2015 17th UKSIM-AMSS International Conference on Modelling and Simulation

Artificial Neural Network Model in Stroke Diagnosis

Lela Mirtskhulava
Department of Computer Science
Iv. Javakhishvili Tbilisi State University
Tbilisi, Georgia
lela.mirtskhulava@tsu.ge

Gillian Pearce
School of Engineering and Applied Science
Aston University
Aston, UK
gpearce2011@gmail.com

Julian Wong
Department of Cardiac, Thoracic & Vascular Surgery
National University Heart Centre
Singapore
Julian_wong@nuhs.edu.sg

Salah Al-Majeed
Systems Engineering Department
Military Technological College
Muscat, Oman
Salah.Almajeed@mtc.edu.om

Abstract — **The aim of this paper is to present a model of ANN and to use it in diagnostic approaches for stroke by using the data that can serve as inputs for ANNs. We not only consider the usefulness of ANN to the field of stroke medicine but also evaluate the application of ANNs to other branches of human medicine. In our model we use clinical symptoms, various types of biochemical data and various outputs of imaging devices available to clinical specialists. Each type of data provides information that must be evaluated and used during the process of stroke diagnosis. For streamlining the diagnostic process and in order to help reduce incidences of potential misdiagnosis, artificial intelligence methods can be employed. The adaptive learning algorithm can be used with diverse types of medical data and integrated into categorized outputs.**

Keywords - stroke; artificial network model; feedforward neural network; medical diagnosis; backpropagation algorithm.

I. INTRODUCTION

Every year, 15 million people worldwide suffer a stroke. Nearly six million die and another five million are left permanently disabled. Stroke is the second leading cause of disability, after dementia. Disability may include loss of vision and / or speech, paralysis and confusion. Globally, stroke is the second leading cause of death above the age of 60 years, and the fifth leading cause of death in people aged 15 to 59 years old. Stroke is less common in people under 40 years, although it does happen. Stroke is the third leading cause of death in the United States. In 2000, stroke accounted for 7% of all deaths – 15,409 Canadians. More than 140,000 people die each year from stroke in the United States. In young people the most common causes of stroke are high blood pressure or sickle cell disease. In the developing world, however, the incidence of stroke is increasing. In China, 1.3 million people have a stroke each year and 75% live with varying degrees of disability as a result of stroke. The predictions for the next two decades suggest a tripling in stroke mortality in Latin America, the Middle East, and sub-Saharan Africa [1].

According to the World Health Organization, 15 million people suffer stroke worldwide each year. Of these, 5 million die and another 5 million are permanently disabled. High blood pressure contributes to more than 12.7 million strokes worldwide. Europe averages approximately 650,000 stroke deaths each year. In developed countries, the incidence of stroke is declining, largely due to efforts to lower blood pressure and reduce smoking. However, the overall rate of stroke remains high due to the aging of the population [2].

A stroke is a "brain attack". It can happen to anyone at any time. It occurs when blood flow to an area of brain is cut off. When this happens, brain cells are deprived of oxygen and begin to die. When brain cells die during a stroke, abilities controlled by that area of the brain such as memory and muscle control are lost.

The extent to which a person is affected by their stroke depends on where the stroke occurs in the brain and how much of the brain is damaged. For example, someone who had a minor stroke may only have minor problems such as temporary weakness of an arm or leg. People who have major strokes may be permanently paralyzed on one side of their body or lose their ability to speak. Some people recover completely from strokes, but more than 2/3 of survivors will have some type of disability.

Each year nearly 800,000 people experience a new or recurrent stroke. A stroke happens every 40 seconds. Stroke is the fourth leading cause of death in the U.S. Every 4

978-1-4799-8713-9/15 $31.00 © 2015 European Union
DOI 10.1109/UKSim.2015.33

minutes someone dies from stroke. Up to 80 percent of strokes can be prevented. Stroke is the leading cause of adult disability in the U.S.

Artificial neural networks (ANNs) are widely used in science and technology with applications in various branches of chemistry, physics, and biology [1]. Advanced computational methods, including ANNs, utilize diverse types of input data that are processed in the context of previous training history. On a defined sample database to produce a clinically relevant output, for example the probability of a certain pathology or classification of biomedical objects is evaluated. Due to the substantial plasticity of input data, ANNs have proven useful in the analysis of blood and urine samples of diabetic patients [2], diagnosis of tuberculosis [3-4], leukemia classification [5], analysis of complicated effusion samples [6], and image analysis of radiographs or even living tissue research[7].

