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Artificial Neural Network Model in Stroke Diagnosis

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***Abstract* – We present a model of an Artificial Neural Network (ANN) applied to stroke diagnosis. We use input data related to stroke that serves as inputs for the ANN. These data include clinical symptoms together with stroke risk factors. Each type of data provides input that is evaluated and used during the ANN processing. The adaptive learning algorithm can be used with a plethora of types of medical data and integrated into categorizedoutputs.**

Keywords - stroke; artificial network model; medical diagnosis

I. INTRODUCTION

It is thought that some 15 million people worldwide suffer a stroke yearly. Of those 15 million, approximately six million die and a further five million are left with permanently disability. Stroke is believe to be the second leading cause of disability, after dementia. Disabilities associated with stroke include loss of vision, speech, paralysis, aphasia, dyspahasia and many more. Worldwide, stroke is believed to be the second leading cause of death in people above the age of 60 years, and is thought to be the the fifth leading cause of death in the age group 15 to 59 years. Although stroke occurs less in people under 40 years, people of this age group can suffer stroke. High blood pressure is a common cause of stroke, but other causes can include hypercholesterolemia, hyperlipidaemia, and smoking. In the developing world, however, the incidence of stroke is increasing. [1] [16]. In spite of attempts to reduce these risk factors in populations the overall rate of stroke remains high due to an increasing aged population [2].

A stroke otherwise known as a "brain attack", cerebro-vascaular accident or cerebro-vascaular incident, can occur at any time. It occurs when blood flow in a vessel in the cerebral vasculature supplying an area of the brain is cut off. When this happens, brain cells supplied by that vessel are deprived of oxygen and begin to die. When brain cells die during a stroke, this has a profound effect on the functions that are controlled by that area of the brain e.g. memory and control over muscle movement may be severely affected or lost. It is therefore important to diagnose stroke in any individual as quickly as possible, such that the patient may be transferred to hospital in order to facilitate fast effective treatment. Such treatments include dissolving the blood clot with an anti-thrombolytic such as Alteplase or mechanical blood clot removal devices, in the case of strokes caused by clots of blood in a vessel supplying the brain. In the case of haemorrhagic stroke, where the blood supply is cut off due to a burst vessel in the brain, a craniotomy may be performed to reduce the inter cranial pressure and/or drugs such as mannitol and dexamethasone may be used to decrease the raised inter-cranial pressure.

II. BACKGROUND

The extent to which a person suffers disability as a result of their stroke depends on where the stroke occurs in the brain and how much of the brain is actually damaged. For example, someone who had a small stroke affecting only a relatively small area of the brain may only suffer minor problems e.g weakness of a hand. Patients who suffer a major stroke may be left with permanent paralysis on one side of their body or lose their ability to speak. Some patients recover completely from strokes, but about 66% of stroke survivors will have some type of disability.[3]

Artificial neural networks (ANNs) are widely used in science and technology with applications in chemistry, physics, and biology [4]. A database is used to produce a clinically relevant output. The input data has "plasticity". ANNs have been shown to be useful in the analysis of e.g. blood and urine samples in conditions such as diabetes, diagnosis of tuberculosis, and classification of the leukemias [5-9].

One style of ANN treats the nodes as 'artificial neurons'. This is the underlying principal of an artificial neural network (ANN). An artificial neuron is a computational model based on the natural neurons that occur in the brain. Natural neurons in the brain receive signals via synapses situated on the dendrites of the neurons. If the signals received reach a certain level (i.e. surpass a certain threshold), and normally this is via an action potential, the neuron is activated and emits a signal via the axon. This signal is then sent to another synapse, and would activate other neurons etc.

In this paper, we present the application of an Artificial Neural Network (ANN) model to the diagnosis of stroke We will attempt to show the limits of the ANN, and describe the potential future developments of the application of ANN's to the field of stroke medicine.

A neural network is therefore formed by a series of "neurons" (or "nodes") that are organized into many layers. Each neuron in one layer is connected with each neuron in the next layer through a weighted connection. The value of the weighting w_{ij} purports the strength of the connection, i.e. the i^{th} - neuron in a given layer and the j^{th} neuron in the next given layer etc [10].

Consequently, the structure of an ANN is formed by an "input" layer, one or more "hidden" layers, and the "output" layer. The number of neurons in a given layer and the number of layers is dependent on the complexity of the system in question. Therefore, an optimal network structure must be ascertained.

Typically an ANN model has 3 layers and a set of basic rules based on multiplication, summation and activation. At the beginning of the system we have artificial neurons- the inputs and these are weighted. This means in practice that every input value is multiplied with an individual weight. In the middle section of the artificial neuron there is a so-called sum function that sums all weighted inputs and biases. At the exit of the artificial neuron network, the sum of the previously weighted inputs and biases are passed through a so-called activation function that is also known as the transfer function. The basic structure of an ANN is shown in figure 1[10]. By this means data is processed through the ANN.

