Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images

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Abstract— **Tumor is a pre-stage of cancer which has become a serious problem in this era. Researchers are trying to develop methods and treatments to round it. Brain tumor is an exceptional cell enhancement in brain tissue and may not always be seen in imaging tricks. Magnetic Resonance Imaging (MRI) is a technique which is applied to display the detailed image of the attacked brain location. The medical imaging trick plays a significant behavior in identification of the disease. In this paper, the brain MRI image is chosen to investigate and a method is targeted for more clear view of the location attacked by tumor. An MRI abnormal brain images as input in the introduced method, Anisotropic filtering for noise removal, SVM classifier for segmentation and morphological operations for separating the affected area from normal one are the key stages if the presented method. Attaining clear MRI images of the brain are the base of this method. The classification of the intensities of the pixels on the filtered image identifies the tumor. Experimental result showed that the SVM has obtained 83% accuracy in segmentation. Finally, the segmented region of the tumor is put on the original image for a distinct identification.**

Keywords— Brain Tumor; Magnetic Resonance Imaging (MRI); Anisotropic Filtering; Segmentation; SVM Classifier; Morphological Operation

I. Introduction

In human body, among all the organs brain is one of the largest and most complex. It is consisted of more than 100 billion nerves that communicate in trillions of connections called synapses. It may be affected by tumor. An unusual enhancement of tissue in the brain is known as brain tumor. Brain tumors are grouped as follows [1]-[3]:

A. Benign and Malignant Brain Tumors

Benign tumor is less harmful and grows slowly. On the contrary, malignant tumor contains cancer cell and grows rapidly.

B. Primary and Secondary Brain Tumors

The primary brain tumors launch in cells of the brain. Otherwise, the secondary brain tumors start in another part of the body and then propagate to the brain.

C. Naming and Grading Brain Tumors

The origin and container cells of tumor may be known from the name of brain tumor. Pursuant to World Health Organization (WHO) tumors have four categories, grade I, II, III and IV [1]-[3]. Grade I brain cancerous tumor grows slowly and rarely spreads into nearby tissues. The tumor dilates slowly, but may deploy into nearby tissue in grade II brain cancer. The tumor dilates quickly into nearby tissue and the tumor cells look very dissimilar from normal cells in grade III brain cancer. Grade IV brain cancerous tumor grows and dilates very quickly and the tumor cells look like abnormal cells.

II. Literature Review

Brain tumor can be detected using CT (Compute Tomography), MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography) etc. images. Among all of them MRI is preferred for its better performance. Image filtering is a great challenge for noise removal from an image. For this purposes, the common filters such as median filter, adaptive filter, averaging filter, Gaussian filter, un-sharp masking filter etc. are used [4]-[7]. Image segmentation is a technique by which an image is partitioned into various regions. There are many methods for image segmentation and they are thresholding, clustering, level set method etc. [4]. Some methods include supervised and unsupervised learning. In supervised learning, training data sets are provided and in unsupervised learning, data sets are not provided. Morphological operations are used as post processing method for extracting the tumor from the image. In general dilation, erosion, open filter, close filter are used for this purpose. These operations are applied on the binary image and finally by adding all the disjoint objects the tumor is located in the MRI brain input image [2], [3], [7].

III. Proposed Methodology

The proposed system can be summarized in three stages. First stage contains filtering technique which removes noise by using Anisotropic Filter (AF) from the brain MRI image and then adjustment based segmentation which segments the region of the tumor from the filtered image using a structuring element. Third stage contains morphological operation which shows the location of the tumor on the original image. Fig.1 shows the proposed system's flowchart.

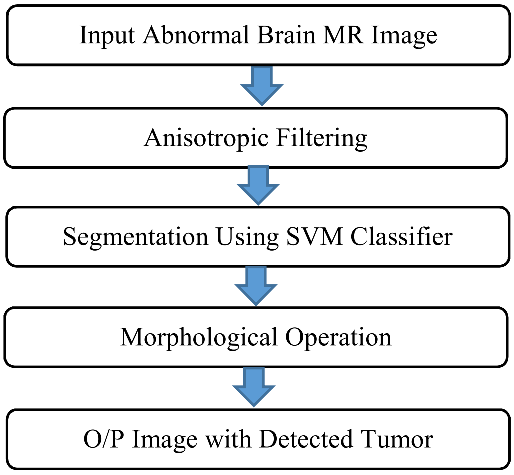
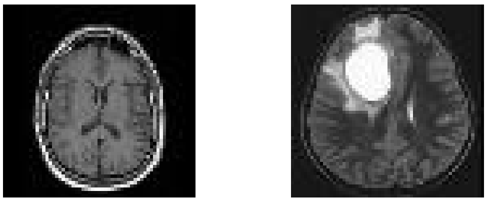


Fig. 1. Flowchart of the proposed system

A. Dataset

A single abnormal MR image [8] is taken as input to detect the tumor. The input image is 256*256 pixels and 8-bit grayscale.



