

## Abnormality Segmentation and Classification of Brain MR Images using Combined Edge, Texture Region Features and Radial basis Function

<sup>1</sup>B. Balakumar and <sup>2</sup>P. Raviraj

<sup>1</sup>Centre for Information Technology and Engineering, M.S. University, Tirunelveli, Tamilnadu, India

<sup>2</sup>Department of CSE, Kalaignar Karunanidhi Institute of Technology, Coimbatore, Tamilnadu, India

**Abstract:** Magnetic Resonance Images (MRI) are widely used in the diagnosis of Brain tumor. In this study we have developed a new approach for automatic classification of the normal and abnormal non-enhanced MRI images. The proposed method consists of four stages namely Preprocessing, feature extraction, feature reduction and classification. In the first stage anisotropic filter is applied for noise reduction and to make the image suitable for extracting the features. In the second stage, Region growing base segmentation is used for partitioning the image into meaningful regions. In the third stage, combined edge and Texture based features are extracted using Histogram and Gray Level Co-occurrence Matrix (GLCM) from the segmented image. In the next stage PCA is used to reduce the dimensionality of the Feature space which results in a more efficient and accurate classification. Finally, in the classification stage, a supervised Radial Basics Function (RBF) classifier is used to classify the experimental images into normal and abnormal. The obtained experimental are evaluated using the metrics sensitivity, specificity and accuracy. For comparison, the performance of the proposed technique has significantly improved the tumor detection accuracy with other neural network based classifier SVM, FFNN and FSVM.

**Keywords:** Classification, feature extraction, MRI, RBF, segmentation, tumor

### INTRODUCTION

Segmentation of tumors on medical images is not only of high interest in serial treatment monitoring of "disease burden" in oncologic imaging, but also gaining popularity with the advance of image guided surgical approaches (Zou *et al.*, 2004). Outlining the tumor contour is a major step in planning spatially localized radiotherapy. On T1 images acquired after administration of a contrast agent (gadolinium), blood vessels and the parts of the tumor, where the contrast can pass the blood-brain barrier are observed as hyper intense areas.

Brain tumor is a cluster of abnormal cells growing in the brain. It may affect any person at almost any age. Brain tumor effects may not be the same for each person and they may even change from one treatment session to the next. Brain tumors can have a variety of shapes and sizes; it can appear at any location and in different image intensities. Brain tumors can be benign or malignant. Low grade gliomas and meningiomas (Ricci and Dungan, 2001), which are benign tumors and glioblastoma multiform is a malignant tumor and represents the most common primary brain neoplasm. Benign brain tumors have a homogeneous structure and do not contain cancer cells. They may be either simply be monitored radio logically or surgically eradicated

and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. They can be treated by radiotherapy, chemotherapy or a combination thereof and they are life threatening. Therefore, diagnosing the brain tumors in an appropriate time is very essential for further treatments. In recent years, neurology and basic neuroscience have been significantly advanced by imaging tools that enable in vivo monitoring of the brain.

In particular, magnetic resonance imaging (MRI) (Armstrong *et al.*, 2004) has proven to be a powerful and versatile brain imaging modality that allows noninvasive longitudinal and 3D assessment of tissue Morphology, metabolism, physiology and function (Prasad, 2006). The information MRI provides, has greatly increased the knowledge of normal and diseased anatomy for medical research and is a critical component in diagnosis and treatment planning. MR imaging is currently the method of choice for early detection of brain tumor in human brain. However, the interpretation of MRI is largely based on radiologist's opinion. According to World Health Organization (WHO), there are 126 types of different brain tumors many of which arise from structures intimately associated with the brain such as tumors of the covering membranes (meningiomas) to posterior fossa. In India, totally 80,271 people are affected by various types of

tumor (2007 estimates). The National Brain Tumor Foundation reported the highest rate of primary malignant brain tumor occurred in Northern Europe, United States and Israel. The lowest rate was found to be in India and Philippines.

