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Research Article

Computer Assisted Diagnosis of Brain Tumor in MRI Images using Texture Features as Input to Ada-boost Classifier

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Abstract: In medical image processing, segmentation is an important and challenging task. It is classically used to identify object contours and extract the object from the image. Tumor Classification is an significant in medical image analysis since it provides information related to anatomical structures as well as possible anomalous tissues necessary to treatment planning and patient follow-up. In this study, a new approach for automatic classification of brain tumor in enhanced MRI images is developed. Our proposed method consists of Five steps: i) Preprocessing ii) Tumor Region Segmentation iii) Feature Extraction using Wavelet and Level set method iv) Feature Selection and v) Feature Classification using Ada-Boost classifier. The experimental results are validated using the evaluation metrics such as sensitivity, specificity and accuracy. Our proposed system experimental results are compared to other neural network based classifier such as Feed Forward Neural Network (FFNN) and Radial Basics Function (RBF). The classification accuracy of proposed method produces better results compared to other leading tumor classification methods.

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

INTRODUCTION

Magnetic Resonance Imaging (MRI), Nuclear Magnetic Resonance Imaging (NMRI), Magnetic Resonance Tomography (MRT) is a medical imaging technique used in radiology to visualize the internal structures of the body in detail. MRI makes use of the property of Nuclear Magnetic Resonance (NMR) to image nuclei of atoms in the body. MRI provides good contrast between the different soft tissues of the body, which makes it especially useful in imaging the brain, muscles, the heart and cancers compared with other medical imaging techniques such as Computed Tomography (CT) or X-rays. Unlike CT scans or traditional X-rays, MRI does not use ionizing radiation. Manual classification of (MR) brain tumor images is a difficult and time-consuming task (Kidwell and Wintermark, 2010). Manual classification is very prone to error due to inter-observer inconsistency and human error. The classification results are highly low-grade which leads to critical results. Thus, an automatic or semi-automatic classification method is highly desirable since it reduces the load on the human viewer, large number of cases can be handled with same accuracy, moreover, results are not affected due to fatigue, data overload, faster communication.

A tumor is an abnormal growth of body tissue. Tumors can be cancerous (malignant) or non cancerous (benign). Brain tumors are not diagnosed early and cured properly so they will cause permanent brain damage or death to patients. It may be of any size, may have a variety of shapes, may appear at any location and may appear in different image intensities. They are created by an abnormal and uncontrolled cell division, usually in the brain itself, but also in lymphatic tissue, in blood vessels, in the cranial nerves, in the brain envelopes (meninges), skull, pituitary gland, or pineal gland. Brain tumors may also spread from cancers primarily located in other organs (metastatic tumors). Any brain tumor is inherently serious and life-threatening because of its invasive and infiltrative character in the limited space of the intracranial cavity. However, brain tumors (even malignant ones) are not invariably fatal, especially lipomas which are inherently benign (Lia *et al*., 2008).

Magnetic Resonance (MR) fragmentation used for brain tissues extraction White Matter (WM), Gray Matter (GM) and Cerebro-Spinal Fluids (CSF).These tissues assist with lots of medical image segmentation applications such as radiotherapy planning, clinical diagnosis, treatment planning and Alzheimer disease. By utilizing wavelet Decomposition for feature extraction and feature vector treat as input to FCM, they have offered a new manipulation or utilization by Fuzzy C-Means (FCM) Clustering. This algorithm was known as Wavelet Fuzzy C-Means (WFCM). The testing with synthetic Brain Web images and true images IBSR

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images have confirmed the effectiveness and stoutness of the planned approach in segmenting noisy Medical (MRI) with real images as compared to the existing approach. By standard FCM and Kernelized Fuzzy C-Means (KFCM) the algorithm results were compared. The presentation of the planned segmentation algorithm provides reasonable results compared with the extra two algorithms (Roy and Bandyopadhyay, 2012).

MTH is a feature extractor and descriptor to extract the image texture feature which integrates the advantages of co-occurrence matrix and histogram. Here, the attribute of co-occurrence matrix and histogram is represented within this feature vector (Jayachandran and Dhanasekaran, 2013a). The efficiency is achieved with brain tissue and tumor segmentation, feature extraction of the segmented regions and the classification based on support vector machine. Magnetic resonance image classification approach using enhanced Texton Co-occurrence Matrix and Fuzzy support vector machine is an one of the best method for classification. It consists of feature extraction and classification (Jayachandran and Dhanasekaran, 2013b). In feature extraction, the advantage of both co-occurrence matrix and histogram to extract the texture feature from every segment to better classification of the image. In classification, fuzzy SVM classifier is used for improving the classification process. In this method only to T1-weighted post contrast brain MRI images.

