International Journal of Advanced Scientific Technologies ,Engineering and Management Sciences (IJASTEMS-ISSN: 2454-356X) Volume.3,Special Issue.1,March.2017

A NEW APPROACH FOR SEGMENTATION OF MEDICAL IMAGES BASED ON MLP CLASSIFIERS

***G.Sumana*[1], *G.Anjan Babu*[2]**

[1]SPMVV, Tirupati.[2]Professor, Department of Computer Science, S.V.University, Tirupati.

Abstract – Accurate segmentation of medical images is a key step in contouring during the most widely used radiographic techniques in diagnosis, clinical studies and treatment planning.The selection of a segmentation process depends on numerous considerations, specifically the nature of the image, the primitives to extort and the segmentation methods. In this paper a novel method is proposed based on MLP neuronal approach for the alternative of the segmentation method taking into account the nature of the input image. First, an assessment of the quality of segmentation by diverse methods and using a variety of criteria of valuation was conceded out. Then, a classification of images, based on a few objective parameters, was performed. The resulting descriptors will be used as input to the neuronal approach to correlate each type of image with the ample segmentation method after learning. We detail the results of the intelligent segmentation method selection obtained on dissimilar databases of medical images. The conversation of these encouraging results allowed us to progress our success rate and cover all varieties of images.

Index terms: Segmentation; criteria of valuation; descriptors; MLP-basis neuronal.

I.INTRODUCTION

Segmentation is the process dividing an image into regions with similar properties such as gray level, color, texture, brightness, and contrast. The role of segmentation is to subdivide the objects in an image; in case of medical image segmentation the aim is to:

1. Study anatomical structure
2. Identify Region of Interest i.e. locate tumor, lesion and other abnormalities
3. Measure tissue volume to measure growth of tumor (also decrease in size of tumor with treatment)
4. Help in treatment planning prior to radiation therapy; in radiation dose calculation

Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Further, the output of segmentation algorithm is affected due topartial volume effect.

1. intensity inhomogeneity
2. presence of artifacts
3. closeness in gray level of different soft tissue

The techniques available for segmentation of medical images are specific to application, imaging modality and type of body part to be studied. For example, requirements of brain segmentation are different from those of thorax. The artifacts, which affect the brain image, are different - partial volume effect is more prominent in brain while in the thorax region it is motion artifact which is more prominent. Thus while selecting a segmentation algorithm one is required to consider all these aspects. There is no universal algorithm for segmentation of every medical image. Each imaging system has its own specific limitations.

Although a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem. Different researchers have done the classification of segmentation techniques in one or another way. Keeping this in point o view we have done the classification of segmentation techniques on the basis of MLP neural classifier.

1.1 Types of segmentation

Segmentation is the most important part in image processing. Fence off an entire image into several parts which is something more meaningful and easier for further process. These several parts that are rejoined will cover the entire image. Segmentation may also depend on various features that are contained in the image. It may be either color or texture. Before denoising an image, it is segmented to recover the original image. The main motto of segmentation is to reduce the information for easy analysis.There are two types of segmentation:

1.1.1 Edge based segmentation

This is the most common method based on detection of edges i.e. boundaries which separate distinct regions. Edge detection method is based on marking of discontinuities in gray level, color etc., and often these edges represent boundaries between objects. This method divides an image on the basis of boundaries.

1.1.2 Region based methods

These methods are based on the principle of homogeneity - pixels with similar properties are clustered together to form a homogenous region. The criteria for homogeneity is most of the time gray level of pixels and this criteria can be specified by following conditions

$$R1 \cup .R2 \cup .R3 \cup ....\cup .Ri=I \quad (1.1)$$

Where R_1, R_2, R_3, ...R_i are the region in the image I,

$$R1 \cap R2 \cap R3 \cap ... \cap Ri=0 \quad (1.2)$$

II. IMAGE CLASSIFICATION

Image classification is a problem that has been around for a long time and has many real world applications. Police can use image recognition and classification to help identify suspects in security footage. Banks can use it to help sort out checks. More recently, Google has been using it in their self driving car program. Traditionally, a lot of different machine learning algorithms have been utilized for image classification; including template matching, support vector machines, kNN, and hidden Markov models. Image classification remains one of the most difficult problems in machine learning, even today. There is also a lot of research involving machine learning and artificial neural networks going on in industry.

