

Research Article

Brain Tumor Detection and Classification of MR Images Using Texture Features and Fuzzy SVM Classifier

¹A. Jayachandran and ²R. Dhanasekaran

¹Department of CSE, PSN College of Engineering and Technology, Tirunelveli, Tamilnadu, India

²Syed Ammal Engineering College, Ramanathapuram, Tamilnadu, India

Abstract: In this study we have proposed a hybrid algorithm for detection brain tumor in Magnetic Resonance images using statistical features and Fuzzy Support Vector Machine (FSVM) classifier. Brain tumors are not diagnosed early and cured properly so they will cause permanent brain damage or death to patients. Tumor position and size are important for successful treatment. There are several algorithms are developed for brain tumor detection and classifications in the field of medical image processing. The proposed technique consists of four stages namely, Noise reduction, 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 features. In the second stage, obtains the texture features related to MRI images. In the third stage, the features of magnetic resonance images have been reduced using principles component analysis to the most essential features. At the last stage, the Supervisor classifier based FSVM has been used to classify subjects as normal and abnormal brain MR images. Classification accuracy 95.80% has been obtained by the proposed algorithm. The result shows that the proposed technique is robust and effective compared with other recent works.

Keywords: Classification, feature extraction, FSVM, MRI, PCA, segmentation, tumor

INTRODUCTION

Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Magnetic Resonance Imaging (MRI) of the brain is a safe and painless test that uses a magnetic field and radio waves to produce detailed images of the brain. MRI images have good contrast in comparison to Computerized Tomography (CT). It provides detailed information regarding healthy brain tissues as well as pathological processes. Based on the treatment plan quantification of brain tissues are essential. Segmentation of tumors in MR images is an essential step for the computation of its volume. A tumor is an abnormal growth of body tissue. Tumors can be cancerous (malignant) or non cancerous (benign) (Jzau-Sheng *et al.*, 1996).

The manual interpretation of brain tumor slices based on visual examination by a physician may lead to missing diagnosis and time consuming when a large number of MRI brain images are analyzed. To avoid human based diagnostic error, computer aided diagnosis system is needed. There are lots of methods for automatic and semi-automatic image classification,

though; most of them fail because of unknown noise, poor image contrast, in homogeneity and weak boundaries that are usual in medical images. Medical images mostly contain complicated structures and their accurate classification is necessary for clinical diagnosis (Pal and Pal, 1993).

In order to enhance the performance of automated image segmentation, especially in the field of brain tissue segmentation from 3D MRI towards classical image deterioration including the noise and bias field artifacts that arise in the MRI acquisition process, Caldairou *et al.* (2009) have proposed to integrate into the FCM segmentation methodology concepts stimulated by the Non-Local (NL) framework. The major algorithmic contributions of this study were the definition of an NL data term and an NL regularization term to effectively handle the intensity in homogeneity and noise in the data. Then, the resulting energy formulation was built into an NL/FCM brain tissue segmentation algorithm. Experiments carried out on both the synthetic and real MRI data, leading to the classification of brain tissues into grey-matter, white matter and cerebro-spinal fluid, have shown a substantial enhancement in performance in the case of higher noise levels, when compared to a range of standard algorithms.

Corresponding Author: A. Jayachandran, Department of CSE, PSN College of Engineering and Technology, Tirunelveli, Tamilnadu, India

This work is licensed under a Creative Commons Attribution 4.0 International License (URL: <http://creativecommons.org/licenses/by/4.0/>).