One type of network sees the nodes as 'artificial neurons'. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons [9].

The World Health Organization reports that 15 million people worldwide suffer stroke; and of these, 5 million die and a further 5 million are left permanently disabled, many severely impaired. Consequently stroke is a major cause of mortality world-wide. Most strokes are caused by a blood clot that occludes an artery in the cerebral circulation. Thrombolytic agents such as Alteplase are used to dissolve blood clots that arise in the cerebral arteries of the brain but there are limitations on their use. Recently screening for patients at risk of strokes and (Transient Ischaemic Attack) TIA's has come into being. If such plaques are detected in the carotid arteries (by Ultrasound), a Carotid endarterectomy (CEA) - a surgical operation - may be performed to remove the occlusive plaque.

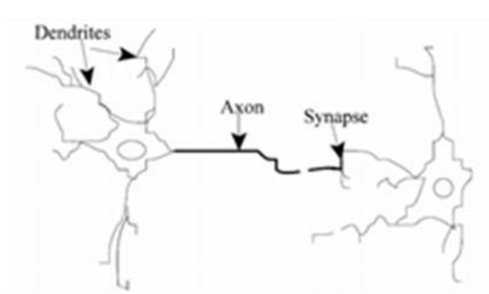

Fig.1. Neural neuron

The aim of this paper is to present Artificial Neural Network model in stroke diagnostic approaches through the enormous variability of data that can serve as inputs for ANNs. Attention will be given to the power of ANNs applications. We will evaluate ANN limits, possible trends, and future developments. (Fig. 2).

Fig.2. Overview of the main applications of Artificial neural networks in medicine

II. Artificial Neural Networks

An ANN is a mathematical representation of the human neural architecture, reflecting its "learning" and "generalization" abilities. For this reason, ANNs belong to the field of artificial intelligence. ANNs are widely applied in research because they can model highly non-linear systems in which the relationship among the variables is unknown or very complex. A review of various classes of neural networks can be found in [8].

A neural network is formed by a series of "neurons" (or "nodes") that are organized in layers. Each neuron in a layer is connected with each neuron in the next layer through a weighted connection. The value of the weight w_{ij} indicates the strength of the connection i^{th} – neuron in a layer and the j^{th} neuron in the next one.

The structure of a neural network is formed by an "input" layer, one or more "hidden" layers, and the "output" layer. The number of neurons in a layer and the number of layers depends strongly on the complexity of the system studied. Therefore, the optimal network architecture must be determined. The general scheme of a typical three-layered ANN architecture is given in Fig. 2.

A. *Mathematical Background*

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is an artificial neuron, that is, a simple mathematical model (function). Such a model has simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron the inputs are weighted which means that every input value is multiplied with individual weight. In the middle section of artificial neuron is a sum function that sums all weighted inputs and bias. At the exit of artificial neuron the sum of previously

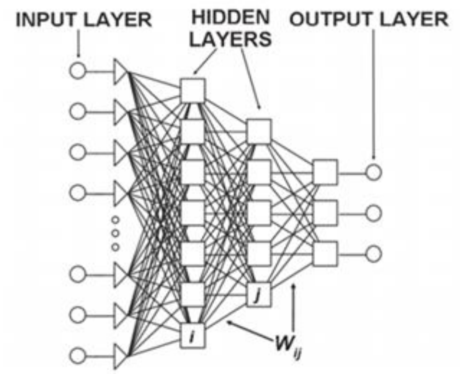

Fig.3. General structure of a neural network

weighted inputs and bias is passed through an activation function that is also called the transfer function Fig. 4.

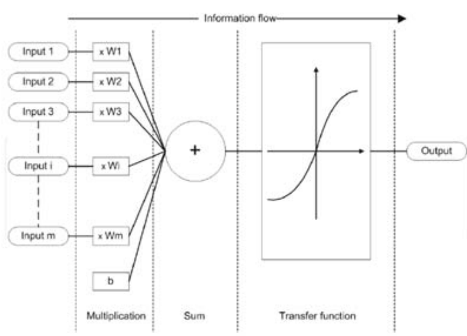

Fig.4. Working principle of an artificial neuron

The neurons in the input layer receive the data and transfer them to neurons in the first hidden layer through the weighted links. Here, the data are mathematically processed and the result is transferred to the neurons in the next layer.

B. Hidden Layers

Hidden units are nodes that are situated between the input nodes and the output nodes. Hidden units allow a network to learn non-linear functions. Hidden units allow the network to represent combinations of the input features. Given too many hidden units, a neural net will simply memorize the input patterns (overfitting). Given too few hidden units, the network may not be able to represent all of the necessary generalizations (underfitting).

