BRAIN TUMOR DETECTION USING FASTER REGION-BASED CONVOLUTIONAL NEURAL NETWORKS ON CT AND MRI SCAN

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ABSTRACT

Brain tumor is the cancerous disease where abnormal cells are found in the brain. This can be cured if we detect the brain tumor at an early stage. In this proposed system the tumor area is marked and the kind of tumor present in the brain is defined based on MRI image of brain. Alex Net model is used as a base model along with Region Proposal Network (RPN) by Faster Region Based-Convolutional Neural Network(R-CNN) algorithm, for the classification of different types of tumors. The proposed system helps to predict the correct type of tumor with better accuracy. Cancer as a disease has taken the form of an epidemic for human beings. This work processes radiograph CT and MRI images to perform detection of brain tumor. The Faster RCNN is used to improve the object detection from the brain images. The database taken is from Google open source brain scans and the system has been developed on MATLAB v2019 for Windows. It reviews image processing for medical imaging and associated state- of-art literature. This work proposes to develop a cost-effective system accessible to medical practitioners on everyday computers.

Keywords: Brain tumor, MRI scan & Neural Networks.

1. INTRODUCTION

The occurrence of uncontrolled and abnormal growth of cells within the skull is specified as brain tumour. It is basically of two types non-cancerous or benign and cancerous or malignant. However, it would be inappropriate to call benign as non-cancerous because it could be fatal too. The tumour can either damage brain cells directly or even indirectly squeeze different areas of the brain as the tumour grows or swelling inside the brain causing severe pain . It is classified by their location in the brain as well as the tissue they are composed of. Whether the tumour is benign or malignant, the reason for this tumour could be either hereditary or it could be developed before birth such as craniopharyngioma. The reason of brain tumour is not very prominent ultimately. Some of the general symptoms of having it are a headache, vomiting, personality or behavioural changes, intellectual decline, abnormalities of eyes or double vision weakness, lethargy, swallowing difficulty, hand tremor etc. Diagnosis of brain tumour is done medically. Some of the ways of diagnosing brain tumour are MRI scan, CT scan and biopsy of the head etc. In CT scan technique image of the brain is taken from several angles and is studied altogether.MRI stands for magnetic resonance imaging. In this method, magnetic imaging techniques and the radio waves are utilized to locate as well as to obtain a digital image of tissues present in the brain. A biopsy is a diagnosis technique where a physical portion of the brain or the tumour present inside the brain is extracted and then studied under microscope. There are different types of biopsy such as needle biopsy, open biopsy etc. From the above-mentioned methods, we have used MRI scan technique in which the MRI images will be processed through MATLAB using our proposed algorithm to specify the tumour and then segment the image to clearly view the tumor.

2. LITERATURE REVIEW

SINGULARITY DETECTION AND PROCESSING WITH WAVELETS

The mathematical characterization of singularities with lipschitz exponents is reviewed. Theorems that estimate local lipschitz exponents of functions from the evolution across scales of their wavelet transform are reviewed. It is then proven that the local maxima of the wavelet transform modulus detect the locations of irregular structures and provide numerical procedures to compute their lipschitz exponents. The wavelet transform of singularities with fast oscillations has a particular behavior that is studied separately. The local frequency of such oscillations is measured from the wavelet transform modulus maxima. It has been shown numerically that one- and two-dimensional signals can be reconstructed, with a good approximation, from the local maxima of their wavelet transform modulus. As an application, an algorithm is developed that removes white noises from signals by analyzing the evolution of the wavelet transform maxima across scales. In two dimensions, the wavelet transforms maxima indicate the location of edges in images.

