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A REVIEW ON CURRENT MRI BRAIN TISSUE SEGMENTATION, FEATURE EXTRACTION AND CLASSIFICATION TECHNIQUES

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ABSTRACT

MRI brain image plays a vital role in assisting radiologists to access patients for diagnosis and treatment. Studying of medical image by the Radiologist is not only a tedious and time consuming process but also accuracy depends upon their experience. So, the use of computer aided systems becomes very necessary to overcome these limitations. Even though several automated methods are available, still segmentation of MRI brain image remains as a challenging problem due to its complexity and there is no standard algorithm that can produce satisfactory results. In this review paper, various current methodologies of brain image segmentation using automated algorithms that are accurate and requires little user interaction are reviewed and their advantages, disadvantages are discussed. This review paper guides in combining two or more methods together to produce accurate results.

KEYWORDS: MRI Brain Image, Tissue Segmentation, Feature Extraction, Neural Network, FCM, Thresholding

INTRODUCTION

Magnetic resonance imaging (MRI) of the brain is a safe and painless test that uses magnetic field and radio waves to produce detailed images of the brain and brain stem. Magnetic resonance imaging differs from computer tomography (CT) because it does not use radiation. MRI can detect a variety of conditions of the brain such as cysts, tumours, bleeding, swelling, structural abnormalities, infections or problems with the blood vessels. MRI of the brain can be useful in evaluating problems such as persistent headaches, dizziness, weakness, seizures and it can help to detect certain chronic diseases of the nervous system such as multiple sclerosis. In some cases, MRI can provide clear images of parts of the brain that can't be seen with an x-ray, CT scan or ultrasound.

There are many different types of pediatric brain tumours ranging from those that can be cured with minimal therapy to those that cannot be cured even with aggressive therapy. Some of the common types are Astrocytomas, Ependymomas, Brainstem gliomas, Germ cell tumours, Craniopharyngiomas. Segmentation of brain into various tissues like gray matter, white matter, cerebrospinal fluid, skull and tumour is very important for detecting tumour, edema, and hematoma. Most research in developed countries has exposed that the death rate of people affected by brain tumor has increased over the past three decades [39]. A tumour is a mass of tissue that grows out of control of the normal forces that regulates growth [50]. Tumours can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull [28]. In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing (Such as edge detection and region growing) based on gray intensities of images. In recent years, the classification of human brain in MRI images is possible via supervised techniques such as k-nearest neighbour, Artificial neural networks and support vector machine(SVM) and unsupervised classification techniques such as self organization map(SOM) and fuzzy C-means algorithm have also been used to classify the normal or pathological T_2 weighted MRI images.

Even though many algorithms are available for detecting brain tumour, the detection rate is still not satisfactory. In this paper, various approaches of MRI brain image segmentation methods are discussed in section 2 and Feature extraction methods are reviewed in section 3. In section 4, the various classifiers used for classifying brain image are discussed and finally the suitable method for segmentation and classification are concluded in section 5.

MRI BRAIN TISSUE SEGMENTATION TECHNIQUES

Various segmentation methods have been cited in the literature for improving the segmentation. Some of the commonly used methods are summarized as in Figure 1.

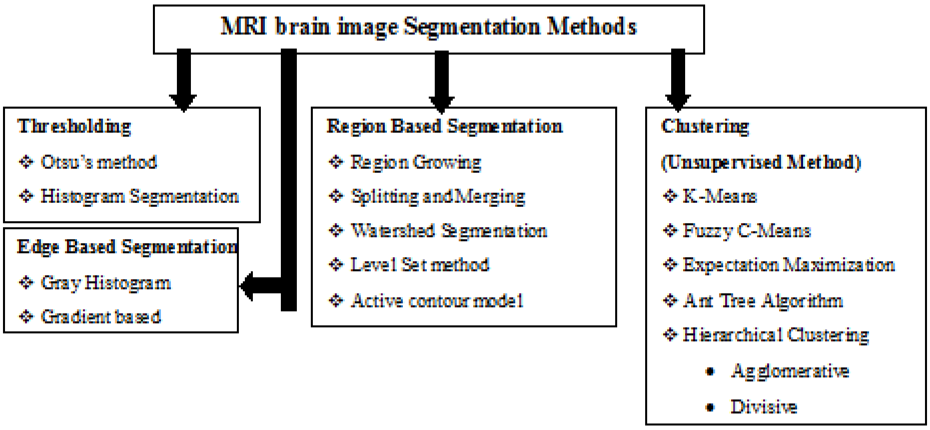

Figure 1: MRI Brain Image Segmentation Methods

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. Thresholding is defined mathematically [62] as Eq. (1). Let f(x,y) be the input image and 'T' be the threshold value then the segmented image g(x,y) is given by,

$$g(x,y) = \begin{cases} 1, & \text{if } f(x,y) > T \\ 0, & \text{if } f(x,y) \le T \end{cases} \tag{1}$$

Using the above Eq. (1), the image can be segmented into 2 groups. If we want to segment the given image into multigroups then we should have multi threshold point.

If we have 2 threshold values, then the above equation becomes as Eq. (2) and this equation segments the image into 3 groups

$$g(x,y) = \begin{cases} a, & \text{if } f(x,y) > T_2 \\ b, & \text{if } T_1 < f(x,y) \le T_2 \\ c, & \text{if } f(x,y) \le T_1 \end{cases} \tag{2}$$

D. Bhattacharyya and Tai-hoon kim [8] have proposed an image segmentation technique to identify the tumor from the brain magnetic resonance imaging (MRI). Several existing thresholding techniques have produced different result in each image. Thus, to produce a satisfactory result on brain tumor images, they have proposed a technique, where the detection of tumor was done uniquely. A survey on available thresholding techniques are provided in the literature [14, 54, 60, 74].

