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A METHOD TO DETECT BRAIN TUMORS IN MAGNETIC RESONANCE IMAGES ON THE BASIS OF HIERARCHICAL SEGMENTATION

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ABSTRACT

In this paper, an efficient method has been presented on the basis of hierarchical algorithms and by using simple feature to detect range of brain tumors in magnetic resonance images. In the proposed framework, various kinds of brain tumors and magnetic resonance images have been taken into account. The proposed method is performed in two steps. In pre-processing step, a procedure is followed to delete details of images proximity. Then, by selecting suitable features, each pixel is transferred to a three-dimensional slice. single-linkage aggregative hierarchical algorithm is applies in this three-dimensional space. On the basis of considered distance criterion, similar pixels are classified. There are various alternatives for distance criterion that can be selected. Also, the proposed algorithm has some parameters. These selecting are on the basis of particles swarm optimization. They must be reduced from the parameters available in the method that must be initialized by the expert. The obtained results show the advantage of the proposed method in comparison to competitive methods.

1. INTRODUCTION

In recent years, imaging based on magnetic resonance images have been taken into account to study brain tumors due to high needs to purpose evaluation of amount of data. Pioneer perspectives applicable in automatic methods to analyze brain tumor images are approximately related to two decades ago. Current methods are developed, and they are closer to usual clinical application.

It is expected that attempts to record brain images involving tumor in standard protocols of magnetic resonance images will make usual clinical methods usual. In order to promote it, methods should be proved. This development is along with evaluating methods by responding tumor to treatment. However, it should be investigated that how automatic methods can study the effects of treatment and Pseudo-development or Pseudo-response on segmentation result in a way that they are interesting for experiment [1]. On the other side, targeting automatic methods in tumor segmentation is investable. Angelina and his colleagues [2] considered this issue in the first comprehensive study of brain tumor longitudinal data. Probably, this research procedure will be investigated more in the future.

Recently, recent methods of magnetic resonance have taken the attention of researchers in terms of analyzing brain tumors like immersion imaging, DTI and magnetic resonance spectrography. These methods are commonly used for tumor ranking and to find the location of the most active fields of tumor. Researchers initialized using machine learning views to rank tumor on the basis of immersion images [3,4,5,6] and to analyze hybrid magnetic resonance data [7,8]. Another field that has taken attention of researcher is image-based modelling of the patient in terms of brain tumor[9,10]. This research contributes to predict progression of tumor and optimization of individual therapy selections.

As it is specified, magnetic resonance images are continuously studied. In this paper, the purpose is to present method to detect brain tumors. The method that is presented in this research is related to the methods of applying clustering algorithms in brain tumors segmentation. It is obvious that determining tumor tissue in magnetic resonance images help recognizing brain cancer on time and appropriately. In addition, by using such analysis, primary clinical information can be presented to physicians diagnose illnesses. Researchers considered as a bridge between medical and computer fields must be only considered as a colleague for physician because diagnosis deals with patients, and some experiments are required to issue final view. The materials of this paper are organized in five sections. In section two, previous studies and literature review are presented in terms of brain tumors segmentation and magnetic resonance images. Section three is related to the method presented in this paper and the way of applying hierarchial segmentation and used features. The results and analysis are presented in section four. At last, section five is dedicated to conclusion, and important future researchers are discussed.

2. Literature Review

Classification requiring data training for learning is a classification model, and new samples can be labeled on the basis of this model. On the other side, clustering is performed in the form of unsupervised method and data is grouped according to special similarity criteria, clustering in brain tumor segmentation was introduced by chad and his colleagues [11], and they analyzed texture patterns of various patterns.

Philips and his colleagues [12] used clustering based on fuzzy tools. Vaidganthan [13] compared this issue with K. clustering that is the nearest neighbor to determine tumor volume during therapy in multi-spectrum and two dimensional image sections. Clark and his colleagues[14] developed this perspective to use knowledge-based techniques. Later, Fletcher-leath and his colleagues[15] combined fuzzy clustering with knowledge-based techniques for segmentation of brain tumor in magnetic resonance images. Variational models can be used to apply limitations after classifying previous tissue. Cobzas and his colleagues [16] combined tissue segmentation by using high dimensional feature set with set-level progression. ponur and his colleagues [17] applied Dirichlet priors to show healthy tissues.

