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Automatic Brain Tissue Detection in Mri Images Using Seeded Region Growing Segmentation and Neural Network Classification

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Abstract: This paper presents a neural network-based method for automatic classification of magnetic resonance images (MRI) of brain under three categories of normal, lesion benign, and malignant. The proposed technique consists of six subsequent stages; namely, preprocessing, seeded region growing segmentation, connected component labeling (CCL), feature extraction, feature Dimension Reduction, and classification. In the preprocessing stage, the enhancement and restoration techniques are used to provide a more appropriate image for the subsequent automated stages. In the second stage, the seeded region growing segmentation is used for partitioning the image into meaningful regions. In the third stage, once all groups have been determined, each pixel is labeled according to the component to which it is assigned to. In the fourth stage, we have obtained the feature related to MRI images using the discrete wavelet transform (DWT). In the fifth stage, the dimension of obtained DWT features are reduced, using the principal component analysis (PCA), to obtain more essential features. In the classification stage, a supervised feed-forward back-propagation neural network technique is used to classify the subjects to normal or abnormal (benign, malignant). We have applied this method on 2D axial slices of 10 different patient data sets and show that the proposed technique gives good results for brain tissue detection and is more robust and effective compared with other recent works.

Key words: Brain Tumor Detection, Seeded Region growing Segmentation, Connected Component labeling, Feature Extraction and Selection, Artificial Neural Network, Classification.

INTRODUCTION

Brain tumor is one of the major causes of death among people. It is evidence that the chances of survival can be increased if the tumor is detected correctly at its early stage. Detection of these tumors from brain is very difficult at the regions where a tumor is overlapped with dense brain tissues. Visually detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue. Nowadays, automatic brain tumor detection in MRI images is very important in many diagnostic and therapeutic applications. In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing (such as edge detection and region growing) based on gray intensities of images. In recent years, those techniques have been combined with *artificial neural networks* (ANNs), *genetic algorithm* (GA), fuzzy logic, and Markov model to improve the performance. Recent works (Chaplot, S., L.M. Patnaik, and N.R. Jagannathan, 2006; Maitra, M. and A. Chatterjee, 2007) have shown that classification of human brain in MRI images is possible via supervised techniques such as artificial neural networks and *support vector machine* (SVM), and unsupervised classification techniques such as *self-organization map* (SOM) and fuzzy c-means. Other supervised classification techniques, such as *k-nearest neighbors* (k-NN) (Fletcher-Health, L.M., L.O., Hall, D.B. Goldgof and F.R. Murtagh, 2001) have also been used to classify the normal/pathological T2-weighted MRI images. In (Ahmed, El-Sayed, T. Hosny, A.Badeeh and M. Salem, 2010) a supervised machine learning algorithm (ANN and k-NN) is used to classify the images into two categories of normal or abnormal. The algorithm in (Murugavalli, S. and V. Rajamani,2007) suggests a high speed parallel fuzzy c-mean algorithm for brain tumor segmentation. In (Suchenddra, M. and K. Jean), a multiscale image segmentation using a *hierarchical self organizing map* (HSOM) is proposed. The algorithm in (Logeswari, T. and M. Karnan, 2010) suggests a HSOM-based technique that is a combination of SOM and graphic mapping technique. (Lashkari, A., 2010) presents a clear description brain tissue using Gabor wavelets and energy, entropy, contrast, and some other statistical features (such as mean, variance, correlation, values

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of maximum and minimum intensity). Even though many algorithms are available for brain tumor detection, the detection rate is still not satisfactory. Also, accurate partitioning of an image into meaningful regions (segmentation) is essential key to success or failure of image classification. Despite numerous efforts and promising results in brain tumor segmentation, accurate and reproducible segmentation and characterization of abnormalities are still a challenging and difficult task because of the variety of the possible shapes, locations and image intensities of various types of tumors (Khotanlou, H., O. Colliot, J.Atif and I. Bloch, 2009). A range of methods including boundary-based, region-based, and knowledge-based have been proposed for automatic segmentation of various structures in the brain. In (Ho, S., E. Bullitt and G. Gerig, 2002) a region-competition level-set method is used for automatic detection and segmentation of meningioma and glioblastoma brain tumor. Another approaches such as (Leemput, K.V., and al, 2001; Moon, N., 2002; Prastawa, M., 2004; Clark, M., 2000) focused on the use of pattern classification techniques for brain tumor segmentation.

The main purpose of this paper is to design and evaluate an automatic computer aided diagnosis algorithm that increases the accuracy of brain tumor detection. To improve tumor detection accuracy, here we present a new algorithm which is a combination of image processing techniques, Automatic seeded region growing segmentation (ASRGS), and ANNs. We tested different segmentation algorithms, such as thresholding, quadtree decomposition, and watershed in conjunction with ANNs classifiers. The results show the ASRGS method is the best method for brain segmentation before ANNs classification.