Otsu's Thresholding

Otsu method is the commonly used thresholding technique. Otsu's thresholding technique is based on a discriminant analysis which partitions the image into two classes C_1 and C_2 at gray levels 'k' such that $C_1 = \{ 0,1,2,3,\ldots, k\}$ and $C_2 = \{ k+1, k+2,\ldots, L-1\}$where, 'L' is the total number of gray levels of the image. Let 'n' be the total number of pixels in the given image and 'n_i' be the number of pixels at the i^{th} gray level. The probability of occurrence of gray level is defined as,

$$P_i = \frac{n_i}{n} \tag{3}$$

'C_1' and 'C_2' are two classes representing the region of interest and the background.

The probabilities of classes C_1 and C_2 are,

$$P_1(k) = \sum_{i=0}^{k} P_i \tag{4}$$

$$P_2(k) = \sum_{i=k+1}^{L-1} P_i = 1 - P_1(k) \tag{5}$$

The mean intensity values of these two classes are

$$m_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^{k} i.P_i \tag{6}$$

$$m_2(k) = \frac{1}{P_2(k)} \sum_{i=k+1}^{L-1} i.P_i \tag{7}$$

where, $m_1(k)$ and $m_2(k)$ are object's center gray and background's center gray.

Disadvantages:

- Otsu method can segment only larger objects from background
- Otsu method fails if the histogram is unimodal or close to unimodal

Local Thresholding

Threshold values are selected locally by dividing an image into sub-images and calculate a threshold value for each part. A local threshold takes more computation time than global thresholding. Its result is satisfactory in background variations in an image. It can extract only small regions [46].

Histogram Thresholding

Histogram thresholding segmentation is based up on thresholding of histogram features and gray level thresholding. Threshold is defined mathematically as Eq. (1)

Algorithm [56, 62].

Step1: The MRI brain image is divided into two equal halves around its central axis and the histogram of each part drawn.

Step2: Threshold point of the histogram is calculated by comparing 2 histograms.

Step3: Segmentation is done using the threshold point for both the halves.

Step4: The detected image is cropped along its contour to find out the physical dimension of the tumour.

Step5: Create an image of the original size, check the segmented image pixel value. If its value is greater than threshold value then assign 255 else 0.

Step6: Segment the tumour area.

Step7: Calculate the area of the tumour

Edge Based Segmentation

Edge based segmentation methods partition an image based on rapid changes in intensity near edges [23, 48]. The result is a binary image. Based on theory there are two main edge based segmentation methods- gray histogram and gradient based method [32]. The result of edge detection technique mainly depends upon selection of threshold T [32]. 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 [23], but takes more time as compared to sobel operator.

Edge detection methods require a balance between detecting accuracy and noise immunity. 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 [32], some parts of the image outline may get undetected and the position of objects may be mistaken. Thus, 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 [69].

Region Based Segmentation

Compared to edge detection method, segmentation algorithms based on region are relatively simple and more immune to noise [32, 79]. Edge based methods partition an image based on rapid changes in intensity near edges whereas region based methods, partition an image into regions that are similar according to a set of predefined criteria [23, 31]. Segmentation algorithms based on region mainly include following methods.

Region Growing

Region growing method is one of the popular segmentation methods. 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 [42]. The region growing is stopped when all pixels belongs to some region.

Region growing segmentation is particularly used for delineation of small, simple structures such as tumours and lesions [20, 57, 59]. The various limitations in using this method are, 1. Sometimes, manual interaction is required to select the seed point. 2. Sensitive to noise so it produces holes or over segmentation in the extracted regions. The discontinuity in the extracted image can be removed by using homotopic region growing algorithm [9].

Region Splitting and Merging

In this method, the image is splitted 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. Quadtree is a common data structure used for splitting. Then comes the merging phase, where two regions are merged if they are adjacent and similar. Similarity can be measured by comparing the mean gray level or using statistical tests. Two regions R_1 and R_2 are merged into R_3 if,

$$H(R1 \cup R2) = \text{True and} \quad (8)$$

$$|m1 - m2| < T \quad (9)$$

Where, m_1 and m_2 are the mean gray level values in the regions R_1 and R_2; T is some appropriate threshold [23]. Merging is repeated until no more further merging is possible. The major advantage of this technique is guaranteed connected regions. The drawbacks of the split and merge technique are, 1.The results depend on the position and orientation of the image, 2. Regular division leads to over segmentation by splitting. This drawback can be overcome by reducing number of regions by using Normalized cuts method. Improved Quadtree method for split and merge is introduced in [19]. In this improved method they have used three steps first splitting the image, second initializing neighbours list and the third step is merging splitted regions. The survey says split and merge algorithm is a fast computation method. Its drawback is lack of sensitivity to image semantics [20, 73]

Watershed Segmentation

Watershed segmentation algorithm can be used if the foreground and the background of the image can be identified. Watershed algorithm is also used to capture weak edges. Selection of seed point is the main drawback of this approach. Random selection of seed point may lead to inappropriate results and increases convergence rate. So, water segmentation is not suitable for MRI brain image.

Snakes

Active contours or snakes are computer generated curves [29] that move within the image to find object boundaries under the influence of internal and external forces. The internal forces are responsible for smoothness while the external forces guide the contours towards the contour of ROI. It requires user interaction, which consists of determining the curve around the detected object [33]. Snake should be placed usually near the boundary of ROI [82]

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. Clustering technique training is done by using pixel features with properties of each class [49, 51, 55 and 70].

K-Means

K-means clustering algorithm is the simplest unsupervised learning algorithm that can solve clustering problem. The procedure followed to classify a given set of data through a certain number of clusters is very simple. 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 re-calculate '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 given by,

$$J(V)=\sum_{i=1}^{c}\sum_{j=1}^{c_i}\left\|x_i-v_j\right\|^2 \tag{10}$$

Where, $\left\|x_i-v_j\right\|$ is the Euclidean distance between x_i and v_j

'C_i' is the number of data points in i^{th} cluster.