AN MR BRAIN IMAGES CLASSIFIER VIA PRINCIPAL COMPONENT ANALYSIS AND KERNEL SUPPORT VECTOR MACHINE

Automated and accurate classification of mr brain images is extremely important for medical analysis and interpretation. Over the last decade numerous methods have already been proposed. In this paper, we presented a novel method to classify a given mr brain image as normal or abnormal. The proposed method first employed wavelet transforms to extract features from images, followed by applying principal component analysis (pca) to reduce the dimensions of features. The reduced features were submitted to a kernel support vector machine (ksvm). The strategy of k-fold stratified cross validation was used to enhance generalization of ksvm. We chose seven common brain diseases (glioma, meningioma, alzheimer's disease, alzheimer's disease plus visual agnosia, pick's disease, sarcoma, and huntington's disease) as abnormal brains, and collected 160 mr brain images (20 normal and 140 abnormal) from harvard medical school website. We performed our proposed methods with four different kernels, and found that the grb kernel achieves the highest classification accuracy as 99.38%. The lin, hpol, and ipol kernel achieves 95%, 96.88%, and 98.12%, respectively. We also compared our method to those from literatures in the last decade, and the results showed our dwt+pca+ksvm with grb kernel still achieved the best accurate classification results. The averaged processing time for a 256x256 size image on a laptop of p4 ibm with 3 ghz processor and 2 gb ram is 0.0448 s. From the experimental data, our method was effective and rapid. It could be applied to the field of mr brain image classification and can assist the doctors to diagnose a patient normal or abnormal in some degree.

A REVIEW ON OTSU IMAGE SEGMENTATION ALGORITHM

Image segmentation is the fundamental approach of digital image processing. Among all the segmentation methods, otsu method is one of the most successful methods for image thresholding because of its simple calculation. Otsu is an automatic threshold selection region-based segmentation method.

BRAIN TUMOR SEGMENTATION BASED ON LOCAL INDEPENDENT PROJECTION-BASED CLASSIFICATION

Brain tumor segmentation is an important procedure for early tumor diagnosis and radiotherapy planning. Although numerous brain tumor segmentation methods have been presented, enhancing tumor segmentation methods is still challenging because brain tumor mri images exhibit complex characteristics, such as high diversity in tumor appearance and ambiguous tumor boundaries. To address this problem, we propose a novel automatic tumor segmentation method for mri images. This method treats tumor segmentation as a classification problem. Additionally, the local independent projection-based classification (lipc) method is used to classify each voxel into different classes. A novel classification framework is derived by introducing the local independent projection into the classical classification model. Locality is important in the calculation of local independent projections for lipc. Locality is also considered in determining whether local anchor embedding is more applicable in solving linear projection weights compared with other coding methods. Moreover, lipc considers the data distribution of different classes by learning a softmax regression model, which can further improve classification performance. In this study, 80 brain tumor mri images with ground truth data are used as training data and 40 images without ground truth data are used as testing data. The segmentation results of testing data are evaluated by an online evaluation tool. The average dice similarities of the proposed method for segmenting complete tumor, tumor core, and contrast-enhancing tumor on real patient data are 0.84, 0.685, and 0.585, respectively. These results are comparable to other state-of-the-art methods.

BRAIN TUMOR SEGMENTATION BASED ON A HYBRID CLUSTERING TECHNIQUE

Image segmentation refers to the process of partitioning an image into mutually exclusive regions. It can be considered as the most essential and crucial process for facilitating the delineation, characterization, and visualization of regions of interest in any medical image. Despite intensive research, segmentation remains a challenging problem due to the diverse image content, cluttered objects, occlusion, image noise, non-uniform object texture, and other factors. There are many algorithms and techniques available for image segmentation but still there needs to develop an efficient, fast technique of medical image segmentation. This an efficient image segmentation approach using k-means clustering technique integrated with fuzzy c-means algorithm. It is followed by thresholding and level set segmentation stages to provide an accurate brain tumor detection. The proposed technique can get benefits of the k-means clustering for image segmentation in the aspects of minimal computation time. In addition, it can get advantages of the fuzzy c-means in the aspects of accuracy. The performance of the proposed image segmentation approach was evaluated by comparing it with some state-of-the-art segmentation algorithms in case of accuracy, processing time, and performance. The accuracy was evaluated by comparing the results with the ground truth of each processed image. The experimental results clarify the effectiveness of our proposed approach to deal with a higher number of segmentation problems via improving the segmentation quality and accuracy in minimal execution time.

3. EXISTING SYSTEM

Image processing is an active research area in which medical image processing is a highly challenging field. Medical imaging techniques are used to image the inner portions of the human body for medical diagnosis. Brain tumor is a serious life altering disease condition. Image segmentation plays a significant role in image processing as it helps in the extraction of suspicious regions from the medical images. The accuracy of classifying the tumor image is low and the process of tumor detection is not automatic. The entire process is time consuming and some pixels are misclassified.