Khotalou and his colleagues [18] combined brain symmetrical features and fuzzy clustering with set- level evolution. Hanamci and his colleagues [19] introduced tumor cut algorithm, and combined tumor segmentation by using cellular machines with set- level evolution on tumor probability map to create spatial smoothing. Proximity communications for spatial setting are considered after primary wexler segmentation. In mostcases , it is performed by using random field method (Markov random fields [20] or discriminative random fields [21]. In recent years, some algorithms based on graph cuts have been[22] commonly used for segmentation. These algorithms used regional features as an energy minimization problem by using proximity communication formulation, and they are solved by graph cut optimization. The result is interpreted as a segmentation problem. In most cases, these methods require inputs provided by the user, so these perspectives are often semi- automatic. since using two- dimeusinal magnetic resonance images have more application than three-dimensional images, two- dimensional images have beenemphasized in this paper. Optimization methods like nature- based algorithms are less important in this regard. It seems that using suitable features with nature-based algorithms create a exact and new work in this field because such algorithms create many answers randomly, and they try to make these responses better. Among nature-based algorithms, some algorithms involving genetic algorithm, particles swarm algorithm, ants algorithm and bee algorithm used for optimization are highly preferred. In this paper, due to higher speed of particles swarm algorithm used for optimization are highly preferred. In this paper, due to higher speed of particles swarm algorithm, it is used more than other algorithms [23]. An appropriate algorithm can be selected aiming all optimization algorithms through studying them exactly, particles swarm algorithm is also called birds algorithm or particles algorithm.

3. The proposed method

One of the solutions used to determine the range of brain tumors in magnetic resonance images is to apply data clustering algorithms. In other words, we consider all data in n-dimensional space, and segmentation or data clustering is considered by using various algorithms. They n-dimensional space is created by using n feature that is extracted.

In image processing science in which our data are pixels, selection of one pixel with its neighbor pixels must be demonstrated if using clustering algorithms are required because each pixel may be located in various classes according to its neighbors. They issue can be shown by selecting appropriate dimensions and features. If there is a relation between one pixel with its neighbors in extracted features, then our segmentation algorithm has surely higher accuracy. Therefore, the main idea of using clustering algorithms in image segmentation is that pixels are mapped in a space whose dimensions are considered as suitable features for segmentation. Then, clustering algorithm is used to determine considered range in this space. The proposed method involves three general steps.

3.1. Pre-processing

As it is shown in figure 1, all magnetic resonance images of brain are divided to three general parts as follows.

1) Skill

2) Internal area of the brain

3) Black area covered the around of head in magnetic resonance images

In the problem that should solved in this paper, area z has been emphasized. In fact, internal area of the brain that is investigated involves the brain itself and tumor. Our purpose is to separate these two areas by hierarchical segmentation methods. Hence, the first action is to separate area two (internal area of the brain) from areas one and three. In this case, we know that what is remained in the picture is the area where segmentation is performed. Unrelated areas do not affect the accuracy of our method.

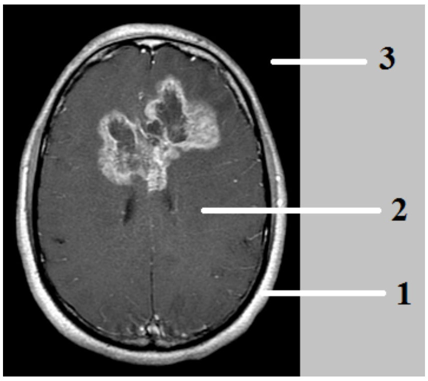

Figure 1: Available areas in magnetic resonance images of the brain

In order to remove and delete skill in magnetic resonance image, one of morphology methods is used. In order to use morphology methods a picture is firstly divided into two levels with a very low value (like 0,1) , and then the image is divided into black and white areas.

After dividing the image into two levels, erosion is used. By applying this operator on two-levels image, diameter of the white area reduces, and its black pixels are added, so the black area of head around.

The difference is that on the feature or tool becomes thicker, and enters the skill area. After deleting the skill, the image is uniform, and details are deleted because it isn't suitable to brain average of several pixels, and this pixel is located in a point in which three is no pixel. In order to use average transfer method, data must be firstly transferred to another space by using suitable features. Three features are extracted from each image pixel.