Wavelet transforms is an effective tool for feature extraction, because they allow analysis of images at various levels of resolution. This technique requires large storage and is computationally more expensive. Hence an alternative method for the dimensionality reduction scheme is used (Sengur, 2008). In order to reduce the feature vector dimension and increase the discriminating power, the principal component analysis is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analysis new data. The level-set method first developed by Osher and Sethian (1988) has found applications in many disciplines. The level set is a numerical analysis technique for tracking interfaces and shape. Some applications of level sets in medical image analysis are extraction of complex shapes such as the human cortex in MRI for neurological disease diagnosis and shape-based approach to curve evolution for the segmentation of medical images (Suri *et al*., 2002). In a recent work (Zhu *et al*., 2007), a binary level-set method has been introduced to reduce the expensive computational cost of redistancing the traditional level-set function. Feature selection, on the other hand, is a technique for selecting a subset of relevant features for building robust learning models. Feature selection has been exploited in many applications such as medical imaging, data mining and lexical works. In medical imaging, various techniques have been used to select the best features from a given set of features (Weisenfield and Warfield, 2004; Novovicova *et al*., 1996).

PROPOSED BRAIN TUMOR CLASSIFICATION METHOD

Brain tumor is a compilation of anomalous cells that grow within the brain or around the brain. Tumors can straightforwardly wipe out all the normal brain

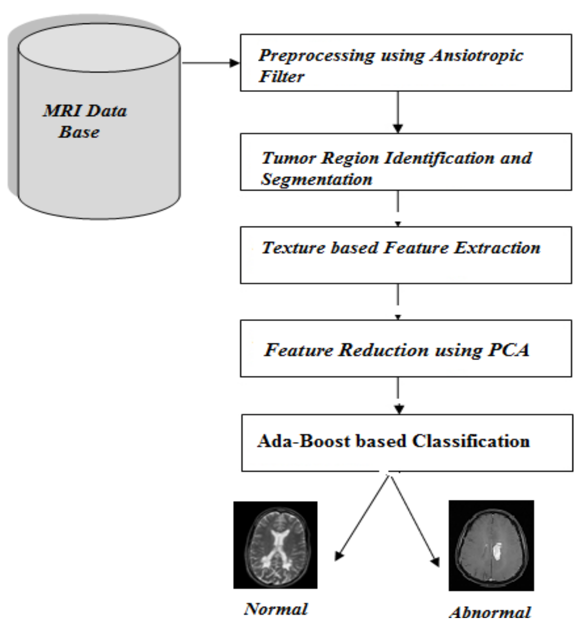


Fig. 1: Overall bock diagram of the proposed system

cells. It can also indirectly harm the strong cells by crowding other components of the brain and producing pain, brain swelling and stress inside the cranium. The process of segmenting tumors in brain MRI images rather than normal scenes is mainly challenging. In the proposed method, DWT and Level set method is used for texture feature extraction and Ada boost classifier is used for texture classification for diagnosis of brain tumor in MRI images. In this method, various texture and intensity based features are extracted using combined level set and DWT. In classification Ada boost is used to classify the experimental images into normal and abnormal class. The overall process is depicted in the block diagram, given in Fig. 1.

Pre-processing: Preprocessing involves removing low-frequency surroundings noise, normalizing the intensity of the individual particle 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. The acquisition system corrupts MR images by generating noise. In order to improve the image quality and anisotropic filtering is used. In Anisotropic filter, diffusion constant related to the noise gradient and smoothing the background noise by filtering an appropriate threshold value is choosen. 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 the process dividing an image into regions with similar properties such as gray level, color, texture, brightness and contrast (Gonzalez and Woods, 2004). The role of segmentation is to subdivide the objects in an image; in case of medical image segmentation the aim is to:

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

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. In this study Quad tree based segmentation algorithm is used for segmentation. Quad tree decomposition is an analysis technique that involves subdividing an image into blocks that are more homogeneous than the image itself.

This is the mixture of splits and merges utilizing the benefit of the two methods. This method is based on quad quadrant tree representation of data whereby image segment is split into four quadrants provided the original segment is non-uniform in properties. After this the four neighboring squares are merged depending on the uniformity of the region (segments). This split and merge process is continued until no further split and merge is possible.