2.1 Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). Fig.1 represents the typical neural network. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements

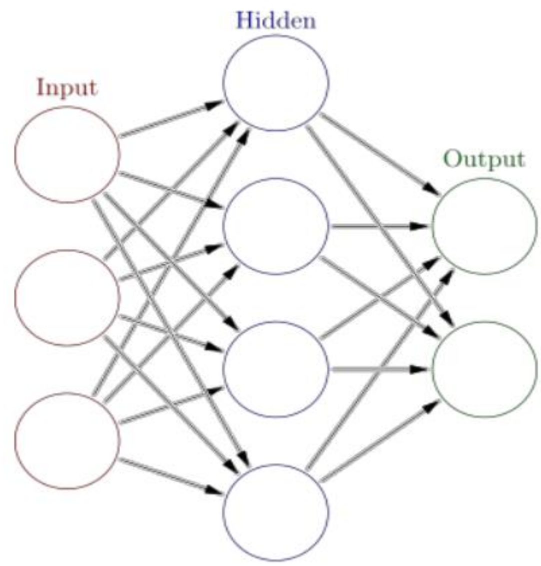

Fig.1. A typical neural network

Artificial Neural Network (ANN) is an informationprocessing Technique based on the way biological nervous systems, process information [19]. Artificial Neural networks came into existence as a result of simulation of biological nervous system, such as the brain on a computer. Neural networks are indicated as a group of nodes called neurons and connections between them. The connections have weights related with them, representing the ―power of those connections. Nowadays neural networks can be applied to problems that do not have algorithmic solutions or problems for which algorithmic solutions are too intricate to be found. In other words the kind of problems in which inputs and outputs variables does not have a clear relationship between them, a neural networks is a proficient approach in such problems.

Most neural network architecture has three layers in its structure. First layer is input layer which provides an interface with the environment, second layer is hidden layer where computation is done and last layer is output layer where output is stored. Data is propagated through successive layers, with the final result available at the ―output layer. Many different types of neural networks are available and multi layer neural networks are the most popular.

2.1.1 Advantages of Neural Networks

- Can be applied to many problems, as long as there is some data.
- Can be applied to problems, for which analytical methods do not yet exist
- Can be used to model non-linear dependencies.
- If there is a pattern, then neural networks should quickly work it out, even if the data is 'noisy'.
- Always gives some answer even when the input information is not complete.

• Networks are easy to maintain

The section II describes the proposed methodology. Conclusion is described in Section III. Then finally, references are presented in Section IV.

III. PROPOSED METHODOLOGY

The proposed method is divided into four parts. In the first one, we present various techniques of segmentation and evaluation of these technical approaches. We studied the techniques used in this work by applying supervised and unsupervised criteria. In the second part, we present the image database and the selected descriptors. Then we present the neural network used for the decision of the best segmentation technique taking into account the image characteristics at the entrance.

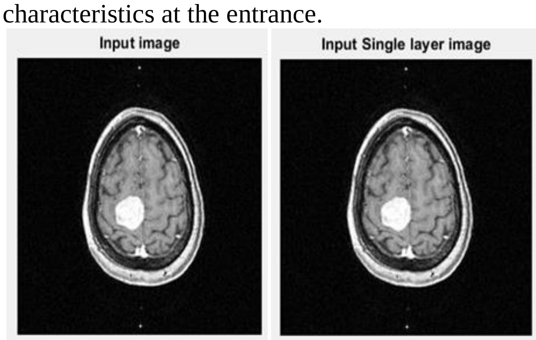

Fig.2: input image and its corresponding single layer image

We divide the evaluation methods into two groups: supervised and unsupervised evaluation, depending on whether the method utilizes a priori knowledge of reference segmentation. In supervised evaluation, the difference between reference segmentation and the output of a segmentation algorithm is computed. We demonstrate how the method is used in the development of a segmentation algorithm for images.