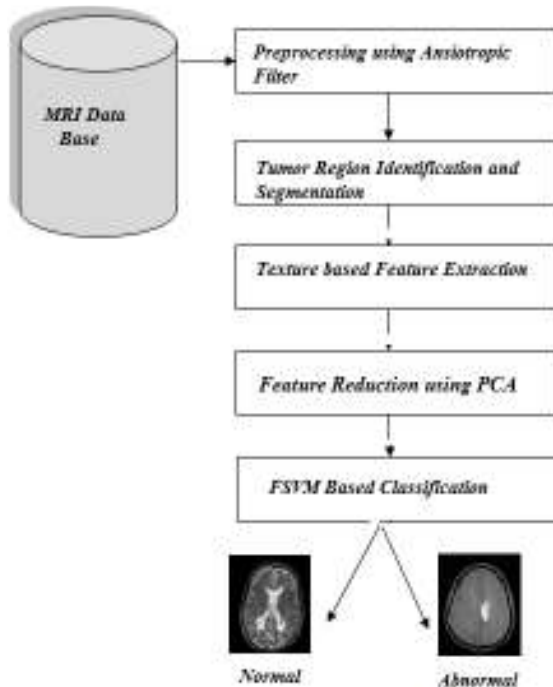


Fig. 1: Overall block diagram of the proposed system

Jayashri and Phadke (2010) have proposed a tumor segmentation scheme based on statistical structural analysis, where the structural analysis on both tumorous and normal tissues has been performed. The local textures in the images could disclose the normal 'regularities' of biological structures. Therefore, the textural features have been extracted using co-occurrence matrix approach. The analysis of level of correlation has permitted to reduce the number of features to the only significant component. The classification has been performed by employing an artificial neural network and fuzzy c-means. They have designed this approach in order to examine the differences of texture features between macroscopic Lesion White Matter (LWM) and Normal Appearing White Matter (NAWM) in Magnetic Resonance Images (MRI) from patients with tumor and Normal White Matter (NWM).

Pradha and Sinha (2010) have proposed a technique for segmentation and identification of pathological tissues (Tumor and Edema), normal tissues (White Matter and Gray Matter) and fluid (Cerebrospinal Fluid) from Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance (MR) images of brain using composite feature vectors comprising of wavelet and statistical parameters, which is contrary to other researchers who have developed feature vectors either using statistical parameter or using wavelet parameters. Here, the intra cranial brain image has been segmented into five segments using k-mean algorithm, which is based on the combined features of the wavelet energy function and statistical parameters that reflect texture properties. In addition to the tumor, edema has also been characterized as a separate class, which is

important for therapy planning, surgery, diagnosis and treatment of tumors. By extracting the feature vectors from small blocks of 4×4 pixels of image corresponding to tissues of tumor, edema, white matter, gray matter and cerebrospinal fluid, the block processing of image has been performed and then employing a back propagation algorithm, the artificial neural network has been trained.

Hassan *et al.* (2009) have proposed a technique for segmenting the brain tumors in 3D magnetic resonance images. Their technique was suitable for different kinds of tumors. Initially, the brain has been segmented using the proposed approach. Then, the suspicious areas have been selected with respect to the approximate brain symmetry plane and fuzzy classification for tumor detection. Here, in the segmentation stage, the tumor has been segmented successfully using the combination of a deformable model and spatial relations. Vagueness and variability have also been considered at all levels using the suitable fuzzy models. Finally, the results obtained on diverse types of tumors have been compared with the manual segmentation results. The overall flow diagram of the proposed system is shown in Fig. 1.

PROPOSED SYSTEM

Pre-processing: It is the first step in our proposed technique. The purpose of these steps is basically Preprocessing involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections and masking portions of images. Anisotropic filter is used to remove the background noise and thus preserving the edge points in the image.

Anisotropic filter: In Anisotropic filter, diffusion constant related to the noise gradient and smoothing the background noise by filtering an appropriate threshold value is chosen. For this purpose higher diffusion constant value is chosen compare with the absolute value of the noise gradient in its edge. Head mask was constructed by thresholding the filtered image. Matching intensity ranges in all the images, the highest and lowest intensities are limited to the interval [0, 255] (Demirkaya, 2002).