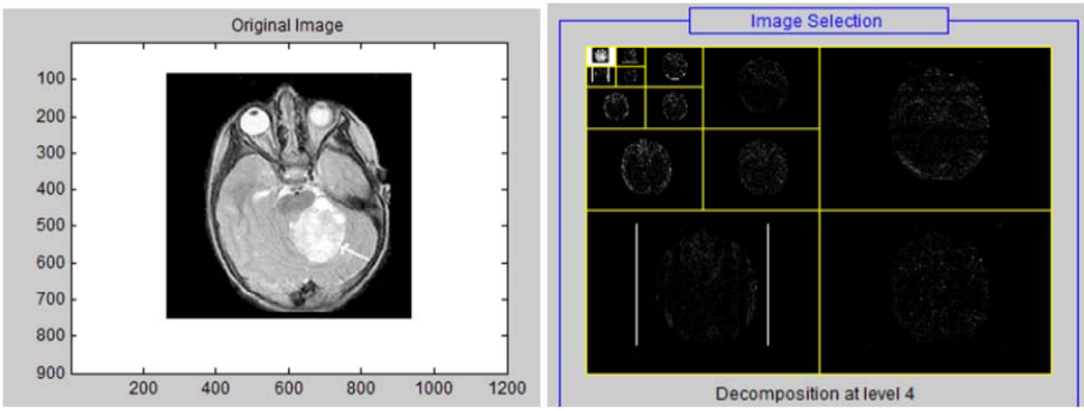
The algorithm for split and merge follows the following steps:

- Define homogeneity criterion. Break image into four square quadrants
- If any resultant square is not homogeneous split it further into four quadrants
- At each level merge the two or more neighboring regions satisfying the condition of homogeneity
- Continue the split and merge until no further split and merge of region is possible

After the segmentation process, the tumor regions are identified using a regionprops algorithm. The regions of the tumor are marked out based on their area properties. The regionprops algorithm measures the properties of image regions. Using the actual number of pixels in the region, the tumor region’s area is segmented. This value is slightly different from the value returned by bwarea, which weights diverse patterns of pixels in a different way. The regionprops calculates the area by measuring the distance between each neighboring pair of pixels around the border of the region.

Feature extraction: Textural features of image are important from image segmentation and classification point of view. Different researchers have used these features to achieve image segmentation, classification and both segmentation as well as classification. The aim of texture based segmentation method is to subdivide the image into region having different texture properties, while in classification the aim is to classify the regions which have already been segmented by one or other method. In this study, discrete wavelet transformation and Level set method are used to extract the texture features from the segmented image then PCA is used to reduce the dimensionality of the feature space which results in a more efficient and accurate classification.

Wavelet based feature extraction: Wavelets are numerical functions that decompose data into different frequency components. Wavelets have emerged as dominant new mathematical tools for analysis of difficult datasets. The Fourier transform provides representation of an image based simply on its frequency content. Hence this representation is not spatially localized while wavelet functions are localized



(a) (b)

Fig. 2: (a) Original image, (b) decomposition at level 4

in space. The Fourier transform decomposes a signal into a spectrum of frequencies whereas the wavelet analysis decomposes a signal into a hierarchy of scales ranging from the coarset scale. Hence Wavelet transform (Hiremath *et al*., 2006) which provides representation of an image at various resolutions is a better tool for feature extraction from images.

The DWT is an implementation of the wavelet transform using a discrete set of the wavelet scales and conversion, the family of wavelet functions is represented in Eq. (1):

$$\psi_{m,n}(t) = 2^{m/2}\psi\left(2^m t - n\right) \tag{1}$$

The wavelet transform decomposes a signal x (t) into a family of synthesis wavelets as given below in Eq. (2) and (3):

$$x(t) = \sum_m \sum_n C_{m,n}\psi_{m,n}(t) \tag{2}$$

where,

$$c_{m,n} = \left\langle x(t), \psi_{m,n}(t)\right\rangle$$

For a discrete-time signal x [n], the wavelet decomposition on I octaves is given by:

$$x[n] = \sum_{i=1 to I}\sum_{k\varepsilon Z} c_{i,k}\, g\left[n-2^i k\right] + \sum_{k\varepsilon Z} d_{I,k} h_I\left[n-2^I k\right] \tag{3}$$

where $c_{i,k}$i = 1…I is wavelet coefficients and $d_{i,k}$i = 1…I is scaling coefficients.