3.1 Unsupervised Evaluation

This does not depend on a correct segmentation. Quantitative segmentation performance measures were developed by several authors for unsupervised evaluation. A set of parameters for unsupervised evaluation including region uniformity, region contrast, line contrast and line connectivity. They assumed that some features should be uniform inside each region, and distinct between adjacent regions.The boundary of an object is located at the edge where the magnitude of intensity gradient is large. Therefore the average gradient magnitude along the boundary is used as a criterion in their validation step. We note that the average gradient magnitude can be considered as an unsupervised performance measure.

3.2 Supervised Evaluation

A supervised evaluation utilizes reference segmentation and measures the difference between the reference segmentation and the output of a segmentation algorithm. The simplest supervised measure is the probability of error.

3.3 Feature extraction

In order to extract the required features from the segmented image, different measures are taken from region and edge based segmentation under supervised and unsupervised evaluation. Here different parameters are calculated. These are used as features for training the neural networks.

3.4 Descriptors of images

In this part, we present the descriptors used in the imagecharacterization. In this work, we limited ourselves to acomprehensive characterization of the images by generaldescriptors in order to cover all possibilities of images.

3.4.1 Fourier frequency

Define The Fourier spectrum varies significantly from one image to another [12]. The Fourier transform allows us to move from a spatial representation of an image to its representation in the frequency domain. It is given by

$$X(f,g) = \iint_{-\infty}^{+\infty} x(t,u)\, e^{-i2\pi(ft+gu)}\, dt\, du \qquad (3.1)$$

(f,g) ϵ IR² : spectral coordinates.
(t,u) : spatial coordinates.
The below fig.3 describes the fourier transform plot.

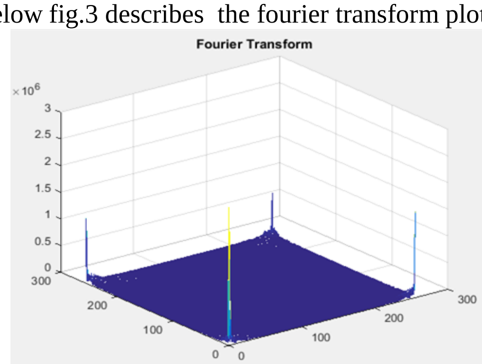

Fig.3: Fourier transform plot

3.4.2 Mean amplitudes

It is a scalar measurement of a positive number characterizing the magnitude of the changes of the digital signal on the image [13]. It is often the maximum deviation from the average value. It T: A given period can be characterized by the following scale:

$$x(f) = \sqrt{\frac{1}{T}\iint_{0}^{T} f^2(t,u)\, dt\, du} \qquad (3.2)$$

(t,u) : spatial coordinates.
f: the digital signal characterizing the given image

3.4.3 Image Standard Deviation

It is the square root of the norm of a vector of the sum of squares of elements [14].

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|Atu - \mu|^2} \quad (3.3)$$

μ the average of Atu.

3.4.4 Angle Phase

It is the time offset between the curves of the image I and the real part of the same image. It is defined as follows:

$$angle(I) = \tan^{-1}(I, real(I)) \quad (3.4)$$

I: an image.