'C' is the number of cluster centres.

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 2 highly overlapping data then k-means will not be able to resolve that there are 2 clusters. Qurat-ul Ain *et al.* [52] has proposed a robust system for brain tumor diagnosis as well as for brain tumor region extraction. Initially, the proposed system has diagnosed the tumor from the brain MR images by bayes classification. After the diagnosis, the K-means clustering and boundary detection techniques have been applied to extract the exact brain tumor region. Here, above 99% accuracy has been achieved for diagnosis. Experimental results have shown that the proposed system has extracted accurately tumor region.

Fuzzy C-Means (FCM)

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

$$V_j=\frac{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^m x_i\right)}{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^m\right)},\ \forall_j=1,2\ldots.c \tag{11}$$

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\left(\frac{2}{m-1}\right)}} \tag{12}$$

Where, 'n' is the number of data points

'V_j' represents the jth cluster centre

'm' is the fuzziness index m €[1,∞]

'c' represents the number of cluster centre

'μ_{ij}' represents the membership of ith data to jth cluster centre.

'd_{ij}'represents the Euclidean distance between ith data and jth cluster centre.

'x_i' is the i^{th} of d-dimensional measured data

'c_j'is the d-dimension centre of the cluster

$\|*\|$ is any norm expressing the similarity between any measured data and the centre.

$dij = \|xi\text{-}cj\|$, $dik = \|xi\text{-}ck\|$

The main objective of fuzzy c-means algorithm is to minmize

$$J(U,V) = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \|x_i - v_j\|^2 1 \le m < \infty \quad (13)$$

Where,

$\|x_i - v_j\|$ is the Euclidean distance between ith data and jth cluster centre.

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 drawback of FCM is 1) the sum of membership value of a data point x_i in all the clusters must be one but the outlier points has more membership value. So, 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 [17]. It only considers image intensity thereby producing unsatisfactory results in noisy images [24].

A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect [24, 40, 2, 64, 18, 78]. Many approaches have been made to modify the existing standard FCM algorithm to improve its performance. Each of the modified FCM algorithms proposes a new membership function for calculating the membership of data points in clusters. A new distance function based on dot product instead of the conventional Euclidean distance [22]. The introduced new membership function is given in Eq.(14).

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d^2(v_i, x_k)}{d^2(v_j, x_k)}\right)^{\left(\frac{1}{m-1}\right)}} \quad (14)$$

Other improved versions of FCM by the modification of the objective function were introduced by [3] and [78]. In the proposed IFCM algorithm of [61] during clustering, each pixel attempts to attract its neighbouring pixels towards its own cluster. Here the attraction depends up on the intensity of the pixel. In MRI brain images, the presence of noise will alter the pixel intensity. Due to this the segmentation may be affected so, instead of modifying the objective function, the measurement of similarity was extended by considering neighbourhood attraction [58].

Chandra, S *et al.* [10] has proposed a Particle Swarm Optimization (PSO) based clustering algorithm. The proposed algorithm has identified the centroids of number of clusters, where each cluster has grouped together the brain tumor patterns, obtained from MR Images. The results obtained for three performance measures have been compared with those obtained from Support Vector Machine (SVM) and Ada Boost. The performance analysis has shown that the qualitative results of proposed model are analogous with those obtained by SVM. Moreover, the different values of PSO control parameters have been selected in order to acquire better results from the algorithm.

Expectation Maximization

A model based tumour segmentation technique was implemented by [44]. This approach uses a modified Expectation Maximization (EM) algorithm to differentiate the healthy and the tumorous tissues. A set of tumour characteristics are presented in this paper which is highly essential for accurate segmentation. But the drawback of this work is the lack of quantitative analysis on the extracted tumour region. The applications of the EM algorithm to brain MR image segmentation were reported by [72] and [37]. A common disadvantage of EM algorithm is that the intensity distribution of brain images is modeled as a normal distribution.

Hierarchical Clustering

Hierarchical clustering 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 2 types of hierarchical clustering. 1. Agglomerative clustering, 2. Divisive Clustering.

In Agglomerative clustering, each element is treated as a single cluster and then merged (agglomerated) until all merge in a single cluster, which results in dendograms formation [36]. The disadvantage of this method is 1) They do not scale well the time complexity of at least $O(n^2)$, where n is the number of total objects. 2) They can never undo what was previously done. Divisive hierarchical is more efficient than Agglomerative hierarchical clustering [36]. Divisive Hierarchical Clustering can be stopped when the goal is achieved.

Ant Tree Algorithm

The Ant tree algorithm [5] was introduced for MRI brain image segmentation. The general Ant-Tree algorithm cannot be used in MRI Brain image segmentation directly [75, 38]. The general Ant-Tree algorithm 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 sim (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).

In improved Ant tree algorithm [38], 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. To overcome this problem, a new method of cluster centre was introduced in [38] to improve the tree model of the ant tree algorithm. In [38] it is proved improved ant tree clustering algorithm can produce better results than k-means and FCM. In addition, the processing speed of the improved ant tree algorithm is much faster than the other two clustering algorithms. But, the algorithm is complex.

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 [38]. 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.

FEATURE EXTRACTION

To represent an image, large amount of data is required which occupies large amount of memory and time. In order to reduce the amount of data, memory and time, the features are extracted from an image. The extracted features contain the relevant information of an image. It can be used as an input to the classifier for image classification and segmentation.

The methods used to extract features from MRI images are, 1) Independent Component Analysis 2) Fourier Transform 3) Wavelet Transform. Fourier transform is used for frequency analysis of an image and wavelet transform is used for time, space and frequency analysis. The type of features that can be extracted from an image are listed in table 1 and table 2.