The proposed algorithm includes six major steps, namely, preprocessing, ASRGS, connected component labeling (CCL), feature extraction, feature dimension reduction, and ANNs classification. The preprocessing step considers the image artifacts due to sensitivity, distortion, resolution, and signal to noise ratio of the imaging system. The preprocessing step contains the enhancement and restoration processes. Noise (or speckle) removal is applied using an *adaptive weighted median filter* (AWMF). The enhancement step is applied by training an ANNs, adjusting the contrast using histogram equalization, and enhancing the edges obtained by Sobel operator. Then, the restoration process is used to delete the degraded effects in imaging systems (such as the object movement during the acquisition process, and pincushion and barrel distortions caused by poor focusing). After the preprocessing step, segmentation is done by a thresholding approach for metadata removal from brain pan image and for detection of brain region from skin-neck-bone and scalp. At last, brain images are segmented to distinguish pathological tissues (such as tumor region from normal tissues) using ASRGS. After segmenting, different objects are grouped using CCL. Then, the data is transformed into DWT. The dimension of obtained DWT features are then reduced using PCA. PCA coefficients are then imposed to supervised BPNN (Back Propagation Neural Network) classifier to classify them into one of several classes (such as normal, lesion, benign or malignant). The obtained results show that the ASRGA can improve the classifier accuracy respect to the other recent works.

Proposed Automatic Tumor Classification Method:

The block diagram of our proposed algorithm is shown in Figure 1. As shown in this figure, after the preprocessing step the images are segmented into isolated objects from each other and from background and the different objects are labeled. The feature extraction and selection step also measures certain properties of labeled objects. These features are then passed through a supervised BPNN classifier that evaluates the presented evidences and makes a decision on the class that each object should be assigned to.

Preprocessing:

In medical images, due to diagnostic and therapeutic applications the removal of noise and artifacts is critical. Specially, in MRI, inhomogeneous magnetic field, patient motion in imaging duration and external noise, are some sources of artifacts and other undesired effects. These form the main causes of computational errors in automatic image analysis and brain tumor detection. Therefore, it is necessary to remove them in the preprocessing procedure before any image analyzes can be performed. In this paper, the preprocessing step consists of image enhancement and image restoration.

Image Enhancement:

Enhancement algorithm is used to make the image more appropriate for the subsequent processes. It can reduce image noise and increase the contrast of structures in regions of interest. Image noise can reduce the capacity of region growing filter to grow into large regions or may result in false edges. Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" and speckle noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. For noise suppression, a *weighted median filter* (WMF) using neural network is constructed in this paper. Here, we use a one-layer network with nine input neurons, and one output indicating the pixel intensity at the mask center. The structure is depicted in Figure 2. The input is nine pixels of noisy intensities and the desired is the noise removed value of the mask center. In the training phase, the basic back-propagation algorithm adjusts the weights in the steepest descent direction; the direction in which the performance function is decreasing most rapidly. After training a weighted median filter is implemented as

$$x_5 = median\{w_1 \times x_1, w_2 \times x_2, ..., w_9 \times x_9) \quad (1)$$

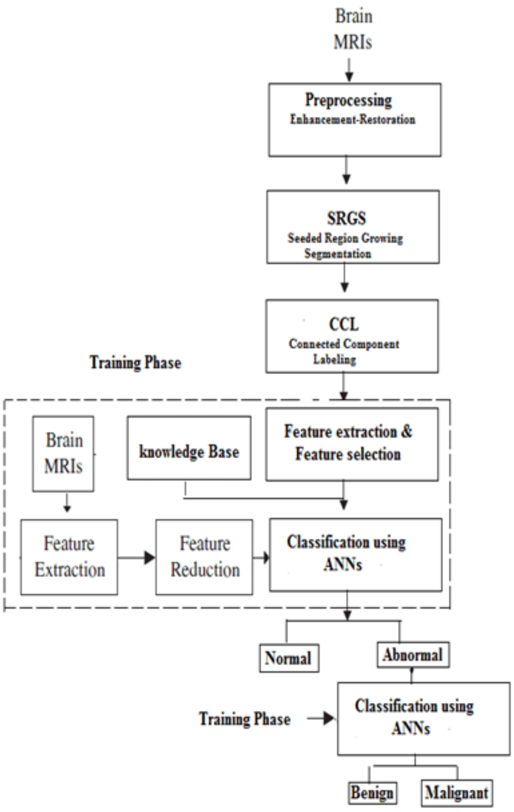


Fig. 1: Block diagram of proposed tumor classification method.

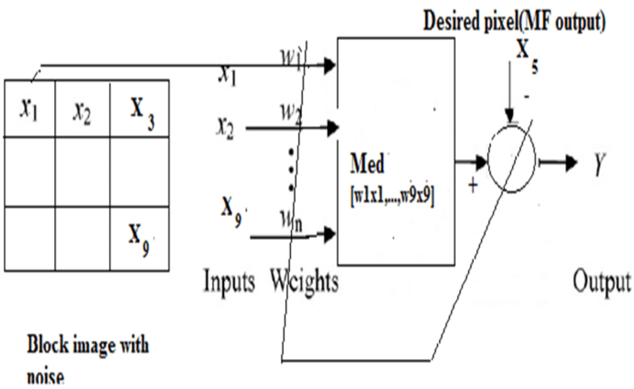
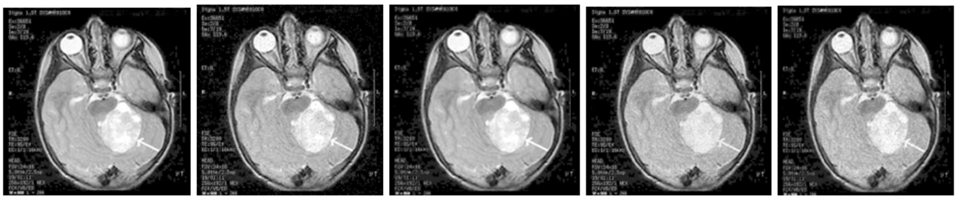


Fig. 2: NN-based model of the best weighted median filter.

