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Performance Evaluation of Hybrid Supervised and Unsupervised Neural Model for Abnormal Tumor Classification in Brain MR Images

D. Jude Hemanth[1], D. Selvathi[2], S. Thamarai Selvi[3]

[1]*Karunya University, Coimbatore, India*

[2]*Mepco Schlenk Engineering College, Sivakasi, India*

[3]*Madras Institute of Technology, Anna University, Chennai, India*

Supervised and unsupervised artificial neural networks have been successfully used for image classification in biomedical applications. Supervised neural networks yield accurate classification results though the computational speed is low. On the contrary, unsupervised neural networks are comparatively faster than supervised networks besides yielding inferior classification accuracy. In this paper, a modified hybrid neural network, namely training free counter propagation neural network (TFCPN) has been proposed for abnormal tumor classification in brain magnetic resonance (MR) images which possess the benefits of both the learning paradigms. The classes of interest are four brain tumor types namely meningioma, astrocytoma. metastase and glioma. A comprehensive feature vector is chosen to discriminate these classes. Classification of brain tumor images is generally in agreement with the expert interpretation of these images. The performance measures of the training free counter propagation network (TFCPN) are compared with the back propagation network (BPN) and the kohonen self organizing map, selected as the representative type for supervised and unsupervised neural networks. Experimental results reveal the superior nature of the hybrid neural network in terms of classification accuracy and convergence rate.

Keywords: *MRI, Classification, TFCPN, BPN, Kohonen Self Organizing Map*

1. INTRODUCTION

Modern medical imaging technology such as (MRI) [1] has given physicians a non-invasive means to visualize internal anatomical structures and diagnose a variety of diseases. Compared to other techniques, MRI has superior soft tissue differentiation, high spatial resolution and contrast and does not use ionizing radiation [2]. MR images are typically interpreted visually and quantitatively by radiologists. The need for quantitative information is becoming increasingly important in clinical and surgical environment. Brain tumors are the leading cause of cancer death among humans [3].Hence early detection and correct treatment based on accurate diagnosis are important steps to avoid any fatal results.

Classification is the grouping of tumors on the basis of their characteristics [4]. Classification of brain MR images has important research and clinical applications. Classified brain can provide an anatomical framework for functional visualization, which has emerged as a promising approach in neuroscience research and in neurosurgical planning. .Brain classification methods can be broadly categorized as manual methods and computer-aided semi automated or automated methods. In recent years, computer-aided classification methods have been developed at a rapid pace to overcome the disadvantages of the manual classification methods. These methods are more automatic, objective and the results are highly reproducible. Various computational algorithms, ranging from semi automated (requiring user interactions) to fully automated have been developed. An important application of classification is in detecting the type of the tumor as it responds to treatment. Therefore an automatic and reliable method for classifying tumor would be a useful tool. Many efforts have exploited MRI's multi-dimensional data capability through multi-spectral analysis for brain tumor classification. Brain tumor classification has been performed using long echo proton MRS signals [5]. The major limitation is the limited number of available spectra for the tumor types which results in inferior classification accuracy [5]. Brain tumor classification has also been implemented using wavelets [6]. But the major drawback is the low convergence rate. Expectation-maximization techniques are also used for brain tumor classification [7]. But the major limitation is the requirement of a spatial probabilistic atlas that contains expert prior knowledge about the brain structures.

Statistical classifiers, Probabilistic classifiers, Artificial Neural Networks (ANN) are some of the widely used image classifiers [8]. The major drawback of the statistical classifiers is its inability to classify accurately. On the other hand, probabilistic classifiers suffer from the setback of difficulty in estimating the conditional probabilities. But ANNs outperform the other classifiers because of its flexibility, scalability, tolerance to faults, accuracy, learning [9].

In general, artificial neural networks are composed of many non-linear computational elements operating in parallel and arranged in patterns reminiscent of biological neural nets. There exists two modes of training for neural networks-supervised and unsupervised. The various training algorithms of ANN are proposed in [10, 11]. A number of designs have been proposed .One among them is the MAXNET scheme [12] which is a simple network used to find node with largest initial input value. But it suffers from the disadvantage of non-flexibility. The clustering Kohonen layer [13] which follows the unsupervised algorithm is also widely used for classification. But it is less accurate in classification problems. On the other hand, Counter propagation networks [11] enjoy the advantages of both supervised and unsupervised paradigms but it is computationally heavy. The feed-forward multilayer back propagation network has been widely used for supervised image classification and Kohonen network has been widely used for unsupervised image classification.