The Intensity Based Feature

Intensity based feature is one of the most widely used feature. The intensity feature such as mean, median, mode, skewness, kurtosis, energy, entropy are considered. Let f(x,y) be a two dimensional function of an image, h(i) be the intensity level of an image, Ng be the total number of gray levels in the entire image and p(i) be the probability density. Then features that can be extracted are,

Table 1: List of Intensity Based Feature

S.No	Feature	Expression
1	Variation (σ^2)	Variance, $\sigma^2 = \sum_{i=0}^{N_g-1}(i-\mu)^2.p(i)$ (15)
2	Mean	Mean, $\mu = \sum_{i=0}^{N_g-1} i.p(i)$ (16) where, $p(i) = \frac{h(i)}{N_x N_y}, i = 0, 1, 2, \ldots \ldots N-1$ (17) $h(i) = \sum_{x=0}^{N_g-1}\sum_{y=0}^{N_g-1}\delta(f(x,y), i),\ i = 0, 1, 2, \ldots \ldots N-1$ (18) $\delta(i, j) = \begin{cases} 1 ; & i = j \\ 0 ; & i \neq j \end{cases}$ (19)
3	Skewness	$\mu^3 = \sigma^{-3} \sum_{i=0}^{N_g-1}(i-\mu)^3.p(i)$ (20)
4	Kurtosis	Kurtosis, $\mu^4 = \sigma^{-4} \sum_{i=0}^{N_g-1}((i-\mu)^4.p(i)) - 3$ (21)
5	Energy (E)	Energy, $E = \sum_{i=0}^{N_g-1}[p(i)]^2$ (22)
6	Entropy (En)	Entropy, $En = -\sum_{i=0}^{N_g-1} p(i).\log_2[p(i)]$ (23)
7	Range (R)	Range, R = Minimum value of pixel intensity and maximum value of pixel intensity in a image.
8	Pixel Orientation (PO)	Pixel orientation, PO = Tan^{-1} {(y - m)/ (x - m)} (24) Where, m – the point which we require to measure the value. x, y – point in the x-axis, y-axis

Texture Feature

Texture is a characteristic of an image that provides higher order description of an image and includes information about the spatial distribution of tonal variations or gray tones. The texture extraction defines the homogeneity or similarity between regions of an image. Texture feature classifies magnetic resonance image of brain in to gray matter, white matter, cerebrospinal fluid and tumour region. The Haralick texture feature [25] are,

Table 2

S.No	Feature	Expression
1	Energy (E) or Angular second moment (ASM) or uniformity	$E = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)^2$ (25)
2	Contrast (Con)	$Con = \sum_{n=0}^{N_g-1} n^2 \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j)^2$ (26)
3	Correlation (Cor)	$Cor = \frac{1}{\sigma_x \sigma_y} \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i,j).p(i,j)^2 - \mu_x \mu_y$ (27)
4	Sum of squares: Variance (σ^2)	$Variance,\ \sigma^2 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-\mu)^2.p(i,j)$ (28)
5	Inverse Difference Moment (IDM)	$IDM = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2}\ p(i,j)$ (29)
6	Sum Average (Mean)	$Mean,\ \mu = \sum_{i=0}^{2(N_g-1)} i.p_{x+y}(i)$ (30)
7	Sum Variance (SV)	$Sum\ Variance,\ SV = \sum_{i=0}^{2(N_g-1)} (i-SE)^2\ p_{x+y}(i)$ (31)
8	Sum Entropy (SE)	$Sum\ Entropy,\ SE = -\sum_{i=0}^{N_g-1} p_{x+y}(i).\log p_{x+y}(i)$ (32)
9	Entropy (En)	$Entropy,\ E = -\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i,j).\log p(i,j)$ (33)
10	Difference Variance (DV)	Difference Variance, DV =Variance of p_{x-y} (34)
11	Difference entropy (DE)	$Difference\ Entropy,\ DE = -\sum_{i=0}^{N_g-1} p_{x-y}(i).\log p_{x-y}(i)$ (35)
12	Inertia (I)	$Inertia,\ I = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-j)^2.p(i,j)$ (36)
13	Cluster shade (CS)	$Cluster\ Shade,\ CS = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i+j-\mu_x-\mu_y)^3.p(i,j)$ (37)
14	Cluster Prominence (CP)	$CP = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i+j-\mu_x-\mu_y)^4.p(i,j)$ (38)

Shape Features

Shape provides the geometrical information of an object in an image. The shape features such as centroid, Eccentricity, area, perimeter, circularity, shape index, solidity, orientation, euler number are considered.

CLASSIFICATION TECHNIQUES

Various Classification methods have been cited in the literature for improving the classification. some of the commonly used methods are summarized as in Figure 2.

KNN

K-Nearest Neighbour (k-NN) classification technique is the simplest technique that provides good classification accuracy [71]. 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 [21]. The k-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but has a slow running time [15].

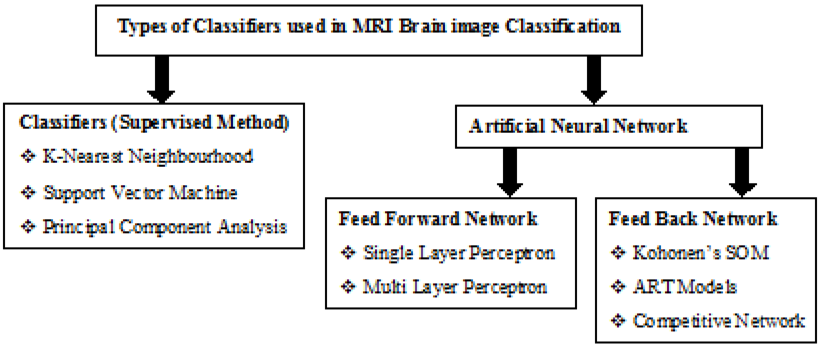

Figure 2: Types of Classifiers Used in MRI Brain Image Classification

SVM

Support Vector Machine is a supervised classifier with associated learning algorithm derived from the statistical theory [65, 66] and it is mainly used for the classification of MRI brain images as normal or abnormal due to its computational efficiency and good performance. It was first developed as an extension of the Generalized Portrait algorithm [67, 68]. It works under the principle of structure risk reduction from statistical learning theory. The SVM classifier is based on the hyperplane that maximizes the separating margin between the two classes.