(a) Normal image (b) Abnormal image

Fig. 2. Brain MRI images [8]

B. Anisotropic Filtering

The main objective of filtering an image is to remove the noises on the digital images. The quality of the image is attacked badly by the noises. There are many ways to get rid of the noise in the image. Most of the image processing algorithms do not work well in the noisy environment. This is why the image filter is used as a pre-processing tool. Among various filter Anisotropic Filter is used in this thesis for denoising purposes. The general anisotropic diffusion equation is introduced to describe the image diffusion process as follows [4]:

$$\frac{\partial x}{\partial t}=div\,(c(m,n,t)\nabla I)=\nabla c\cdot\nabla x+c(m,n,t)\nabla x \quad (1)$$

Where, ∇x denotes image gradient and $c(m,n,t)$ denotes diffusion coefficient. The following notation shows a discretized approximation by the forward and backward differences.

$$I_{i,j}^{t+1}=I_{i,j}^{t}+dt\sum_{(k,l)\in N_4} g\left(I_{k,l}^{t}-I_{i,j}^{t}\right)\cdot\left(I_{k,l}^{t}-I_{i,j}^{t}\right) \quad (2)$$

$$h\left(I_{k,l}^{t}-I_{i,j}^{t}\right)=\frac{c_{k,l}^{t}+c_{i,j}^{t}}{2} \quad (3)$$

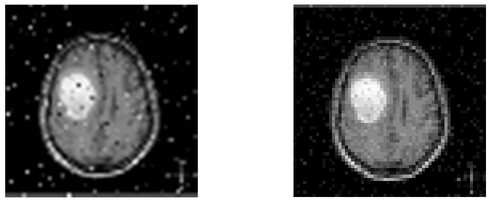
Where, $N_4 = \{(i-1, j), (i+1, j), (i, j-1), (i, j+1)\}$ denotes the 4-neighborhood of the central pixel $I_{i,j}^{t}$. From Eq. (3) we can see that noise pixel has strong diffusion action and signal pixel has weak diffusion action. Thus noise can be removed and signal will be kept. There are many diffusion models to adopt the constant step size for each iteration or whole iterative process of the image. Here a better iteration step is proposed in the Eq. (4).

$$dt=\frac{1}{4}c \quad (4)$$

Where, 1/4 is used to promise the convergence of the Eq. (2). Final output phase image is obtained by iterative process. For iteration process, iteration error (IE) is used for controlling the iterative number and its formula is:

$$IE=\frac{\|I^{n}-I^{n-1}\|}{\|I^{n}\|}\leq T_{ie} \quad (5)$$

When IE is less than or equal to tolerance T_{ie}, the iterative process is stopped.



(a) Noisy Image with Salt & Pepper Noise (b) AF output

Fig. 3. Input and Output for Anisotropic Filter

C. SVM for Image Segmentation

The procedure of distribution an image into multiple parts is known as image segmentation. This is ordinarily applied to identify objects or other relevant information in digital images. Among all of the segmentation techniques Support Vector Machine (SVM) is used here. Let's consider the following simple problem to obtain the optimal hyperplane:

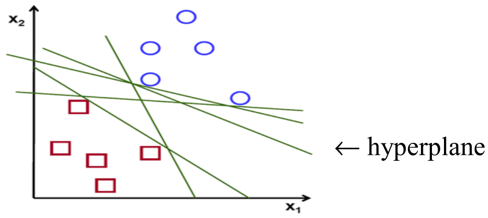


Fig. 4. For a linearly separable set of 2D-pointswhich belong to one of two classes, find a separating straight line [9]

Let's consider the following equation which is used to define a hyperplane:

$$p(x)=\propto_0+\propto^{T}\ z \quad (6)$$

Where, $\propto$ represents the weight vector and $\propto_0$ as the bias. A vast number of various paths by scaling of $\propto$ and $\propto_0$ describe the satisfactory hyperplane. Among all the feasible legation of the hyperplane, the following one is chosen:

$$|\propto_0+\propto^{T}\ z|=1 \quad (7)$$

Where, z represents the training examples closest to the hyperplane. Commonly, support vectors are the nearest training examples to the hyperplane. Now we use the outcome of geometry that gives the difference between a point z and a hyperplane $(\propto,\propto_0)$:

$$D=\frac{|\propto_0+\propto^{T}\ z|}{\|\propto\|} \quad (8)$$

The numerator is equal to one for the canonical hyperplane and the difference to the support vectors is,

$$D_{support\ vectors} = \frac{|\propto_0 + \propto^T z|}{\|\propto\|} = \frac{1}{\|\propto\|} \quad (9)$$