- row number of pixel
- column number of pixel
- Intensity of pixel

We consider the image pixel having its own special intensity. This value along with the location of this pixel involving two row and column values are taken into account as a triple vector so that a three dimensional space is created, and average transformation method is performed in this space. We consider an image as an input. Pixel located in i row and j column is demonstrated in this three-dimensional space as follows.

Pixel intensity (i,j)	**I**	**J**

This point is an indication of corresponding point of (i,j) in three-dimensional space. This vector
must be coordinated for all pixels, and corresponding points of all pixels are obtained in this three dimensional space. An

output sampme of this space is shown in figure 2 for a sample of magnetic resonance images.

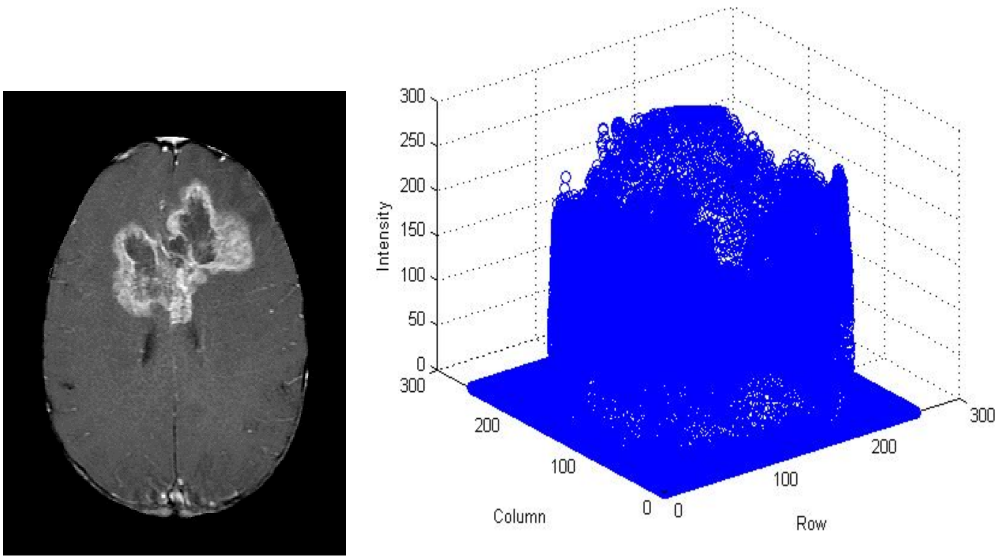

Figure 2: An image sample and a corresponding three-dimensional area

3.2. Hierarchical segmentation

Hierarchical segmentation is a common method in data segmentation, and it is applied on image pixels in this paper. Clustering methods are different, but all of them have a very important and stable principle; that is, maximizing the similarity of intraclass and minimizing the similarity of inter-class.

In order to use one-linkage and top-down hierarchical algorithm, data is firstly transferred to another space by using suitable features. With regard to pre-processing of input images, most details that are not suitable to find tumor range are deleted. Therefore, this segmentation can be performed by using simple features. As it way pointed out in section 3.1, three pixels are extracted from each image pixel:

- Row number of pixel (i),
- column number of pixel (j),
- Intensity of pixel related to pre-processed image (X_{ij})

the difference is that the feature extracted in section 3.1 has been applied on input image, while features extraction is currently performed on pre-processed image. we consider each image pixel that has its own special value. This value along with location of this pixel involving two column and row values is considered as a triple vector so that a three-dimensional space is created. We perform one-linkage hierarchical algorithm is this space. using these three features is appropriate because of the following reasons.

- Firstly, relation existing between pixels can be applied on segmentation by applying column and row numbers.
- Secondly, since one-linkage hierarchical method is performed on pre-processed image, and related areas having same intensity are connected to each other.

After modeling each pixel with these three features, we have a three-dimensional space for each magnetic resonance image like figure 3, and hierarchical algorithm is applied.