Marcel *et al.* (2008) describes a framework for automatic brain tumor segmentation from MR images. The detection of edema is done simultaneously with tumor segmentation, as the knowledge of the extent of edema is important for diagnosis, planning and treatment. Whereas many other tumor segmentation methods rely on the intensity enhancement produced by the gadolinium contrast agent in the T1-weighted image, the method proposed here does not require contrast enhanced image channels. The only required input for the segmentation procedure is the T2 MR Image channel, but it can make use of any additional non-enhanced image channels for improved tissue segmentation. The segmentation framework is composed of three stages. First, we detect abnormal regions using a registered brain atlas as a model for healthy brains. It then makes use of the robust estimates of the location and dispersion of the normal brain tissue intensity clusters to determine the intensity properties of the different tissue types. In the second stage, we determine from the T2 image intensities whether edema appears together with a tumor in the abnormal regions. Finally, apply geometric and spatial constraints to the detected tumor and edema regions.

Vezhnevets and Konouchine (2005) describes a new technique for general purpose interactive segmentation of N-dimensional images. The user marks certain pixels as “object” or “background” to provide hard constraints for segmentation. Additional soft constraints incorporate both boundary and region information. Graph cuts are used to find the globally optimal segmentation of the N-dimensional image. The obtained solution gives the best balance of boundary and region properties among all segmentations satisfying the constraints. The topology of our segmentation is unrestricted and both “object” and “background” segments may consist of several isolated parts.

### PROPOSED METHOD

Our proposed method consists of four phases namely, pre-processing, Segmentation of region of interest, feature extraction and classification, the overall block diagram of the proposed method is shown in Fig. 1. In pre-processing steps Gaussian filter is applied to improve the quality of the input image. In second steps segmenting the region using quad-tree decomposition. In the next steps various edge region and textures based features are extracted using Histogram and second order GLCM. Finally the RBF neural network classifier is applied to classify the images into tumor and non-tumor.

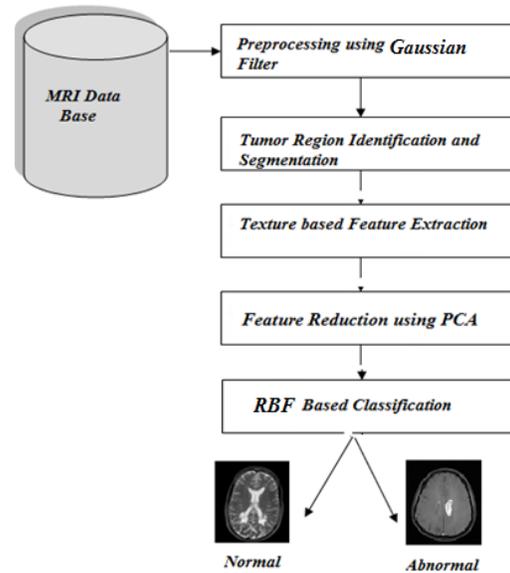


Fig. 1: Overall block diagram of our proposed approach

**Preprocessing:** In our proposed method Gaussian filter (Haddad and Akansu, 1991) is used for removing the noise and enhance the image quality for further processing. It is a linear spatial filter which is used for reducing the high frequency components of an image as a result it smooths the edges of the input image.

Gaussian Smoothing is performed by convolving the input image with the Gaussian function i.e.:

$$G_{\sigma}(x, y) * I(x, y)$$

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where,

$I(x, y)$  = The input image

$G_{\sigma}(x, y)$  = Gaussian smoothing filter with standard deviation  $\sigma$

$X, y$  = The spatial coordinates

$*$  = The convolution operator

Gradient operator is then applied to the smoothed image to find edges in the image which have been suppressed by the Gaussian filter i.e.:

$$\nabla(G_{\sigma}(x, y) * I(x, y))$$

where,  $\nabla$  is the gradient operator which calculates the directional changes in intensity values.

