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Early Diagnosis of Ischemia Stroke using Neural Network

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Abstract: Technological and computing evolution promoted new opportunities to improve the quality of life, in particular, the quality of early detection of acute disease. Many intelligent systems have been developed with the purpose of enhancing health-care and providing better health care facilities at reduced cost. Artificial Intelligent techniques are indeed worth exploring and integrating in the medical system for diagnosis, prediction and prescription. The aim of this paper is to determine a noninvasive method that the general population can easily use to detect whether a patient has cerebral ischemia stroke. The problem addressed in this paper is prediction of possibility of cerebral ischemia and it is estimated from symptoms and risk factors given by the patients. Exactly early prognosis of cerebral ischemia stroke has practical importance in medicine. A feed forward neural network with back propagation was used for decision of cerebral ischemia stroke prediction. Developed Neural network model with appropriate training provides an accuracy of 99.99%.

Key words – Feed forward neural network, MATLAB, cerebral ischemia stroke.

I. INTRODUCTION

Brain is the control center of the body. It controls thoughts, memory, speech and movement. It regulates the function of many organs. When the brain is healthy, it works efficiently and automatically. However, when disorders occur, the results can be devastating.One of the common disorder of brain is stroke also called brain attack (a medical emergency). Stroke is a major cause of death and disability in both the developed and the less developed countries [1] [2].Stroke consumes an important part of the total healthcare costs (i.e. excluding social care and indirect costs) in Europe and USA [3].

Stroke is characterized by the sudden loss of blood circulation to a region of the brain, resulting in a corresponding loss of neurological function. There are two kinds of strokes: ischemia and hemorrhage [4]. Ischemia strokes occur when there is a lack of blood supply to the brain. A hemorrhage stroke occurs when a blood vessel is damaged in the brain. A hemorrhage stroke is thought to be more life threatening than an ischemia. In fact, heart attacks and ischemic strokes is so similar that the American Heart Association life threatening than an ischemia. In fact, heart attacks and ischemic strokes are so similar that the American Heart Association now calls them brain attacks. About 80 percent of all strokes are ischemic.

Employing the technology especially artificial neural network (ANN) techniques in medical applications could result in reducing the mortality rate, cost, time, medical error and need of human expertise. In this paper, neural network model is used to detect cerebral ischemia stroke with the help of physical symptoms and risk factors provided by the patients. Once the neural network model is trained, it will predict the possibility of ischemia stroke depending upon the training data provided (accuracy of training data).

In section II are explained the symptoms and risk factors of cerebral ischemia stroke. Section III gives overview of neural network architecture. Section IV describes the design of neural network model. Section V deals with discussions and results. Section VI concludes the paper.

II SYMPTOMS AND RISK FACTORS OF ISCHEMA STROKE

Ischemia Stroke can cause paralysis, affect language, vision, and cause other problems. The symptoms of stroke usually come on suddenly. The suddenness of onset distinguishes stroke from other conditions such as migraine or brain tumors. Treatments are available to minimize the potentially devastating effects of stroke, but to receive them; one must recognize the warning symptoms and what are the risk factors that increase the probability of brain attack.The symptoms and risk factors of brain diseases vary widely depending on the specific problem. In some cases, damage is permanent. In other cases, treatments such as surgery, medicines or physical therapy can correct the source of the problem or improve symptoms.

The American Stroke Association has identified several factors that increase the risk of ischemia stroke. Some of risks are uncontrollable such as increasing age, family health history, race and gender [5]. But other controllable risks factors are following:

High blood pressure - High blood pressure is the most important risk factor for stroke. In fact, stroke risk varies directly with blood pressure.

Smoking - In recent years, studies have shown cigarette smoking to be an important risk factor for stroke. The nicotine and carbon monoxide in cigarette smoke damage the cardiovascular system in many ways.

Diabetes – It is an independent risk factor for stroke and is strongly correlated with high blood pressure. People with

diabetes often also have high cholesterol and are overweight, increasing their risk even more.
Carotid artery disease - The carotid arteries in neck supply blood to brain. A carotid artery damaged by atherosclerosis (a fatty buildup of plaque in the artery wall) may become blocked by a blood clot, which may result in a stroke.
Transient ischemic attacks (TIAs) - TIAs are "mini strokes" that produce stroke-like symptoms but with no lasting damage. They are strong predictors of stroke. A person who's had one or more TIAs is almost 10 times more likely to have a stroke than someone of the same age and sex who hasn't.
These risk factors can be reduced or treated by changing the lifestyle or environment or can be modified with a healthcare provider's help.