4. PROPOSED SYSTEM

Our work proposes a system based on the morphological operation of erosion, denoising, and thres holding based tumor segmentation method. The scans are fed into the program from the database. The tumor, if present, is detected using the region shrinking approach using seed pixels , and the segmented tumor is displayed. Brain scans are taken from open source Google image. Databases of available radiograph format owing to simplicity. MATLAB has been used to implement the system on a Windows 10 64-bit kernel system. we start with reading the images from their source in the system.

4.1 METHODOLOGY

The part of the image containing the tumor normally has more intensity then the other portion and we can assume the area, shape and radius of the tumor in the image. We have used these basic conditions to detect tumor in our code and the code goes through th following steps.

5. BLOCK DIAGRAM

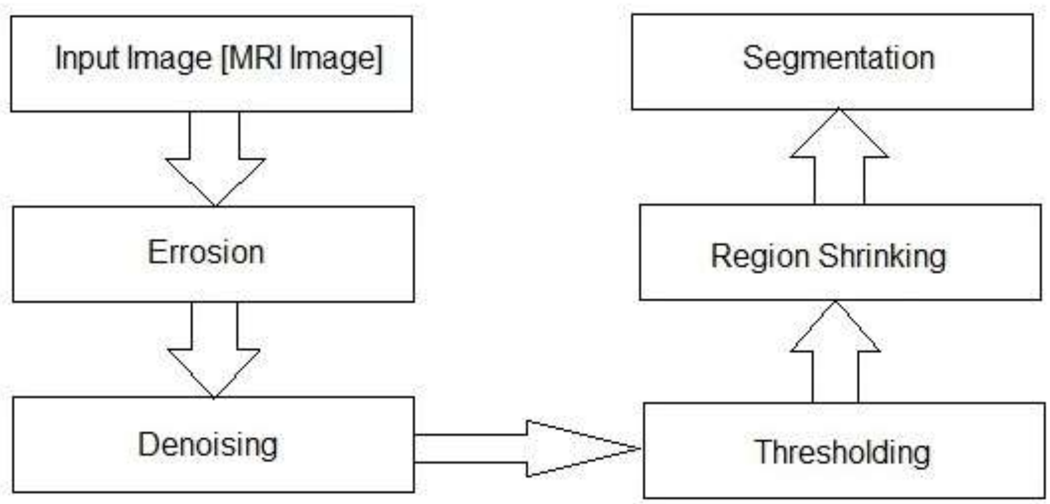


Figure: 1 Block Diagram

6.1 IMAGE PROCESSING

An image may be defined as a two-dimensional function f (x, y), where x & y are spatial coordinates, & the amplitude off at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y & the amplitude values of f are all finite discrete quantities, we call the image a digital image. The field of DIP refers to processing digital image by means of digital computer. Digital image is composed of a finite number of elements, each of which has a particular location & value. The elements are called pixels. Vision is the most advanced of our sensor, so it is not surprising that image play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the EM spectrum imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate also on images generated by sources that humans are not accustomed to associating with image.

There is no general agreement among authors regarding where image processing stops & other related areas such as image analysis& computer vision start. Sometimes a distinction is made by defining image processing as a discipline in which both the input & output at a process are images. This is limiting & somewhat artificial boundary. The area of image analysis (image understanding) is in between image processing & computer vision. There are no clear-cut boundaries in the continuum from image processing at one end to complete vision at the other. However, one useful paradigm is to consider three types of computerized processes in this continuum: low-, mid-, & high-level processes. Low-level process involves primitive operations such as image processing to reduce noise, contrast enhancement & image sharpening. A low- level process is characterized by the fact that both its inputs & outputs are images. Mid-level process on images involves tasks such as segmentation, description of that object to reduce them to a form suitable for computer processing & classification of individual objects. A mid-level process is characterized by the fact that its inputs generally are images but its outputs are attributes extracted from those images. Finally, higher- level processing involves “Making sense” of an ensemble of recognized objects, as in image analysis & at the far end of the continuum performing the cognitive functions normally associated with human vision.

6.2 TUMOR

A tumor or tumor is the name for a neoplasm or a solid lesion formed by an abnormal growth of cells (termed neoplastic) which looks like a swelling. Tumor is not synonymous with cancer. A tumor can be benign, pre-malignant or malignant, whereas cancer is by definition malignant.