Segmentation: Segmentation is a significant process to extract pertinent information from intricate medical images. Segmentation has extensive application in medical field (Aaron *et al.*, 2003). The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic (s). When applied to a stack of images, typical in medical imaging, the resulting

contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

Skull stripping: Is a vital process in brain image analysis, which involves removal of the scalp tissue, skull and Dura. In the proposed technique, skull stripping is used for the segmentation of brain tissues. The steps involved in the skull stripping process are:

- Binarization via Thresholding
- Morphological Operation
- Tumor region identification

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

μ : The position relation of two pixels

Different values of μ decide the distance and direction of two pixels. Normally Distance (D) is 1, 2 and Direction (θ) is 0° , 45° , 90° , 135° 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 and 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 liner 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.

Classification using FSVM: In-order to detect the tumor in the input MRI images after the feature extraction process. Here we use the Fuzzy based Support Vector Machine classifier to classify the image into tumorous or not. In 1995, Support Vector Machine (SVM) was developed. It is derived from the statistical theory invented by Vapnik (1982). In 2002 Fuzzy SVM (FSVM) has been developed, which is an effective supervised classifier and accurate learning technique. Which was first proposed by Lin and Wang (2002) Here Fuzzy membership function is applied to each input data of SVM.

The fuzzy training set can be expressed as the following equation:

$$\{(x_i, y_i, s), i = 1, 2, \dots, n; x_i \in R^d; y_i \in \{1, -1\}; \lambda < s_i < 1\}$$

Here λ is a small positive number.

All hyperplanes in R^d are parameterize by a vector (w) and a constant b . Can be expressed as $w \cdot x + b = 0$.

The inputs to FSVM algorithm are the feature subset selected via GLCM. In our technique, the brain has been classified into two classes: normal and abnormal brain. Then, classification procedure continues to divide the abnormal brain into malignant and benign tumors and each subject is represented by a vector in all images. FSVM follows the structural risk minimization principle from the statistical learning

theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs (Zhang *et al.*, 2006). A Fuzzy support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space (Kim and Park, 2003). The lagrange multiplier function is:

$$W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j K(x_i \cdot x_j)$$

Subject to: $w = \sum \alpha_i y_i x_i$

$$\sum \alpha_i y_i = 0$$

In Nonlinear data, the input space X can be mapped into higher dimensional feature space Ψ . It's become linearly separable. The mapping function Ψ should be in accordance with Mercer's theorem (Huang and Chen, 2005):

$$K(x, x_i) = \psi(x)^t \psi(x_i)$$

where, $K(x, x_i)$ is Kernel function
It can be chosen from the following functions:

Polynomial learning machine kernel function:

$$K(x, x_i) = (x \cdot x_i + 1)^i, i = 1, 2, 3, \dots, n$$

Linear network kernel function:

$$K(x, x_i) = x^T x_i$$

Radial-Basis Function (RBF) kernel function:

$$K(x, x_i) = \exp(-g \|x - x_i\|^2), i = 1, 2, 3, \dots, n, g > 0$$

In FSVM the cost C is multiplied by the fuzzy membership function. It is the major difference between SVM and FSVM, different input points can make the result of SVM and FSVM. Here FSVM uses Fuzzy membership function instead of fixed weights to prevent noisy data (Wang and Chiang, 2007). In this study the values of C and g are selected by trial and error procedure.

RESULTS AND DISCUSSION

This section describes the experimental results of our proposed Segmentation technique using brain MRI images with and without tumors. Our proposed approach is implemented in MATLAB (MATLAB version 7.10). Here, we have tested our proposed tumor