Earlier researchers have suggested many interesting findings with the supervised and unsupervised neural networks. Arora and Foody [14] concluded that the supervised neural networks would produce the most accurate classification results. E. Hosseini Aria, J. Amini, M.R.Saradjian [15] revealed the high convergence rate of the back propagation neural network for image classification. P. H. Mahonen and p. J. Hakalal [16] concluded that kohonen networks are fast and robust than the supervised neural networks. Kidong Lee, David Booth and Pervaiz Alam [17] show the inferior nature of kohonen networks in terms of classification accuracy.

Thus, it is evident that the conventional techniques suffer from the disadvantage of either inaccuracy or low convergence rate. So, there is a necessity for a technique which yields high classification accuracy at a high convergence rate. In this paper, the use of training-free counter propagation network [18] which possesses the advantages of both supervised learning and unsupervised learning has been explored. Since, this technique is devoid of training, high classification accuracy can be achieved at high convergence rate. Twelve textural features are extracted from each of the images. Classification of the brain tumor images has been performed with the training-free counter propagation network and the results are compared with the performance measures of back propagation network and kohonen self organizing map. TFCPN shows optimal results in terms of classification accuracy and convergence rate.

2. PROPOSED METHODOLOGY.

This research paper proposes an efficient methodology for classification of brain tumor images. In this method, different features are extracted from the images (provided by radiologist) and given as inputs to the neural network for classification. Classification is performed using training-free counter propagation network, back propagation network and Kohonen self-organizing map. The performance measures of these three techniques are analyzed and compared. The proposed technique for image classification is shown in Figure 1.

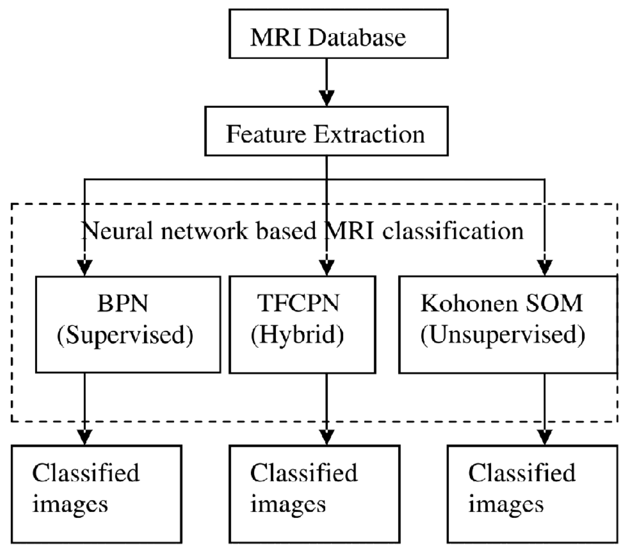

Figure 1: Proposed Methodology

The proposed method comprises of the following stages viz. MRI database (provided by radiologist), feature extraction and neural based MRI classification.

2.1. MRI Database

A set of MR brain tumor images comprising of the four tumor types namely meningioma, astrocytoma, glioma and metastase are collected from radiologists. The images used are 256*256 gray level images with intensity value ranges from (0 to 255). Initially, these MRI images are normalized to gray level values from (0 to 1) and the features are extracted from the normalized images. Since normalization reduces the dynamic range of the intensity values, feature extraction is made much simpler. Some samples of the MRI database have been displayed in Figure 2.

