Classification of Hematomas in Brain CT Images using Neural Network

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Abstract—*Hematoma is common in traumatic brain injuries. An automatic detection and classification system helps doctors in analyzing the medical images. CT scan is the preferred method in traumatic brain injuries due to little cost, extensive availability, fast scanning and superior contrast. This paper deals with automated system to detect and classify the type of hematomas using artificial neural network algorithm for CT images of different patients. The methodology comprised of four phases, first preprocessing performed on the brain CT images, second histogram based centroids initialization for K-means clustering algorithm to segment the image in different clusters based on the intensity values of pixels. Third phase consists of features extraction from segmented image. In fourth phase, artificial neural network has been created and trained according to the features extracted from the image. Trained artificial neural network (ANN) classifies the types of hematoma according to their features.*

Keywords — Artificial Neural Network (ANN); CT scan; Hematoma; Histogram; K-Means Clustering; Segmentation;

I. INTRODUCTION

Brain Hematoma is caused due to a sudden injury in brain and blood leaks out from the blood vessels in the brain [1]. Brain Hematomas can be Epidural Hematoma (EDH), Subdural Hematoma (SDH) and Intracerebral Hematoma (ICH). All these hematomas are hyper dense in nature and brighter than the other brain tissue.EDH involve bleeding between the skull and the dura matter of the brain and has a biconvex shape while a SDH is in between dura and subarchnoid layer of the brain having a crescent shape.ICH on the other hand is a blood clot inside the brain having a circular shape and is very difficult to identify because it resembles with tumor.

Imaging is an essential tool of the medical science to visualize the anatomical structures of the human body. Medical image analysis for identification and classification is an important task for many applications [2]. There are various brain scanning techniques available which are used for extracting information by the radiologist. Computed tomography (CT) is a non invasive technique to give [3] images of each part of the human being body. CT scans use the radiation as X-rays which is detected by a series of sensors that feed information into a powerful computer. CT scan can show the structure of the brain, blood vessels, other tissues and any abnormality within the skull. CT scan is common imaging system in hospitals for head injured unconscious patients. CT scan, in comparison to the other techniques is preferred because of its extensive availability, little cost, fast scanning and superior contrast. With the help of computer-aided system detection of any kind of disease in brain is fast and useful for further processing and doctors may confirm their diagnosis.

The aim of the research is to develop a non-invasive diagnostic tool for the detection and classification of brain Hematomas. The system will be helpful for diagnosis and the treatment will be started earliest possible. The overall organization of the paper is as follows. After the introduction, section II discusses related and recent research. Section III describes methodology that comprises of four phases; preprocessing, segmentation, feature extraction and training of artificial neural network. In the next section IV we will explain experiments performed on data and will show and interpret the results of our method. Lastly, we conclude the paper and discuss the future work.

II. RELATED RESEARCH

Many researchers have been working to find out the suitable algorithm for identifying hematomas of brain images in the past three decades. A prominent work in this area was contra-lateral symmetry based algorithm to detect stroke in CT scan images volume [4].

A similar method was also proposed using symmetry and skull region extraction by means of a thresholding technique slice by slice. This approach, detects mid line according to the skull contour [5]. Another noted accomplishment in this area is a rule-based approach of lesion analysis from CT brain images [6]. The method is composed of automatic determination of head symmetry axis and calculation is based on moments.

The mid line detection approach fails if the image is not symmetric. This happens when the trauma is too severe or due to patient's movement. A different method for automated segmentation of CT images of brain [7] uses images enhancement and genetic algorithm (GA) to segment the image. Several methods based on multi-resolution thresholding [8], region-growing [9], atlas based models [10], artificial neural networks (ANN) and expert system [11] that diagnoses the intracranial hematomas by combining machine vision and knowledge discovery technique have also been proposed. Many generations of medical image analysis [12] were purported and many software tools are presented with some strengths and

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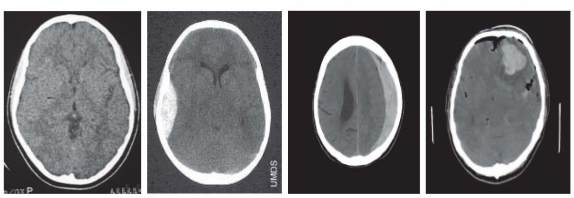
weaknesses but no single method is sufficient. Even though a lot of research on abnormalities detection in brain images like edema, contusion, tumor, hematoma, etc has been done, still there is room for further research due to the low accuracy level in the current methods. Another thing is that simply using one technique cannot solve the problem and does not give the fully automatic method for detection and classification. So the hybrid methods that combine the strengths of different methods are needed to solve the problem. Here we developed automated detection and classification system that combines the strengths of different methods to solve the problem that is robust towards image rotation and works on images with different resolutions.

