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# Segmentation Techniques to Detect Abnormal Tissues in Brain MR Images -A Review

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## Abstract

The information system based on image analysis by segmentation techniques has wide range of utilities. The information system based on research on image analysis includes, but not limited to industrial inspection, tracking of objects in a sequence of images, traffic control systems, classification of terrains visible in satellite images, geomorphological mapping of land surfaces, crop analysis in agriculture, and treatment planning in medical science. This paper is focused to study and review the tradeoff between various approaches for analyzing the abnormalities in brain MR Images by segmentation techniques. We preferred to use MRI compared to other brain imaging techniques due to its quality parameters for the purpose of detecting abnormalities. The result leads to plan precise treatment for the medical practitioners. In addition, the proposed study has given roadmap to improve accuracy and precision to detect abnormal tissues using classification and clustering methods of Image Segmentation.

***Keywords :***

Brain MR Image, Image Segmentation, Segmentation Techniques

## Introduction

Segmentation is the process of separating an observed image into its homogeneous or constituent regions. It simplifies or changes the representation of an image into something that is more meaningful and easier to analyse. It is important in many computer vision, medical field and image processing application (El-Baz, et.al., 2013; Kang et. al., 2009) Recent medical imaging research faces the challenge of detecting abnormal tissues like tumor from brain MR Images obtained through Magnetic Resonance Imaging technique. Normally, to produce images of soft tissue of human body, MR Images are used by experts

(Kekre et. al., 2009) . For analysing and detection of various tissues, image segmentation is required.

Image segmentation plays an important role in medical imaging applications to understand anatomical structures of human body (Kelkar and Gupat, 2008). Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other medical imaging modalities provide an effective means for mapping the anatomy of a subject. These technologies are used for diagnosis and treatment planning (Balhar et. al. 2010;Bhagwat et. al., 2013).

MRI is an advanced medical imaging technique providing rich information about the human soft-tissue anatomy. It is widely used by medical practitioners in order to visualize the structure and function of the human body (Rogowska, 2009;Lin et. al., 2006). It produces the very detailed images of the body in any direction. It offers much greater contrast between the diverse soft tissues of the body than the computer tomography (CT). It is different from CT as it does not use ionizing radiation, but uses an effective magnetic field to line up the nuclear magnetization of hydrogen atoms in water in the body (Luts et. al., 2007;Othman et. al., 2011;Pal, 1993).

In the medical imaging community, accurate and reproducible segmentation and characterization of abnormalities are still a challenging and difficult task because of variety of the possible shapes, locations and image intensities of various damaged tissues (Cox, 2005;Pan et. al., 2004;Li et. al., 2006).

This research study is categorised into analytical grouping approach as multiple variable and parameters are considered for experiment based on their classified values (Jain and Mao, 1996;El-Sayed at. el., 2010).

This paper will present the current status of various methods of segmentations in medical imaging applications (Jabbar and Mehrotra, 2008). Current segmentation approaches will be reviewed with advantages and disadvantages of various methods (Corso et. al., 2006;Jiang et. al., 2009;Juang et. al., 2007).

***Rational of the Study***

Accurate detection of the type of brain abnormality is highly essential for treatment planning in order to minimize diagnostic errors. The accuracy can be improved by using computer aided diagnosis (CAD) systems. The basic concept of CAD is to provide a computer output as a second opinion to assist radiologists' image interpretation and to reduce image reading time. This improves the accuracy and consistency of radiological diagnosis. However, segmentation of brain MR Images is pretty difficult task due to variation in size, shape, location, intensity of different tissues.

Several general-purpose algorithms and techniques have been developed for this purpose. Manual segmentation is also possible but is a time-consuming task and level of confidence is low. Another problem with manual and semiautomatic segmentations is that the segmentation is subject to variations both between observers and within the same observer. It is noted quantified average variation in volume between individuals performing the same segmentation task as well as variation within individuals repeating the task more than once at some time interval. So automatic methods are preferable.

Methods for performing segmentations vary widely depending on the specific application, imaging modality, and other factors. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver.

Segmentation of medical images involves following problems.