2.2. Feature Extraction

The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another pattern [19]. The extracted feature should provide the characteristics of the input type to the classifier by considering the

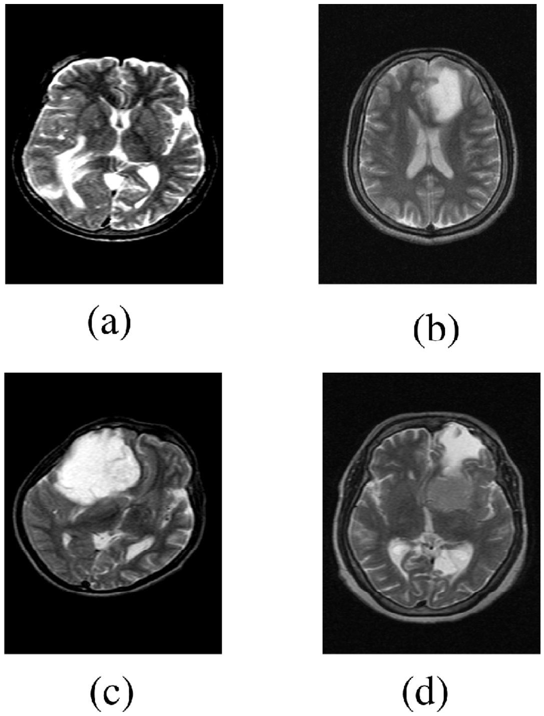

Figure 2: Sample data set: (a) Metastase (b) Glioma (c) Astrocytoma (d) Meningioma

description of the relevant properties of the image into a feature space. Twelve features based on the first order histogram and the gray level co-occurrence matrices (GLCM) have been used in this work

2.2.1. Features Based On First Order Histogram

The various features such as mean, standard deviation, skew ness, kurtosis, energy and entropy based on the first order histogram are computed using the formulae given next.

The first order histogram estimate of $p(b)$ is simply

$$P(b) = \frac{N(b)}{M} \tag{1}$$

where $b = a$ gray level in the image

M = total number of pixels in a neighborhood window centered about an expected pixel.

$N(b)$ = the number of pixels of gray value b in the same window that $0 \le b \le L$-1.

Then the following measures have been extracted by using first order probability distribution.

Mean:

$$S_M = \bar{b} = \sum_{b=0}^{L-1} bp(b) \tag{2}$$

Standard deviation:

$$S_D = \sigma_b = \left[\sum_{b=0}^{L-1} \left(b - \bar{b}\right)^2 p(b)\right]^{1/2} \tag{3}$$

Skewness:

$$S_S = \frac{1}{\sigma_b^3} \sum_{b=0}^{L-1} \left(b - \bar{b}\right)^3 p(b) \tag{4}$$

Kurtosis:

$$S_K = \frac{1}{\sigma_b^4} \sum_{b=0}^{L-1} \left(b - \bar{b}\right)^4 p(b) - 3 \tag{5}$$

Energy:

$$S_N = \sum_{b=0}^{L-1} \left[p(b)\right]^2 \tag{6}$$

Entropy:

$$S_E = -\sum_{b=0}^{L-1} p(b) \log_2 \left\{p(b)\right\} \tag{7}$$

2.2.2. Features Based On Gray Level Co-Occurrence Matrices

Spatial gray level co-occurrence estimates image properties related to second-order statistics. Haarlick [20] suggested the use of gray level co-occurrence matrices (GLCM) which have become one of the most well-known and widely used texture features. GLCM $\{P_{(d,\theta)}\ (i, j)\}$ represents the probability of occurrence of a pair of gray-levels (i, j) separated by a given distance d at angle θ. The commonly used unit pixel distances and the angles are 0°, 45°, 90° and 135°.A detailed algorithm of calculation of GLCM $\{P_{(d,\theta)}\ (i, j)\}$ has been given in [21].

Notations:

$$p_x(i) = \sum_{j=1}^{N_g} p(i, j)\ ; \quad p_y(j) = \sum_{i=1}^{N_g} p(i, j) \tag{8}$$

$$p_{x+y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j), k = 2,3.......2N_g ; i + j = k \tag{9}$$

$$p_{x-y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j), k = 0,1........N_g - 1; |i - j| = k \tag{10}$$

$p(i, j)$ = gray level co-occurrence matrix.

The features such as contrast, inverse difference moment, correlation, variance, sum average and difference entropy are calculated using the formulae given below.