Figure 3 shows the WMF effect on images that are degraded by “salt & pepper” and speckle noise. Also, in this paper, for contrast enhancement purposes, a local area histogram equalization is used and for edge enhancement the horizontal and vertical Sobel edge detectors are used.



(a) (b) (c) (d) €

Fig. 3: (a) Original image. (b) Degraded image with "salt & pepper" noise. (c) WMF result of image (b). (d) degraded image by speckle noise. (e) WMF result of image (d).

Image Restoration:

The basic goal of restoration is to improve the quality of images and attempts to reconstruct (or recover) the degraded image by using a prior knowledge of the degradation phenomenon. An image might be degraded by noise, blurring, and distortion during acquisition and transmission in the imaging systems. Image restoration tries to remove (or reduce) these degradations using the *point spread function* (PSF) that directly characterizes the image degradation process. In this paper, to restore the images we apply the inverse of the blurring and distortion transformation on degraded images.

Blur Cancellation:

A blurred (or degraded) image can be approximately described by

$$g(x,y)=h(x,y)*f(x,y)+n(x,y) \tag{2}$$

where g is the blurred image, h is the distortion operator (the point spread function), f is the original image, and n is noise.

Taking the Fourier transform from Eq. 2 we get

$$G(u,v)=F(u,v).H(U,v)+N(u,v) \tag{3}$$

To remove this degradation, the Wiener filter is used in this paper. The Wiener filter is an optimal filter in the sense that it delivers the best estimate of the original, (*i.e.*, it finds an estimate of the uncorrupted image such that the mean squared error between them is minimized). However, in order to strictly realize the minimum mean squared error estimation the signal-to-noise ratio needs to be known as

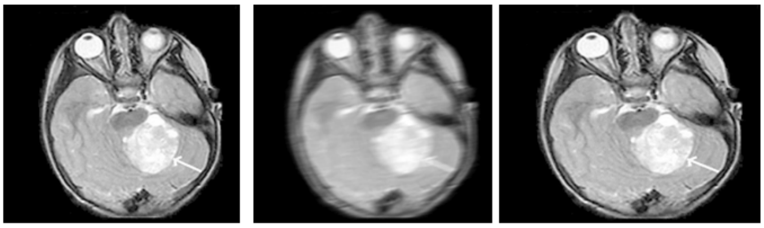
$$\hat{F}(u,v)=\frac{1}{[H(u,v)]}.\frac{[|H(u,v)|^2]}{[|H(u,v)|^2+(|N(u,v)|^2/F(u,v)|^2)]} \tag{4}$$

where $|N(u,v)|^2/F(u,v)|^2$ is the inverse of signal-to-noise ratio of the image averaged over all frequencies (that can be considered as an adjustable empirical parameter chosen to balance the sharpness against noise). The qualities of restored images obtained by Wiener filtering are superior to those obtained from direct inverse filtering.

To illustrate this effect we took a clear image and deliberately blurred it by convolving it with a PSF. We used the "fspecial" function to create a PSF that simulates a motion blur; with the length of blur in pixels, LEN=31, and the angle of blur in degrees THETA=11. Once the PSF is created, the example uses the "imfilter" function to convolve the PSF with the original image, I, to create the blurred image. In this paper, deblurring is applied using the Wiener filter. We used the simplest syntax for Wiener filter in Matlab as

Deconvwnr(A, PSF, NSR)

where A is the blurred image, PSF is the point spread function, and NSR is the noise-power-to-signal-power ratio. The blurred image formed in Step 2 is noise removed, so we used 0 for NSR. Deblurring by wiener filter is shown in Figure 4.



(a) (b) (c)

Fig. 4: (a) Original Image. (b) Blurred image (LEN=31, TETH=11. (c) Deblurred image using Wiener filter.

Periodic Noise:

In an imaging system, periodic noise is typically caused by presence of the electrical interference, especially in presence of a strong mains power signal during the image acquisition or transformation. This type of noise is most effectively reduced with frequency domain filtering, which isolates the frequencies occupied by the noise and suppresses them using a notch (narrow band reject) filter. Figure 5 shows the periodic noise reduction step. The noise can be mostly removed by filtering out the relevant spots in the Fourier domain and taking the inverse Fourier transform. Figure 6 shows a degraded brain image with periodic noise. The 2D FT is shown in Figure 6(b). Then, by deleting the relevant spots in 2D FT and taking the inverse Fourier transform the periodic noise is deleted; as shown in Figure 6(c).

