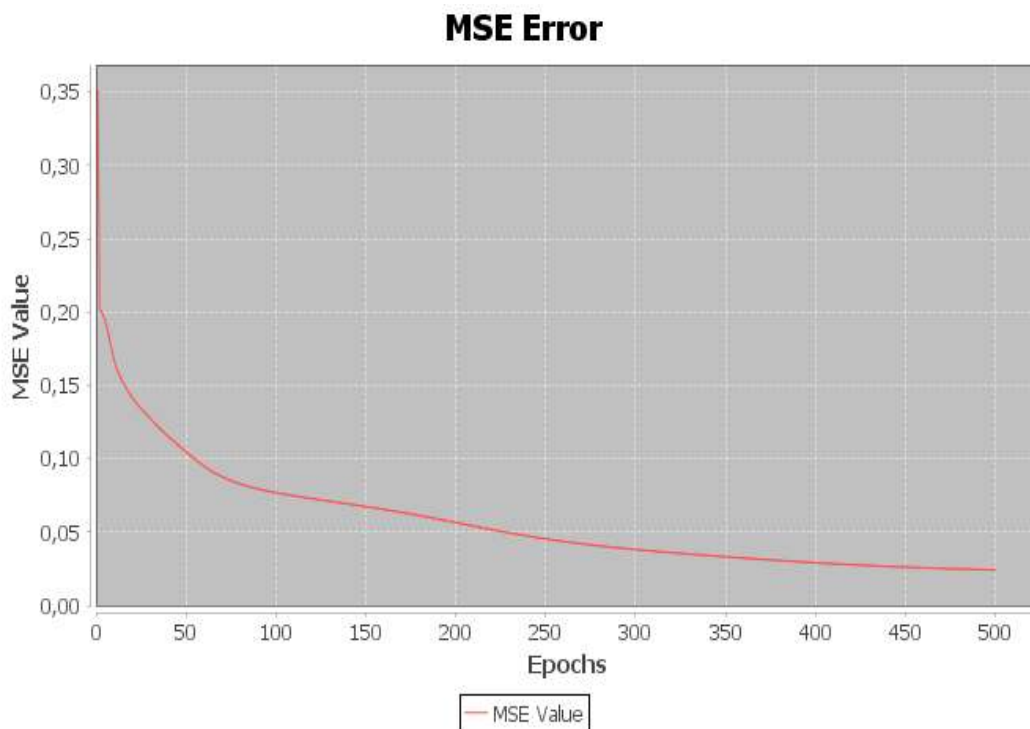


Figure 1 - The value MSE for hidden layer: *siglog* and output layer: *siglog*

The fall of the MSE is fast; nevertheless, the experiments showed a slight delay in the decrease in the first's epochs.

The graph shows a comparison between the real (yellow line) and the estimated (black line) values (Figure 2). The neural network works good.