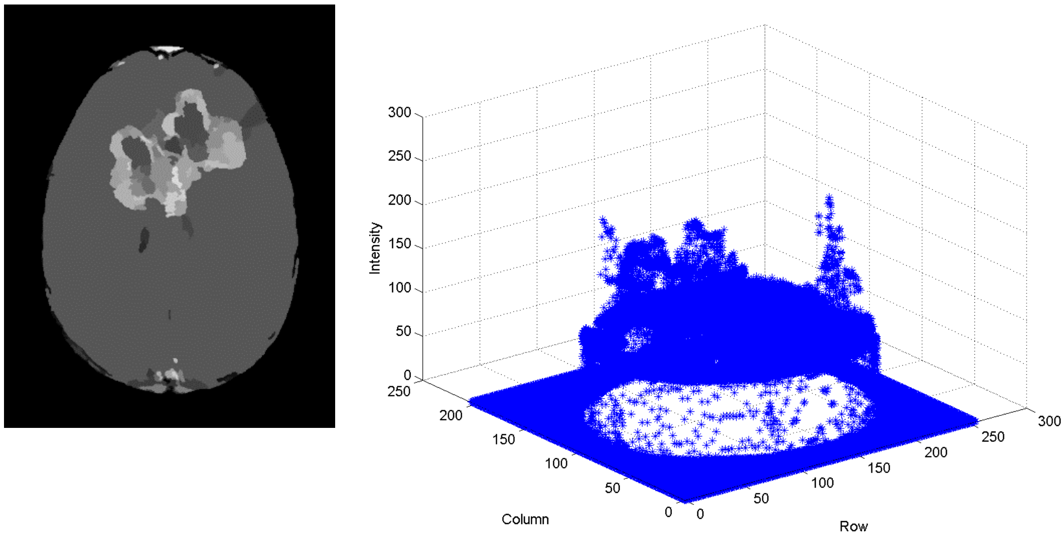

Figure 3: A sample of three-dimensional sample for pre-processed magnetic resonance image

Single-linkage hierarchical algorithm is on the basis of the least distance. If there are two sets of A and B, then the distance of A and B sets are equal to two points of A and B having minimum distance.

Distance $(A,B)=\min\{d(a,b);\ a\in A,\ b\in B\}$ (1)

when algorithm is applied, points are combined in our three-dimensional space having minimum distance, and some clusters are created. In order to merge the clusters, clusters having minimum distance are combined. This procedure continues until obtaining a cluster that involves all points. The difference between three-dimensional space before and after applying average transfer method is obviously specified in comparing figures 2 and 3. It is completely clear that many image pixels have and intensity after applying age transfer method. Also, working in space of figure 3 is easier than the space of figure 2.

Two points must be taken into account.

1) The procedure of executing hierarchical algorithms continues until all data become a cluster, and task of stopping this procedure is usually dedicated to the expert.

2) In dendrogram of this three-dimensional space, beginning point is required to separate a class from other classes. In other words, if we have a tumor point, and if we know that this hierarchical procedure must be stopped in a level. Then we can easily distinguish tumor area with the area without tumor like figure 4.

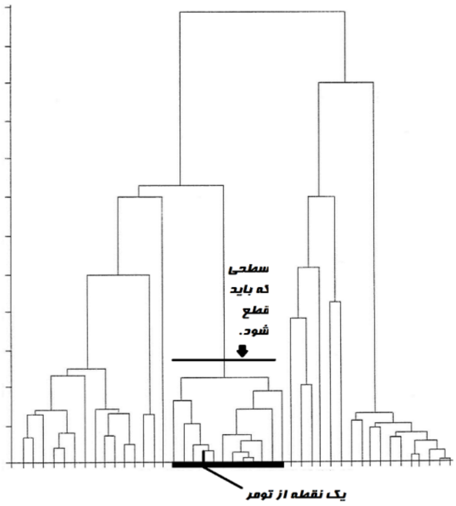

Figure 4: If we specify a point of tumor along with the level in which dendrogram must be cut, then all pixels of black area involve tumor, and other pixels are classified as pixels that do not have tumor.

As it is specified in figure 4, in order to use hierarchical algorithms, the level in which clustering must be stopped should be specified by the expert, and the point is beginning point of tumor segmentation. There are two solutions in this regard. The first one is that physician initiates tumor segmentation procedure by automatic method to find a beginning point. Both issues are studied in section 4.