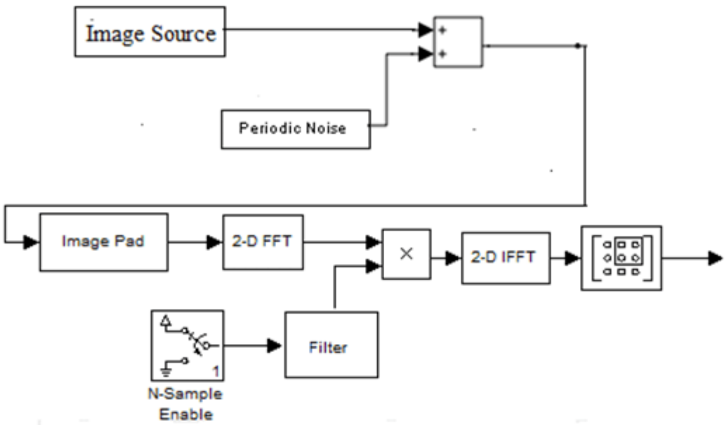
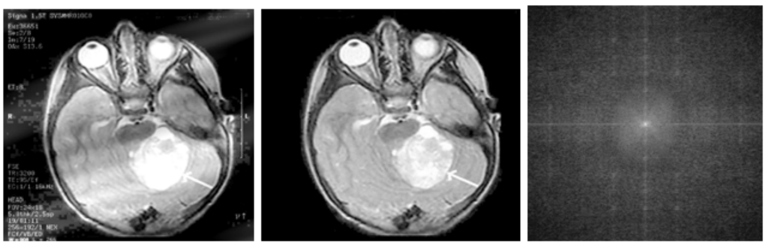


Fig. 5: Periodic noise reduction method.



(a) (b) (c)

Fig. 6. (a) Image degraded by periodic noise. (b) Removal of corresponding frequencies in Fourier domain. (c) Restored image.

Geometric Degradation:

An image can be geometrically distorted within an imaging system, due to unequal magnification within the field of view. Extreme wide-angle and low-angle lenses produce very significant barrel and pin-cushion, respectively.

Barrel distortion perturbs an image radially in outward from its center. Distortion is greater as we move farther from the center, resulting in convex sides as shown in Figure 7(a). Pin-cushion distortion is the inverse of barrel distortion. It is because the cubic term has a negative amplitude. Distortion is still greater we going farther from the center but it results in concave sides, as can be seen in Figure 7(b). In this paper, barrel/pincushion distortion process within the region bounded by control points can be modeled by a pair of bilinear equations as

$$\begin{aligned} x' &= c_0 + c_1 x + c_2 y + c_3 xy \\ y' &= d_0 + d_1 x + d_2 y + d_3 xy \end{aligned} \tag{5}$$

The coefficient can be calculated if, in each image, four corresponding control points are known. In this paper, the coefficients are used to transform all pixels within the quadrilateral bounded by the control points to recover the image.

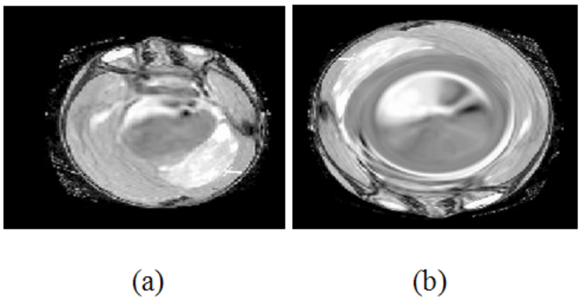


Fig. 7: (a) Image with barrel distortion. (b) Image with pincushion distortion.

Automatic Seeded Region Growing Segmentation (ASRGS):

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 quadtree 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. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. For this reason, in this paper, considerable care is done to select and improve of a rugged segmentation. To select the best segmentation method, We applied different segmentation algorithms, such as thresholding, watershed, region splitting/merging , and region growing to Brain images as below.

1. Watershed segmentation:The watershed algorithm for brain segmentation is described below.
2. Computation of gradient magnitude using Sobel operator.
3. Computation of foreground markers using a set of morphological techniques called “opening-by-reconstruction” and “closing by reconstruction”.
4. Computation of background markers.
5. Computation of watershed transform of segmentation function.

The watershed segmentation results for a patient brain images (fig. 8) are shown in figure 9.

Thresholding:

In thresholding method the im2bw function is used to convert the grayscale image into a binary image. The function graythresh automatically computes an appropriate threshold using Otsu’s method. These results are shown in figure 10.

Region Splitting and Merging Using Quadtree Decomposition:

Quadtree decomposition is an analysis technique that involves subdividing an image into blocks that are more homogeneous than the image itself. In this paper we perform quadtree decomposition using the qtdecomp (Matlab) function. This function works 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.

Figure 11 shows a representation of quadtree decomposition. Each black square represents a homogeneous block, and the white lines represent the boundaries between blocks. Notice how the blocks are smaller in areas corresponding to large changes in intensity in the image.

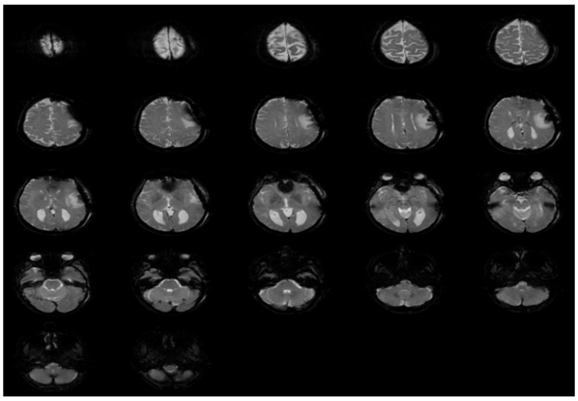


Fig. 8. 22 axial slices of MRI brain images with tumor.