6.3 TYPES OF TUMOR

BENIGN TUMOR

A benign tumor is a tumor that lacks all three of the malignant properties of a cancer. Thus, by definition, a benign tumor does not grow in an unlimited, aggressive manner, does not invade surrounding tissues, and does not spread to non-adjacent tissues (metastasize). Common examples of benign tumors include moles and uterine fibroids.

6.4 MALIGNANT

Malignancy (from the Latin roots mal- = "bad" and -ignis = "fire") is the tendency of a medical condition, especially tumors, to become progressively worse and to potentially result in death. It is characterized by the properties of anaplasia, invasiveness, and metastasis. Malignant is a corresponding adjectival medical term used to describe a severe and progressively worsening disease. The term is most familiar as a description of cancer.

6.5 PREMALIGNANT

A precancerous condition (or premalignant condition) is a disease, syndrome, or finding that, if left untreated, may lead to cancer. It is a generalized state associated with a significantly increased risk of cancer.

6.6 IMAGE SEGMENTATION

Segmentation subdivides an image into its constituent regions or objects. The level of detail to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects are regions of interest in an application have been detected. Image Segmentation is the process of identifying features in images and marking them as distinct from one another. Segmentation is separation of structures of interest from the Background and each other. Another way of extracting and representing information from an image is to group pixels together into regions of similarity. This process is commonly called segmentation. In 2D we would group pixels together according to the rate of change of their intensity over a region. Classically, image segmentation is defined as the partitioning of an image into non- overlapping, constituent regions that are homogeneous with respect to some characteristic such as intensity or texture. If the domain of the image is given by, then the segmentation problem is to determine the sets $S_k \subset \Omega,$ whose union is the entire domain . Thus, the sets that make up a segmentation must satisfy

$$\Omega = \bigcup_{k=1}^{K} S_k$$

where $S_k \cap S_j = \phi \text{ for } k \neq j,$ and each S_k is connected. Ideally, a segmentation method finds those sets that correspond to distinct anatomical structures or regions of interest in the image. When the constraint that regions be connected is removed, then determining the sets S_k is called pixel classification, and the sets themselves are called classes. Pixel classification, rather than classical segmentation, is often a desirable goal in medical images, particularly when disconnected regions belonging to the same tissue class require identification. Determination of the total number of classes K in pixel classification can be a difficult problem. Often, the value of K is assumed to be known based on prior knowledge of the anatomy being considered.

6.7 MRI

Magnetic resonance imaging (MRI), or nuclear magnetic resonance imaging (NMRI), is primarily a medical imaging technique used in radiology to visualize detailed internal structure and limited function of the body. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does, making it especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging. Unlike CT, MRI uses no ionizing radiation. Rather, it uses a powerful magnetic field to align the nuclear magnetization of (usually) hydrogen atoms in water in the body. Radio frequency (RF) fields are used to systematically alter the alignment of this magnetization. This causes the hydrogen nuclei to produce a rotating magnetic field detectable by the scanner. This signal can be manipulated by additional magnetic fields to build up enough information to construct an image of the body.

7. PROPOSED WORKING

MRI image of the brain is processed for the detection of the tumor using MATLAB. The proposed methodology employed here comprises of three stages. Initially pre-processing of given MRI image is done then edge detection of brain is conducted and finally, segmentation displays the tumor region vividly. K-means clustering algorithm has also been implemented as an alternative method of segmentation. K-means clustering displays other important tissues and edges along with the tumor region.

7.1 PROPOSED ALGORITHM FOR DETECTION OF BRAIN TUMOR

Step 1: Take MRI image of the brain as an input.

Step 2: Convert it into equivalent grayscale image.

Step 3: Apply filtering methods for removing noise.

Step 4: Apply image enhancement techniques.

Step 5: Perform edge detection using Sobel, Prewitt and Canny algorithms.

Step 6: Implement segmentation technique and clustering algorithm for proper detection of tumor region.

7.2. PRE-PROCESSING STAGE

Image pre-processing aims in noise removal and to improve the clarity of image or altering the quality of image to suit a purpose. The functions performed at the pre-processing stage are described as follows.

1)RGB to Grayscale Conversion: As the name indicates,the image may consist of shades of grey. A ‘gray’ color is one in which the red, green and blue elements have similar intensity in RGB space. A grayscale image contains the grayscale values but some MRI images consist of primary (RGB) content These images need to be converted into grayscale image which range from 0 to 255 pixel values where range 0 defines the pure black color and range 255 defines pure white color.