- There is a large number of damaged tissues which differ greatly in size, shape, location, composition and homogeneity. Therefore, in some cases, their border with normal tissues cannot very well defined on images for radiology experts.
- Image contains noise that can alter the intensity of a pixel such that its classification becomes uncertain.

- Images have finite pixel size and are subject to partial volume averaging where individual pixel volumes contain a mixture of tissue classes so that intensity of a pixel in the image may not be consistent with any one class.

MR images are often corrupted by a low-frequency spatially varying artifact known as the bias field. This is mainly caused by the variation of the interaction between the human body and the magnetic field. Although such artifacts have little impact on visual diagnosis, the performance of most automatic image analysis techniques, especially intensity-based segmentation, can degrade dramatically. The above statistics demonstrates that the manual segmentation has no confidence in tracking the various damaged tissues during the patient follow-up process.

***Objective of the Study***

The analysis of medical image is directly based on four steps: 1) image filtering, 2) segmentation, 3) feature extraction, and 4) analysis of extracted features by pattern recognition system or classifier. This research would address above difficulties using a soft computing approach. In this research study, an attempt has been made to present an approach for tissue characterization of MR images by utilizing segmentation tool. The present approach will directly combine second, third, and fourth steps into one algorithm. Proposed approach would eliminate the need for explicit modelling of mixed classes where each point can belong to more than one class.

***Learning objectives***

- Identify major processes involved in formation of brain MR images
- Recognize and Classify the imaging modality from their visualizations
- Describe fundamental methods for image enhancement
- Enhance brain MR images using appropriate software
- Appraise efficacy and drawbacks of several techniques for image segmentation

**Literature Review**

Segmentation of brain MR Images helps to overcome the time taking process of manual segmentation of large datasets. It also ensures reproducibility which is normally affected by inter and intra observer variability. However, automated systems are not without problems to achieve these objectives. In recent years, many methods have been suggested for automation of scanning, imaging and identification of abnormal tissues from brain MR Images (Deshmukh and Jadhav, 2014). Generally, such methods can be classified as follows:

- Thresholding (Histogram Segmentation, Otsu's method)
- Region Based Segmentation (Region Growing, Splitting and Merging, Watershed, Level Set etc.)
- Edge Based Segmentation (Gradient based method)
- Supervised Method – Classifiers (K-nearest Neighbourhood, Support Vector Machine, Principal Component Analysis, Markov random field, Decision tree, Knowledge based, Bays classifier etc.)
- Unsupervised Method – Clustering (K-means, Fuzzy C-means, N-cut algorithm, ExpectationMaximization, Hierarchical clustering, Ant Tree Algorithm etc.)
- Artificial Neural Network (Feed Forward Network, Feed Backward Network etc.)
- Hybrid Approach

Following section shows various literature survey of different segmentation techniques and their trade-offs.

**Segmentation Techniques**

***Thresholding***

Thresholding is one of the frequently used method for image segmentation. This method is effective for images with different intensities. Using this method, the image is partitioned directly into different regions based on the intensity values. The basic idea of thresholding is to select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. Thresholding creates binary images from grey-level ones by turning all pixels below some threshold to zero and all pixels about that threshold to one (Pham et. al., 2006)

There are two types of thresholding methods – Global and Local thresholding. Global thresholding method selects only one threshold value for the entire image. It is used for bimodal images. It is simple and faster in computation time only if the image has homogeneous intensity and high contrast between foreground and background. In Local thresholding, threshold values are selected locally by dividing an image into sub-images and calculate a threshold value for each part. It takes more computation time than global thresholding. Its result is satisfactory in background variations in an image.

***Histogram thresholding***

It is based up on thresholding of histogram features and gray level thresholding. The MRI brain image is divided into two equal halves around its central axis and the histogram of each part drawn. Threshold point of the histogram is calculated based on the comparison technique made between two histograms. The detected image is cropped along its contour to find out the physical dimension of the damaged tissue.