Contrast:

$$S_C = \sum_i \sum_j (i - j)^2 P(i, j) \tag{11}$$

Inverse difference moment:

$$S_I = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j) \tag{12}$$

Correlation:

$$S_O = \frac{\sum_i \sum_j (ij)\, p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (13)$$

where μ_x, μ_y, σ_x, σ_y are the means and standard deviations of p_x and p_y.

Variance:

$$S_V = \sum_i \sum_j (i-\mu)^2 p(i,j) \quad (14)$$

Sum average:

$$S_A = \sum_{i=2}^{2N_g} i p_{x+y}(i) \quad (15)$$

Difference entropy:

$$S_F = -\sum_{i=0}^{N_g-1} p_{x-y}(i) \log\{p_{x-y}(i)\} \quad (16)$$

The features used in this paper are selected based on the previous works [20, 22]. These features work well especially for MRI brain tumor images.

2.3 Training Free Counter Propagation Neural Network based Classification

In this work, a modified counter propagation neural network [18] namely training free counter propagation neural network (TFCPN) is proposed for MRI brain tumor classification. TFCPN possess the advantages of both the supervised and unsupervised neural networks. The performance measures of TFCPN are further compared with the Back propagation network and Kohonen network to show its superior nature over the supervised and unsupervised neural networks.

Counter propagation neural networks [11] that belong to the category of hybrid neural networks, function as statistically optimal self programming look up table. The weight adjustment criterion between the input and the competition layer follows the Kohonen unsupervised learning rule and weight adjustment between the competition and the output layer follows the supervised learning rule. Though it possesses the benefits of both the learning paradigms, the convergence time period can be further reduced by modifying the weight adjustment criterion. This modified counter propagation network namely, TFCPN guarantees high convergence rate.

In supervised and unsupervised neural networks like BPN and Kohonen, the weight adjustment process occurs across all connection weights for given learning coefficients. Also, a large number of iterations are required for the connection weights for stability. For each training instance, a new set of connection weights minimizing the system error must be calculated. Moreover, the stabilized weights do not guarantee a global minimum for the system error. But, in TFCPN, when the number of neurons in the competition layer is equal to the number of training sets, no weight adjustment of the network is necessary. The weights between the input layer and the competition layer will be equal to the input and the weights of the link between the competition layer and the output layer will be the desired output. Since, TFCPN is devoid of training, the convergence time period is highly reduced. Thus, TFCPN function essentially as a partial self-organizing look-up table and is taught in response to a set of "illustrations" with the help of a "recording algorithm" rather than through "training examples" with the help of "learning algorithm".

2.3.1. Network Design

A TFCPN consists of three layers: the input layer, the competition layer and the output layer. Given the input training set $(\overline{X}_i, \overline{Y}_i)$ $i = 1, 2......N$, where $\overline{X}_i = (x_{i1}, x_{i2}......x_{in})$ and $\overline{Y}_i = (y_{i1}, y_{i2}.....y_{in})$, the configuration of the network is as follows: number of neurons in the input layer = *n*, number of neurons in the competition layer = *N*, number of neurons in the output layer = *p*.

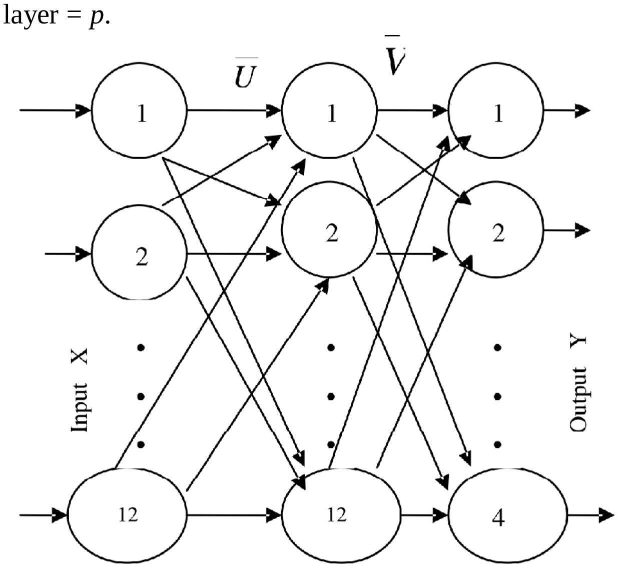

Figure 3: Topology of TFCPN

Figure 3 shows the topology of TFCPN. The number of neurons in the competition layer is equal to the training set and hence architecture of 12-12-4 is used for TFCPN in this work.