III. NEURAL NETWORK OVERVIEW

Neural networks (NN) are inspired by nervous systems found in biological organisms. A neural network is designed to capture relationships among dependent and independent variables in a given sample data set. Unlike parametric models used in statistical techniques, ANN does not require any restrictive a priori assumptions about the relationship among independent and dependent variables [6]. In addition, they are adaptive and can respond to structural changes in the data generation process in ways that parametric models cannot.
An ANN consists of a number of connected nodes each of which is capable of responding to input signals with an output signal in a predefined way. These nodes are ordered in layers. A network consists of one input layer, one output layer, and an arbitrary number of hidden layers in between.
The architecture of NN widely used for classification problem is Feed Forward Neural Network with associated error Back Propagation (BP) learning algorithm for minimizing the observed sum of squared errors over a given set of data. The nodes are connected such that each node is connected to all nodes of the previous and the successive layer (if such layers exist). The input layer is only connected forward to the first hidden layer and the output layer only backward to the last hidden layer. The error is then back propagated through the network and weights are adjusted as the network attempts to decrease the error by optimizing the weights.
All connections are assigned a weight (a real number). The training or learning of the network occurs through the introduction of cycles of data patterns (epochs or iterations) to the network. One problem with neural network training is the tendency of the network to memorize the training data after an extended learning phase. If the network over learns the training data it is more difficult for the network to generalize to a data set that was not seen by the network during training. Therefore, it is common practice to divide the data set into a learning data set that is used to train the network and a validation data set that is used to test network performance.
In medical practice, ANNs are generally used to diagnose and monitor the prognosis of a disease. ANNs have been used to determine prognosis in trauma, prognosis after cardiopulmonary resuscitation, outcome of treatment for ovarian cancer, prognosis in acquired immunodeficiency syndrome (AIDS), predicting mortality of patients with end-stage liver disease, prognosis for patients with colonic cancer, detecting extensive coronary artery disease, predicting length of stay in the intensive care unit following cardiac surgery and predicting the risk of death for small-cell lung cancer patients [7,8,9,10,11,12,13].

IV. DESIGN OF THE NEURAL NETWORK FOR ISCHEMIA STROKE

In recent years, neural network technology has been widely adopted for prognosis of medical problem, in which BP network is commonly used (14-17). The model created in this paper is a BP neural network model with 10 inputs which are combination of symptoms and risk factors of ischemia stroke provided by the patients .The presence of symptom and risk factor is 1 and absence is 0.In this model single hidden layer has been used. Output layer consists of one node which represents the probability of occurrence of ischemia stroke. Fig 1 shows the model of feed forward neural network with input layer, hidden layer and output layer.

A.Input layer

The input layer of a neural network is determined from the characteristics of the application input. For prognosis of ischemia stroke we used 10 inputs which are combination of symptoms and risks factors. Following symptoms [18] and risk factors [5] are the input to the neural network:

S1 Sudden numbness or weakness of face, arm or leg, often one side of the body.
S2 Sudden confusion, trouble speaking or understanding.
S3 Sudden trouble seeing in one or both eyes.
S4 Sudden trouble walking, dizziness loss of balance or co-ordination.
S5 Sudden severe headache with no known cause.
R6 High blood pressure
R7 Diabetes
R8 Transitory ischemic attack
R9 Stenos carotid artery
R10 Smoking

The sample data prepared [4, 5, 18] on the basis of symptoms and risk factors studied by many expert doctors was applied to this model and trained the model.

B.Hidden Layer

Hidden layer automatically extracts the features of the input and reduces its dimensionality further [6]. There is no specific rule that dictates the number of hidden layers. Usually, one hidden layer is used. The reason for this is that one hidden layer is sufficient to approximate any continuous function to an arbitrary precision. In this model we chose one hidden layer with 20 neurons & logistic sigmoid functions (fig2).

C. Output layer

The output layer of the network is designed according to need of the application output. Since the output of the neural network is expected to predict the presence or absent of the ischemia stroke. So if output is 1 disease is present & if it is 0 disease is absent. It is assumed that the actual output of the neuron in the output layer is yj(t) at time t and the expected output dj(t), so the network error function E(t) at the time t will be defined as follows:

$$E(t)=\frac{1}{2}\sum_{j=1}^{q}(y_j(t)-d_j(t))^2,$$

q is the number of neurons in the output layer and is one for this neural network ; ε is a pre-set error margin. The model stopped testing when E(t) was less than ε of the desired model [6].