***Otsu method***

It is type of global thresholding in which it depends only on gray value of the image. This method gives better result in salt and pepper noise but does not give on Gaussian noise. Another issue related to it is its low processing rate (Selvaraj and Dhanasekaran, 2012)

**Region Based Segmentation**

***Region Growing***

This method starts with a seed pixel and grows the region by adding the neighbouring pixels based on threshold value. When the growth of a region stops, another seed pixel which does not belong to any other region is chosen and the process is repeated. This method is particularly used for delineation of small, simple structures such as tumours and lesions. [9] The various limitations in using this method are: Sometimes, manual interaction is required to select the seed point, Sensitive to noise so it produces holes or over segmentation in the extracted regions. The region growing is stopped when all pixels belongs to same region (Murugavalli and Rajamani, 2007)

***Region splitting and merging***

In this method, the image is split into various regions depending on some criterion and then it is merged. The whole image is initially taken as a single region and then internal similarity is computed using standard deviation. If too much variety occurs then the image is split into regions using thresholding. This is repeated until no more splits are further possible. The drawbacks are: results depend on the position and orientation of the image; regular division leads to over segmentation by splitting (Dewangan and Sharma, 2012)

***Watershed segmentation***

This method can be used if the foreground and the background of the image can be identified. It is also used to capture weak edges. Selection of seed point is the main drawback of this approach.

segmentation, an image looks like a surface where bright pixels are considered as mountain tops and dark pixels are considered as valleys. Some valleys have punctures which are slowly merged into water that will be poured and then it will start to fill the valleys.

***Level Set Model***

This model is based on moving curves and surfaces with curvature based velocities. The curves or surfaces are represented as the zero level set of a higher dimensional hyper surface. It solves the problem of corner point producing and curve breaking. Since the edge-stopping function depends on the image gradient, only objects with edges defined by gradients can be segmented.

***Edge Based Segmentation***

This method partitions an image based on rapid changes in intensity near edges. The result is a binary image.

***Gradient based method***

In this method the difference between two neighbouring pixel values is considered. So, when there is an abrupt change in intensity near edge and there is little image noise then gradient based method works well. Common edge detection operators used in gradient based method are Sobel operator, Canny operator, Laplace operator, Laplacian of Gaussian (LOG) operator & so on, Canny is most promising one, but takes more time as compared to Sobel operator. Edge detection algorithms are suitable for images that are simple and noise-free as well often produce missing edges or extra edges on complex and noisy images. If the level of detecting accuracy is too high, noise may bring in fake edges making the outline of images unreasonable and if the degree of noise immunity is too excessive, some parts of the image outline may get undetected and the position of objects may be mistaken.

**Classifiers**

***K-Nearest Neighbour***

The k-NN algorithm is based on a distance function and a voting function in k-Nearest Neighbours, the metric employed is the Euclidean distance. The k-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but has a slow running time.

***Support Vector Machine***

SVM is a supervised classifier with associated learning algorithm derived from the statistical theory. It works under the principle of structure risk reduction from statistical learning theory. Instead of minimizing an objective function based on the training samples (such as mean square error), the SVM attempts to minimize the bound on the generalization error (i.e., the error made by the learning machine on the test data not used during training). As a result, an SVM tends to perform well when applied to data outside the training set.This method claimed to be the better than rule based systems but the accuracy is low. The biggest limitation lies in choice of the kernel. It has high algorithmic complexity and extensive memory requirements of the required quadratic programming in large-scale tasks.

***Principal Component Analysis***

PCA is used to extract principal features. It uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. PCA is mainly used to reduce the large dimensionality of the data by removing the redundant features. Limitations are: The covariance matrix is difficult to be evaluated in an accurate manner and Even the simplest invariance could not be captured by the PCA unless the training data explicitly provides this information.

***Markov Random Field***

This technique possesses ability to encode both spatial and statistical properties of an image. It has isotropic behaviour and works on local dependencies. Computing probability and parameter estimation are difficult. The method requires estimating threshold and does not produce accurate results most of the time.

***Decision Tree***

In a classification tree, the decision tree classification structure is constructed to distinguish different classes through statistical analysis. Decision trees classify multidimensional spatial data through recursive partitioning steps. Each vector consisting of N sampled data in an M-dimensional space. The subspaces can be illustrated easily to maximize the overall class separation for the M-dimensional spatial data set. The class separation is maximized during the partitioning step, and is subsequently processed as the basis for further partitioning to the M-dimensional spatial data set (Sumitra and Saxena, 2013).