The following equation that is two times the difference to the nearest examples represents the margin, denoted as M.

$$M = \frac{2}{\|\propto\|} \quad (10)$$

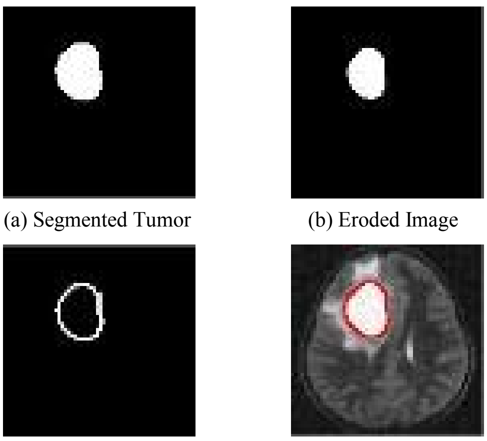
Ultimately, maximizing problem for M is identical to the minimizing problem for a function $R(\propto)$ subject to several confines. To classify correctly all the training examples z the confines model for the hyperplane is,

$$\min_{\propto,\propto_0} R(\propto) = \frac{1}{2}\|\propto\|^2 \textit{subject to } y_i(\propto^T\ z_i + \propto_0) \geq 1\ \forall_i, (11)$$

Where, y_i represents each of the labels of the training examples. This is a problem of Lagrangian optimization which can be solved using Lagrange multipliers to attain the weight vector $\propto$ and the bias $\propto_0$ of the satisfactory hyperplane.

D. *Morphological Operation*

Morphology is an instrument to extract image features useful in the legation and recital of region shape such as-boundaries, skeletons and convex hulls. For morphological operation structuring element (kernel) is required .The structuring element used in practice is generally much smaller than the image often a 3*3 matrix. Morphological Opening is applied to the image after segmentation. The two important operations of morphology are: *a) Dilation:* It works by object expansion, hole filling and finally adding all the disjoint objects and *b) Erosion:* It shrinks the object. Foreground pixel background is eroded away in the binary image by erosion operation. Morphological Opening is applied to image (a) after converting it into binary image. To segment out the tumor location from the image it is required to create a Binary tumor masked window. Normally, higher intensities comparing with other surrounding tissues are held by an abnormal brain MR image. By putting the tumor mask on dilated brain MR image the final image is obtained with detected tumor. Fig. 5 displays the resultant images of morphological operation with detected tumor.



(a) Segmented Tumor (b) Eroded Image

(c) Tumor Outline (d) Detected Tumor

Fig. 5. Output for Morphological Operation

IV. Results and Discussion

In this work, we have tried to accurately detect the tumor in MRI abnormal brain images. To fulfill the required intention noise removal using Anisotropic filtering, segmentation using SVM and morphological operations are performed.

A. *Performance Analysis of AF*

Three types of noises (Gaussian, Speckle and Salt & pepper noise) are added to the input image and then MSE and PSNR value are calculated as following:

$$MSE = \frac{1}{pq}\sum_{i=0}^{p-1}\sum_{i=0}^{q-1} \| h(i,j) - g(i,j) \|^2 \quad (12)$$

$$PSNR = 20\ log10\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (13)$$

Where,

h symbolizes the matrix data of our original image
g symbolizes the matrix data of our degraded image in question
p symbolizes row number of intensity values of the images and i symbolizes the index of that row
q symbolizes column number of intensity values of the images and j symbolizes the index of that column
$\boldsymbol{MAX_f}$ is the maximum signal value that exists in our original "known to be good" image

The following table contains MSE and PSNR value for various filters for Gaussian noise, Speckle noise and Salt & Pepper noise that are added with the original MRI brain input image to measure the performance of the filters:

TABLE I. PSNR & MSE VALUE CALCULATING FOR VARIOUS FILTERS

Method	PSNR Value(dB)	MSE Value	Noise Type
Average Filter	72.96504	0.00329	Gaussian noise
	73.18470	0.00423	Speckle noise
	75.41298	0.00287	Salt & pepper noise
Median Filter	73.16688	0.00289	Gaussian noise
	74.14841	0.00250	Speckle noise
	80.88641	0.00097	Salt & pepper noise
Mean Filter	71.77146	0.00432	Gaussian noise
	71.82192	0.00427	Speckle noise
	73.69922	0.00277	Salt & pepper noise
Wiener Filter	72.43547	0.00371	Gaussian noise
	72.44510	0.00370	Speckle noise
	71.65028	0.00445	Salt & pepper noise
High Pass Filter(HPF)	68.47065	0.00643	Gaussian noise
	65.46914	0.00527	Speckle noise
	67.17279	0.00608	Salt & pepper noise
Anisotropic Filter	273.90257	0.00231	Gaussian noise
	75.21810	0.00208	Speckle noise
	77.92357	0.00123	Salt & pepper noise