III. METHODOLOGY

This paper proposes a fully automatic method to identify and classify the types of hematomas from 2D brain CT scan images. Fig.1. shows normal brain CT image and three types of hematoma i.e. Epidural (EDH), Subdural (SDH) and Intracerebral (ICH) respectively.

Methodology is divided in four phases. In the first step preprocessing is performed on image to remove noise from the image. After that brain is extracted using morphological operators to remove the effects of artifacts in the next step. Second phase consists of segmenting the image automatically into regions by grouping them. This is done using histogram based threshold calculation and applying these thresholds as initial cluster centre and number of clusters to K-Means clustering algorithm.

Third phase is statistical, shape and texture based features extraction. These features are presented to neural network. Fourth and final phase, artificial neural network (multilayer perceptron model) has been created and trained according to the training samples presented to the system.



(a) Normal (b) EDH (c) SDH (d) ICH

Fig.1. Original CT scan image

A Preprocessing

Preprocessing is the initial step for extracting the region of interest from the brain CT images. Patient information and other marks should be removed so that small level of pixel details will not disturb the segmentation operation and gives high degree of accuracy and reliability. Here we propose a morphological operators (Erosion and Dilation) based algorithm to extract the brain portion [15].

Step 1. Load the original gray level brain image. Apply the median filtering to remove the noise. Select max pixel value in the image, as skull is having max pixel value or 255. Assign all maximum value pixels to 0.

Step 2. Convert image into black and white image using Otsu's thresholding method [16].

Step 3. Using greatest connected component, the region whose area is the biggest, is extracted. Erosion operation is performed on image to remove small disconnected objects.

Step 4. Fill the holes in the binary image using dilatation operation that eliminates all remaining black spots on the image. This resultant image is the mask of original image.

Step 5. The region of interest, brain, is extracted using the AND operator between the filtered image and the mask obtained in step 4 and this is Extracted image in which all artifacts are removed.

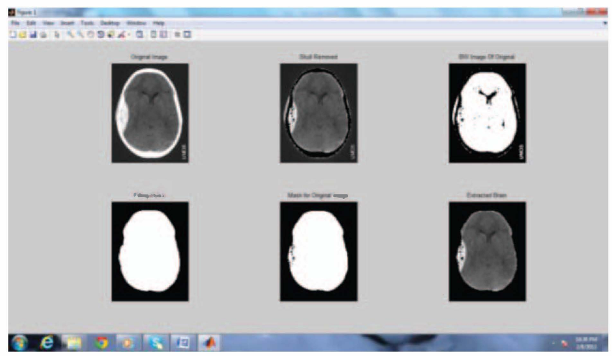


Fig.2. Result of algorithm

B. Automatic Segmentation

We used peak detection algorithm [17] to find peaks of image histogram. Exact number of peak value is chosen as initial count of clusters for K-Means clustering algorithm [18] and gray level value (thresholds) between the two adjacent peaks [19] are the initial centroids for those number of clusters K as shown in Fig 3. K-Means clustering algorithm assigns each pixel value to a particular group that has the closest centroid. When all pixels have been assigned a group, positions of the K centroids in each group is recalculated and the all steps are repeated until there are no changes in value of centroids of each group. This produces objects into different groups or clusters. The highest intensity value cluster is picked and this is the segmented region as shown in Fig. 4.