2.3.2. Training Algorithm

The learning algorithm proceeds in two steps. In the first step, each component of the training instance $\overline{X}_i$ is presented to the input layer. Let U_{ij} is the arbitrary initial weights vector assigned to the links connecting input node i with the competition node j and V_{jq} be the arbitrary weights vector assigned to the links connecting competition node j and output node q. The transfer function of the competition layer is defined by the Euclidean distance d_j between the weight vector $\bar{U}_j$ and the input vector $\bar{X}_k$ as

$$d_j = \left\|\bar{U}_j - \bar{X}_k\right\| = 1/2\left(\sum_i \left(U_{ij} - X_{ki}\right)^2\right)^{1/2} \; ....j = 1, 2\ldots N \tag{17}$$

For each $\bar{X}_k$, each node in the competition layer competes with the other nodes, and the node with the shortest Euclidean distance wins. The output of the winning node is set to 1 and the rest to 0. Thus, the output of the j[th] node in the competition layer is

$$Z_j = 1.0 \text{ if } d_j < d_i,$$
$$Z_j = 0.0 \text{ .... Otherwise} \tag{18}$$

The weight adjustment between the input and the competition layer selects the weight vector $\bar{U}_m$ such that

$$\left\|\bar{X} - \bar{U}_m\right\| = \min\left\{\left\|\bar{X} - \bar{U}\right\|\right\}_j$$
$$j = 1, 2\ldots\ldots\ldots N \tag{19}$$

Here, $\bar{U}_m$ indicates the associated weights of the winning neurons that are closest approximations to the input $\bar{X}$. Now we obtain the minimum value for the right hand side of Equation (19) when

$$\left\|\bar{X} - \bar{U}_m\right\| = 0$$

i.e.,
$$\bar{X} = \bar{U}_m \tag{20}$$

Similarly for the weight adjustments between the competition layer j and the output layer q, the weight vector $\overline{V_m}$ is selected such that

$$\left\|\bar{Y} - \bar{V}_m\right\| = \min\left\{\left\|\bar{Y} - \bar{V}\right\|\right\}_q \tag{21}$$
$$q = 1, 2\ldots..p.$$

Here, $\bar{V}_m$ indicates the associated weights of the winning neurons that are closest approximations to the input $\bar{Y}$. Now we obtain the minimum value for the right hand side of Equation (21) when

$$\bar{V}_m = \bar{Y} \tag{22}$$

Thus the weight vectors U_{ij} and V_{jq} are calculated without any training algorithm. Now, whenever an input is supplied to the input layer, the same procedure is followed to calculate the weight vectors and the output is calculated using the formula

$$y_{kq}{}^t = \sum_{j=1}^{N} V_{jq} Z_j \tag{23}$$

Since $Z_j = 1$ for the winner neuron, only one neuron yield an output value of 1. Each output neuron corresponds to a class and hence the input image belongs to the class for which the corresponding neuron yields a value of 1.

3. SUPERVISED AND UNSUPERVISED NEURAL NETWORKS BASED CLASSIFICATION

3.1. Back Propagation Neural Network (BPN)

Back propagation network [9] is the primarily used supervised artificial neural network. Prior to training, the selection of architecture plays a vital role in determining the classification accuracy.

3.1.1. Network Design

In this work, a three layer network is developed. An input vector and the corresponding desired output are considered first. The input is propagated forward through the network to compute the output vector. The output vector is compared with the desired output, and the errors are determined. The errors are then propagated back through the network from the output to input layer. The process is repeated until the errors being minimized. The input layer of network contains 6 neurons, corresponding to 6 features of each MR image. The output layer contains 4 neurons corresponding to 4 predefined tumor categories in the classification. When designing a neural network, one crucial and difficult step is determining the number of neurons in the hidden layers [23]. The hidden layer is responsible for internal representation of the data and the information transformation input and output layers. If there are too few neurons in the hidden layer, the network may not contain sufficient degrees of freedom to form a representation. If too many neurons are defined, the network might become over trained [24]. Therefore, an optimum design for the number of neurons in the hidden layer is required. In this research, we used one hidden layer with a number of different neurons to determine the suitable network. Table 1 shows the error of network for four cases.