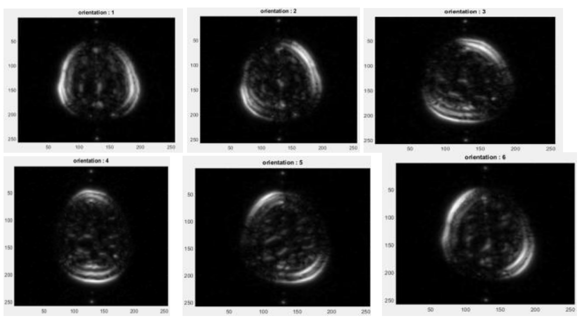

Fig.4: Sequence of six orientations of input image

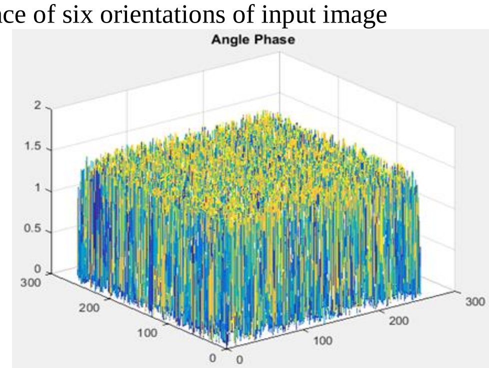

Fig.5: Angle phase plot

3.5. Neural network techniques

The parameters that are used to perform classification are the measures of region and edge based segmentations. In the present study, to train and test the network, a total number of 50 samples are used then one output parameter is displayed. Then, a feed-forward Backpropgation Neural Network is built by taking 29 input parameters of the extracted features and the basic information.

The training is done by using the extracted features. The Algorithms mentioned in the nntraintool shown below in Fig.6. Here the data which is collected is divided randomly. Then that random data is used for training by using a learning method called Levenberg-Marquardt Method. The Levenberg-Marquardt algorithm adaptively varies the parameter updates between the gradient descent update and the Gauss-Newton update is in equ.3.5.

$$[J^TWJ + \lambda I]h_{lm} = J^TW(y - \hat{y}) \quad (3.5)$$

where small values of the algorithmic parameter λ result in a Gauss-Newton update and large values of λ result in a gradient descent update. The parameter λ is initialized to be large so that first updates are small steps in the steepest-descent direction. If any iteration happens to result in a worse approximation $\left(x^2(p + h_{lm}) > x^2(p)\right)$, then λ is increased. Otherwise, as the solution improves, λ is decreased, the Levenberg-Marquardt method approaches the Gauss-Newton method, and the solution typically accelerates to the local minimum.

