Designing an Artificial Neural Network Model for the Prediction of Thrombo-embolic Stroke

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ABSTRACT

In this study, a functional model of ANN is proposed to aid existing diagnosis methods. This work investigated the use of Artificial Neural Networks (ANN) in predicting the Thrombo-embolic stroke disease. The Backpropogation algorithm was used to train the ANN architecture and the same has been tested for the various categories of stroke disease. This research work demonstrates that the ANN based prediction of stroke disease improves the diagnosis accuracy with higher consistency. This ANN exhibits good performance in the prediction of stroke disease in general.

Keywords: Artificial Intelligence, BPN, Neural Network, Thrombo-embolic Stroke.

1. INTRODUCTION

Neural networks provide a very general way of approaching problems. When the output of the network is continuous, it is performing prediction and when the output has discrete values, then it is doing classification. A simple rearrangement of the neurons and the network becomes adept at detecting clusters. Computer Assisted Decision Support in medicine has at least the role of enhancing the consistency of care. Secondly, it has the potential to cover rare conditions, since no clinical expert can be expected to possess encyclopedic knowledge of all of the exceptional manifestations of diseases, even within a specialist domain. Thirdly, the expanding range of patient information that is made available in electronic form, makes it feasible to more accurately quantify important clinical indicators, such as the relative likelihood for competing diagnoses or the clinical outcome. In some cases, computer-assisted diagnoses have been claimed to be even more accurate than those by clinicians.

Stroke is a life-threatening event in which part of the brain is not getting enough oxygen. There are different types of stroke namely Brain Attack, Embolic Stroke, Thrombotic Stroke, Ischemic Stroke, Cerebrovascular Accident (CVA). Medical personnel treating a stroke are challenged to treat the patient as quickly as possible to avoid permanent tissue damage or death. Strokes were responsible for more deaths and nearly half of those deaths occurred outside of a hospital. Stroke is the third leading cause of death, behind heart disease and cancer. Most recovery occurs during the first few months following a stroke. According to the National Institute of Health, the risk of stroke is greater – and the recovery process is slower. Thrombo embolic strokes are caused by fatty deposits (plaques) that have built up in the arteries carrying blood to the brain. This slows blood flow and can cause clots to form on the plaques that narrow or block the flow of oxygen and nutrients to the brain. It is also caused by a blood clot formed in another part of the body that breaks loose, travels through the bloodstream, and blocks an artery carrying oxygen and nutrients to the brain. When travelling through the body the blood clot is called an embolus [1]. A hemorrhagic stroke is caused when an artery supplying blood bleeds into the brain. The broken blood vessel prevents needed oxygen and nutrients from reaching brain cells. One type of hemorrhagic stroke is caused when an artery that has weakened over time bulges (called an aneurysm) and suddenly bursts [2]. Thrombo-embolic Stroke can be classified as Transient Ischemic attacks (TIA), Evolving Stroke, Completed Stroke, Residual Squeal, Classical Stroke, Inappropriate Stroke, Anterior Cerebral Territory Stroke, Posterior Cerebral Stroke, Middle Cerebral Territory Stroke. Hemorrhagic Stroke can be classified as Cerebellar stroke, Thalamic Stroke and Cortical Stroke. In this paper, we propose an artificial neural network model for the prediction of Thrombo Embolic Stroke disease. The rest of the paper discusses about related studies, the proposed model, results and discussion along with conclusion.

2. RELATED STUDIES OF ANN IN MEDICINE

ANNs appear to be a valid candidate for the reliability analysis. Given a number of predictor variables, an opportunely structured and trained Multi Layer Perceptron (MLP) can identify the “causal path” leading to a certain value of the potential objective variables, with a certain degree of confidence. [3]. Several studies have applied neural networks in the diagnosis of cardiovascular disease, primarily in the detection and classification of at-risk people from their ECG waveforms [4]. In the works of [5], the application of neural networks to classify normal and abnormal (pathological) ECG waveforms and the abnormal ECG recordings had six different disease conditions. The classifier was able to recognize these waveforms with 70.9% accuracy.