Initially, images from all the four classes are used to train the BPN with 5 neurons in the hidden layer. The network is trained with few images from each class and the rest are used for the testing phase. The number of misclassifications in each class is observed individually and the classification error in percent is calculated. This procedure is repeated with different neurons (5 to 20) in

Table 1
Four networks with different neurons 'n' in hidden layer

Class	*Training data*	*Error (per cent)*			
		(a) $n = 5$	*(b)* $n = 10$	*(c)* $n = 15$	*(d)* $n = 20$
Metastas	40	8.28	9.12	2.05	7.17
Astrocytoma	40	0.25	0.37	0.07	1.15
Glioma	40	12.4	9.48	3.1	9.89
Meningioma	40	1.34	1.37	0.04	0.98
Average		5.56	5.05	1.31	4.8

the hidden layer of the BPN. The average error value for all the classes with different neurons in the hidden layer is calculated. The error values for BPN with 5,10,15,20 hidden neurons are shown in table 1. As seen in table 1, a network with 15 neurons in hidden layer have the minimum error, so it is the best case for designing network in this case. Thus architecture of 6-15-4 for the BPN is used in this work.

3.1.2. Training Algorithm

There are several training algorithms for feed forward networks. All these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. The gradient is determined using a technique called back propagation, which involves performing computational backwards through the network. The simplest implementation of back propagation learning adjusts the network weights in the direction in which the performance function decreases more rapidly. The algorithm used in this work is extracted from [25].

3.2. Kohonen Self-organizing Map

One type of the unsupervised neural networks, which posses the self-organizing property, is called kohonen self-organizing map [9]. Similar to statistical clustering algorithms, these kohonen networks are able to find the natural groupings from the training data set. As the training algorithm follows the "winner take-all" principle, these networks are also called as competitive learning networks.

3.2.1. Network Design

The topology of the Kohonen self-organizing map is represented as a 2-Dimensional, one-layered output neural net. Each input node is connected to each output node. The dimension of the training patterns determines the number of input nodes. There is no particular geometrical relationship between the output nodes in the competitive learning networks. During the process of training, the input patterns are fed into the network sequentially. Output nodes represent the 'trained' classes and the center of each class is stored in the connection weights between input and output nodes. The architecture used in this work is 6-4.

3.2.2. Training Algorithm

The kohonen self-organizing map uses the competitive learning rule for training the network. It uses the "winner-take all" principle in which a winner neuron is selected based on the performance metrics. The weight adjustment is performed only for the winner neuron and the weights of all other neurons remain unchanged. A detailed training algorithm has been furnished in [26].

4. IMPLEMENTATION

The MR slices were acquired on a 0.2 Tesla, Siemens–magnetom CONCERTO MR Scanner (Siemens, AG Medical Solutions, Erlangen, Germany) from Devaki MRI and CT scans Madurai, INDIA. The scan image was taken with axial, 2D, 5mm thick slice, with a slice gap of 2mm, with 246*512 acquisition matrix and with the field of view of 250mm.The T2 (TR/TE of 4400/ 118ms) and T2-FLAIR (TR/TE of 6160/89ms) weighted images were collected using Turbo Spin Echo (TSE) sequences. In this study, 374 abnormal images from four different classes are used. The data set used for this classification problem is as shown in Table 2.

Table 2
Data set for brain tumor classification

Tumor type	*Training data*	*Testing data*	*No. of images/ class*
Meningioma	31	71	102
Astrocytoma	31	51	82
Metastase	31	65	96
Glioma	31	63	94
Total abnormal images		374	

The textural features are extracted from each slice and then these features are given as inputs to the classifier. Twelve features based on first order histogram and the gray level co-occurrence matrices are used in this work. The classification is then performed using BPN, TFCPN and Kohonen network and their performance measures are analyzed.