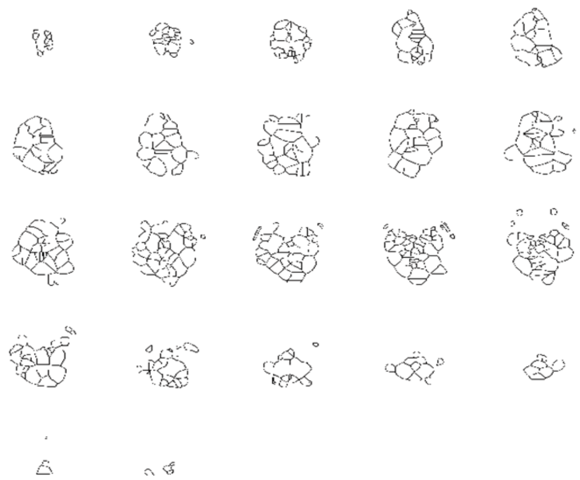


Fig. 9. Watershed segmentation results of figure 8.

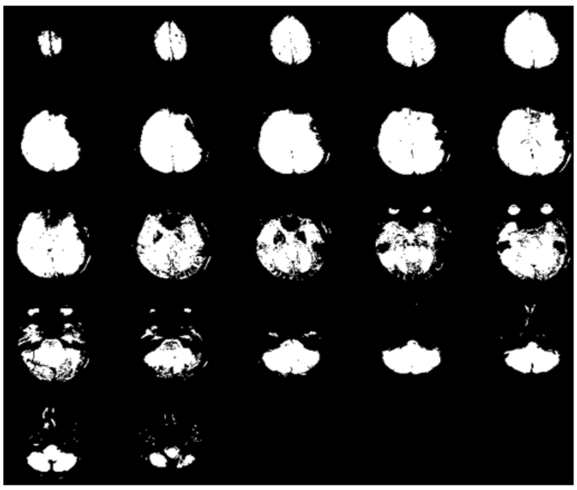


Fig. 10: Thresholding segmentation results of fig. 8.

Fig. 11: Quadtree decomposition results.

Automatic Seeded Region Growing Segmentation (ASRGS):

The proposed ASRGS algorithm for brain segmentation is described below.

1. Input image=I; (x,y)=seed point; t=maximum intensity distance; mean of region=I(x,y);
2. Start region growing until distance between the mean of region and new pixels become higher than a certain threshold(t).
3. Add new 4-neighbors pixels.
4. Add neighbor if inside and not already part of the segmented area.
5. Add pixel with intensity nearest to the mean of the region, to the region.
6. Calculate the new mean of the region.
7. Save the x and y coordinates of the pixel (for the neighbour add proccess.
8. Return 2

Here, thresholding segmentation is used to distinguish brain regions from scalp and pathological tumor tissues from normal tissues. Segmentation, hierarchically, starts by brain detection from skin-neck-bone and ventricles and finally tumor detection from brain images. For detecting brain regions from scalp the algorithm in [9] is used. In that algorithm, the Dicom images were previously anonymized to remove patient information by using the DICOMREAD and DICOMWRITE commands from the image processing toolbox. Then, brain mask is obtained by thresholding. Segmentation results are shown in Figure 12.

After brain detection from other parts (such as skin-neck-bone and ventricle) using thresholding segmentation, the ASRGS algorithm is used to separate different parts of brain such as tumor. In ASRGS the region is iteratively grown by comparing all unallocated neighbouring pixels to the region. The difference between a pixel's intensity value and the region's mean, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process stops when the intensity difference between region mean and new pixel become larger than a certain threshold (Fig. 13).

From these results we see that the proposed method (ASRGS) is the most stable and has the best Jaccard score.

Connected Component Labeling:

After ASRGS segmentation, once all groups have been determined, each pixel is labeled according to the component to which it is assigned to. The labeling of connected components in an image is central to many automated image analysis applications (Dougherty, G., 2009).

A two-pass algorithm for labeling connected components comprises three distinct phases.

1. The image is scanned row-wise until it comes to a pixel p whose pixel value is 1. Based on this information, provisional labeling of p occurs as follows:
   - If all four neighbors have pixel values of 0, assign a new provisional label to p, else
   - If only one neighbor has a pixel value of 1, assign its provisional label to p, else
   - If more than one of the neighbors have pixel values of 1, assign one of the provisional labels to p and make a note of the equivalences.
2. The equivalent label pairs are sorted into equivalences classes and a unique label is assigned to each class.
3. In the final step, a second scan is made through the image, during which each label is replaced by the label assigned to its equivalence classes.

Feature Extraction and Feature Dimension Reduction:

After image segmentation and labeling, a feature extraction step reduces the data by measuring certain properties or features of the labeled objects. The features are higher-level representations of structure and shape, and should be chosen to preserve the information that is important in image. Also, to decrease the dimension of extracted features, the *principal component analysis* (PCA) is used. To decrease the number of features per object, feature selection, choosing the most informative subset of features, and not using the others.