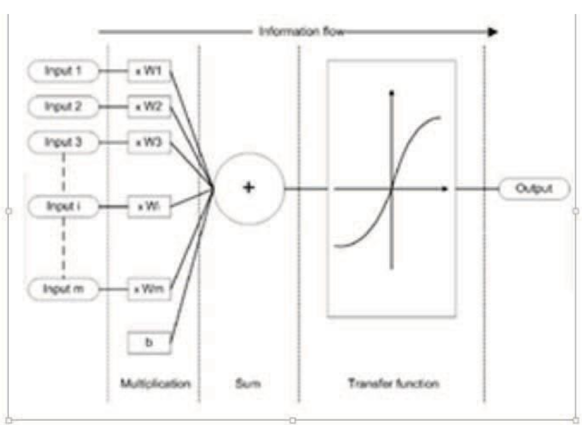

Figure 1. The basic structure of an ANN [10]

For purposes of developing and investigating the application of ANN's to stroke diagnosis, we employ the equations below in [10]. Hidden layers contain units that may be regarded as nodes that are situated between the input nodes and the output nodes. Hidden units allow the network to use combinations of the input features. However one problem that can arise is that if there are too many hidden units, the ANN will then memorize the input patterns (so- called overfitting). On the other hand, given too few hidden units, the network may not be able to use all of the necessary generalizations (this is called, underfitting). The output of the ANN maybe positive, negative or uncertain [10].

In the final analysis, the neurons in the last layer provide the network's output. The j-th neuron in a hidden layer processes the incoming data by: a) calculating the weighted sum and adding a "biasing" according to Equation (1):

$$n_j = \sum_{i=1}^{m} w_i p_i + b_i \quad (j=1,2,\ldots n) \qquad (1)$$

b) transforming the net n_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:

$$S(t) = 1/(1+e^{-t}) \qquad (2)$$

TABLE 1. RISK FACTORS FOR STROKE AND STROKE SYMPTOMS [12][15].

	Patient Symptom
1	Acute paraesthesia of arm or leg, (frequently unilateral)
2	Acute Confusion, dysphasia or affected cognitive function
3	Vision affected unilaterally or bilaterally
4	Acute problems with mobility, vertigo, coordination, or balance
5	Acute severe headache of unknown aetiology
6	Diabetes
7	Hypertension
8	Previous TIA or mini stroke
9	Carotid artery stenosis (due to atheromatous plaque)
10	Facialweakness
11	Smoking
12	Armweakness
13	Speechdisturbances(aphasia)
14	Hemiparesis or hemisensory aspects affected
15	Diplopia
16	Ataxia

III. THE MODEL

Feed-forward neural networks [11] are used extensively and are successfully used in models involving classification, forecasting of various types, and problem solving. Feed-forward back propagation neural networks are used in the diagnosis of diseases. They have only one "rule" and that is that information must flow in ne direction from input to output with no back-loops. There are however no limitations on the number of layers, the type of transfer function used in the individual artificial neurons or the number of connections between the individual artificial neurons in the ANN.

The model applied in this paper is a neural network model with 16 inputs which are a combination of patient symptoms and risk factors associated with stroke. The presence of a given symptom and risk factor is depicted by 1 and absence is depicted by 0. In this model two hidden layers have been used. The output layer consists of one node which represents the probability that stroke will occur.

The input layer of the neural network is determined by the properties of the application input. To determine the probability that stroke will occur, we use 16 inputs which are a combination of symptoms and risks factors, as shown in table 1. These input parameters are based on stroke risk factors and symptoms associated with [12]

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

$$E = \frac{1}{N}(t_i - a_i)^2 \tag{3}$$

The weight change on a given layer is given by Equation (4):

$$\Delta w_{ij} = -\alpha(dE/dw_{ij}) \tag{4}$$

where a is a positive constant called the learning rate. In order to achieve a faster learning rate, and avoid local minima, an additional term may be used and Equation 4 then becomes:

$$\Delta w_{ij}^{k} = -\alpha(dE/dw_{ij}) + \beta\Delta w_{ij}^{k-1} \tag{5}$$

Where β is the "momentum" term and the term Δw_{ij}^{k-1} in equation (5), is the change of the weight wij from the (k- 1)-th learning cycle. The learning rate controls the weighted update rate in accordance with the the new weight change. The role of the momentum is to act as a type of stabilizer, in relation to the previous weight change.

IV. RESULTS AND DISCUSSION

We used the Neural network toolbox in Matlab to evaluate the performance of the stroke diagnosis network. We show an example where stroke has been diagnosed using a two-layer feed-forward network with 16 inputs and 20 sigmoid hidden neurons together with linear output neurons. The Levenberg-Marquardt back propagation algorithm [13] was used to train the network. Training is automatically stopped when generalization ceases to improve, as indicated by an increase in the mean square error (MSE) of the validation samples. The network was simulated in the testing set. Figure 2 indicates the training state values. The results were very good. The best validation performance is 0.0014027 at epoch 12 as shown in Figure.3. The mean squared error (MSE) is the average squared difference between outputs and targets.