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. To maximize the margin between the classes [80], its kernel is used to control the empirical risk and classification. There are many kernel functions such as linear, polynomial of degree and Radial basis function (RBF). Among these kernel functions, a radial basis function proves to be better for MRI brain images [80, 84]. Sumesh et al. [85] proved SVM with polynomial kernel of degree 3 shows better results than those with linear or RBF kernel. Sumesh et al. [85] also proved level based normal-abnormal classification shows better result than non-level based classification.

SVM has two stages; training and testing stage. SVM trains itself by features given as an input to its learning algorithm. During training SVM selects the suitable margins between two classes. Features are labeled according to class associative with particular class. SVM is an attractive and systematic method for two class problems. In this research work, many authors [1, 11, 12, 34, 47] are classifying MRI brain images into two separate classes such as normal and abnormal using Support Vector Machine. Support Vector machine based classification of various levels of MR glioma images are performed [77]. This method claimed to be the better than rule based systems but the accuracy is low.

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 [32, 48], 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. Neural network segmentation 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 [81], 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.

Neural network based segmentation have three basic characteristics:-

- High parallel ability and fast computing [32].
- Improve the segmentation results when the data deviates from the normal situation [81].
- Reduced requirement of expert intervention during the image segmentation process.

However there are some drawbacks of neural networks based segmentation, such as:-

- Some kind of segmentation information should be known beforehand.
- Neural network should be trained using learning process beforehand [32]
- 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 2 categories.

- Feed-Forward Network
- Feed-Backward Network or Recurrent Network

In feed-forward network, the neurons are arranged in layers that have unidirectional connections between them. Feed forward networks produce 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. Feed forward network is also called as memory less network. In feedback network, the neurons are arranged in layers that have bidirectional connections between them [55, 82]. Feedback networks produce a set of values which is updated based on the output values fed. Feedback network is also known as dynamic network because the output values depend up on the previous state values.

Back Propagation Algorithm

Back Propagation algorithm [27, 53] is used in layered feed-forward ANN. 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 used is Back Propagation algorithm. 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 ANN, the activation function of the artificial neuron is a weighted sum.

$$A_j(\overline{x}, \overline{w}) = \sum_{i=0}^{n} x_i W_{ji} \tag{39}$$

The most commonly used output function, sigmoid function is given as

$$O_j(\bar{x},\bar{w}) = \frac{1}{1+e^{A_i(\bar{x},\bar{w})}} \tag{40}$$

The sigmoid function is ‘1’ for +ve number 0.5 for zero and ‘0’ for –ve number. The Error function for the output of each neuron is given as

$$E_j(\bar{x},\bar{w},\bar{d}) = \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \tag{41}$$

A maximum likelihood method was compared with a neural network technique for tissue classification [16]. In this study, neural network provided better boundary definition than maximum likelihood. Hall *et al.* [24] compared MR-image segmentation techniques based on supervised multilayered neural networks [53] and the unsupervised fuzzy C-means algorithm [7]. These segmentation techniques were tested on MR images from healthy volunteers and selected patients with brain tumours surrounded by edema. The supervised and unsupervised segmentation techniques used in this study produced broadly similar results.

Badran *et al.* [6] have proposed a computer-based technique for identifying the tumor region accurately in the brain via MRI images. Here, the classification has been performed on a brain tumor image for identifying whether the tumor is a benign or malignant one. The steps involved in the proposed algorithm were preprocessing, image segmentation, feature extraction and image classification via neural network techniques. Finally, using the region of interest technique, the tumor area has been located.

R. Mishra [43] has developed an efficient system, where the Brain Tumor has been diagnosed with higher accuracy using artificial neural network. After the extraction of features from MRI data by means of the wavelet packets, an artificial neural network has been employed to find out the normal and abnormal spectra. Normally, the benefit of wavelet packets is to give richest analysis when compared with the wavelet transforms and thus adding more advantages to the performance of their proposed system.

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 [26]. Many researchers proved that the multi-layer propagation with 3 layers can perform arbitrarily complex classification.

SOM

Self-organizing maps (SOM) is an unsupervised clustering network that maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units [63]. Input data is classified according to their grouping in input space and neighbouring neuron. SOP consists of two layers: Input layer and competitive layer. The number of neurons in first layer is equal to dimension of input and the number of neurons in the second layer is equal to number of classes or clusters. Each connection from input layer to a neuron in competitive layer is assigned with a weight factor. The SOM functions in two steps. Firstly, finding the winning neuron i.e. the most similar neuron to input by a similarity factor like Euclidean distance, and secondly, updating the weight of winning neuron and its neighbour pixels based on input.

The famous unsupervised approach developed by [35] uses a linear update rule for the weights. This network is used for classification of tissues in MR brain images. Chou *et al.* [13] previously introduced kohonen’s SOM for segmentation of dual-echo MR images. When Chou *et al.* [13] used the SOM of kohonen, only normal tissues (white matter, gray matter and cerebrospinal fluid) were classified in the MR brain images. Their technique was not able to classify the abnormal tissue in the brain images. To overcome this drawback, Javad *et al.* [4] classified the unknown tissue as a tumour.