In Marquardt's update relationship is defined in equ.3.6 as

$$[J^TWJ + \lambda diag(J^TWJ)]h_{lm} = J^Tw(y - \hat{y})(3.6)$$

The values of λ are normalized to thevalues of J^TWJ

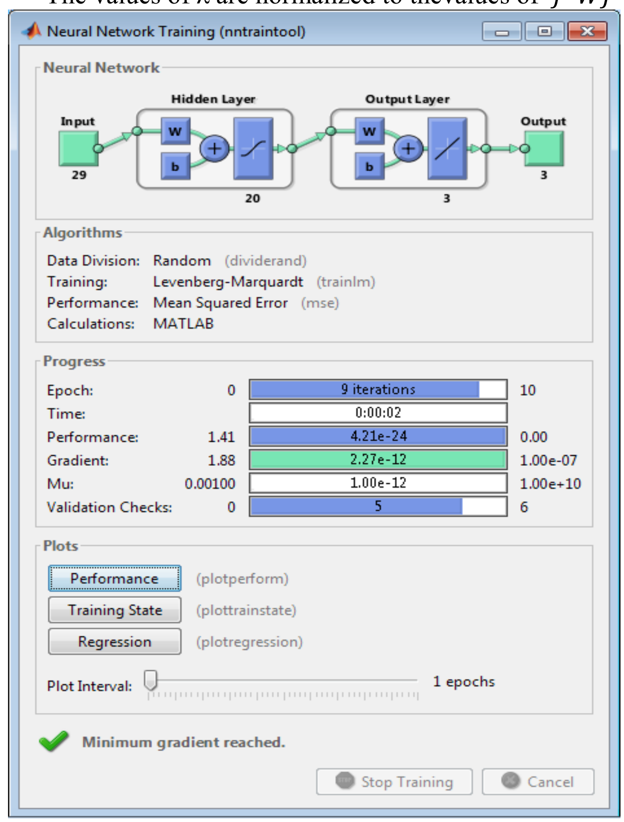

Fig.6. nntraintool

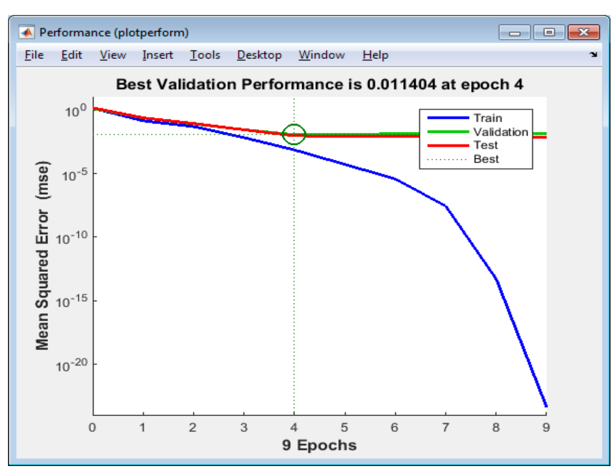

Fig.7. Best validation performance at epoch4

Then the performance is evaluated after the training is completed. Then the values are generated. The performance is evaluated by taking epochs and mean square error is shown in Fig.7. The graph shown below describes the performance oferror at 9 epochs. The train data is indicated with a blue line, the test data with a red line. The best validation is taken at the point where both train and testare equal. Here the best validation is at epoch4and the value of validation performance is 0.011404.

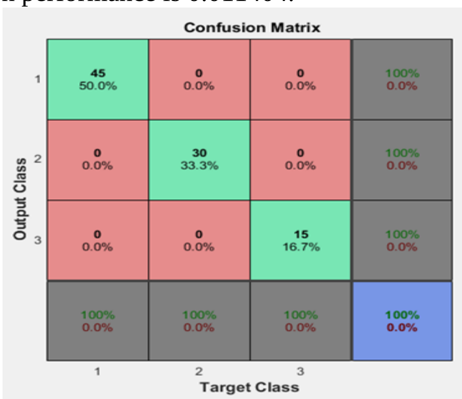

Fig.8: Confusion matrix

The Confusion matrix shown in fig.8 consists of output classes and target classes. The performance of the system can be evaluated using the regression models.Theplot shown in fig.9 reveal the information of training and the validation of target and output classes. In the graph the input is represented as data denoted by ‘o’. Then the dotted line represents the linearity of output and the target. The fit value starts at 0 and it is a straight line throughout the training ends at 1. The R value is 0.99262

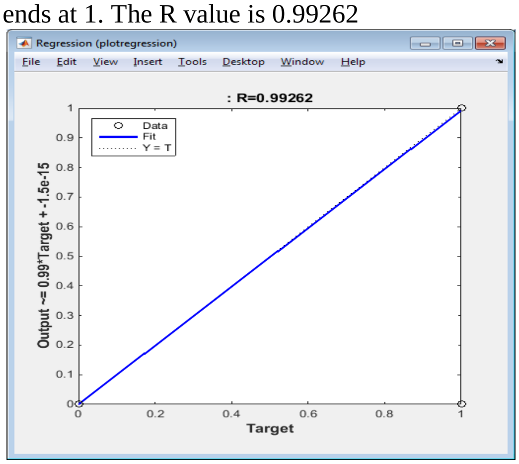

Fig.9: Plot of training and validation for output with respect to target classes

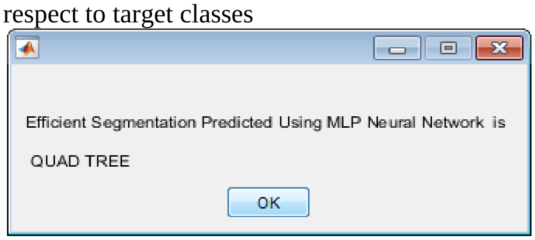

Fig.10: Efficient segmentation using MLP neural network

The dialogue box represented in fig.10 reveals that the efficient segmentation method using MLP classifier is QUAD TREE. The DBI at different values is shown in fig.11 below.