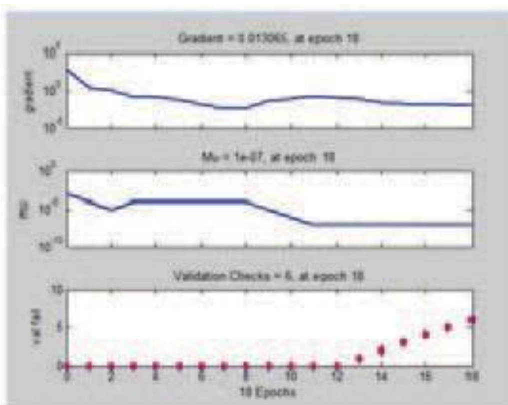

Figure.2.The Training state values

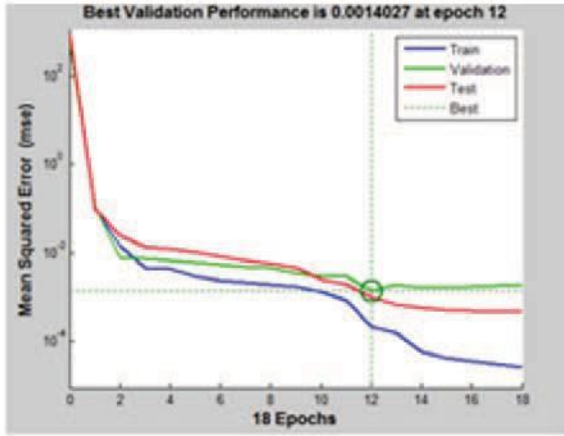

Figure 3. TheEpochs

V. CONCLUSIONS

In this paper we have presented an artificial neural network for the medical diagnosis of stroke. This study set out to evaluate the performance of the ANN as applied to stroke diagnosis. Our study indicated that the feed-forward back propagation neural network with supervised learning may potentially be useful in diagnosing stroke. ANN's are therefore potentially useful as an adjunct in helping medical staff to analyze, model, and interpret a plethora of complex clinical data related to particular medical applications. The results showed that the proposed ANN could potentially be useful for identifying stroke in patients. Artificial neural networks that have the capacity to learn by example, and training, provide a very flexible structured tool in medical diagnosis. We feel that our modelling may be further extended by using more input data in the ANN. This data could involve including individual patient data and use of stroke scoring systems as parameters. It may also be possible to develop the ANN such that it could be used to potentially predict the prognosis of an individual stroke patient. That prognosis could then be compared with actual stroke outcome/prognosis for particular patients. We also in our second paper (Mirtskhulava et al 2015) consider how ANN's might be applied to the detection and diagnosis of noctural stroke in particular[14].

REFERENCES

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

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

[3] Werner Hacke, M.D., Markku Kaste, M.D., Erich Bluhmki, Ph.D.,Miroslav Brozman, M.D., Antoni Davalos, M.D., Donata Guidetti,M.D., Vincent Larrue, M.D., Kennedy R. Lees, M.D., Zakaria Medeghri, M.D., Thomas Machnig, M.D., Dietmar Schneider, M.D., Rudiger von Kummer, M.D., Nils Wahlgren, M.D., and Danilo Toni,M.D. for the ECASS Investigators Thrombolysis with Alteplase 3 to 4.5 Hours after Acute Ischemic Stroke N Engl J Med 2008; 359:1317- 1329September 25, 2008DOI: 10.1056/NEJMoa0804656

[4] Filippo Amato, Alberto L6pez1, Eladia Maria, Pena-Mendez, Petr Vanhara, Ales Hampl, Josef Havel1. Artificial neural networks in medical diagnosis. J Appl Biomed. 11: 47-58, 2013. DOI 10.2478/v10136-012-0031-x.ISSN1214-0287

[5] 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.

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

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

[8] 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.

[9] 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.

[10] Filippo Amato et al Journal of Applied Biomedicine. Artificial neural networks in medical diagnosis. J Appl Biomed. 11: 47-58, 2013. DOI 10.2478/v10136-012-0031-xISSN 1214-0287

[11] http://www.fon.hum.uva.nl/praat/manual/Feedforward_neural_networ ks_1 What_is_a_feedforward_ne.html.

[12] http://www.webmd.com/heart/atrial-fibrillation-stroke-11/stroke- causes-risks

[13] http://uk.mathworks.com/help/nnet/ref/trainlm.html

[14] Mirtskhulava, L., et al 2015 Stroke Monitoring using Smartphone Sensors and Artificial Neural Network Soft Sensors. UKSIM Cambrdige UK.

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

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