2) Noise Removal using Median Filtering: Filtering is atechnique used for eliminating the noise present within an image. During the conversion of an image from RGB to gray some sort of noise creeps into the image. Thus, this noise needs to get removed using filtering. It is applied to eradicate the noises such as salt and pepper from the converted grayscale image. It exchanges the value of the pixel in the centre with the median of the intensity values in the neighbouring pixels.

3) Image Enhancement: Acquired image may have defectssuch as poor contrast. These defects have huge impact on the contrast of an image. When contrast is poor, the contrast enhancement technique comes

into play. In this case, the gray level of each pixel is scaled for improving the contrast. The visualization of the MRI image is improved through contrast enhancement technique

7.3. EDGE DETECTION TECHNIQUES

Edge detection is an image processing approach used for tracing the boundaries of an object within the image. The algorithm works by finding sudden rise or fall in each pixel intensity and displaying only those sudden changes in the pixels. This change in the pixel is passed through an adequate convolution masks and the outcome is represented as the edge of the image.

1)Sobel Edge Detection Technique: Sobel operator is agradient operator. The relative gradient magnitude can be obtained by applying this operator in every point of the input image. Setting convolution mask c=2, we get two Sobel operators Mx and My by passing it through 3x3 convolution masks, shown in TABLE I. The process of appending individual element of the image to its local neighbours weighted by a kernel is called convolution.

2)Canny Edge Detection Technique: Canny edgedetection approach first involves the smoothing of an image i.e. removal of noise from the image. The objective of this step is to convert the blurred or irregular edges of the image into sharp edges and obtain a continuous and regular edges. This is principally processed by conserving all local maxima present in the gradient image and erasing everything else. The algorithm is given below.

Step 1: In order to erase the noise, apply a Gaussian filter to smoothen the image.

Step 2: Find the intensity gradients of the image.

Step 3: Implement non-maximum constraints to eliminate spurious reaction to edge detection.

Step 4: Implement double threshold to figure out possible edges.

Step 5: Finally to track edge by hysteresis, finalize the edge detection by suppressing all distinct edges which are relatively weak and are not connected to the strong edges.

The Gaussian filter is implemented for the removal of the Gaussian noise from the image because it is an essential part of the canny edge detection technique. Thus, it is explained below in detail. To sharpen the image a Gaussian filter is implemented. The noise on the edge detectors can be reduced by brightening the image by applying Gaussian filter. Every pixel of the image is passed through a 5×5 Gaussian mask. As all edge detection outputs are affected by noise, therefore it is necessary to eliminate the noise to avert false detection caused by noise.

The Gaussian filter kernel of size (2k+1)×(2k+1) is provided.

Hij= (2Êı2)-1exp(-(i-(k+1))2+(j-(k+1))2)/2 ı2);1” i, j (2k+1)(1)

Here is an example of a 5×5 Gaussian filter which is used to create the adjacent image where A is the value of pixel currently being processed and B is the value obtained after passing it through Gaussian mask. Note that every pixel of the image has to be passed through the Gaussian mask .It is necessary to judge that the choice of the size of the Gaussian kernel affects the detector's performance. The greater the mask's size, lesser is the detector's sensitivity in respect to noise. The blurring of the image increases with the increase in the Gaussian filter kernel size. A mask of matrix 5×5 is a pretty good size commonly considered for most of the cases, but this may vary depending on specific situations .

3)Prewitt Edge Detection Technique: To determine approximations, the derivatives of two kernels of matrix 3x3 are convoluted with the original image, one for the horizontal changes and another one for the vertical changes. Setting convolution mask c=1, we get two Prewitt operators Mx and My by passing it through 3x3 convolution masks.

7.4. SEGMENTATION IMAGE

Segmentation is the major step and the most vital task in image processing. Its purpose is to extract the details from an image. The automation of medical image segmentation has established various applications in diverse areas like verdict for patients, treatment management planning and computer-aided operation. Boundary approach (thresholding), edge-based approach and region-based approach are the three major techniques widely used in segmentation. For this project, boundary approach has been used. Let's have a conception about this method in brief. In thresholding technique, pixels are assigned to arrange according to the range of values in which a pixel lies. This is the easiest and popular method used in segmentation. Here, g(x,y) is the location of the every individual pixel of the image and T is the threshold value. The threshold value T is predefined in this algorithm. If the value of the current pixel f(x,y)" T then pixel g(x,y) is allotted the value 0. Otherwise, the pixel g(x,y) is allotted the value 1. When all the values of "g" are displayed then a segmented image will be obtained. Determining on the intensity values of the pixels, they are partitioned. Segmentation by thresholding can be done in the following three ways i.e. global thresholding, variable thresholding and multiple thresholding. They are discussed as follows.