The Study [6] suggested that the role of the ANN, which uses non-linear statistics for pattern recognition in predicting one-year liver disease-related mortality using information available during initial clinical evaluation. MLP with sigmoidal feed-forward and standard Back-Propagation (BP) learning algorithm was employed as a forecaster for bacteria-antibiotic interactions of infectious diseases. Comparing ANN ensembles with logistic regression models we found the former approach to be better in terms of ROC area and calibration assessments. Both ANN and logistic regression models showed intra-method variations, as a result of training the models with different parts of the study population. This variation was larger for the ANN ensemble models [7].

The studies of application of ARTMAP in medicine include classification of cardiac arrhythmias [8] and treatment selection for schizophrenic and unipolar depressed in-patients [9]. Another study revealed that fully connected feed forward MLP and BP learning rule, were able to predict patients with colorectal cancer more accurately than clinicopathological methods. They indicate that NN predict the patients’ survival and death very well compared to the surgeons. The study [10] presents their study for the diagnosis of Acute Myocardial Infarction. The results show that NN performance is 0.84 and 0.85 under ROC.

A neural network can provide a considerable improvement in the diagnosis of early acute allograft rejection, though further development work is needed before this becomes a routine diagnostic tool. The selection of cases used to train the network is crucial to the quality of its performance. There is scope to improve the system further by incorporating clinical information[11]. Another methodology, which is based on ANNs, has been developed for the detection of ischaemic episodes in long-duration ECG recordings [12] . The raw ECG signal containing the ST segment and the T wave of each beat is the input to the beat-classification system, and the output is the classification of the beat. The use of the ANN model as a data mining tool is very promising for new knowledge discovery in nephrology, to model complex behaviour of different molecular markers of dialysis treatment and for online treatment monitoring. [13]. The Study [14], presented a fully automated method using ANNs were compared with the clinical interpretation. The neural networks trained with both perfusion and ECG-gated images had a 4–7% higher specificity compared with the corresponding networks using perfusion data only, in four of five segments compared at the same level of sensitivity. The addition of functional information from ECG-gated MPS is of value for the diagnosis of myocardial infarction using an automated method of interpreting myocardial perfusion images.

3. THE PROPOSED MODEL

3.1 Patient Data

The data for this study have been collected from 50 patients who have symptoms of stroke disease. The data have been standardized so as to be error free in nature. All the fifty cases are analyzed after careful scrutiny with the help of the Physicians. Table-1 below shows the various input parameters for the prediction of stroke disease.

Sl.No.	Parameters
1	Age
2	Sex
3	Pre-stroke mobility
4	Hypertension
5	Diabetes Mellitus
6	Myocardial infarction
7	Cardiac failure
8	Atrial fibrillation
9	Smoking
10	High blood cholesterol
11	Alcohol abuse
12	Weakness of Left Arm and Left leg
13	Weakness of Right Arm and Right leg
14	Slurring of Speech
15	Giddiness
16	Headache
17	Vomiting
18	Memory Deficits
19	Swallowing Difficulties
20	Loss of Vision
21	Isolated vertigo
22	Transient Double Vision
23	Sudden difficulty in walking , dizziness or loss of balance
24	Hand / Leg numbness
25	Transient loss of consciousness

TABLE 1: Input Parameters for Prediction of Stroke

3.2 Feature Selection

Data are analyzed in the dataset to define column parameters and data anomalies. Data analysis information needed for correct data preprocessing. After data analysis, the values have been identified as missing, wrong type values or outliers and which columns were rejected as unconvertible for use with the neural network[15]. Feature selection methods are used to identify input columns that are not useful and do not contribute significantly to the performance of neural network. In this study, Backward stepwise method is used for input feature selection. The removal of insignificant inputs will improve the generalization performance of a neural network. This method begins with all inputs and it works by removing one input at each step. At each step, the algorithm finds an input that least deteriorates the network performance and becomes the candidate for removal from the input set. Table 2 shows the finalized input parameters after applying feature selection method.