The performance of anisotropic filter is shown in following figures:

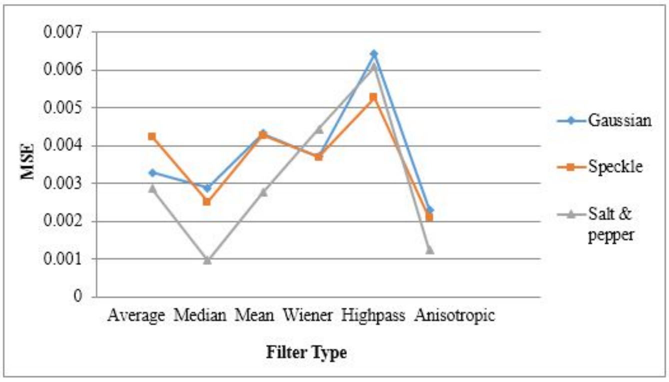


Fig. 6 (a). MSE value comparison for Gaussian, Speckle and Salt & Pepper noise among various filters

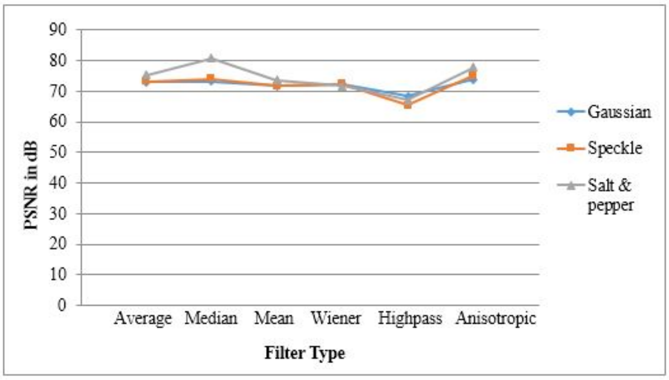


Fig. 6 (b). PSNR value comparison for Gaussian, Speckle and Salt & Pepper noise among various Filters

After noise removal, SVM classifier segments the image properly and then morphological operations are performed. Accuracy is the measure of successful classification. The accuracy is given by:

$$Accuracy = \frac{Number\ of\ correctly\ classified\ test\ samples}{Total\ samples} * 100\ \% \qquad (14)$$

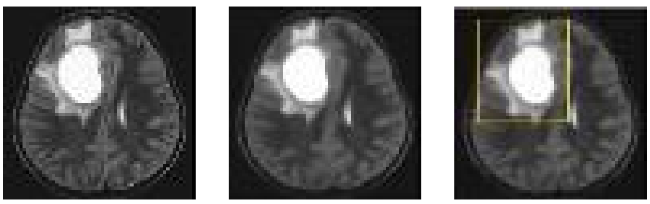
For segmentation purpose 369 pixels are taken and out of them 307 pixels are correctly classified.

$$\text{So, the accuracy} = \frac{307}{369} * 100\ \%$$

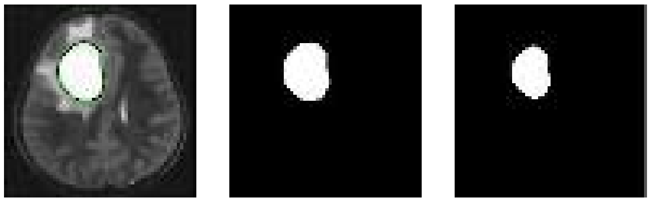
$$= 0.832 * 100\ \%$$

$$= 83\ \%$$

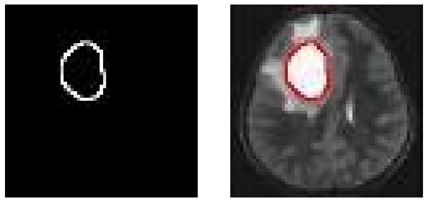
The following figure shows the final output with every step's response.



(a) (b) (c)



(d) (e) (f)



(g) (h)

Fig. 7. Combine O/P for various operations for MRI brain Image: (a) Input Image; (b) Filtered Image; (c) Locating Bounding Box; (d) SVM Classifier O/P; (e) Segmented Tumor; (f) Eroded Image; (g) Tumor Outline; (h) Detected Tumor.

V. Conclusion

The MRI brain Input image may contain various noise. For proper segmentation and for morphological operation's performance the input images should be noise free. That is why we have used the anisotropic filter for its better performance. SVM classifier is used for segmentation purpose which classifies the pixels into two classes. Since we have designed our system for any MRI brain input image hence SVM is selected with kernel for unsupervised learning. Morphological operations are used to extract the tumor from the segmented region. Finally the system is able to detect the tumor accurately.

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