The experiments are carried out on an IBM PC Pentium with processor speed 700 MHz and 256 MB RAM. The software used for the implementation is MATLAB (version 7.0) [27], developed by Math works Laboratory.

5. RESULTS AND DISCUSSIONS

In the following, the classification performance of the three classifiers is reported. The performance criterion used in this work is the classification accuracy and the convergence rate. Initially, the binary classification of the brain tumors is carried out with the classifiers. The classification accuracy of the three classifiers for the binary classification is as shown in Table 3.

Table 3
Classification accuracy for binary classification of the classifiers

Classes	*BPN*	*TFCPN*	*Kohonen Network*
Meningioma vs. Astrocytoma	93.33%	92.66%	69.54 %
Meningioma vs.Metastas	94.55%	94.55%	72%
Meningioma vs.Glioma	88%	89%	73.66%
Astrocytoma vs.Metastas	94.66%	91.2%	72.66%
Astrocytoma vs.Glioma	85.54%	82.2%	69.55%
Metastase vs.Glioma	90.66%	89.5%	76%

The binary classification is performed using all the three networks with two neurons in the output layer. Since there is high correlation between the astrocytoma and the glioma images, the neural networks find the classification process very difficult which results in inferior results. On the contrary, the correlation between metastas and meningioma images are very less which results in high classification accuracy. Thus there is an inconsistency among the classifiers in classifying the images. This analysis has been performed to show that the Kohonen neural network yields inferior results even for two input cases. From the above table, the inferior nature of the unsupervised neural networks in terms of accuracy is proved.The classification accuracy is also calculated for the multiclass classification of the brain tumors. Table 4 shows the classification accuracy of the three classifiers in the multiclass approach.

Table 4
Classification accuracy for multiclass classification of the classifiers

Classes	*BPN*	*TFCPN*	*Kohonen Network*
Meningioma vs. Astrocytoma vs. Metastas vs.Glioma	86.54%	85.66%	72.54%

In the multiclass classification, quantitative analysis is performed with four neurons in the output layer. The overall classification accuracy is less for multiclass classification because the probability of an image being successfully classified is less (only 25%).But in binary classification, the probability of an image being successfully classified is high (50%). The Kohonen neural network yields inferior results than the other two neural networks because it works in an unsupervised manner where no target vector is available for training. Thus from the above analysis, it is evident that Kohonen neural network is inferior to BPN and TFCPN in terms of classification accuracy. The performance of the classifiers in terms of successful and false classifications is illustrated in the confusion tables given below. Table 5 illustrates the performance analysis of the BPN.

Table 5
Successful and false classification analysis of BPN

	Class1	*Class 2*	*Class 3*	*Class 4*
Meningioma	64	4	2	1
Glioma	3	55	2	3
Astrocytoma	2	0	47	2
Metastase	2	5	4	54

In the above table, class 1 corresponds to meningioma, class 2 corresponds to glioma, class 3 corresponds to astrocytoma and class 4 corresponds to metastase. Among the 71 meningioma images, 64 images have been successfully classified and the remaining 7 images have been misclassified. Similarly, 55 images have been successfully classified in glioma, 47 images have been successfully classified in astrocytoma and 54 images have been successfully classified in metastse. From table 5, it is evident that the correct classification rate is high for back propagation network. Since BPN is trained in a supervised manner, the number of false classifications is very low. Table 6 illustrates the performance analysis of the Kohonen network.

Table 6
Successful and false classification analysis of Kohonen network

	Class 1	*Class 2*	*Class 3*	*Class 4*
Meningioma	52	9	5	5
Glioma	4	48	8	3
Astrocytoma	7	3	37	4
Metastase	5	9	7	44

In the above table, 52 images have been successfully classified in meningioma, 48 images have been successfully classified in glioma, 37 images have been successfully classified in astrocytoma and 44 images have been successfully classified in metastse. Table 6 illustrates the high misclassification rate in Kohonen network. As, it is trained without a target vector, the misclassification rate is high. Table 7 illustrates the performance analysis of the TFCPN network.