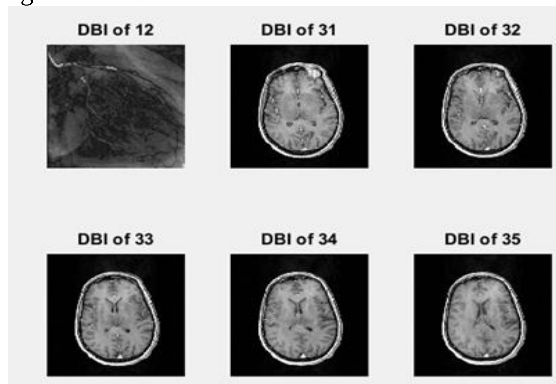

Fig.11: DBI of input image at different values

IV.CONCLUSIONS

In this paper, we proposed an MLP-based neuronal network for the choice of the segmentation method taking into account the input image characteristics. First, an evaluation of the quality of segmentation and various methods using various evaluation criteria was conducted. Then, a characterization of the images, based on the overall objective parameters, was performed. We put these descriptors with an indication of the nature of the image at the input of the MLP and we obtained for each image the appropriate segmentation method after the network learning. Our results show the consistency and reliability of our approach. A rate of good decision of 89.552 in the choice of the segmentation method is obtained on different medical images. These encouraging results allow us to plan further work to improve our success rate, integrate other segmentation approaches, use other evaluation criteria, add descriptors to the nature of the image and cover a wider range of images.

REFERENCES

[1] J.-P Cocquerez, et S. Philipp. Analyse d’images: filtrage et segmentation. Imprimé en CEE, septembre, 1995.

[2]RAMOS, O. and REZAEI, Babak, Scene Segmentation and Interpretation, Image Segmentation using Region Growing. MSc in Computer Vision and Robotics, 2010.

[3] S. Chabrier. Contribution à l'évaluation de performances en segmentation d'images. Thesis, december, 2005 Bourges.

[4] W. A. Yasnoff, J. K. Mui, and J. W. Bacus. Error measures for scene segmentation. Pattern Recognition, 9: 217–231, 1977.

[5] Q. Huang and B. Dom. Quantitative Methods of Evaluating Image Segmentation. International Conference on Image Processing (ICIP’95) Washington DC, USA, 3:53–56, 1995.

[6] N. Mhamda Bouloudani, Utilisation des critères de performance pour la segmentation automatique des images cytologiques couleur. Thèse, ecole nationale polytechnique d’Alger, janvier, 2009.

[7] HasanMuaidi,"Levenberg-Marquardt Learning Neural Network For Part-of-Speech Tagging of Arabic Sentences",WSEAS TRANSACTIONS on COMPUTERS. 2008.

[8] C. Odet, B. Belaroussi, and H. Benoit-Cattin. Scalable Discrepancy Measures for Segmentation Evaluation. ICIP, 1 : 785–788, September 2002.

[9] Zhong, Mingyu. An analysis of misclassification rates for decision trees. Diss. University of Central Florida Orlando, Florida, 2007.

[10] M. D. Levine et Ahmed M. Nazif. Dynamic Measurement of Computer Generated Image Segmentations. IEEE Transaction on Pattern Analysis and Machine intelligence, PAMI-7(2): 155–164, March 1985.

[11] E. Corteel, et J. Lavadou, Comparaison entre les filtres de Tomita/Tsuji et de Nagao/Matsuyama. Project MBAI, mars, 2000.

[12] Weeks, Arthur R. Fundamentals of electronic image processing. Bellingham: SPIE Optical Engineering Press, 1996.

[13] Hooper, Andrew, et al. A new method for measuring deformation on volcanoes and other natural terrains using InSAR persistent scatterers.
Geophysical research letters 31.23 (2004).

[14] Kohonen, Teuvo. Correlation matrix memories. Computers, IEEE Transactions on 100.4 (1972): 353-359.

[15] N. Kerkeni. Les reseaux de neurones artificiels comme outil d'aide a la décision. Thesis, Laboratoire Cristal ENSI, septembre, 2001.

[16] KERKENI Asma, BENABDALLAH, Asma, MANZANERA, Antoine, et al. A coronary artery segmentation method based on multiscale analysis and region growing. Computerized Medical Imaging and Graphics, 2016, vol. 48, p. 49-61.