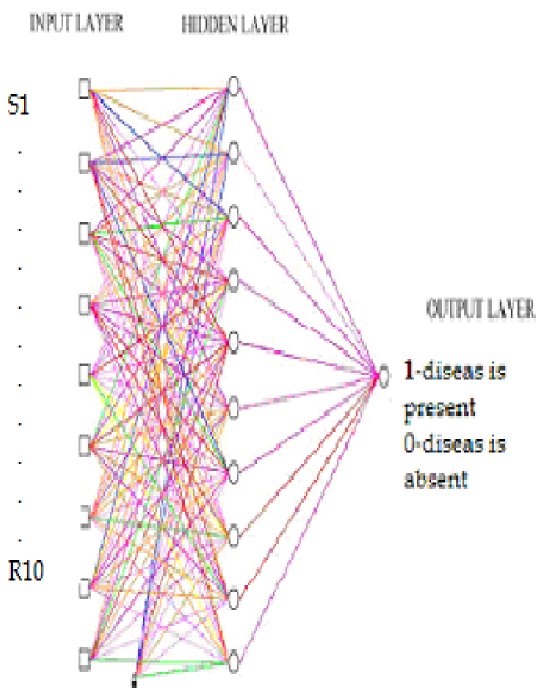

Fig 2: Hidden layer

Depending upon the accuracy of data, number of training samples, and error for termination of training, the test results were above 98% to 99.99%. In order to optimize the training algorithm to be employed, all the major algorithms were considered and the number of epochs used to train for different values of MSE was tabulated (table 1). Clearly, the Levenberg-Marquardt (LM) algorithm was found to be most efficient.

Table 1: Comparison of Training Algorithms

Training Algorithms	1E-01	1E-02	1E-03	1E-04	1E-05
LM	3	3	5	6	9
GDX	110	176	190	218	269
RP	8	12	13	16	21
CGF	2	18	19	20	21
BFG	4	13	25	29	36

V. DISCUSSION OF RESULTS

In this study, we used neural network program written in MATLAB language to determine the best possible test results. We found that NN is easy to use and is faster in producing diagnoses that are 99.99% correct. We provided 280 samples of patients with 10 combining risk factors and symptoms for cerebral ischemia stroke. In Fig. 3, the number of iterations is indicated for the 280 sample training data set versus the error rate.Fig.4 depict the performance curves of training data sets with respect to number of epochs. The limit for training error was kept at 1e-8.The network was validated and tested with datasets. Two third data are used for validation and one third data are used for testing. Fig 5,shows satisfactory test performance of training, validation and test data sets with respect to epochs.

The Regression analysis function compares the actual outputs (A) of the neural network with the corresponding desired outputs (T) [6].It returns the correlation coefficient (R)between them, and also the slope(m) and the A-intercept (c)of the best-linear-fit equation : A= mT+c.The values of m and R can be in the range [0.0,1.0].The more the values of m and R are near to 1.0 and the more the value of c is near to zero, more correct the response of the network. Regression graph also shown in fig.6. As can be seen, an accuracy of 99.99% was achieved in training the NN so as to create output same as targets.

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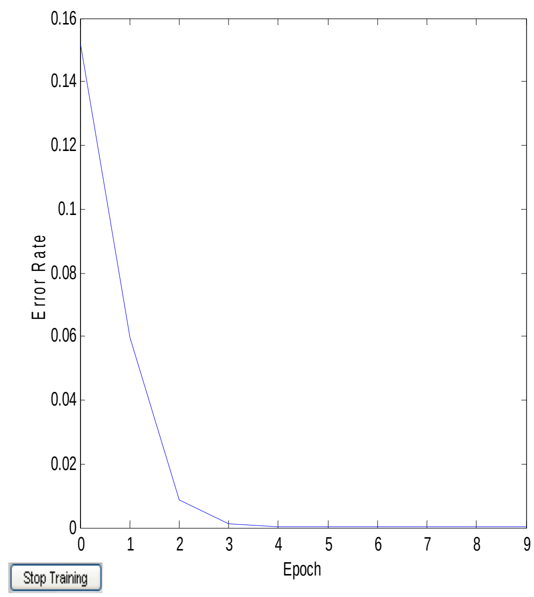