Input column name	Code	Importance %
Hypertensive	X1	1.626103
Diabetes	X2	4.229285
Myocardial	X3	0.043249
Cardiac failure	X4	0.001659
Atrial fibrillation	X5	0.034991
Smoking	X6	2.061142
Blood cholesterol	X7	8.831646
left arm&leg	X8	19.209636
Right arm &leg	X9	2.832501
Slurring	X10	1.776497
Giddiness	X11	3.64891
Headache	X12	15.646755
Vomiting	X13	0.535259
memory deficits	X14	1.485701
Swallowing	X15	5.224413
Vision	X16	7.366008
Double vision	X17	1.13867
Vertigo	X18	15.471004
Numbness	X19	0.136173
Dizziness	X20	8.700397

TABLE 2: Percentage of Importance of Input Data

3.3 Neural Network Architecture

The architecture of the neural network used in this study is the multilayered feed-forward network architecture with 20 input nodes, 10 hidden nodes, and 10 output nodes. The number of input nodes are determined by the finalized data; the number of hidden nodes are determined through trial and error; and the number of output nodes are represented as a range showing the disease classification. The most widely used neural-network learning method is the BP algorithm [16]. Learning in a neural network involves modifying the weights and biases of the network in order to minimize a cost function. The cost function always includes an error term a measure of how close the network's predictions are to the class labels for the examples in the training set. Additionally, it may include a complexity term that reacts a prior distribution over the values that the parameters can take.

The activation function considered for each node in the network is the binary sigmoidal function defined (with $\sigma = 1$) as output = $1/(1+e^{-x})$, where x is the sum of the weighted inputs to that particular node. This is a common function used in many BPN. This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing. Figure 1 shows the architecture of the specialized network for the prediction of stroke disease. The complete set of final data (20 inputs) are presented to the generic network, in which the final diagnosis corresponds to output units.

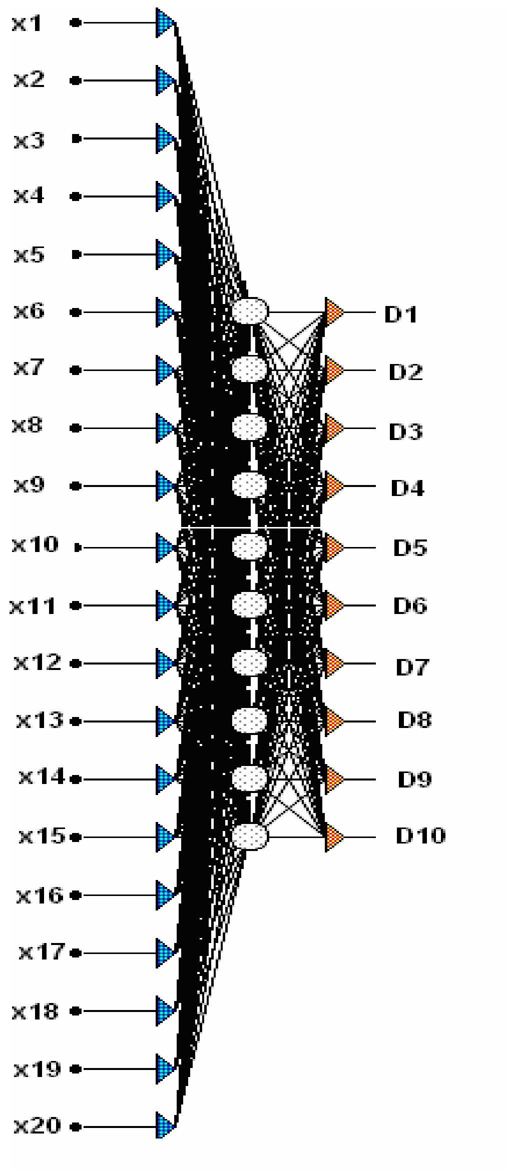

FIGURE 1: Artificial Neural Network Architecture for the prediction of stroke disease

The net inputs and outputs of the j hidden layer neurons can be calculated as follows

$$net_j^h = \sum_{t=1}^{N+1} W_{ji} x_i$$

$$y_j = f(net_j^h)$$

Calculate the net inputs and outputs of the k output layer neurons are

$$net_k^o = \sum_{j=1}^{J+1} V_{kj} y_j$$

$$Z_k = f(net_k^o)$$

Update the weights in the output layer (for all k, j pairs)

$$v_{kj} \leftarrow v_{kj} + c\lambda(d_k - Z_k) Z_k (1 - Z_k) y_j$$

Update the weights in the hidden layer (for all i, j pairs)

$$w_{ji} \leftarrow w_{ji} + c\lambda^2 y_j(1-y_j)x_i(\sum_{k=1}^{k}(d_k - z_k)z_k(1-Z_k)v_{kj})$$

Update the error term

$$E \leftarrow E + \sum_{k=1}^{k}(d_k - z_k)^2$$

and repeat from Step 1 until all input patterns have been presented (one epoch). If *E* is below some predefined tolerance level , then Stop. Otherwise, reset *E = 0*, and repeat from Step 1 for another epoch.