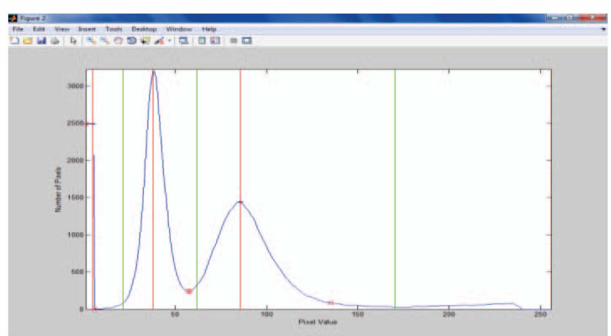


Fig.3. Peak of image histogram and threshold values in between two peaks

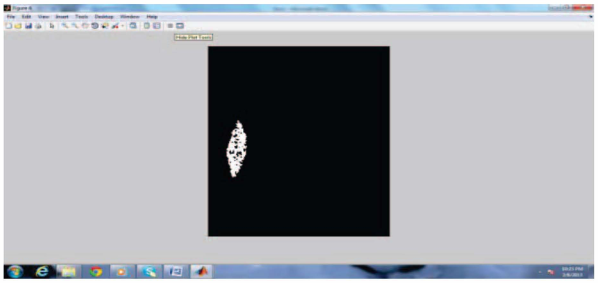


Fig.4. Segmented region of original image

C. *Feature Extraction*

Next step is extracting the features from the segmented image. Features are the characteristics of the objects that are used as inputs to the classifiers where they are assigned a class. The feature of an object actually distinguishes one input pattern from another pattern. We extracted the following features from segmented image.

1) *Shape Features*

The shape features gives the overall idea how the region looks like in general [20].

- Length of major axis of the fitting ellipse.
- Length of minor axis of the fitting ellipse.
- Circularity: $(4\pi\text{*area})/(\text{perimeter})^2$.
- Eccentricity: The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length.
- Solidity: Area of region/convex hull of region
- Extent: Area of region/ area of the bounding box.
- Ratio of minor axis to bounding box width.

2) *Intensity Feature*

Intensity based features are first order statistics depends only on individual pixel values of an image I.

- Mean is average value of an array

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_i \quad (2)$$

- Variance describing how far the numbers lie from the mean.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(I_i - \mu)^2 \quad (3)$$

- Skewness is a measure of the asymmetry of the data around the sample mean.

$$\text{Skewness} = \frac{\sum_{i=1}^{N}(I_i - \mu)^3}{(N-1)\sigma^3} \quad (4)$$

where μ is the mean, σ is the standard deviation; N is the number of data points.

- Kurtosis is a measure of how outlier-prone a distribution is.

$$\text{Kurtosis} = \frac{\sum_{i=1}^{N}(I_i - \mu)^4}{(N-1)\sigma^4} \quad (5)$$

where μ is the mean, σ is the standard deviation and N is the number of data points.

3) *Texture features*

These features are described more precisely as Gray Level Cooccurrence Matrix (GLCM) features i.e. occurrences of some gray-level values that can be described by a matrix of relative frequencies $P_{\theta,d}(i, j)$. It describes how frequently two pixels with gray-levels i and j appear in the window separated by a distance d in direction θ. Here P(i,j) is the $[i,j]^{th}$ entry in a gray-tone spatial dependence matrix.

All features obtained from GLCM are functions of the distance d and the orientation θ. If an image is rotated than the values of the features will be different. To make image rotation invariant, the resulting values for the four directions (for each d) are averaged out. Four co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal (0°, 45°, 90°, 135°). Fifth matrix is constructed as the average of all the four preceding matrices. This generates features that are rotation invariant. Texture Features extracted are [21]:

- Contrast measures local level variations in the image.

$$\text{Contrast}=\sum_{i,j}|i-j|^2 Log\, P(i-j) \quad (6)$$

- Inverse Difference Moment (Homogeneity) is a measure that takes high values for low-contrast images.

$$\text{Homogeneity}=\sum_{i,j}\frac{P(i,j)}{1+|i-j|} \quad (7)$$

- Angular Second Moment (ASM) measures the smoothness of the image.

$$\text{ASM}=\sum_{i,j} P(i,j)^2 \quad (8)$$

- Correlation Coefficient is a measure of how correlated a pixel is to its neighbor over the whole image.

$$\text{Corr.Coeff}=\sum_{i,j}\frac{(ij)P(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \quad (9)$$

where $\mu_x,\mu_y,\sigma_x,\sigma_y$ are the mean and standard deviation of p_x, p_y ,the partial probability density functions respectively.