3.3. Optimization by using swarm particles method

Particles swarm method is a general method to find the answer in a n-dimensional space. Specified number of particles are randomly produced in the next n space, and the initial speed is dedicated to each of them. These particles move in a reply space on the basis of fitness function to reach the best answer. Each particle is measures in a time period on the basis of this fitness function. Using particles swarm method is very common in previous researches due to detecting unspecified parameters [26]. In this paper, this algorithm is used to determine available window dimensions in average transfer (window is considered in the form of a square) and suitable distance type used in hierarchical algorithm. Then, length of available particles is two. The first cell shows dimensions of average transfer algorithm and the second cell demonstrates distance type used in hierarchical algorithm. Using particles swarm method is as follows.

- Specified numbers of particles are randomly created.
- for each particle: An image is randomly selected among all images.
- The method presented in this article is performed on that image by using values of this particle.
- Its precision value is measured by using ground-truth image
- The particle with the best precision is selected, and values of this particle are used to execute the algorithm on all images.

when two binary images involving a and b are exclusive, and binary image of c is produced (a^b=c), all points of image c that are white are result of differences of a and b images. The particle that can reduce this difference, and when there are lower differences between two images, more suitable values are found for required parameters that mean dimensions of average transfer method and suitable criterion of distance for hierarchical method.

4. Obtained results and discussion

In order to evaluate and analyze the proposed method, we perform it on a valid data set to detect brain tumors we perform it on a valid data set to detect brain tumors magnetic resonance images, and we study and investigate it from all various aspects. what is considered in selecting this dataset sizes, various locations and different brain tumors so that we can be space of the results obtained by our method.

The source of used image is Harrard data set. Since magnetic resonance images of this dataset are very different, they are used in most research fields. In other words, images of this data set are different in terms of size of images, size of tumor, head direction and tumor location. Due to these differences, robust and reliable tests and experiments are performed. Twenty images are used, and it involves all three types of tumor involving meningioma, metastasis and glioma in the brain. All images and specified tumor area are available. After applying the proposed method on dataset and obtaining segmentation results, we can obtain accuracy value of the proposed method through comparing outputs of proposed method and data set hand label images.

The initial part of proposed algorithm is determining suitable distance type and dimensions of efficient window to apply average transfer method. In this step, an image is randomly selected, and the related method is tested to obtain two required parameters to execute this algorithm optimally. After applying the proposed method on this image, the selected distance criterion is Euclidean distance. This choice is considered by particles swarm algorithm among the following distances

Euclidean, City-block, CHebysheb, Cosine, Jackardin addition to distance type, the window used in average trans for method was selected from range of [1,10]. The suitable value proposed by particles swarm algorithm in 5.00017. All the particles that are randomly produced in this algorithm are arrays with length of two. the first cell of these arrays (window dimension) is a random number between 1 and 10. Also,the second cell is a random number between 1 and 5. This shows distance type of mentioned distance criteria. Particles swarm algorithm require a set of initial parameters for execution. These parameters have been presented in table 1.

Table 1: The value of parameters used in particles swarm algorithm

Particles length	**2**
Particles number	**20**
Epoch number	**10**
C_1	**2**
C_2	**2**
W	**0,3**
Initial speed of particles	**Zero**

In order to remove skill, erosion operator has been used and in this case, a structuring element is considered as a disk type, and its radius to 5percent of the image length. This approximation is used to remove skill. It is obvious that if disk diameter is considered as 6 or 4 pixel instead of 5 pixel, it will not considerably affect the procedure of removing skull. It is sufficient that disk diameter does not increase considerably. Skull is removed because intensity of skill bone may be similar to tumor intensity in magnetic resonance image (figure 5). Since intensity is considered as a feature is this paper, it is possible that there is some problems and ambiguity in transferring pixels to new spaces and performing hierarchical procedure.

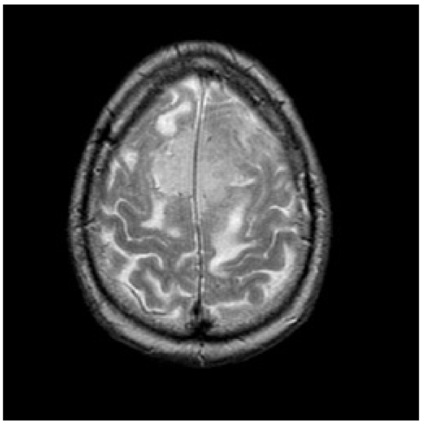

Figure 5: similarity of tumor intensity and skill bone intensity.