The inputs to the models were 20 variable training parameters and the output indicated the point at which training should stop. The following are the results generated from the input given to the neural network after going through the process of careful training, validation and testing using Neuro Intelligence tool. Table 3 shows the various categories of Stroke diseases and their classification.

Output	**Code**
TIA	D1
Left Hemiplegia	D2
Right Hemiplegia	D3
Dysphasia	D4
Monoplegia	D5
Left Hemianopia	D6
Aphasia	D7
Right Hemianesthesia	D8
Dysphagia	D9
Quadruplegia	D10

TABLE 3: Output Classification

4. RESULTS AND DISCUSSION

The Data have been analyzed using Neuro-intelligence tool [17].During analysis, the column type is identified. During data analysis, the last column is considered as the target one and other columns will be considered as input columns. The dataset is divided in to training set, validation set and test set.

Sl.No	**Data Partition set**	**Records**	**Percentage**
1.	Training set	34	68%
2.	Validation set	8	16%
3.	Test set	8	16%
4.	Ignored set	0	0%
	Total	50	100%

TABLE 4: Data Partition Set

Training a neural network is the process of setting the best weights on the inputs of each of the units. The goal is to use the training set to produce weights where the output of the network is as close to the desired output as possible for as many of the examples in the training set as possible. Also it has been proved that Genetic Algorithm and Back-Propagation neural network hybrids in selecting the input features for the neural network reveals the performance of ANN can be improved by selecting good combination of input variables [18]. The training set is a part of the input dataset used for neural network training, i.e. for adjustment of network weights**.** The validation set is a part of the data are used to tune network topology or network parameters other than weights. For example, it is used to define the number of units of to detect the moment when the neural network performance started hidden to deteriorate. To choose the best network (i.e. by changing the number of units in the hidden layer) the validation set is used. The test set is a part of the input data set used to test how well the neural network will perform on new data. The test set is used after the network is ready (trained), to test what errors will occur during future network application. This set is not used during training and thus can be considered as consisting of new data entered by the user for the neural network application.

Figure 2 shows the various data set errors with respect to training set, validation set and the best network. After training through repeated iterations it reaches the level of best network.

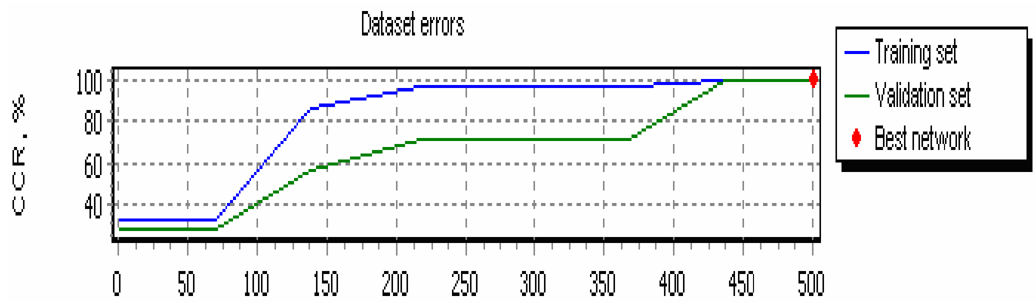

FIGURE 2: Data Set Errors

In the diagnosis of stroke , it is not always possible to make a clear-cut determination of disease, because of variability in the diagnostic criteria, age at onset, and differential presentation of disease. Mapping such diseases is greatly simplified if the data present a homogeneous genetic trait and if disease status can be reliably determined. Here, we present an approach to determination of disease status, using methods of artificial neural-network analysis. The Network errors have been shown graphically in figure 3. After 150 iterations, the network error has been decreased and from 300 iterations it is almost 0.