***Bayesian Classifier***

It is a Statistical classifier. It performs Probabilistic prediction i.e. predicts class membership probabilities Based on Bayes' Theorem. A simple Bayesian classifier, naïve Bayesian classifier, has comparable performance with decision tree and selected neural network classifiers. Each training example can incrementally increase/decrease the probability that a hypothesis is correct - prior knowledge can be combined with observed data (Tolias and Panas, 19998). Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured. An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Bayesian makes assumptions about prior behaviour. It requires that you choose a model. A good prior model can improve accuracy. But model mismatch can impair accuracy (Shrimani and Shanthi, 2013).

**Clustering**

A Clustering is one of the most useful techniques in MRI Segmentation, where it classifies pixels into classes, without knowing previous information or training. It classifies pixels with highest probability into the same class.

***K-means***

K-means clustering is the simplest unsupervised learning algorithm that can solve clustering problem. In K-means 'K' centres are defined, one for each cluster. These clusters must be placed far away from each other. The next step is to take a point belonging to a given data set and associate it to the nearest centre. When no point is pending, the first step is completed and early grouping is done. The second step is to recalculate 'k' new centroids as barycentre of the clusters resulting from the previous step. After having 'K' new centroids a new binding has to be done between the same data set points and the nearest new centre. A loop has been generated. As a result of this loop, the k centres change their location step by step until centres do not move any more. Finally this algorithm aims at minimizing an objective function known as squared error function.

K-means algorithm is fast, robust and easier to understand. It also gives better result when data set are well separated from each other. But, if there are two highly overlapping data then k-means will not be able to resolve that there are two clusters.

***Fuzzy C-mean***

FCM clustering is an unsupervised method for the data analysis. This algorithm assigns membership to each data point corresponding to each cluster centre on the basis of distance between the cluster centre and the data point. The data point near to the cluster centre has more membership towards the particular centre.

Generally, the summation of membership of each data point should be equal to one. After each iteration, the membership and cluster centres are updated according to the formula. The first loop of the algorithm calculates membership values for the data points in clusters and the second loop recalculates the cluster centres using these membership values. When the cluster centre stabilizes the algorithm ends. The FCM algorithm gives best result for overlapped data set and also gives better result than k-means algorithm. Here, the data point can belong to more than one cluster centre. The main drawbacks of FCM are: 1) the algorithm has difficulty in handling outlier points. 2) due to the influence of all the data members, the cluster centres tend to move towards the centre of all the data points. It only considers image intensity thereby producing unsatisfactory results in noisy images.

***Expectation maximization***

This approach is used to differentiate the healthy and the damaged tissues. But the drawback is the lack of quantitative analysis on the extracted tumour region. A common disadvantage is that the intensity distribution of brain images is modelled as a normal distribution.

***Hierarchical clustering***

This method works by grouping data objects into a tree of clusters. Hierarchical clustering doesn't require specifying the number of clusters. Hierarchical clustering is deterministic. There are two types of hierarchical clustering: Agglomerative clustering and Divisive Clustering. The basic process of hierarchical clustering for a given set of N items to be clustered and NxN distance Matrix. In Agglomerative clustering, each element is treated as a singleton cluster and then merged (agglomerated) until all merge in a single cluster, which results in dendograms formation. Dendograms are horizontal lines which when cut at a point you get a specific part or element and explains how clustering helps forming an image. Divisive hierarchical is more efficient than Agglomerative hierarchical clustering. Divisive Hierarchical Clustering can be stopped when the goal is achieved. The main disadvantage is they do not scale well: time complexity of at least $O(n^2)$, where n is the number of total objects. They can never undo what was done previously.

***Ant tree algorithm***

The general Ant-Tree algorithm cannot be used in MRI Brain image segmentation directly. It produces a hierarchical structure in an incremental manner in which the ants join together. In this algorithm, each ant represents as a single datum from the data set and it moves in the structure according to the similarity (i, j) with the other ants already connected in the tree under construction. In order to make a partition of the whole data set, a more appropriate decision is made when determining the place in which each ant will be connected, either to the main support (generates a new cluster) or to another ant (refines an existing cluster) (Warfield and Duda, 2001).