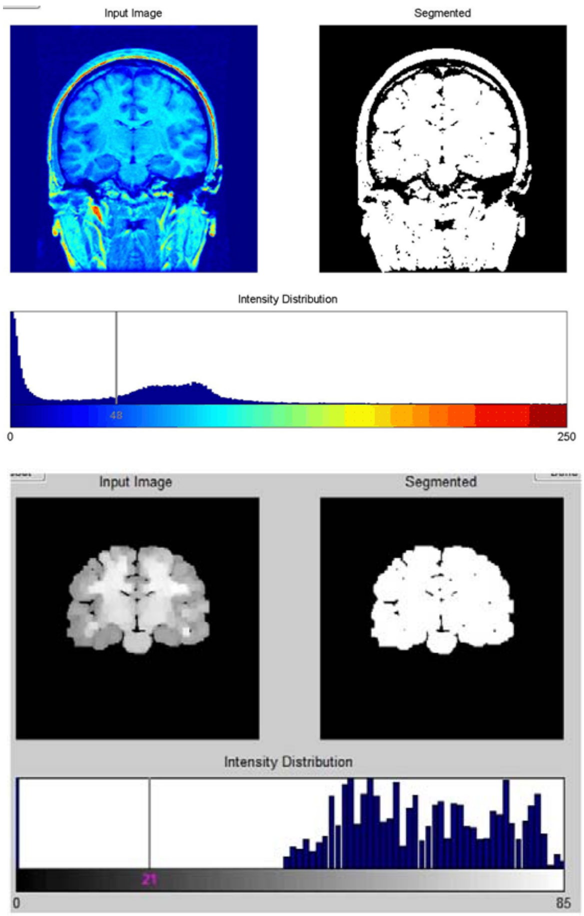


Fig. 12: (a) Original image. (b) Segmented image. (c) Histogram of image (a). (d) Segmented brain region. (e) Brain mask. (e) Brain histogram.

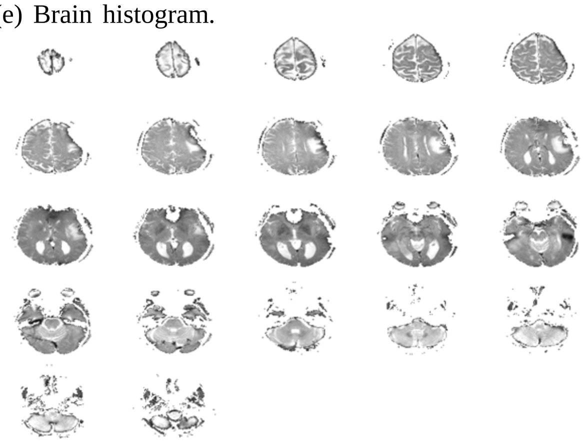
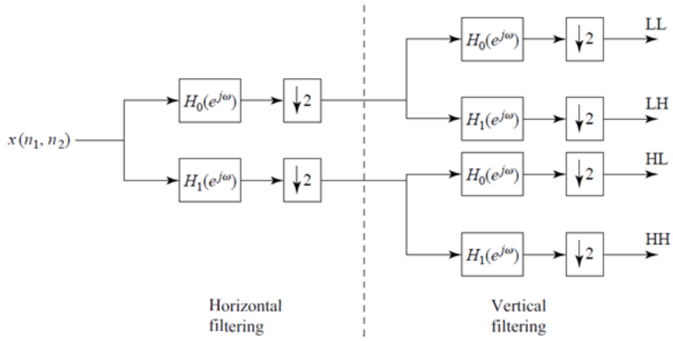


Fig. 13: ASRGS results of fig. 8.

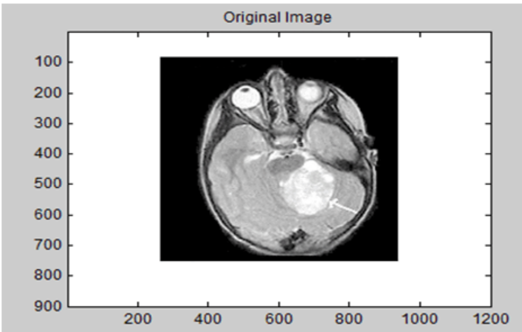
Feature Extraction:

In this paper, the feature extraction of MRI images is obtained using DWT domain subimages. The DWT is implemented using cascaded filter banks in which the lowpass and highpass filters satisfy certain specific constraints. The basic scheme of DWT decomposition and its application to brain images is shown in Figure 14. For feature extraction, only the subimage LL is used for DWT decomposition at next scale. Also, the LL subimage at 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. The DWT results are shown in figure 15.

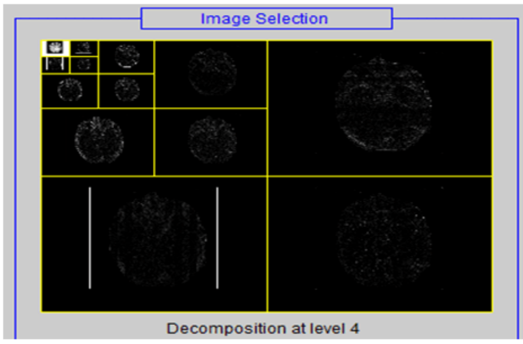


(a)

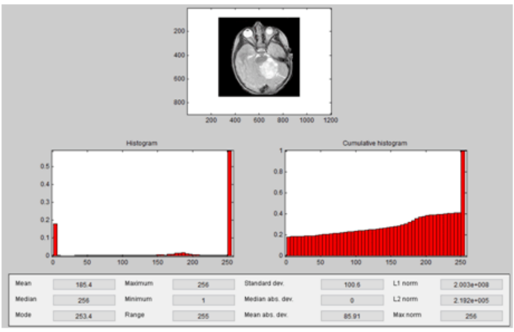
Fig. 14: 2D wavelet transform decomposition.