**Segmentation:** Segmentation refers to partitioning an image into meaningful regions, in order to distinguish objects (or regions of interest) from background. There are two major approaches, region-based method (such as region growing, split/merge using quad tree

decomposition) in which similarities are detected and boundary-based method (such as thresholding, gradient edge detection), in which discontinuities are detected and linked to form boundaries around regions. Segmentation of nontrivial images is one of the most difficult tasks in image processing. Its accuracy determines the eventual success or failure of computerized analysis procedures. Quad tree decomposition is an analysis technique that involves subdividing an image into blocks that are more homogeneous than the image itself. In this study we perform quad tree decomposition using the `qtdecomp` (Matlab) function. This function studies by dividing a square image into four equal-sized square blocks and then testing each block to see if it meets some criterion of homogeneity (e.g., if all the pixels in the block are within a specific dynamic range). If a block meets the criterion, it is not divided any further. If it does not meet the criterion, it is subdivided again into four blocks and the test criterion is applied to those blocks. This process is repeated iteratively until each block meets the criterion.

**Feature extraction process:** In our proposed method Features are extracted both edge and texture region. Histogram is used to extract the feature in edge region and second order GLCM is used for extract the features in Texture.

- **Feature extraction in the edge region using histogram:** Edges in images constitute an important feature to represent their content. An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. The extraction process of edge information consists of the following stages
  - An image is divided into 4\*4 sub-images
  - Each sub-image is further portioned into non-overlapping image block with a small size
  - The edges in each image block are categorized into five types: vertical, horizontal, 45\* diagonal, 135\* diagonal and non-directional edges
  - Thus, the histogram for each sub-image represents the relative frequency of occurrence of the five types of edges in the corresponding sub-image
  - After examining all image blocks in the sub-image, the five-bin values are normalized by the total number of blocks in the sub-image. Finally, the normalized bin values are quantized for the binary representation
- **Texture based feature extraction process:** Gray Level Co-occurrence Matrix (GLCM) is an estimate of the second-order statistical information of neighboring pixels of an image. It is estimated of a joint probability density function (PDF) of gray level pairs in an image

It can be expressed the following equation:

$$P_{\mu}(i, j) \quad (i, j = 0, 1, 2, \dots, N-1)$$

where,

$i, j$  = The gray level of two pixels

$N$  = The grey image dimensions

$\mu$  = The position relation of two pixels

Different values of  $\mu$  decides the distance and direction of two pixels. Normally Distance (D) is 1, 2 and Direction ( $\theta$ ) is  $0^0, 45^0, 90^0, 135^0$  are used for calculation (Ondimu and Murase, 2008). Texture features can be extracted from gray level images using GLCM Matrix. In our proposed method, five texture features energy, contrast, correlation, entropy and homogeneity are experiments. These features are extracted from the segmented MR images and analyzed using various directions and distances.

Energy expresses the repetition of pixel pairs of an image:

$$k1 = \sum_{i=0}^{N-1} \sum_{j=0}^{k-1} p_{\mu}^2(i, j)$$

Local variations present in the image are measured by Contrast. If the contrast value is high means the image has large variations:

Correlation is a measure linear dependency of gray level values in co-occurrence matrices. It is a two dimensional frequency histogram in which individual pixel pairs are assigned to each other on the basis of a specific, predefined displacement vector:

Entropy is a measure of non-uniformity in the image based on the probability of Co-occurrence values, it also indicates the complexity of the image:

$$k4 = - \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} p_{\mu}(i, j) \log(p_{\mu}(i, j))$$

Homogeneity is inversely proportional to contrast at constant energy whereas it is inversely proportional to energy:

**Feature reduction using PCA:** The principal component analysis and Independent Component Analysis (ICA) are two well-know tools for transforming the existing input features into a new lower dimensional feature space. In PCA, the input feature space is transformed into a lower-dimensional feature space using the largest eigenvectors of the correlation matrix. In the ICA, the original input space is transformed into an independent feature space with a dimension that is independent of the other dimensions. PCA (Latifoglu *et al.*, 2008) is the most widely used subspace projection technique. These methods provide a

suboptimal solution with a low computational cost and computational complexity. Given a set of data, PCA finds the linear lower-dimensional representation of the data such that the variance of the reconstructed data is preserved. Using a system of feature reduction based on PCA limits the feature vectors to the component selected by the PCA which leads to an efficient classification algorithm. So, the main idea behind using PCA in our approach is to reduce the dimensionality of the texture features which results in a more efficient and accurate classifier.

**Final classification:** In this section, we present the basic characteristics of the RBF neural network architecture (Haralambos *et al.*, 2008) and the proposed training method for developing neural network classifiers.

An RBF neural network is a special three-layered network. The input nodes pass the input values to the internal nodes that formulate the hidden layer. The non-linear responses of the hidden nodes are weighted in order to calculate the final outputs of the network in the output layer.

A typical hidden node in an RBF network is characterized by its center, which is a vector with dimension equal to the number of inputs to the node. The activity value ( $v$ ) of the *lead* node is the Euclidean norm of the difference between the input vector  $y$  and the node center  $\hat{y}_1$  and is given by:

$$v(y) = \|y - \hat{y}_1\|$$

The output function of the node is a radially symmetric function. A typical choice, which is also used in this study, is the Gaussian function:

$$f(v) = \exp(-v^2 / \sigma^2)$$

where,  $\sigma$  is the width of the node.

In the proposed training method, the calculation of the hidden node centers is based on the fuzzy means clustering algorithm (Darken and Moody, 1990), while the connection weights are obtained using linear regression. The fuzzy means clustering algorithm initially produces a fuzzy partition in the input space, by defining a number of triangular fuzzy sets on the domain of each input variable. Multidimensional grid of the input space is produced using centers of these fuzzy sets. The knots of the grid constitute the set of candidates for becoming hidden node centers. The rigorous selection algorithm is chosen using the most appropriate knots and is used as centers in the produced RBF network model. The idea behind the selection algorithm is to place the centers in the multidimensional input space, so that there is a minimum distance between the center locations. At the same time the algorithm

assures that for any input example in the training set there is at least one hidden node that is close enough according to a distance criterion. The above algorithm has a number of advantages compared to the standard k-means clustering technique, which is the most popular algorithm for selecting the centers of an RBF network (Moody and Darken, 1989).

- It is orders of magnitude faster since it does not involve any iterative procedure. More precisely, the fuzzy means method needs only one pass of the training data, while the k-means technique requires several iterations to converge. For a more detailed comparison based on the number of distance calculations required by the two algorithms, the reader is referred to the publication (Leonard and Kramer, 1991).
- It is repetitive, i.e., for the same initial fuzzy partition, it always produces the same network as far as both the structure and the parameter values are concerned.
- It computes not only the hidden node centers, but also the size of the network.

After the determination of the hidden node centers, the widths of the Gaussian activation function are computed using the p-nearest neighbor heuristic (Sarimveis *et al.*, 2002). Up to this point, we follow exactly the same procedure that is used in a standard neural modeling problem based on input-output data. However, in the classification problem the data concerning the output variable cannot be introduced in the training procedure in the traditional numerical way, since they are discrete and qualitative.

## EXPERIMENTAL RESULTS

The proposed method has been implemented using the Mat lab environment. The proposed system has been tested on the data set of real brain MR images consisting of tumor and non-tumor. It is collected from the publicly available resources. The following Fig. 2 shows some of the samples tumor and non-tumor images.