In the above table, 61 images have been successfully classified in meningioma, 54 images have been successfully classified in glioma, 44 images have been successfully classified in astrocytoma and 56 images have been successfully classified in metastse. Table 7 illustrates the high successful classification rate of TFCPN .The

Table 7
Successful and false classification analysis of TFCPN

	Class 1	*Class 2*	*Class 3*	*Class 4*
Meningioma	61	5	2	3
Glioma	3	54	4	2
Astrocytoma	4	1	44	2
Metastase	2	5	2	56

successful classification rate is equivalent to the back propagation network Thus from the above analysis, it is evident that Kohonen neural network is inferior to BPN and TFCPN in terms of classification accuracy.

The performance of the three classifiers is further analyzed on the basis of the convergence rate i.e., the training time and the testing time. Training time refers to the time required by the classifier to derive classification rules that will allow it to classify the images. Testing time refers to the time required by a trained classifier to classify the untrained images. The training time taken for the three classifiers is as shown in Figure 4.

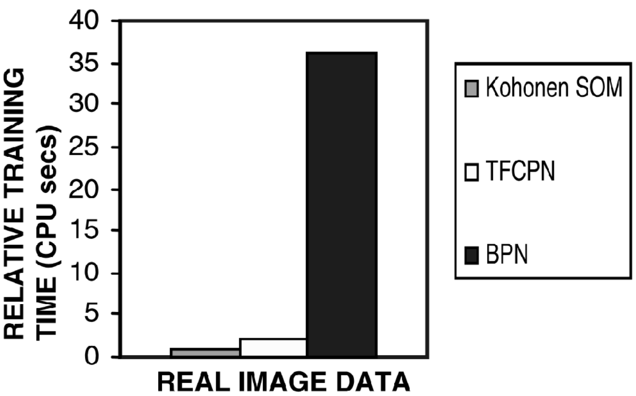

Figure 4: Comparison of training time of the classifiers

The training time period on the real MR image data are 0.9 CPU s for the kohonen network, 1.970 CPU s for the TFCPN and 36.150 CPU s for the BPN. The testing time taken for the three classifiers is as shown in Figure 5. The convergence rate of TFCPN is much faster then BPN and the Kohonen network because the weight adjustment technique is not required in TFCPN.

The testing time for the real MR image data are 0.015 CPU s for the kohonen network, 0.07 CPU s for the TFCPN and 0.315 CPU s for the BPN neural network. Since no weight adjustment is required, the testing time period is very low for the TFCPN.

The training time and the testing time for the BPN is very much higher than the time taken by the TFCPN and Kohonen network Thus from the above analysis, it is evident that BPN is inferior to TFCPN and Kohonen network in terms of convergence rate.

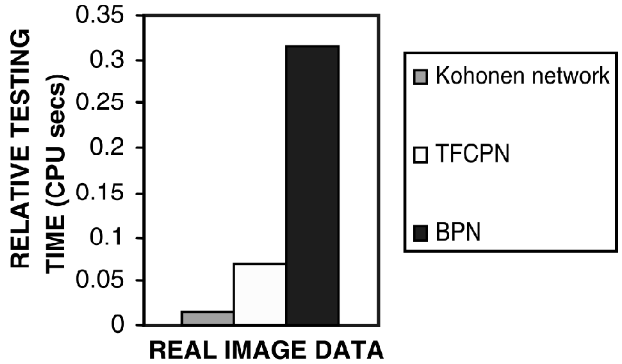

Figure 5: Comparison of testing time of the classifiers

6. CONCLUSION

Even though supervised neural networks guarantee high classification accuracy, they are computationally heavy. On the other hand, the unsupervised networks are faster but yields poor classification accuracy. But the hybrid neural network yields a comparable classification accuracy and convergence rate. Thus from the above results, it is evident that the hybrid neural network is the optimal neural model in terms of classification accuracy and convergence rate for MRI brain tumor classification.

This classification technique can also be extended for voxel-level description of the tissues. A comprehensive set of features derived from pixels of known class can be used as training sets and their corresponding classes are represented by the output layer neurons. The target vector is obtained by setting all desired outputs typically to zero except one output which represents the class of the input pixel. The above mentioned methodology of classification can be implemented by selecting equal number of hidden layer neurons and input features. This classification technique can also be implemented with a different set of features.

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