(a)



(b)



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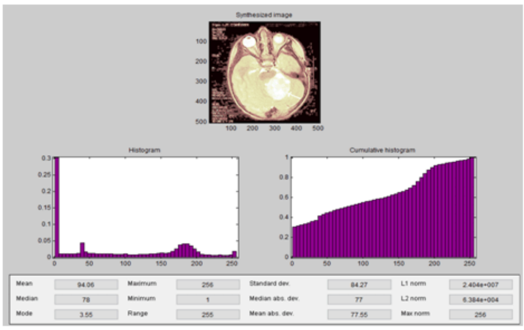
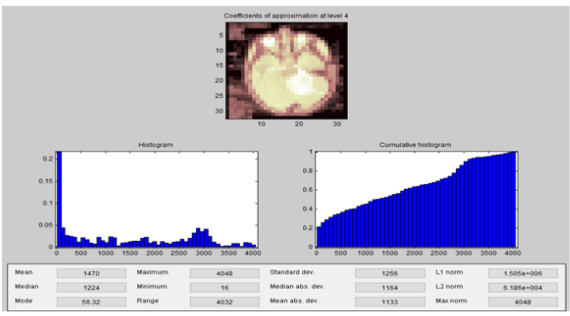


(d)



(e)

Fig. 15: (a) Original image. (b) Decomposition at level 4. (c) Histogram and cumulative histogram of original image. (d) Histogram and cumulative histogram of synthesized image. (e) Histogram and cumulative histogram of decomposed image at level 4.

Feature Dimension Reduction:

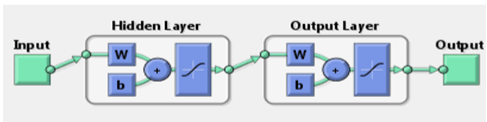
The principal component analysis is a well-known tool to efficiently reduce the dimension of extracted features. We use the PCA algorithm proposed in (El-Sayed Ahmed El-Dahshan, T. Hosny, A. Badeeh, M. Salem, 2010), so that the size of the input matrix (DWT output) is reduced from 256 to 9. The values of these features are then passed through a classifier that evaluates the presented evidence and makes a decision on the class that each object should be assigned to. Feature extraction and feature dimension reduction are necessary to reduce the input data for ANNs classification. It is necessary to reduce the dimensionality of the classification task by measuring essential properties or features of the objects.

Classification Using ANNs:

For brain image classification, as normal or abnormal, we use a neural network to classify inputs into a set of target categories. In this paper, to classify a brain tumor as normal or abnormal (benign or malignant), based on feature selection parameters, a BPNN is used. The Neural Network Toolbox in Matlab is used to select data, create and train a network, and evaluate its performance using mean squared error and confusion matrices. A two-layer feed-forward network, with sigmoid hidden and output neurons, can classify vectors arbitrarily well; given enough neurons in its hidden layer. The network is trained using scaled conjugate gradient back-propagation (trainscg). Brain classification is based on nine features, extracted from feature selection stage. The data set consists of 600 samples. "tumorInputs" is an 9×600 matrix, whose rows are selected features from feature selection stage. "tumortarget" is an 2×600 matrix, where each i^{th} column indicates which category the i^{th} tumor belongs to; with a 1 in one element and zeros in the other elements as normal and abnormal, respectively.

After classifying the images to normal and abnormal, abnormal images are applied to a similar BPNN for detection of benign or malignant tissues.

The input and target data are interred to the network during training, and the network is adjusted according to its occurred error. Training stops automatically when generalization stops improving; as indicated by an increase in the mean squared error of validation samples. Percent error indicates the fraction of misclassified samples. A value of 0 means no misclassifications, and 100 indicates maximum misclassifications. Figure 16 shows the training results of confusion matrix and receiver operating characteristic. Testing phase has no effect on training and provides an independent measure of network performance during and after training.



(a)

(b) (c) (d)

Fig. 16: (a) ANNs structure. (b) Training state gradient. (c) Confusion matrix. (d) Receiver operating characteristic.

Experimental Results and Discussion:

In this paper, an automatic brain tumor classifier was proposed. The proposed technique was implemented on a real human MRI dataset (50 normal, 550 abnormal (300 bening and 250 maltignant) provided by the Harvard medical school website (http://med.harvard.edu). The algorithm described in this paper is developed and successfully trained in Matlab version 7.10.0 using a combination of image processing, pattern recognition and wavelet toolbox. We algorithm was run on a personal computer with 2 GHZ Pentium V processor and 4 GB of memory, running under windows-7 operating system. For evaluate the proposed algorithm we used the metrics of sensitivity, specificity, and accuracy as

$$Sensitivity=TP/(TP+FN); \tag{6}$$

$$Specificity=TN/(TN+FP); \tag{7}$$

$$Accuracy=(TP+TN)/(TP+TN+FP+FN) \tag{8}$$

where:
TP: true positive, the classification result is positive in presence of clinical abnormality.
TN*: true negative*; the classification result is negative in absence of clinical abnormality.
FP: *false positive*, the classification result is positive in absence of clinical abnormality.
FN: *false negative*, the classification result is negative in presence of clinical abnormality.