A new unsupervised MRI segmentation method based on self-organizing feature map was presented by Yan Li and Zheru Chi [76]. Their algorithm included extra spatial information about a pixel region by using a Markov Random Field (MRF) model. The MRF term improved the segmentation results without extra data samples in the training set. The cooperation of MRF into SOM has shown its great potentials as MRF term models the smoothness of the segmented regions. It verified that the neighbouring pixels should have similar segmentation assignment unless they are on the boundary of two distinct regions.

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 [30] performed superiorly when compared with other segmentation techniques. The SOM is combined with FCM for brain image segmentation [45] 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 [11]. This report revealed that the hybrid SVM is better than the kohonen neural networks interms 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. A modification of conventional SVM such as Least square SVM for brain tumour recognition is proposed by [41]. A Hybrid approach for pattern classification is reported by [39]. 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.

Mehdi jafari and shohreh kasari [84] combined automatic region growing method neural network classifier to segment and classify the brain image. Their proposed method achieved 100% sensitivity rate and 96% specific rate. Eltaher mohammed Hussein *et al*. [85] proved that elman network gives better result when compared to BPNN and RNN networks.

Venkateswara reddy et al. [86] proposed a method combining modified FCM and SVM for MRI image segmentation and classification. They proved their method produced better results in detecting tumour when compared to the other combination of KFCM+NN, FCM+NN, FCM+SVM.

CONCLUSIONS

Many image segmentation methods and classifiers have been developed in the past several decades for segmenting MRI brain images and classifying it as normal or abnormal. The survey shows that BPN classifier with increase in nodes gives fast and accurate classification that can be effectively used for segmenting MRI brain images with high level of accuracy and the log sigmoid function is the best activation function for the medical image recognition application. The survey also shows that Elman network gives better result compared to BPNN and RNN network. Also SVM can classify the brain image as normal or abnormal more accurately than SOM neural network. At last it is concluded that even though several hybrid methods have been developed but still it remains a challenging task. One hybrid method tries to prove it is superior than other existing hybrid methods. Thus it is very hard to specify the superior method. In this work, the merits and demerits of various automated techniques for brain tumour identification is analyzed in detail.

REFERENCES

1. N. Abdullah, U. K. Ngah, S. A. Aziz, “Image Classification of brain MRI using Support Vector Machine,” Imaging systems and Techniques (IST), 2011, IEEE International conference on 17-18 May 2011.
2. S.T Acton, D.P Mukherjee, “Scale space classification using area morphology,” IEEE Trans Image Process 9(4), 2000, pp.623–635.
3. M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, T. Moriarty, “A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data,” IEEE trans. medical imaging, 21(3), 2002, pp.193-199.
4. Javad Alirezaie, M. E Jernigan, C. Nahmias, “Automatic segmentation of cerebral MR images using Artificial Neural Network,” IEEE transactions on nuclear science, 1998, vol 45, no.4.
5. H. Azzag, N. Monmarche, M. Slimane, G. Venturini, “Ant Tree: A New model for clustering with Artificial Ants,” IEEE, 2003, pp.2642-2647.
6. E. F. Badran, E. G. Mahmoud, N. Hamdy,"An algorithm for detecting brain tumors in MRI images", Proceedings of the International Conference on Computer Engg. and Systems (ICCES), 2010, pp:368 - 373.
7. J. C. Bezdek, “Pattern Recognition with Fuzzy objective function algorithms” New York, 1981.
8. D. Bhattacharyya, Kim Tai-hoon, "Brain Tumor Detection Using MRI Image Analysis", Communications in Computer and Information Science, Vol: 151, 2011, pp: 307-314.
9. B. H. Brinkmann, A. Manduca, R. A. Robb, “Optimized homomorphic unsharp masking for MR grayscale inhomogeneity correction,” *IEEE T. Med. Imag.*, 17, 1998, pp.161–171.
10. S. Chandra, R. Bhat, H. Singh, "A PSO based method for detection of brain tumors from MRI", Proceedings of the World Congress on Nature & Biologically Inspired Computing, Coimbatore, 2009, pp. 666 - 671.
11. S. Chaplot, L. M. Patnaik, “Classification of magnetic resonance brain images using wavelets as input to support vector machines and neural networks,” Biomedical Signal Processing and Control, 2006, pp. 86-92.
12. S. Chaplot, L. M. Patnaik, “Brain Tumor Diagnosis with wavelets and Support Vector Machine,” proceeding of 3rd international Conference on intelligent Systems and Knowledge Engineering, 2008.
13. T. Chou, C. Chen, W. Lin, “Segmentation of dual-echo MR images using neural networks”, Proceeding SPIE, medical imaging, 1993, pp.220-227.
14. M. H. Chowdhury, W. D. Little., “Image thresholding techniques” IEEE pacific Rim conference on communications, computers and signal processing, proceedings 17-19 may 1995, 1995, pp.585-589.
15. L. P. Clarke, R. P. Velthuizen, S. Phuphanich, J. D. Schellenberg, J. A. Arrington, M. Silbiger, “MRI: Stability of Three Supervised Segmentation Techniques”, Magnetic Resonance Imaging, 11: pp. 95-106, 1993.
16. L. P. Clarke, “MR image segmentation using MLM and artificial Neural Network,” Medical physics, Vol.18, No.3, 1991, pp.673.
17. E. Cox, “ Fuzzy Modeling and Genetic Algorithms for Data mining and Exploration,” Elsevier, 2005.
18. R. N. Dave, “Characterization and detection of noise in clustering,” Pattern Recogn Lett 12(11):657–664, 1991.

19. Deeplai Kelkar and Surendra Gupta “Improved Quadtree method for split merge image segmentation”, Emerging Trends in Engineering and Technology, 2008, ICETET.

20. L. Pharm Dzung , Xu Chenyang, Jerry L. Prince, “A Survey of Current Methods in Medical Image Segmentation,” Technical Report JHU / ECE 99-01, Department of Electrical and Computer Engineering, 1998.