Fig. 3 Graph of SSE error versus epochs of Ischemia Stroke

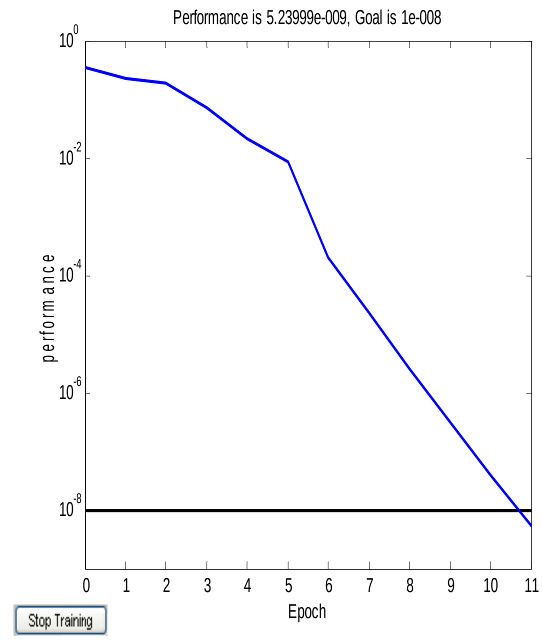

Fig.4 Graph of Training data (Performance v/s Epochs) for Ischemia Stroke

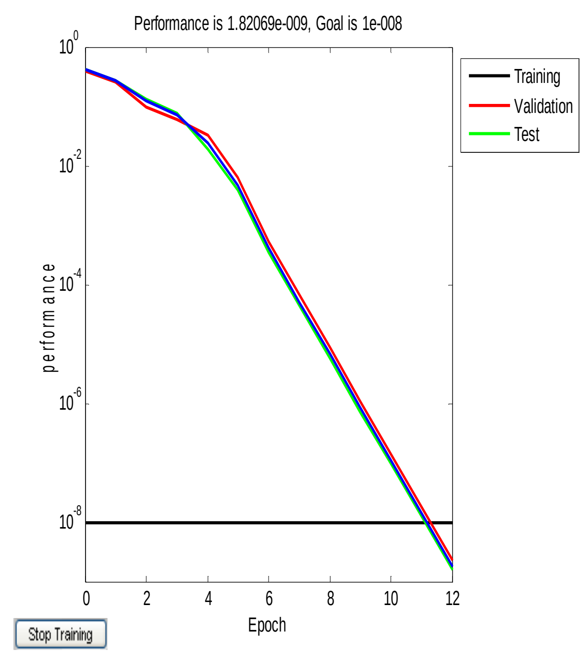

Fig 5. Graph of performance of training, validation and test data sets with respect to epochs for ischemia stroke

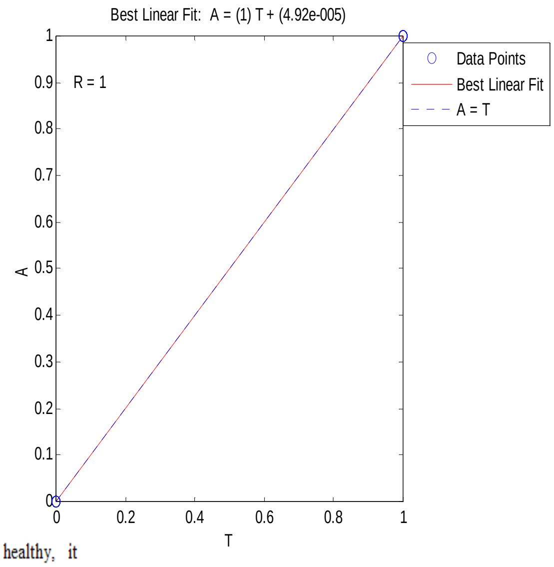

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Fig. 6 Regression Curve for Ischemia Stroke

VI. CONCLUSION

Many times people feel uneasiness, pain and they do not know the cause nor do they see a doctor to determine the problem. ANN based model has been used to develop a system in which patients would be able to self-diagnose themselves before undergoing a more thorough examination. Prognosis of early diagnosis of stroke with ANN models has the best performance in large data sets. Regarding this MATLAB program was developed to model and train NN. In this model accuracy of 99.99% was achieved and we notice that it might be good at predicting Ischemia stroke.

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