- Entropy is a measure of randomness and takes low values for smooth images.

$$\text{Entropy}= -\sum_i \sum_j P(i,j)\log P(i,j) \qquad (10)$$

D. Classification

Organizing the data into different groups on the basis of their properties consists of training and testing phase. In training phase, properties of image called features are isolated and a unique description of each classification category is created. In testing phase, these features are used to classify images in categories. The accuracy of classification methods must be high because the diagnosis and treatment is based on this categorization.

An artificial neural network (ANN) is a computational model that is an effort to simulate the human brain [22]. ANN structure consists of highly interconnecting processing elements called, neurons that operates in parallel. A subgroup of processing elements in ANN forms a layer in the network. The input layer is the first layer and last layer is called output layer. Between the input and output layer, there may be additional layers called hidden layers. Fig. 5 shows the structure of neural network.

A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. 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 [23].

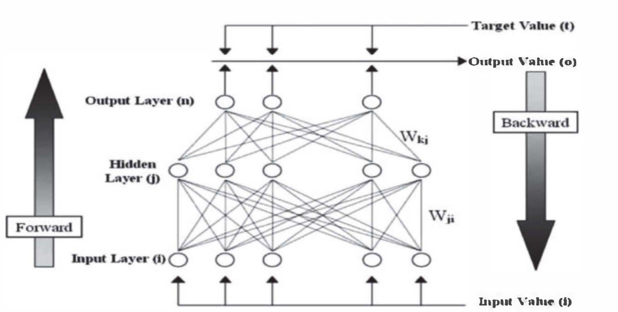


Fig.5. feed Forward neural network architecture with error back-propagation.

The nodes are connected such that each node is connected to all nodes of the previous and the successive layer. 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.

Back propagation algorithms have been commonly used for the training of ANN application consists of two passes, Forward pass in which the network is activated on one example and the error of output layer is computed. In backward pass, the network error is used for updating the weights. These weights are iteratively adjusted so that the overall error measure 'E' is minimized. This can be implemented by

$$\Delta W_{ji}(n+1) = \eta\,(\delta_{pj} O_{pi}) + \alpha\,\Delta W_{ji}(n) \qquad (11)$$

Where η is the learning rate, n is the number of iterations, α is the momentum and δ_{pj} is the error signal.

The network performance and convergence depends on many parameters like initial weights, learning rate, momentum used and number of nodes in the hidden layer during the training. All input connections are assigned a weight. The training of the network occurs through the many cycles of data patterns presented to the network. These cycles are called epochs or iterations. The data set is divided into a learning and validation set. Learning data set is used to train the network in supervised mode and validation data set is used to test the network performance.

IV EXPERIMENTAL RESULTS

The entire methods are implemented in MATLAB 7.9 on window 7. Computer configuration consists of 2.93 GHz CPU, 4 GB of RAM and 1GB graphics Card. The experiment data consists of 100 brain CT images. The images are of same quality but with different resolutions. The input images have hematoma of different types, having different shapes and at different locations. The input image is segmented into clusters of different intensities values. If it is a normal brain image the classification process stops and message is displayed but if it is an abnormal image process automatically selects the cluster of highest intensity value that depicts the hematoma region in the image.

We extracted 16 features per image, these 16 features are presented to MLP as input pattern and 3 output classes are generated for three types of hematoma ie. EDH,SDH and ICH. Fig. 6 shows the proposed network architecture and division of training, testing and validation samples set values. Transfer functions used is tan-sigmoid in both the hidden layer and output layer. 30 hidden neurons are used in hidden layer and learning parameter is set to 0.05 and max number of epoch is set to 1000.