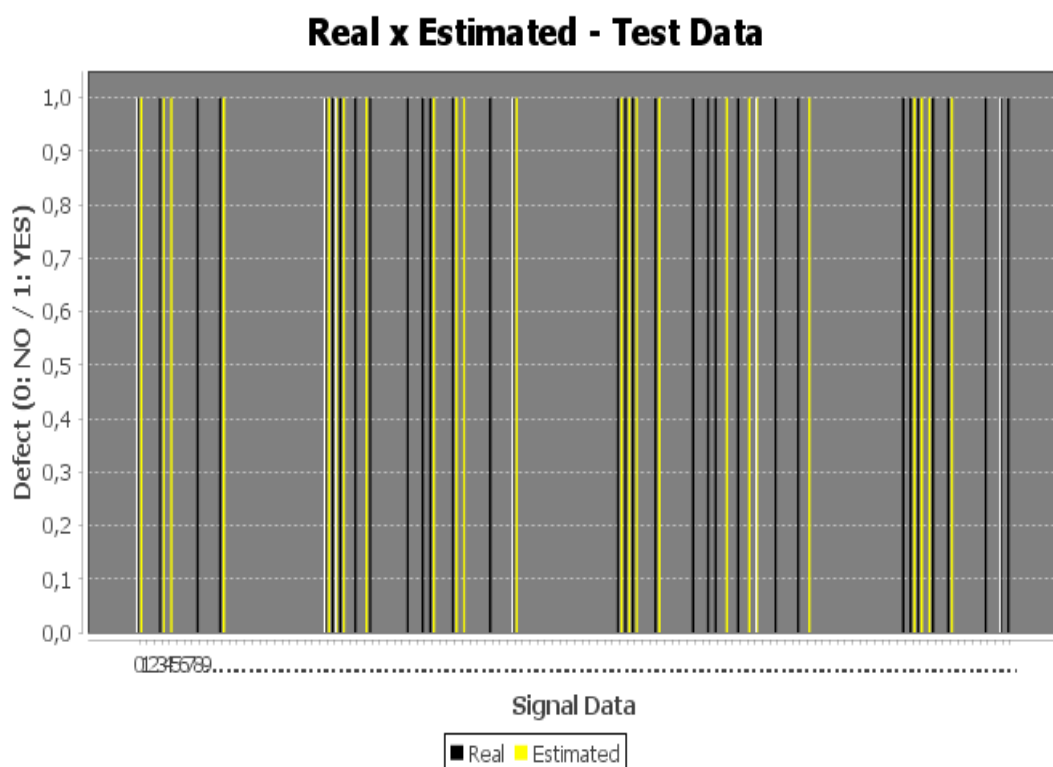


Figure 2 - The expected class along with the classification estimated by the neural network

Conclusions. This study aimed to evaluate artificial neural network in disease diagnosis. The multilayer perceptron neural network is proposed to diagnose the diabetic retinopathy. The neural network is implemented by means of the Java language.

Artificial neural networks showed acceptable results in dealing with data represented in symptoms. Their use makes the diagnosis more reliable and therefore increases patient satisfaction. However, despite their wide application in modern diagnosis, they must be considered only as a tool to facilitate the final decision of a clinician, who is ultimately responsible for critical evaluation of the ANN results.

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. Haykin S. Neural Networks. A Comprehensive Foundation. Second edition. – New Jersey: Prentice Hall, 2008. -1103 p.
5. Herbert Schildt Java. The Complete Reference Ninth edition, 2014, 1372 p.
6. Fábio M. Soares, Alan M.F. Souza, Neural Network Programming with Java, - Birmingham, 2016. -244 p.
7. Bishop C. M. Neural Networks for Pattern Recognition. Oxford University Press, 1995.
8. Matveeva N.A. Using Neural Networks programming on Java for solving the problem of signal recognition. - Dnipro: «System technologies», 2019. -Вип. 1(110). –S. 25-59.

Received 08.02.2021.

Accepted 11.02.2021.

Искусственные нейронные сети в медицинской диагностике

Искусственные нейронные сети находят множество применений в приложениях для медицинской диагностики. В статье изучаются случаи ренопатии при диабете 2 типа. Данные - это симптомы болезни. Многослойные сети перцептронов (MLP) используются в качестве классификатора, чтобы различать больного и здорового человека. Результаты применения искусственных нейронных сетей для диагностики ренопатии на основе выбранных симптомов показывают способность сети распознавать заболевания, соответствующие симптомам человека. В процессе моделирования протестированы различные параметры, структуры и алгоритмы обучения нейронных сетей.

Штучні нейронні мережі в медичній діагностиці

Останнім часом штучні нейронні мережі знаходять безліч застосувань в медичній діагностиці. У статті розглядаються випадки ренопатії при цукровому діабеті 2 типу. Це одне з найбільш важких ускладнень цукрового діабету, яке вражає судини сітківки очного яблука.

У якості вхідних даних беруться медичні показники, які характеризують симптоми хвороби. Багатошарові перцептрони (MLP) використовуються в якості класифікаторів, які вказують на загрозу захворювання.

Створення нейронної мережі виконувалося на мові програмування Java. Для навчання MLP спочатку використовувався алгоритм навчання зі зворотним поширенням помилки, потім - алгоритм Левенберга - Марквардта. Були проведені дослідження щодо визначення кращих параметрів мережі, таких як: функції активації вхідних і прихованих нейронів та визначення кількості нейронів в прихованому шарі. В експериментах використовувалися гіперболічна тангенціальна функція активації (Hypertan) і логістична сигмоїдальна функція активації (Siglog).

Результати застосування штучних нейронних мереж для діагностики ренопатії на основі обраних симптомів показують здатність мережі розпізнавати захворювання.

Однак, незважаючи на широке застосування штучних нейронних мереж у сучасній діагностиці, їх слід розглядати лише як інструмент, який полегшує остаточне рішення клініциста, який в кінцевому результаті несе відповідальність за критичну оцінку результатів мережі.

Матвєєва Наталія Олександрівна – доцент, к.т.н., доцент кафедри електронних обчислювальних машин Дніпровського національного університету імені Олеся Гончара.

Матвеева Наталия Александровна – доцент, к.т.н., доцент кафедры электронных вычислительных машин Днепропетровского национального университета имени Олеся Гончара.

Matveeva Nataliya Olexandrivna – candidate of technical sciences, associate professor of the department of electronic computers of the faculty of physics electronics and computer systems of the Oles Honchar Dnipro National University.