In improved Ant tree algorithm, the tree structure of ant tree algorithm ensures that the new ants don't need to search the entire data set when they are connected to the structure. Usually each sub-tree is directly connected to the support as a cluster. So, the hierarchical structure of the tree contains a large number of redundant information.

The ant tree algorithm successfully segments the MR brain into white matter, gray matter and cerebrospinal fluid in a better way than FCM and k-means algorithm. In addition, the processing speed of the ant tree algorithm is better than the other two algorithms (FCM, k-means) which are suitable for segmenting large scale MR brain images instantly. But a drawback is the algorithm complexity (Wen-Hung et. al., 2009).

**Artificial Neural Network**

Neural Network based segmentation is totally different from conventional segmentation algorithms. In this, an image is firstly mapped into a Neural Network. Where every Neuron stands for a pixel, thus image segmentation problem is converted into energy minimization problem. The neural network was trained with training sample set in order to determine the connection and weights between nodes. This includes two important steps feature extraction and image segmentation based on neural network. Feature extraction is very crucial as it determines input data of neural network, firstly some features are extracted from the images, such that they become suitable for segmentation and then they were the input of the neural network. All of the selected features compose of highly non-linear feature space of cluster boundary.

Basic characteristics:

• High parallel ability and fast computing.

• Improve the segmentation results when the data deviates from the normal situation.

• Reduced requirement of expert intervention during the image segmentation process.

Drawbacks:

• Some kind of segmentation information should be known beforehand.

• Neural network should be trained using learning process beforehand.

• Period of training may be very long, and overtraining should be avoided at the same time.

Based on the architecture, Artificial Neural Network can be grouped into two categories: Feed-Forward Network and Feed-Backward Network or Recurrent Network

In feed-forward network, the neurons are arranged in layers that have unidirectional connections between them.

**Feed-Forward Network**

It produces only one set of output values. It is called as static network because, the output values does not depend on previous output values. The output values are produced only based on current input. In feedback network, the neurons are arranged in layers that have bidirectional connections between them. It produces a set of values which is updated based on the output values fed.

***Back Propagation Algorithm***

It is used in layered feedforward ANN. This algorithm works for feed-forward networks with continuous output. In this network, the neurons are organized in layers and send their signals in the forward direction. The errors generated are propagated in the backward direction. The network receives the input by neurons in the input layer and the output of the network is given by the neurons on an output layer. The network consists of one or more intermediate hidden layers. Supervised learning is used in Back Propagation algorithm i.e., Examples of both the input and the output to be computed is given to the algorithm. The error between the input and the computed output is calculated. The network is trained with random weights and later the weights are adjusted to get the minimal error. The network will be perfect if the error is minimal. In back propagation, the weights and thresholds are changed each time an example is presented, such that the error gradually reduces. This is repeated until there is no change in the error.

MR image segmentation based on feed forward neural networks relies heavily on the training set used for their supervised training. The training set is constructed by selecting feature vectors from a single MR image or an ensemble of MR images and reflects the judgment of the human experts who assign labels to the feature vectors according to the tissues they represent.

**Hybrid Techniques**

Several hybrid neuro-fuzzy approaches for MRI brain image analysis are reported in the literature. A combinational approach of SOM, SVM and fuzzy theory implemented by performed superiorly when compared with other segmentation techniques. The SOM is combined with FCM for brain image segmentation but this technique is not suitable for tumours of varying size and convergence rate is also very low.

A hybrid approach such as combination of wavelets and support vector machine (SVM) for classifying the abnormal and the normal images is used by. This report revealed that the hybrid SVM is better than the neural networks in terms of performance measures. But, the major drawback of this system is the small size of the dataset used for implementation and the classification accuracy results may reduce when the size of the dataset is increased.

The combination of SVM and fuzzy rules is experimented in this work. The results revealed that the proposed hybrid approach is accurate, fast and robust.

Apart from these, various other hybrid approaches are presented in literature. Next study will represent their comparisons and results.

**Research Gap**

General imaging artefacts such as noise, partial volume effects, and motion can also have significant consequences of the performance of segmentation algorithms. There is currently no single segmentation method that yields acceptable results for every medical image. There are various methods available and can be applied to a variety of data. Selection of an appropriate approach to a segmentation problem can therefore be a difficult task. So, this research will show comparison of various methods of segmentation on brain MRI images in terms of different parameters like accuracy, time, performance etc. Using these results, this research will propose a way to optimize the performance to achieve desired output.