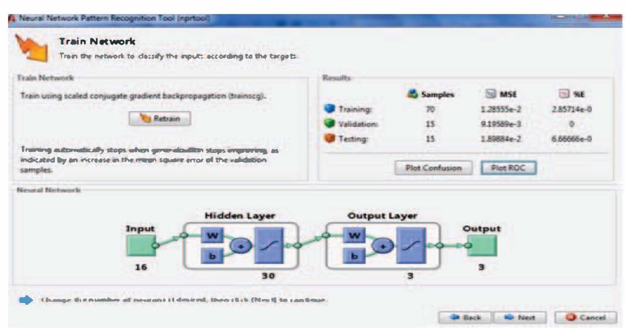


Fig.6.The proposed ANN architecture in matlab toolbox

The network is trained with 70% of sample size and samples are randomly divided into training, validation and testing sets. Scaled conjugate gradient back propagation algorithm was used to train the network that has fast convergence rate and takes small training time. Training automatically stops when generalization stops improving. Fig.7 shows the training network showing all training parameters and progress of training that stops at 44th epoch.

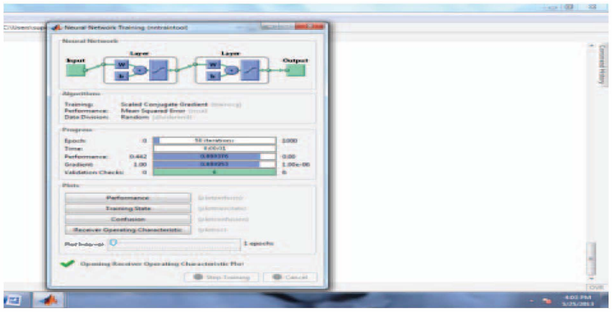


Fig.7. Neural network training window snapshot

Performance of the network was measured in terms of mean squared error. Fig.8 depicts the performance curves of training data sets with respect to number of epochs. Best validation performance is 0.0091959 at epoch 15.Training stop after 6 validation checks to avoid overfitting.

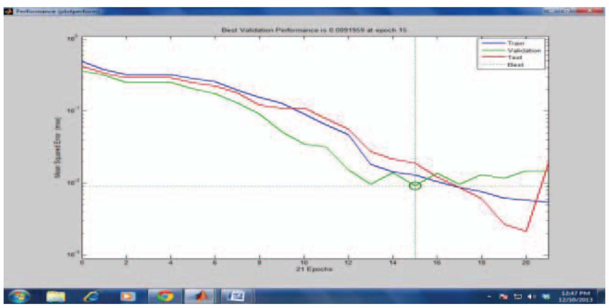


Fig.8. Performance curve of ANN

In Fig.9 all training, validation and testing confusion matrices are shown. The confusion matrix shows the percentages of correct and incorrect classifications. Correct classifications are the green squares on the matrices diagonal and incorrect classifications are shown in red squares. There is misclassification in two types during training, no misclassification during validation but one misclassification during testing. Training confusion matrix has 97.1% classification accuracy as shown in blue square. Testing confusion matrix has 93.3% classification accuracy as shown in blue square. Overall confusion matrix shows 97% classification accuracy that means three patterns are misclassified.

Fig.9. Confusion matrix

CONCLUSION & FUTURE WORK

The feed-forward back propagation neural network with supervised learning is proposed to detect and classify the hematoma in brain CT images. The input dataset (features) to train the artificial neural network are obtained from segmented CT scanned images. The results indicate that the system has an overall accuracy of 97% in classifying hematomas when evaluated against a specialist recommended medical referral decision. Directions for future work:

- Classification can be improved using different types of training algorithm.
- Classification can be improved by refining the features.
- Comparing MLP with other classifiers like RBF, SVM, Bayesian network and WEKA.
- Techniques for finding the location and exact size of hematomas using expert knowledge.
- Study of severity with aging of the hematomas such as chronic SDH.

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REFERENCES

[1] B. D. Chaurasia, Human Anatomy: Regional & Applied (Dissection & clinical) vol. 3: Head, Neck & Brain, CBS Publishers, 2008.

[2] Atam P. Dhawan, H. K. Huang, Dae Shik Kim, Principles and Advanced Methods in Medical Imaging and Image Analysis, World Scientific, 2008.

[3] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, 2nd ed., Beijing: Publishing House of Electronics Industry, 2007.

[4] Mayank Chawla, Saurabh Sharma, Jayanthi Sivaswamy, and L. T. Kishore, “A method for automatic detection and classification of stroke from brain CT images,” Annual International Conference of the IEEE, pp. 3581-3584. IEEE, 2009.