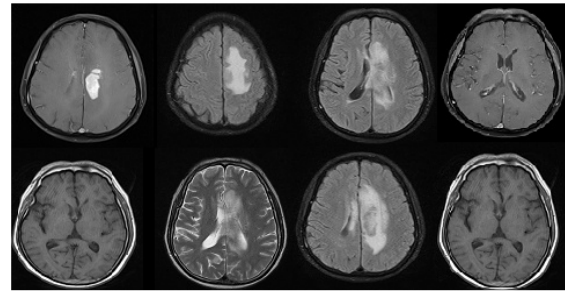


Fig. 2: Sample MRI image dataset

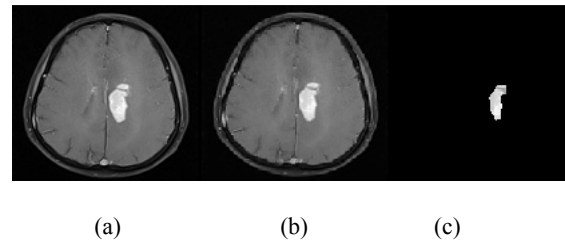


Fig. 3: (a) Original image (b) filtered image (c) segmented image

detection technique using medical images taken from the publicly available sources.

MRI image dataset description: For our proposed method, we have collected the various tumor and non tumor MRI images from south Indian area severity analysis which is undergone for processing the images. This image dataset contains 80 brain MRI images. In which, a total of 60 T1-weighted gadolinium enhanced MR images were tumorous. These 3D DICOM real images were obtained from Government Medical College Hospital, Tirunelveli, Tamilnadu, India, using SIEMENS 1.5 Telsa MR Unit. In each case, only T1-weighted post contrast (Gadolinium) images, Spin-Echo (SE) sequence (TR = 480 ms, TE = 8.7 ms), Matrix size is 256*256 and the slice thickness is 1 mm used for analysis. The sample images are shown in the Fig. 2.

Experimental results: An efficient Fuzzy SVM based method is proposed to segment brain tumor from MR images. The proposed method can successfully segment a tumor provided that the parameters are set correctly. The obtained experimental results from the proposed technique are shown in Fig. 3. In testing phase, the testing dataset is given to the proposed technique to find the tumors in brain images and the obtained results are evaluated through evaluation metrics namely, sensitivity, specificity and accuracy (Wen *et al.*, 2010).

Sensitivity is a measure which determines the probability of the results that are true positive such that person has the tumor. Specificity is a measure which determines the probability of the results that are true negative such that person does not have the tumor.

Table 1: Detection accuracy of the proposed approach and exiting methods

Evaluation	Texture feature + SVM	Texture feature + FFNN	Our proposed
Input MRI image dataset			
True Positive (TP)	17	15	19
False Positive (FP)	2	2	1
True Negative (TN)	8	8	9
False Negative (FN)	3	5	1
Specificity	0.85	0.75	0.95
Sensitivity	0.80	0.80	0.90
Accuracy	0.83	0.77	0.94

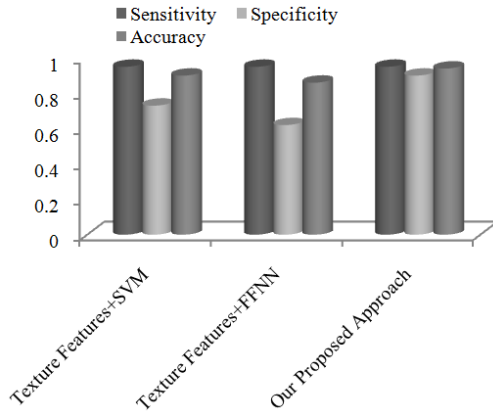


Fig. 4: Comparison graph of our proposed and existing work

Accuracy is a measure which determines the probability that how much results are accurately classified:

$$Sensitivity = TP / (TP + FN)$$

$$Specificity = TN / (TN + FP)$$

$$Accuracy = (TN + TP) / (TN + TP + FN + FP)$$

where,

- TP : True Positive
- TN : True Negative
- FN : False Negative
- FP : False Positive

The performance of our proposed technique is evaluated by means of Textures features with FSVM in terms of the evaluation metrics values TP, FP, FN, TN, Sensitivity, specificity and accuracy, our proposed method is better performance comparing to other leading methods. The obtained experimental results of the proposed system are given in Table 1.