21. A. El-Sayed, El-Dahshan, M. S. Abdel-Badeeh, H. Y. Tamer, “A Hybrid Technique for Automatic MRI Brain Images Classification”, digital Signal Processing, Vol. 20, Issue 2, March 2010, 2010, pp. 433-441.

22. Frank Klawonn and Annette keller, “Fuzzy Clustering based on Modified Distance measures”, Available: http://citeseer. istpu.edu /fuzzy_clustering_62

23. Rafael C. Gonzalez, E. Woods. Richard, “Digital Image Processing”, Pearson Education., 3rd Edition.2007

24. L. O. Hall, A. M. Bensaid, L. P. Clarke, R. P. Velthuizen, M. S. Silbiger, J. Bezdek. “A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain,” IEEE Trans Neural Network, Vol.3, 1992, pp.672–682

25. R. M. Haralick, I. Dinstein and K. Shanmugam, “Textural features for image Classification,” IEEE Trans on systems man and cybernetics. Vol. 3, 1973, pp. 610 – 621.

26. N. Jabbar, M. Mehrotra, “Application of fuzzy neural network for image tumor description,” Proc. of World Academy of Science, Engineering and Technology; 34, 2008, pp.575-77.

27. A. K. Jain, J. Mao, “Artificial Neural Networks: A Tutorial”, IEEE Press, 1996, pp. 31-44

28. J. Jaya, K. Thanushkodi, “Exploration on selection of medical images employing New Transformation Techniques,” IJCSI International journal of computer science issues, Vol.7, Issue 3, No.4, 2010.

29. X. Jiang, R. Zhang, S. Nie, “Image Segmentation Based on PDEs Model: a Survey”, IEEE conf., pp. 1-4, 2009.

30. C. Juang, S. Chiu, S. Chang, “A self organizing TS-type fuzzy network with support vector learning and its application to classification problems,” IEEE Trans. on Fuzzy Systems 2007; 15, 2007, pp.998-1008.

31. H. G. Kaganami, Z. Beij, “Region Based Detection versus Edge Detection”, IEEE Transactions on Intelligent information hiding and multimedia signal processing, 2009, pp. 1217-1221.

32. W. X. Kang, Q. Q. Yang, R. R. Liang, “The Comparative Research on Image Segmentation Algorithms”, IEEE Conference on ETCS, 2009, pp. 703-707.

33. P. Karch, I. Zolotova, “An Experimental Comparison of Modern Methods of Segmentation”, IEEE 8th International Symposium on SAMI, 2010, pp. 247-252.

34. A. Kharrat, K. Gasmi, M. B. Messaoud, N. Benamrani, M. Abid, “A hybrid Approach for Automatic classification of Brain MRI using Genetic Algorithm and Support vector Machine,” Leonardo journal of sciences, ISSN: 1582-0233, 2009, pp.71-82, issue-17.

35. T. Kohonen. “Self organizing maps,” springer-verlarg berlin, 5.

36. Kshitij bhagwat, Dhanshri more, sayali shinde, Akshay Daga, “Comparative study of brain tumour detection using k means, Fuzzy c means and Hierarchical clustrering algorithms,” International journal of scientific and engineering research, vol. 4, issue 6, 2013, pp. 626-632.

37. K. V. Leemput, F. Maes, D. Vandermeulen, P. Suetens, “Automated model-based tissue classification of MR images of brain,” IEEE Transaction medical imaging, Vol.18, 1999, pp.897-908.

38. Li chenling, Zeng wenhua, Zhuang Jiahe, “An Improved Ant Tree Algorithm for MRI Brain Segmentation,” Proceedings of 2008 IEEE International symposium on IT in medicine and Education, pp.679-683.

39. C. Lin, C. Yeh, S. Liang, J. Chung, N. Kumar, “Support-vector based fuzzy neural network for pattern classification,” IEEE Trans. on Fuzzy Systems; vol. 14, 2006, pp.31-41.

40. P. L. Lions, J. M. Morel, T. Coll, “Image selective smoothing and edge detection by nonlinear diffusion”. SIAM J Numer Anal 29(1), 1992, pp.182–193

41. J. Luts, A. Heerschap, A. Johan, S. Huffel, “A combined MRI and MRSI based multiclass system for brain tumour recognition using LS-SVMs with class probabilities and feature selection,” Artificial Intelligence in Medicine; vol. 40, 2007, pp.87-102.

42. M. Mancas, B. Gosselin, B. Macq, “Segmentation using a Region Growing Thresholding,” Proceedings of the Electronic imaging Conference of the International society for optical imaging (SPIE/EI 2005), San Jose, 2005.

43. R. Mishra, "MRI based brain tumor detection using wavelet packet feature and artificial neural networks", Proceedings of the International Conference and Workshop on Emerging Trends in Technology, 2010.

44. N. Moon, E. Bullitt, K. Leemput, G. Gerig, G “Model based brain and tumor segmentation,” Int. Conf. on Pattern Recognition 2002, 2002, pp.528-531,

45. S. Murugavalli, V. Rajamani, “An improved implementation of brain tumor detection using segmentation based on neuro fuzzy technique,” 2007, Journal of Computer Science; 3:841-46.

46. O.Wirjadi (2007): “Survey of 3D image Segmentation Methods,” Technical report.

47. M. F. B. Othman, N. B. Abdullah, N. F. B. Kamal, “ MRI brain classification using Support vector machine,” IEEE, Centre for Artificial Intelligence & Robotics (CAIRO), Universiti Teknologi Malaysia, 2011.

48. N. R. Pal, S. K. Pal, “A Review on Image Segmentation Techniques”, Pattern Recognition, Vol. 26, No. 9, 1993, pp. 1277-1294.

49. Pan Lin ,Yong Yang., Chong-Xun Zheng., Jian-Wen Gu “An Efficient Automatic Framework for Segmentation of MRI Brain Image”, Proceedings of the Fourth International Conference on Computer and Information Technology(CIT’04), IEEE, 2004.