Ultimately, the neurons in the last layer provide the network's output. The j-th neuron in a hidden layer processes the incoming data (xi) by:

a) calculating the weighted sum and adding a "bias" term (θj) according to Equation (1):

$$net_j = \sum_{i=1}^{m} x_i \times w_{ij} + \theta_j \quad (j = 1,2,\ldots,n) \qquad (1)$$

where y_{ij} and y_{ij} * are the actual and network's j-th output corresponding to the i-th input vector, respectively.

b) transforming the net_j through a suitable mathematical "transfer function", and c) transferring the result to neurons in the next layer. The most commonly used transfer function is the sigmoid one:

$$f(x) = 1/(1 + e^{-x}) \qquad (2)$$

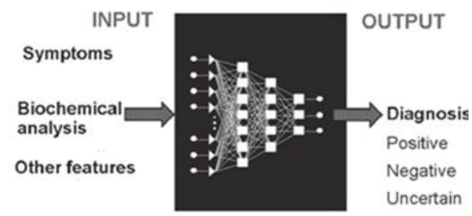

Fig.5. ANNs-based diagnosis

C. Overview og ANNs in Medical Diagnosis

There are several reviews concerning the application of ANNs in medical diagnosis. The concept was first outlined in 1988 in the pioneering work of [11] and since then many papers have been published. The general application of ANNs in medical diagnosis has previously been described [12]. For example, ANNs have been applied in the diagnosis of: (*i*) colorectal cancer (13), (*ii*) multiple sclerosis lesions [14], (*iii*) colon cancer [15], (*iv*) pancreatic disease [16], (*v*) gynecological diseases [17], and (*vi*) early diabetes [18]. In addition, ANNs have also been applied in the analysis. It is indicated that too high number of nodes might lead to overfitting. A novel, general, fast, and adaptive disease diagnosis system has been developed based on learning vector quantization ANNs. This algorithm is the first proposed adaptive algorithm and can be applied to completely different diseases, as demonstrated by the 99.5% classification accuracy achieved for both breast and thyroid cancers. Cancer, diabetes, and cardiovascular diseases are among the most serious and diverse diseases. The amount of data coming from instrumental and clinical analysis of these diseases is quite large and therefore the development of tools to facilitate diagnosis is of great relevance.

Patient code	MEDICAL DATA					DIAGNOSIS
1	$data_{1,1}$	...	$data_{1,i}$	...	$data_{1,m}$	POSITIVE
2	$data_{2,1}$	...	$data_{2,i}$	...	$data_{2,m}$	POSITIVE
3	$data_{3,1}$	...	$data_{3,i}$	...	$data_{3,m}$	POSITIVE
...	...					
k	$data_{k,1}$	...	$data_{k,i}$	...	$data_{k,m}$	NEGATIVE
k+1	$data_{k+1,1}$	...	$data_{k+1,i}$	...	$data_{k+1,m}$	NEGATIVE
...	...					
n	$data_{n,1}$	...	$data_{n,i}$	...	$data_{n,m}$	NEGATIVE

Fig.6.Training database structure

III. THE MODEL

Feed-forward neural networks are widely and are successfully used models for classification, forecasting and problem solving. A typical feed-forward back propagation neural network is proposed to diagnosis diseases and has only one condition: information must flow from input to output in only one direction with no back-loops. There are no limitations on the number of layers, type of transfer function used in individual artificial neurons or the number of connections between individual artificial neurons.

The model created in this paper is a neural network model with 16 inputs which are a combination of symptoms and the risk factors of stroke provided by the patients. The presence of symptom and risk factor is 1 and absence is 0. In this model two hidden layers have been used. Output layer consists of one node which represents the probability of occurrence of stroke.

TABLE I. DIAGNOSIS VARIABLES OF DATASETS USED IN THE STUDY

Patients symptoms	
1.	Sudden numbness or weakness of face, arm or leg, often one side of the body
2.	Sudden confusion, trouble speaking or understanding
3.	Sudden trouble seeing in one or both eyes
4.	Sudden trouble walking, dizziness loss of balance or coordination.
5.	Sudden severe headache with no known cause
6.	High blood pressure
7.	Diabetes
8.	Transitory ischemic attack
9.	Stenos carotid artery
10.	Smoking
11.	Facial weakness
12.	Arm weakness
13.	Speech disturbance (Aphasia/Dysarthria)
14.	Hemiparesis or hemisensory disturbance
15.	Ataxia
16.	Diplopia / visual loss

The input layer of a neural network is determined from the characteristics of the application input. For prognosis of stroke we used 16 inputs which are a combination of symptoms and risks factors.