**Proposed Method**

We would like to propose more precise method to detect abnormalities from brain MR Images based on research questions faced from literature survey such as

- Is there any single segmentation method that yields acceptable results for every medical image?
- Which classification approach is suitable for a specific study?
- How much time is required to classify an image using different techniques and platforms?
- How to get more accurate segmentation results?

***Research design with procedure:***

The MR image will obtain and convert it to data form in MATLAB environment such as basic arithmetic operations and indexing, including logical indexing reshaping and reordering.

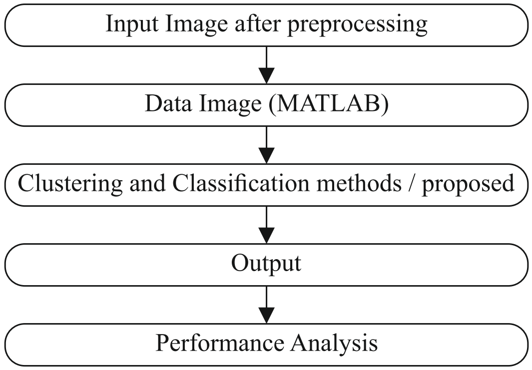
MATLAB stores an intensity image as a single matrix, with each element of the matrix corresponding to one image pixel

.Normal image (prior image) and abnormal image (diagnostic image) are converted to matrix format automatically while the image being read in the MATLAB environment.
Both images are converted to binary images. The region of interest is determined by subtracting the normal image with abnormal image.

***Research method with justification:***

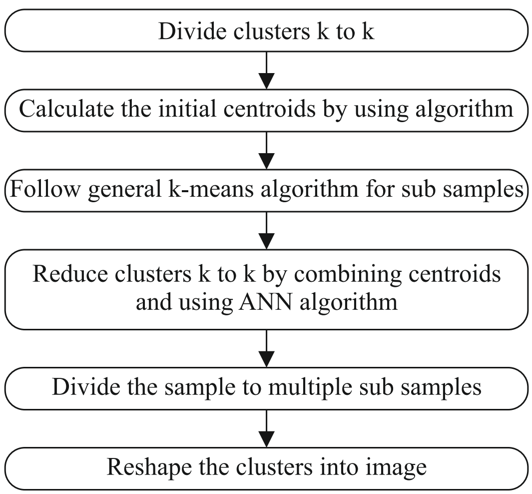
This research study is categorized into analytical study. Here this study uses the facts/information already available and analyze these to make an evaluation of the material. This research will use statistical techniques which are used for establishing relationships between the data and unknown and evaluate the accuracy of the results obtained using proposed approach that utilize a histogram based Fuzzy C-Means clustering with spatial probability and other methods like ANN. Proposed method outline is as follows

**Fig.1 Research Design Procedure**




- As shown in below figure, initially segment MR image into k clusters and find centroids using k-means algorithm.
- Repeat this process iteratively till desirable clusters are marked.
- Then according to criteria reduce clusters and use ANN algorithm. So multiple sub samples are generated as per interest.
- Finally, combine all clusters and reshape the image to get required outcome.:

**Fig.2 Research Method with Justification**



**Summary And Conclusion**

Many image segmentation methods have been developed in the past several decades for segmenting brain MR Images, but still it remains a challenging task. A segmentation method may perform well for one brain MR Image but not for the other images of same type. Thus it is very hard to achieve a generic segmentation method that can be commonly used for all MR brain images. In this work, the merits and demerits of various automated techniques of segmentation are analyzed. Proposed approach utilizes a histogram based Fuzzy C-Means clustering with spatial probability and ANN to improve accuracy to detect abnormalities from Brain MR Images. Several novel hybrid approaches may be developed through the ideas conveyed using this paper.

**Future Scope**

In future, the proposed method will be implemented on different datasets to achieve ROI i.e. abnormal tissues from brain MR images, more appreciable in terms of accuracy and precision when associated to other related approaches.

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