These criteria are listed in Table 1.

Table 1: different Classified Groups.

Actual Group	Normal	Abnormall
Normal	TN	FP
Abnormal	FN	TP

To evaluate the tumor's detection accuracy, the algorithm performance is compared with the decisions made by four expert radiologist experts.

For brain tumor classification, a two step algorithm was used. In the first step, a BPNN was used to classify the brain into normal or abnormal. The experiment results for normal and abnormal classification are listed in Table 2. According to this results, a classification with 100% sensitivity rate and 98% specifity rate is obtained.

In the second step, a BPNN was used to classify abnormal image to benign or malignant. The results for benign or malignant classification are shown in Table 3. According to this results, a classification with 99.5% sensitivity rate and 96% specifity rate was obtained.

Table 2: Iiresults of Normal/abnormal Classification.

	Normal	Abnormal
Normal	49	1
Abnormal	0	450

Table 3: Iiiresults of Benign/malignant Classification.

	Benign	Malignant
Benign	299	1
Malignant	0	250

Moreover, we compared our method with other methods, which are listed in Table 4. It is clear that our proposed method earns the highest classification accuracy.

Table 4: Classification Accuracy Comparison.

Approach	Classification Accuracy
DWT+SOM[2]	94
DWT+SVM[2]	96
DWT+PCA[2][11]	97

Also, in any computer aided analysis the execution time is one of the important parameters of medical image segmentation and classification. For implementing this algorithm, a computer program has been developed using MATLAB 7.10.1 software on a Pentium V processor, 2GHz with windows 7 operating system. The algorithm takes about 60 seconds on average to segment 256×256 images. The performance of the neural network train is shown in Figure 17.

Conclusion:

In this paper, we have developed a novel neural network-based classifier to distinguish normal and abnormal (benign or malignant) brain MRIs. The proposed technique consists of six stages, namely, preprocessing, Automatic seeded region growing segmentation, connected component labeling, feature extraction, feature dimension reduction, and classification. In the preprocessing stage, the enhancement and restoration techniques are used to provide a more proper image for subsequent automated analysis. In the segmentation stage, the automatic seeded region growing is used for partitioning an image into meaningful regions. In the third stage, once all groups have been determined, each pixel is labeled according to the component to which it is assigned to. In the fourth stage, we have obtained the features related to MRI images using discrete wavelet transform. In the fifth stage, the number features of MRI are reduced, using the principal component analysis. In the classification stage, a supervised feed-forward back-propagation neural network technique is used to classify subjects as normal or abnormal (benign, malignant). We applied this method on 600 images (50 normal, 250 benign and 300 malignant). A classification with 100% sensitivity rate and 96% specifity rate was obtained. According to experimental results, the proposed method is efficient for classification of human brain into normal and abnormal classes. The classification performances of this study show that the proposed method is fast, easy to operate, non-invasive, and inexpensive. Extension of developed techniques for classification of different types of brain tumor is the topic of our future research. Also, we will try to develop this algorithm for classification of other tumors such as breast cancers.

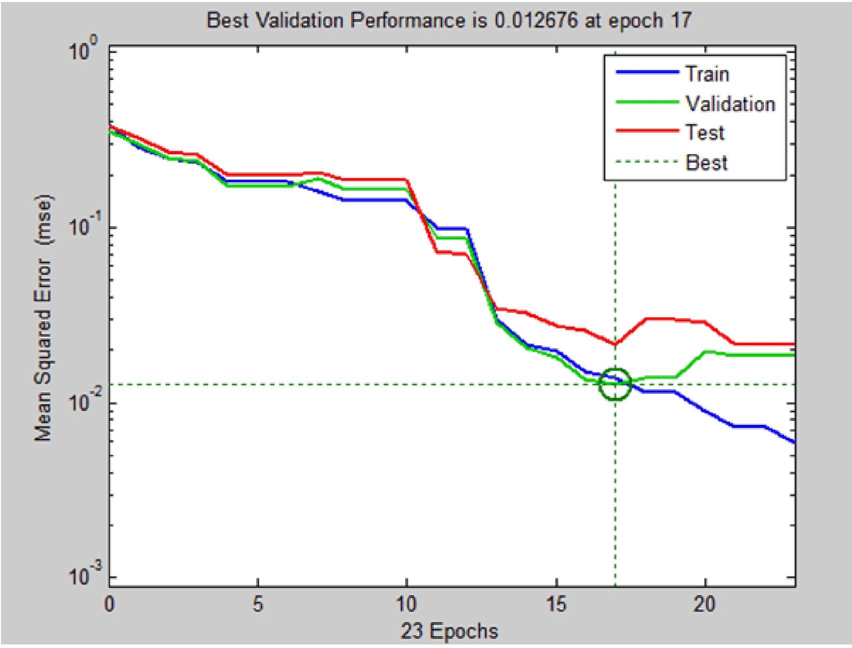


Fig. 17: Performance measure for ANN trained to detect brain tumor.

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