[5] T.Hara, N.Matoba, X.Zhou, S.Yokoi, H.Aizawa, H.Fujita, K.Sakashita and T.Matsuoka, “Automated detection of extradural and subdural hematoma for content-enhanced CT images in emergency medical care,” Proceeding of SPIE, 2007.

[6] W.L. Zhang, X. Z. Wang, “Extraction and classification for human brain CT images,” Proceedings of Sixth International Conference on Machine Learning and Cybernetics, IEEE 2007, pp. 1155-1156.

[7] R. Ganesan, S. Radhakrishnan, “Segmentation of computed tomography brain images using genetic algorithm,” International Journal of Soft Computing, 2009, pp.157-160.

[8] J. S. Duncan, N. Ayache, “Medical image analysis: progress over two decades and the challenges ahead,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2000, 22(1), pp. 85-106.

[9] R. M. Haralick, L. G. Shapiro, “Image segmentation techniques,” Computer Vision, Graphics and Image Processing, 1985, 29(1), 100-132.

[10] T. Chan, "Computer aided detection of small acute intracranial hemorrhage on computer tomography of brain," Computerized Medical Imaging and Graphics, 2007, 07(4-5), pp. 285-298.
[11] Tech, KV Ramana M, Raghu B. Korrapati, "Neural network based classification and diagnosis of brain hemorrhages," International Journal of Artificial Intelligent and Expert Systems (IJAE), 7.
[12] D. J. Withey, Z. J. Koles, "Medical image segmentation: methods and software," In Noninvasive Functional Source Imaging of the Brain and Heart and the International Conference on Functional Biomedical Imaging, 2007. NFSI-ICFBI 2007.
[13] S. M. Smith, "Fast robust automated brain extraction," Human Brain Mapping, 2002, 17: pp. 143-155.
[14] Bouchaib Cherradi, Omar Bouattane ,Mohamed Youssfi, Abdelhadi Raihani, "Brain Extraction and Fuzzy Tissue Segmentation in Cerebral 2D T1-Weigthed Magnetic Resonance Images," International Journal of Computer Sciences Issues, 2011,vol.8 issue 3.
[15] N. Otsu, "A Threshold selection method from gray level histograms," IEEE Transactions on System Man and Cybernetics, 1979, vol. 9, no. 1, pp. 62-66.
[16] D.L. Pham, C. Xu, J. L. Prince, "Current methods in medical image segmentation," Annual Review of Biomedical Engineering, 2000, vol. 2 no. 1, pp. 315-338.
[17] M. I. Sezan, "A Peak Detection algorithm and its application to histogram-based image data reduction," Computer Vision, Graphics and Image Processing, 1990, 49, pp. 36- 51.
[18] B. Sharma, K. Venugopalan, "Automatic segmemtation of brain CT scan images," International Journal of Computer Applications, vol. 40, no.10, February 2012.
[19] H. P. Ng, H. H. Ong, K.W.C. Foong, P. S. Goh, W. L. Nowinski, "Medical image segmentation using K-means clustering and improved watershed algorithm," IEEE Southwest Symposium on Image Analysis and Interpretation, 2006, pp. 61-65.
[20] Gong, R. Liu, C. L. Tan, N. Farzad, C. K. Lee, B. C.Pang, Q. Tian, S. Tang, and Z. Zhang, "Classification of CT brain images of head trauma," in Proceedings of the 2nd IAPR International Workshop on Pattern Recognition in Bioinformatics , 2007, pp. 401-408
[21] N. Aggarwal N, R. Aggrawal, "First and second order statistics features for classification of magnetic resonance brain images," Journal of Signal and Information Processing, 2012, vol. 3, no. 2, pp. 146-153.
[22] S. Haykin, Neural Network - A Comprehensive Foundation; a Computational Approach to Learning and Machine Intelligence, Macmillan, NY, 1994.
[23] T. Anita, B. Surekha, S.N. Mishra, "Early diagnosis of ischemia stroke using neural network," Proc. Int. Conf. Man-Machine System, 2009, (Batu Ferringhi, Penang 2009).