Comparative analysis: 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 Radial Basics Function (RBF). The performance analysis has been made by plotting the graphs of evaluation metrics such as sensitivity, specificity and the accuracy. By analyzing the plotted graph, the performance of the proposed

technique has significantly improved the tumor detection compared with FFNN and RBF. The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in Fig. 4. The accuracy level proved that the proposed algorithm graph is good in detecting the tumors in the brain MRI images.

CONCLUSION

In this study we have developed an automated brain MRI diagnostic system with normal and abnormal classes. The medical decision making system was designed with the texture Features and the Supervised learning Methods (FSVM) 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. The proposed algorithm achieves the classification percentage is more than 95%. Also the performances if this study shows the advantages of this technique: it is rapid, easy to operate, non-invasive and inexpensive.

REFERENCES

- Aaron, L., C. Joshua and W. Ross, 2003. Interactive GPU-Based level sets for 3D brain tumor segmentation. University of Utah, School of Computing, Technical Report UUCS-03-004, April 16.
- Caldairou, N.P., P. Habas, C. Studholme and F. Rousseau, 2009. A non-local fuzzy segmentation method: Application to brain MRI. Lect. Notes Comput. Sc., 5702: 606- 613.
- Demirkaya, O., 2002. Anisotropic diffusion filtering of PET attenuation data to improve emission images. Phys. Med. Biol., 47: 271-278.
- Hassan, K., C. Olivier, A. Jamal and B. Isabelle, 2009. 3D brain tumor segmentation in MRI using fuzzy classification: Symmetry analysis and spatially constrained deformable models. Fuzzy Set. Syst., 160(10): 1457-1473.
- Huang, Y.L. and D.R. Chen, 2005. Support vector machines in sonography: Application to decision making in the diagnosis of breast cancer. J. Clin. Imag., 29: 179-184.

- Jayashri, J. and A.C. Phadke, 2010. Feature extraction and texture classification in MRI. *Proceeding of International Conference on Computer Technology*, 2: 130-136.
- Jzau-Sheng, L., C. Kuo-Sheng and M. Chi-Wu, 1996. Segmentation of multispectral magnetic resonance image using penalized fuzzy competitive learning network. *Comput. Biomed. Res.*, 29: 314-326.
- Kim, D. and J. Park, 2003. Network-based intrusion detection with support vector machines, *Lect. Notes Comput. Sc.*, 2662: 747-756.
- Latifoglu, F., K. Polat, S. Kara and S. Gunes, 2008. Medical diagnosis of atherosclerosis from carotid artery Doppler signals using Principal Component Analysis (PCA), k-NN based weighting pre-processing and Artificial Immune Recognition System (AIRS). *J. Biomed. Inform.*, 41: 15-23.
- Lin, C.F. and S.E. Wang, 2002. Fuzzy support vector machines. *IEEE T. Neural Networ.*, 13(2): 464-471.
- Ondimu, S.N. and H. Murase, 2008. Effect of probability-distance based Markovian texture extraction on discrimination in biological imaging. *Comput. Electron. Agr.*, 63: 2-12.
- Pal, N.R. and S.K. Pal, 1993. A review on image segmentation techniques. *Pattern Recogn.*, 26(9): 1277-1294.
- Pradha, N. and A.K. Sinha, 2010. Development of a composite feature vector for the detection of pathological and healthy tissues in FLAIR MR images of brain. *J. ICGST-BIME*, 10(1): 1-11.
- Vapnik, V.N., 1982. *Estimation of Dependences Based on Empirical Data*, Secaucus. Springer-Verlag, New York.
- Wang, T.Y. and H.M. Chiang, 2007. Fuzzy support vector machine for multi-class text categorization. *Inform. Proc. Manage.*, 43: 914-929.
- Wen, Z., Z. Nancy and W. Ning, 2010. Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS implementations. *Proceeding of the SAS Conference*. Baltimore, Maryland, pp: 9.
- Zhang, K., H.X. CAO and H. Yan, 2006. Application of support vector machines on network abnormal intrusion detection. *Appl. Res. Comput.*, 5: 98-100.