The wavelet and the scaling coefficients are given by:

$$c_{i,k} = \sum_n x[n]\, g_i^*\left[n - 2^i k\right] \tag{4}$$

$$d_{i,k} = \sum_n xv[n]\, h_l^*\left[n - 2^l k\right] \tag{5}$$

where,

$g_i\,[n - 2^i k]$ = Represent discrete wavelet sequences
$h_l\,[n - 2^l k]$ = Represent scaling wavelet sequences
* = Represents complex conjugate

The feature extraction of MRI images is obtained using DWT domain subimages. The DWT Novovicova *et al*. (1996) is implemented using cascaded filter banks in which the lowpass and highpass filters satisfy particular constraints. For feature extraction, only the subimage LL is used for DWT decomposition at next scale. The LL submerge at the last level is used as output features. Using this algorithm, using a 4-level DWT, the size of the input matrix is reduced from 65536 to 64 (Fig. 2).

Level-set-based feature extraction: Level-set-based shape modeling is an important research topic in computer vision and computer graphics. In this study, we implement a more recent work (Zhu *et al*., 2007) on binary level-set representation for object shape detection. Consider the basic definition of level set given as Eq. (6):

$$\varphi t + F\,|\nabla\varphi| = 0, \quad \text{given } \varphi\,(x, t = 0) \text{ and}$$
$$\varphi t + Fo\,|\nabla\varphi| + U\,(x, y, t)\,\nabla\varphi = \varepsilon K\,|\nabla\varphi| \tag{6}$$

where, Fo $|\nabla\varphi|$ is the motion of the curve in the direction normal to front, U (x, y, t) $\nabla\varphi$ is the term that moves the curve across the surface and $\varepsilon K\,|\nabla\varphi|$ is the speed term dependent upon curvature. In our study, U (x, y, t) is the gradient of image and $\varepsilon K\,|\nabla\varphi|$ is approximated using a central difference. We first convert the MRI to binary image. The level set is used on these binary images to track the shape at the boundary of images. Note for binary images, only digital derivative approximations exist at the boundary. The Gaussian filter creates a larger attraction range allowing the level sets to be attracted to the boundary. These steps iterate and stop when the boundary is completed upon convergence.

Feature reduction: Feature selection methods can be divided into feature ranking methods and feature subset selection methods. The feature ranking methods compute a ranking score for each feature according to its discriminative power and then simply select the top ranked features as final features for classification. 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 (Guyon and Elisseeff, 2003). PCA 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.

Proposed brain tumor classification: After feature extraction process, In-order to detect the presence of the tumor in the input MRI image, we perform the final classification step. Here we use the Ada-Boost classifier to classify the image into tumors or not.

The Ada-Boost algorithm, introduced by Freund and Schapire (1994), solved many of the practical difficulties of the earlier boosting algorithms (Schapire, 1999). In the following, a brief introduction of Ada-boost algorithm is provided. The algorithm takes as input a training set $(x1, y1), ..., (x_m, y_m)$ where each x_i belongs to some domain or instance space X and each label y_i is in some label set Y. For two class problem, Y = {-1, +1}. Initially, all weights are set equally, but on each round, the weights of incorrectly classified examples are increased so that the weak learner is forced to focus on the hard examples in the training set. The weak learner's job is to find a weak hypothesis h_t: X → {-1, +1} appropriate for the distribution D_t:

$$\in_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i] \sum_{i:h_t(z_t \neq y_t} D_t(i) \tag{7}$$

Notice that the error is measured with respect to the distribution D_t. The pseudo code is provided as follows: Given: $(x1, y1), ..., (x_m, y_m)$.

where,

$$x_i \in X, y_i \in Y = \{-1, +1\}$$

Initialize:

$$D_1(i) = 1/m \text{ for t = 1, 2, ….T}$$

Train weak learner using distribution D_t.
Get weak hypothesis ht: X → {-1, +1} with error:

$$\in_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i]$$

Choose:

$$\alpha_t = \frac{1}{2}\ln(\frac{1-\in_t}{\in_t})$$

Update:

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t} \tag{8}$$

where, Z_t is the normalization factor (chosen so that D_{t+1} will be a distribution). Break if $s_t = 0$ or $s_t \geq 1/2$ and set T = t - 1.
Output the final hypothesis:

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x)) \tag{9}$$

EXPERIMENTAL RESULTS

The proposed method has been implemented using the Mat lab environment. It has been tested on real brain MRI images consisting of normal and abnormal brain images. In the 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 (Zhu *et al*., 2010):