In average transfer method, window is considered in the form of a square whose side length is obtained as 5,0017 by particles swarm algorithm. In segmentation on dendrogram, two values must be specified:

- The first value shows the level in which dendrogram must be cut
- The second value shows pixels related to tumor

The first value is determined by the expert in hierarchical methods [24,25]. This determination is performed in two procedures.

- The expert determines the number of illnesses. It must be cut in a level in which the number of our considered clusters is estimated; for example, when the number of clusters was equal to 5, dendrogram procedure stops.

A value is considered as Input to determine the level that must be cut, instance, stop dendrogram level in level 5. In the method proposed in this paper, the second mode has been used. The first one is useful when each image section is considered as a cluster. It's not useful when all brain sections are considered as a class called non-tumor. In other words, The first mode is effective when we have all grey brain cells, while cells of brain, meninges curtain, skull and edemu. We consider all areas that are not related to tumor as a class called non-tumor. The level in which dendrogram must be cut is determined With the start of segmentation is determined by an expert.

As it is shown in table 7, the presented method of beginning point specified by the expert presents appropriate answers, and it has higher precision. This is also true for efficiency of the proposed method.

Table 2: The value of level in which clustering must be cut

Image number	1	2	3	4	5	6	7	8	9	10
Level	2500	2500	3400	5600	2600	2500	2200	1700	3800	5800
Image number	11	12	13	14	15	16	17	18	19	20
level	2100	1700	550	600	900	3700	2300	2400	2400	2000

The remained point is computing precision of the proposed method and comparing it with similar methods. since test conditions of this paper is similar to grow- cut [27] and Tumor-cut [28] methods in terms of data set and image type, the results of these methods can be compared by using coefficient criterin of Dice that is a favouralle criterion for comparing labeled output binary image and manual binary image. If consider A and B in mentioned A and B images, Dice coefficient isdefinedas follows:

$$(2)\text{Dice (A, B)}=\frac{2TP}{2TP+FP+FN}$$

This criterion shows the quality of segmentation of a method. It's sufficient to dedicatelabeled binary image and output of proposed method to this formula. Table 7 shows comparing this paper with new similar methods. Figures 6, 7 and 8 show input images,outputs obtained from determining beginning point by the expert .

Table 3: comparing the method of this paper with new similar methods

The name of method	Grow- out [27] (2005)	Tumor- Cut [28] (2012)	The proposed method (beginning point specified by expert)
Criterion value Dice	68,56	79, 00	80,44

According to table 3, it must be concluded that the method proposed in this research has suitable precision, so some actions can be taken into account in future researches to find in automatic method to specify beginning point of segmentation.

5. CONCLUSION

In this paper , an efficient method has been pretested on the basis of hierarchical algorithm by using simple futures to detect brain tumor range in magnetic resonance images. In the proposed framework, various types of brain tumors and magnetic resonance imagers have been considered. The method of this research is composed of the following basic steps.

1)pre-processing: Reneving skill and deleting datails lacking information about segmerntation by using average transfer method.

2) Hierarchical Segmentation: mapping image pixels in new three-dimensional space to specify tumor range by using single-linkage algorithm

3) Using particles swarm algorithm: In average transfer method, a parameter whose window is determined is used. Aslo, in hierarchical method, the distance criterion is used to find similar points. These two parameters are optimized nby using particles swarm algorithm, and an appropriate value is found for window dimensions and appropriate distance criterion

One of the most important characteristics of the method proposed in this paper is that the presented method has acceptable execution speed due to using simple algorithms of image processing and simple and suitable features. In addition, smultaneous combination of expert power and power of image processing methods is considered for optimal segmentation. Since specigyingthe rang of brain tumors is crucial for the patient health, physucians using intelligent methods. There are some parameters in the presented method. Although they can be automatically found, they can be initialized by the expert. In addition the presented method doesnot rely on special conditions of tumor or special imaging type. The presented method relies on a special type of tumor (Gioma, metastasis, meningionoa), special location of tumor in the head, special type of magnetic resonance images (T_2FLAIR, T_1C, T_2,T_1), direction of head in image or tumor size. It is tested in all images of data set, and it involves all of them. The obtained in this paper to dind the range of brain tumors in magnetic resonance images.

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