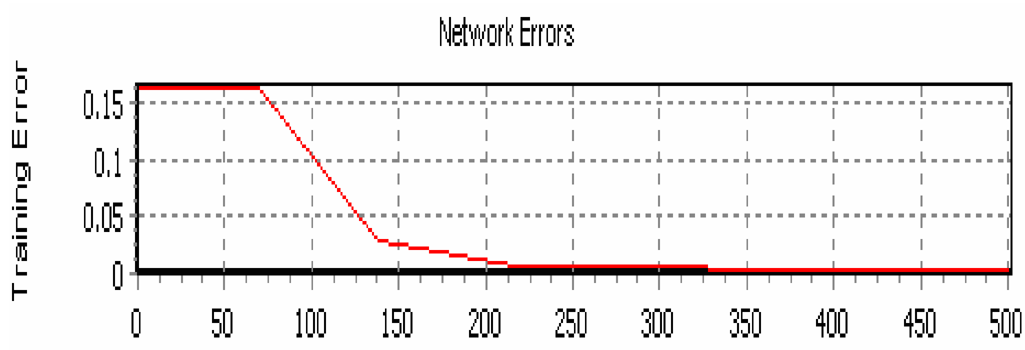

FIGURE 3: Network Errors vs. Training Error

The trained network has been tested with a test set, in which the outcomes are known but not provided to the network, to see how well the training has worked.. We used diagnostic criteria and disease status to train a neural network to classify individuals as "affected" by several categories of stroke as given below .

The analysis shows clearly that 32% of the respondents have the symptoms of Left Hemiplegia; 14% each have the symptoms of TIA and Right Hemiplegia respectively; 10% of the patients have the symptoms of Dysphasia and 6% are suffering from Monoplegia. 8% each have the symptoms of Left Hemianopia and Aphasia. In the meantime, 4% have the symptoms of Right Hemianesthesia. 2% each have the symptoms of Dysphagia and Quadruplegia respectively and is diagrammatically depicted in figure 4.

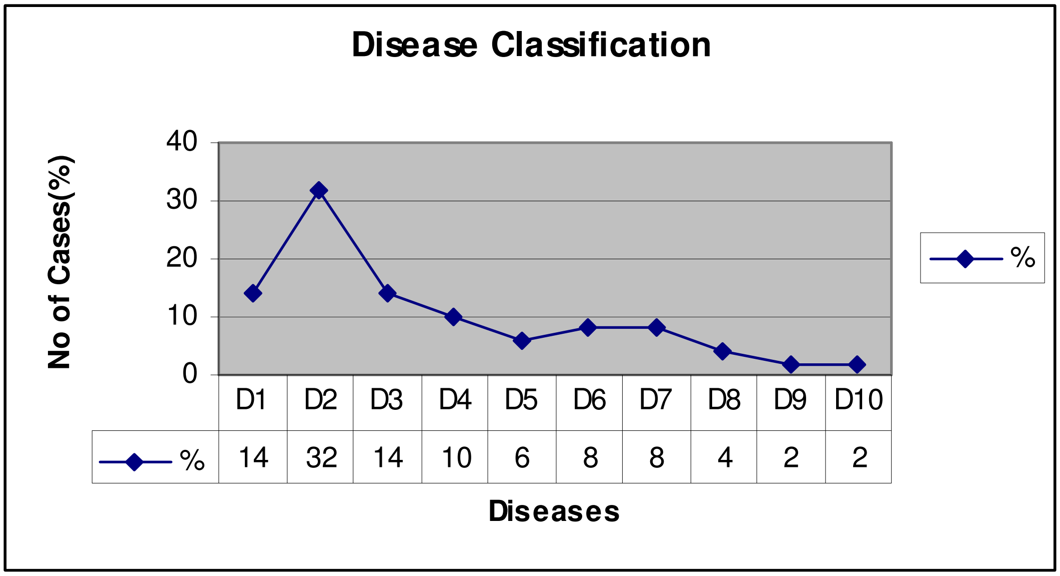

FIGURE 4: Various Stroke Diseases vs. Number of Cases

5. CONCLUSION

Neural networks have been proposed as useful tools in decision making in a variety of medical applications. Neural networks will never replace human experts but they can help in screening and can be used by experts to double-check their diagnosis. In general, results of disease classification or prediction task are true only with a certain probability. This work described here shows that the prediction of risk from stroke gives best results on the dataset used. The results generated by this system have been verified with the physicians and are found correct. This ANN model helps the doctors to plan for a better medication and provide the patient with early diagnosis as it performs reasonably well even without retraining. In conclusion, when the ANN was trained and tested after optimizing the input parameters, the overall predictive accuracy obtained was 89%.

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