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

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

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

where, TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive. As suggested by above equations, Sensitivity is the proportion of true positives that are correctly identified by a diagnostic test. Specificity is the proportion of the true negatives correctly identified by a diagnostic test. Accuracy is the proportion of true results, either true positive or true negative, in a population. It measures the degree of veracity of a

Table 1: Detection accuracy of the proposed method with various classifier approaches in testing data set

Evaluation metrics		DWT+RBF	DWT+FFNN	Proposed method
Input MRI image data set	TP	37	35	38
	TN	8	8	9
	FP	2	2	1
	FN	3	5	2
	Sensitivity	0.925	0.875	0.95
	Specificity	0.730	0.620	0.90
	Accuracy	0.900	0.860	0.94
	Total error (%)	12.500	17.500	7.50

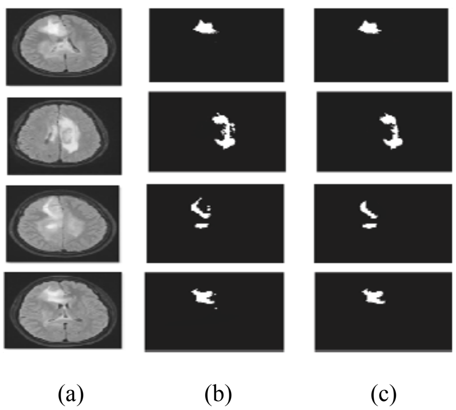


Fig. 3: (a) Original image, (b) manual segment, (c) proposed method

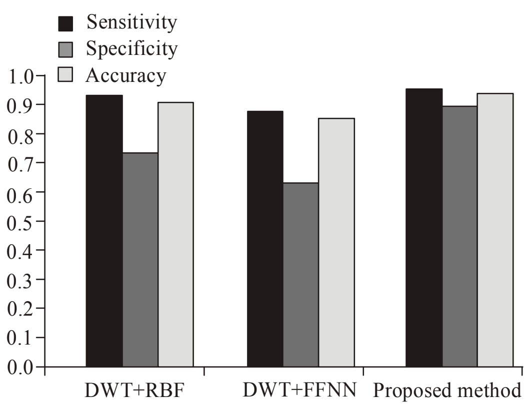


Fig. 4: Comparative analyses graph of ETCM with FSVM, RBF and FFNN

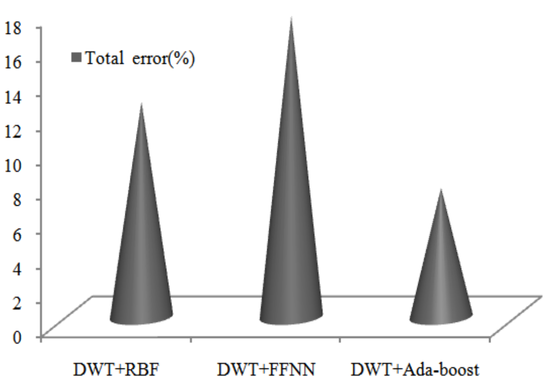


Fig. 5: Comparative error bar of the existing and proposed methods

diagnostic test on a condition. The obtained experimental results from the proposed technique and manual segmentation result is shown in Fig. 3.

The proposed system classification process are two stages namely training stage and testing stage. In train stage we have utilized 30 images (20 tumor images and 10 non-tumor images) and the remaining 50 images for testing purpose. The obtained experimental results of the existing and proposed methods are given in Table 1. By analyzing the results, the proposed method has a better performance. The outcomes of the experimentation proved with 94% of accuracy in Ada boost classifier based method with detection of tumors from the brain MRI images.

The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in Fig. 4. Also the proposed system error rate is less to other classifier; it is shown in Fig. 5. In this study, the proposed method is compared to the other neural network classifier Feed Forward Neural Network (FFNN) and Radial Basis Function (RBF). The proposed model yields better overall results to other classifier in terms of above evaluation metrics.

CONCLUSION

In this study, we have developed a neural network-based classifier to differentiate normal and abnormal brain MRI images. The proposed technique consists of four steps, especially, preprocessing, segmentation, feature extraction using DWT with Level-set method and classification using Ada-boost classifier respectively. In the preprocessing stage, an anisotropic filter is used to remove the noise and thus preserving the edge point of the image. In the segmentation, quadtree is used for partitioning an image into important regions. In the fourth the features are extracted using DWT with Level-set and finally to classify normal and abnormal brain MRI images Ada-boost is used. According to experimental results, the proposed method is efficient for classification of human brain into normal and abnormal classes.

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