The performance of the proposed method is evaluated in terms of sensitivity, Specificity and Accuracy (Wen *et al.*, 2010). Where Sensitivity is a measure which determines the probability of the results that are true positive such that a person has the tumor. Specificity is a measure which determines the probability of the results that are true negative such that a person does not have the tumor. Accuracy is a measure which determines the probability that how many results are accurately classified. The obtained

Table 1: Detection accuracy of the proposed approach in training and testing data set

Evaluation metrics	GLCM+SVM	GLCM+FFNN	GLCM+FSVM	Our proposed approach
Input MRI image data set				
True Positive (TP)	37	35	37	38
True Negative (TN)	8	8	8	9
False Positive (FP)	2	2	2	1
False Negative (FN)	3	5	3	2
Sensitivity	0.95	0.95	0.95	0.95
Specificity	0.73	0.62	0.73	0.9
Accuracy	0.9	0.86	0.9	0.94

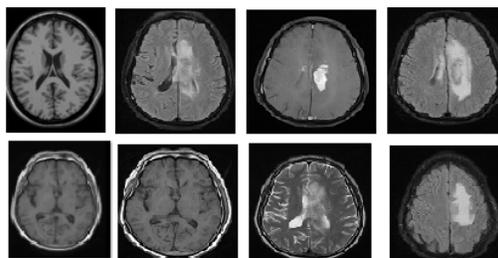


Fig. 2: Samples T1-weighted tumor and Non-tumor MR images

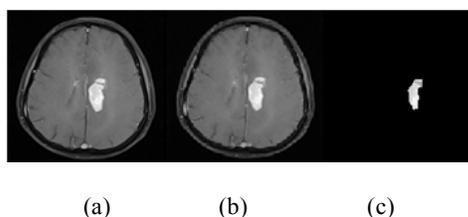


Fig. 3: (a) Original image, (b) Filtered image, (c) Segmented image

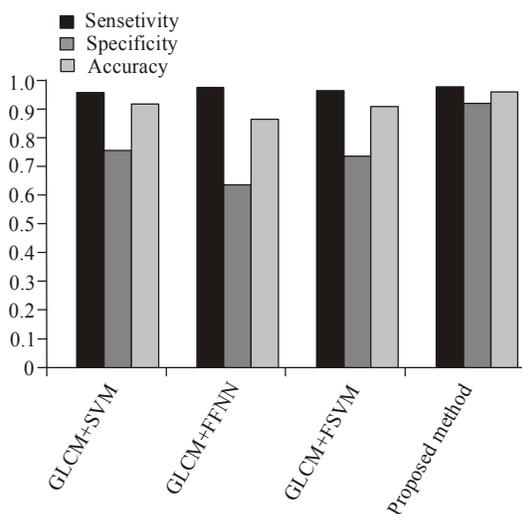


Fig. 4: Comparative analysis graph of existing and proposed method

experimental results of the proposed method are given in Table 1. The obtained experimental results from the proposed technique are shown in Fig. 3.

$$\text{Sensitivity} = TP / (TP + FN)$$

$$\text{Specificity} = TN / (TN + FP)$$

where,

TP = For True Positive

TN = For True Negative

FN = For False Negative

FP = For False Positive

We have compared our proposed tumor detection technique other neural network techniques. The neural networks we have utilized for comparative analysis are Feed Forward Neural Network (FFNN) and Support Vector Machine (SVM). The performance of the proposed technique has significantly improved the tumor detection compared with SVM, FFNN and FSVM. The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in Fig. 4.

## CONCLUSION

We have developed an automated brain MRI diagnostic system with normal and abnormal classes. The medical decision making system was designed by the GLCM, the principal component analysis and RBF that we have built gave very promising results in classifying the healthy and brain patient having lesion. The benefit of the system is to assist the physician to make the final decision without hesitation. According to the experimental results, the proposed method is efficient for the classification of the human brain into normal and abnormal. Classification percentage of more than 97%. The stated results show that the proposed method can make an accurate and robust classifier. The classification performances if this study shows the advantages of this technique: it is rapid, easy to operate, non-invasive and inexpensive.

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