The hidden layer automatically extracts the features of the input and reduces its dimensionality further. Two hidden layers are used. In this model we chose one hidden layer with 20 neurons and logistic sigmoid functions.

We can predict the presence or absent of stroke based on the output of the neural network. So if output is 1 stroke is present and if it is 0 stroke is absent. The network error function E(t) at the time t will be defined as follows:

$$E = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}(y_{ij} - y_{ij}^{*})^2 \qquad (3)$$

where yij and yij * are the actual and network's j-th output corresponding to the i-th input vector, respectively.

The current weight change on a given layer is given by Eq. (4):

$$\Delta w_{ij} = -\eta(dE/dw_{ij}) \qquad (4)$$

where η is a positive constant called the *learning rate*. To achieve faster learning and avoid local minima, an additional term is used and Eq. 4 becomes:

$$\Delta w_{ij}^{k} = -\eta(dE/dw_{ij}) + \mu\Delta w_{ij}^{k-1} \qquad (5)$$

where μ is the "momentum" term and Δw_{ij}^{k-1} is the change of the weight wij from the $(k-1)$-th learning cycle. The learning rate controls the weight update rate according to the new weight change and the momentum acts as a stabilizer, being aware of the previous weight change.

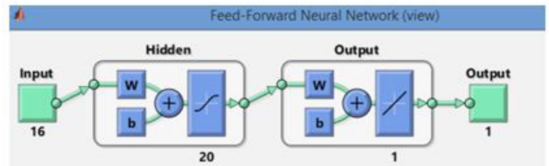

Fig.7. The proposed stroke diagnosis network

IV. EVALUATING PERFORMANCE

Neural network toolbox in Matlab is used to evaluate the performance of the proposed stroke diagnosis network. Stroke has been diagnosed and a two-layer feed-forward network with 16 inputs and 20 sigmoid hidden neurons and linear output neurons was created for this purpose. The given net can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer as shown in Fig.6. The Levenberg-Marquardt back propagation algorithm was used to train the network. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error (MSE) of the validation samples. The results showed healthy and unhealthy person states. The network was simulated in the testing set. The results were very good. Best validation performance is 0.0014027 at epoch 12 as shown in Fig.9. The mean squared error (MSE) is the average squared difference between outputs and targets.

Optimal Neural Network design able of improving settling time and rise time of controllers based on genetic-fuzzy techniques were developed in [21]. Main task of the given paper was to design an algorithm for the optimization of fuzzy rules weights attempting to decrease the timing parameters values. To do this, it is necessary to find the best training sample for suitable Neural Networks.

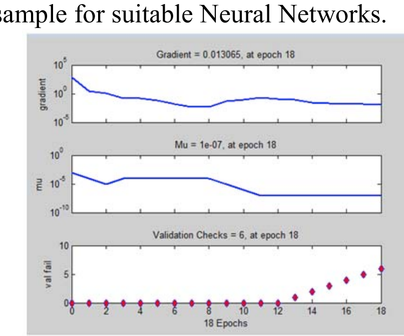

Fig.8.Training state values

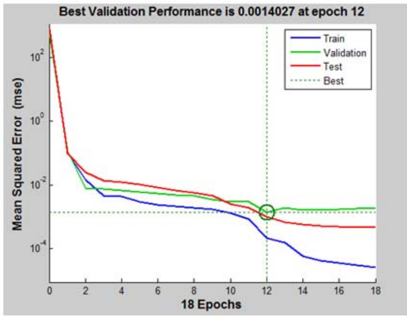

Fig.9. Epochs

V. CONCLUSIONS AND FUTURE WORK

In this paper we have developed an artificial neural network for medical diagnosis. This study aimed to evaluate an artificial neural network in stroke diagnosis. The feed-forward back propagation neural network with supervised learning is proposed to diagnose stroke. The Artificial neural network provide a powerful tool to help medical staff to analyze, model and make sense of complex clinical data across a broad range of medical applications. Artificial neural networks showed significant results in dealing with data represented in symptoms. The results showed that the proposed diagnosis neural network could be useful for identifying the affected person. Artificial neural networks with the ability to learn by example are provided a very flexible and powerful tool in medical diagnosis offering very useful applications to modern medicine.