1) Global Thresholding:

Here, only one threshold value is applied on all images. This method is put in use when the pixel value of the defected portion and the background are fairly consistent over the entire image.

T: $g(x, y) = 1$, if $f(x, y) > T$

T: $g(x, y) = 0$, if $f(x, y) <= T$

2) Variable Thresholding:

Here, in every image the threshold value of the image varies. There are two main varieties of these methods available which are discussed below.

a)Local or Regional Thresholding: Here, a grayscale image is taken as input and gives a binary image as output. T depends on the neighborhood of pixels at (x, y).

b)Adaptive Thresholding: In this technique, the threshold value at each pixel location depends upon the neighboring pixel intensities.

3)Multiple Thresholding:

Here, multiple threshold values are calculated by applying this technique to the given image, the image is segmented into certain brightness regions corresponding to one background.

a. $g(x,y) = p$, if $f(x,y) > T2$

b. $g(x,y) = q$, if$T1< f(x,y)$ "<= T2

c. $g(x,y) = r$, if$f(x,y)$ "<=T1T2

7.5. CLUSTERING

Clustering is a process of representing the image into various divisions for easier analysis and detailed study of the meaningful portions of the image. The image is divided in such a manner that each segment of the image shares certain similar characteristics such as intensity, texture or color. The collected set of segmented image builds up the entire image. In the proposed method, the k-means algorithm is implemented for accurate prediction of the brain tumor regions.

Steps involved in the algorithm are discussed below in details.

Step 1: Set k different points where k indicates total number of regions of the image.

Step 2: Assign each pixel to the kth point that has the closest centered as per their Euclidean distance.

Step 3: When each pixel of the image is assigned to a cluster then the k's position is recalculated.

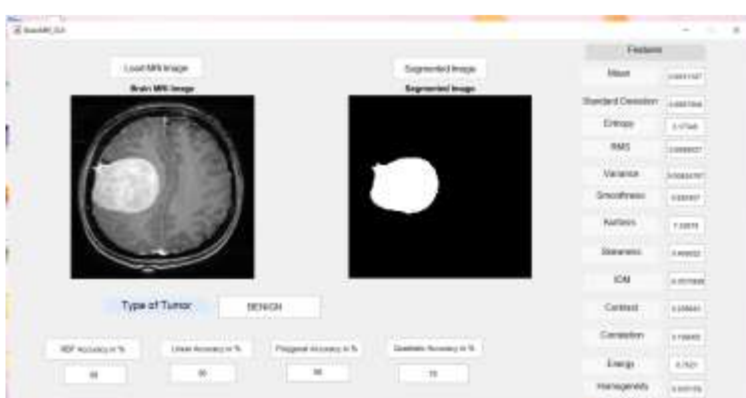
Step 4: Repeat steps 2 and 3 until the centered "k" does not change.

Step 5: Display each divided cluster separately to view k number of clusters.

8. CONCLUSION

The brain tumor detection and classification system are implemented using CWT, DWT and SVMs. The proposed method uses different levels for wavelets, the high accuracy part is obtained using CWT. The CWT prevents the loss of edges in segmentation. The result shows that SVMs having the proper sets of training data are able to distinguish between abnormal and normal tumor regions and classify them correctly as a benign tumor, malign tumor or healthy brain. In practice, SVMs have significant computational advantages. Five times improvement in computation speed (22 vs. 110 ms) for our proposed method. This classification is very important for the physician in establishing a precise diagnostic and recommending a correct further treatment. The obtained results show that CWT provides higher computation comparing with DWT. Even if the computation time is longer, if we are mainly interested in visualization, matching and feature detection, it is better to use CWT. If we are interested in de-noising, compression, restoration, then DWT is often more appropriate. A hybrid approach is recommended in solving properly the detection and classification problems in brain tumors.

9. SCREENSHOTS



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