Future work will concern for developing Artificial Neural Network app to diagnose diseases such as meningitis. The person puts a glass on the rash-is it blanches then it is not meningitis, if it does not then it is. The app takes a photo and sends it to a hospital doctor who does the diagnosis. For designing Artificial Neural Network the optimization algorithm to the genetic-fuzzy controllers will be applied.

REFERENCES

[1] http://www.strokecenter.org/patients/about-stroke/stroke-statistics

[2] http://www.world-heart-federation.org/cardiovascular-health/stroke

[3] Filippo Amato, Alberto López1, Eladia María, Peña-Méndez, Petr Vaňhara, Aleš Hampl, Josef Havel1. Artificial neural networks in medical diagnosis. J Appl Biomed. 11: 47–58, 2013. DOI 10.2478/v10136-012-0031-x. ISSN 1214-0287

[4] Catalogna M, Cohen E, Fishman S, Halpern Z, Nevo U, Ben-Jacob E. Artificial neural networks based controller for glucose monitoring during clamp test. PloS One. 7: e44587, 2012.

[5] Er O, Temurtas F, Tanrıkulu A. Tuberculosis Disease Diagnosis Using Artificial Neural Networks. J Med Syst. 34: 299–302, 2008.

[6] Elveren E, Yumuşak N. Tuberculosis disease diagnosis using artificial neural network trained with genetic algorithm. J Med Syst. 35: 329–332, 2011.

[7] Dey P, Lamba A, Kumari S, Marwaha N. Application of an artificial neural network in the prognosis of chronic myeloid leukemia. Anal Quant Cytol Histol. 33: 335–339, 2012.

[8] Barwad A, Dey P, Susheilia S. Artificial neural network in diagnosis of metastatic carcinoma in effusion cytology. Cytometry B Clyn Cytom. 82: 107–111, 2012.

[9] Barbosa D, Roupar D, Ramos J, Tavares A and Lima C. Automatic small bowel tumor diagnosis by using multi-scale wavelet-based analysis in wireless capsule endoscopy images. Biomed Eng Online. 11: 3, 2012.

[10] Aleksander I, Morton H. An introduction to neural computing. Int Thomson Comput Press, London 1995.

[11] Gregorio Romeo, Gillian Pearce and Julian Wong, Analysis of the "GPATD": Geometrical Influence on Blood Clot Extraction using CFD Simulation. 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation. Emmanuel College, University of Cambridge, Cambridge, UK.

[12] Mirtskhulava Lela, Al-Majeed Salah, Gillian Pearce, Gogoladze Tamar, Ivane Javakhishvili. Blood clotting prediction model using Artificial Neural Networks and Sensor Networks. GESJ: Computer Science and Telecommunications 2014|No.3(43). ISSN 1512-1232

[13] Szolovits P, Patil RS, Schwartz W. Artificial Intelligence in Medical Diagnosis. Ann Intern Med. 108: 80–87, 1988.

[14] Alkim E, Gürbüz E, Kiliç E. A fast and adaptive automated disease diagnosis method with an innovative neural network model. Neur Networks. 33: 88–96, 2012.

[15] Spelt L, Andersson B, Nilsson J, Andersson R. Prognostic models for outcome following liver resection for colorectal cancer metastases: A systematic review. Eur J Surg Oncol. 38: 16–24, 2012.

[16] Mortazavi D, Kouzani AZ, Soltanian-Zadeh H. Segmentation of multiple sclerosis lesions in MR images: a review. Neuroradiology. 54: 299–320, 2012b.

[17] Ahmed F. Artificial neural networks for diagnosis and survival prediction in colon cancer. Mol Cancer. 4: 29, 2005.

[18] Bartosch-Härlid A, Andersson B, Aho U, Nilsson J,Andersson R. Artificial neural networks in pancreatic disease. Br J Surg. 95: 817–826, 2008.

[19] artosch-Härlid A, Andersson B, Aho U, Nilsson J,Andersson R. Artificial neural networks in pancreatic disease. Br J Surg. 95: 817–826, 2008.Siristatidis C, Chrelias C, Pouliakis A, Katsimanis E, Kassanos D. Artificial neural networks in gyneacological diseases: Current and potential future applications. Med Sci Monit. 16: 231–236, 2010.

[20] Shankaracharya, Odedra D, Samanta S, Vidyarthi A. Computational intelligence in early diabetes diagnosis: a review. Rev Diabet Stud. 7: 252–262, 2010.

[21] Pelusi, D. Designing neural networks to improve timing performances of intelligent controllers (2013) Journal of Discrete Mathematical Sciences and Cryptography, 16 (2-3), pp. 187-193.