50. Panos Kotsas, “Non-rigid Registration of medical image using an Automated method,” World Academy of Science, Engineering and Technology, 2005.

51. D. Pham, C. Xu, L. Prince, “A survey of Current methods in medical image segmentation”, Annual review of Biomedical Engineering, vol 2, 1998, pp. 315-338.

52. Qurat-ul Ain., Irfan Mehmood., M. Naqi Syed., M. Arfan Jaffar, "Bayesian Classification Using DCT Features for Brain Tumor Detection", Lecture Notes in Computer Science, Vol:6276, 2010, pp: 340-349.

53. D. Rumelhard, J. Mcclelland, “Parallel Distributed Processing”, MIT Press, Cambridge, Mass.1986

54. P. K. Sahoo, S. Soltani, A. K. C. Wong, Y. C. Chen, “A Survey of thresholding techniques,” Computer vision

Graphics image process (CVGIP), Vol.41, 1988, pp.233-260.

55. D. Selvaraj, R. Dhanasekaran, “MRI brain tumour detection using feed-forward neural network,” Proceedings of EXCITE 2012, 2012, pp.171-174.

56. D. Selvaraj, R. Dhanasekaran, “Automatic detection of brain tumour from MRI brain image by histogram thresholding and segmenting it using region growing,” KJCS, vol.7, issue 2, 2013, pp.1-7.

57. D. Selvaraj, R. Dhanasekaran, “MRI brain tumour detection by histogram and segmentation by modified GVF model,” IJECET, Vol.4, issue 1, 2013, pp.55-68.

58. D. Selvaraj, R. Dhanasekaran, “MRI brain tumour segmentation using IFCM and comparison with FCM and k-means,” Proceedings of NC-Event 2013. 2013, pp. 47-52.

59. D. Selvaraj, R. Dhanasekaran, “Segmentation of cerebrospinal fluid and internal brain nuclei in brain magnetic resonance images,” IRECOS, Vol.8, issue 5, 2013, pp.1063-1071.

60. M. Sezgin, B. Sankar, “Survey over image thresholding techniques and Quantitative performance evaluation” J. Electron imaging 13(1), 2004, pp.146-165.00

61. Shah shen., William sandham., Malcolm granat., Annette sterr “MRI fuzzy segmentation of brain tissue using neighbourhood attraction with neural network optimization” IEEE transactions on information technology in biomedicine, Vol. 9, No.3, 2005.

62. P. K. Srimani, Mahesh Shanthi, “A Comparative study of different segmentation techniques for brain tumour detection”, IJETCAS, 2013, pp. 192-197.

63. D. Tian, L. Fan, “A brain MR images segmentation method based on SOM neural network,” 1st international conference on bioinformatics and biomedical engineering, 2007, pp 686–689.

64. Y. A. Tolias, S. M. Panas, “On applying spatial constraints in fuzzy image clustering using a fuzzy rule-based system,” IEEE Signal Process Letter 5(10), 1998, pp.245–247

65. V. Vapnik, “Statistical Learning Theory,” Wiley, New York, 1998.

66. V. Vapnik, “The Nature of Statistical Learning Theory”, Springer, New York, 1995.

67. V. Vapnik, A. Chervonenkis, “A note on class of perceptron”, Automation and Remote Control, 24, 1964.

68. V. Vapnik, A. Lerner, “Pattern recognition using generalized portrait method”, Automation and Remote Control, 24, 1964.

69. S. Varshney, N. Rajpal, R. Purwar, “Comparative Study of Image Segmentation Techniques and Object Matching using Segmentation”, Proceeding of International Conference on Methods and Models in Computer Science, 2009, pp. 1-6.

70. J. Wang, J. Kong, L. Yinghua, Q. Miao B. Zhang, “A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constraints”, CMIG, Vol.32, 2008, pp.685-698.

71. S. Warfield, Duda, “K-Nearest Neighbour Classification”, 2001.

72. W. M. Wells, W. E. L. Grimson, R. Kikinis, F. A. Jolesz, “Adaptive segmentation of MRI data,” IEEE transaction medical imaging, Vol.15, No.4, 1996, pp.429-442.

73. D. Withey, Z. Koles, “Medical image segmentation: Methods and software, Noninvasive functional source imaging of the brain and heart and the international conference on functional biomedical imaging,” 6th international symposium, 2007, pp.140-143.

74. S. Xavierarockiaraj, K. Nithya, R. Maruni Devi, “Brain tumour Detection using Modified Histogram thresholding – Quadrant approach,” Journal of computer application s, Vol.5, No.1, 2012, pp.21-25.

75. Xiaochun Yang, Weidong zhao, Li pan, “An Improved clustering algorithm based on Ant-Tree,” IEEE, 2008, pp.1855-1858.

76. Li, Yan, Chi Zheru, "MR Brain Image Segmentation Based on Self-Organizing Map Network", International Journal of Information Technology, vol. 11, No. 8, 2005.

77. J. Yang, G. Li, Ye. C. Geng, “Degree prediction of malignancy in brain glioma using support vector machines”, Computers in Biology and Medicine 2006; 36, 2006, pp.313-25.

78. D. Q. Zhang, S. C. Chen, “A Novel kernelized fuzzy c-means algorithm with application in medical image segmentation,” Artificial intelligence, Vol.32, 2004, pp.37-52.

79. H. Zhang, J. E. Fritts, S. A. Goldman, “Image Segmentation Evaluation: A Survey of unsupervised methods”, computer vision and image understanding, 2008, pp. 260-280.

80. K. Zhang, H. X. CAO, H. Yan, “Application of support vector machines on network abnormal intrusion detection”, Application Research of Computers, Vol.5, 2006, pp.98-100.

81. C. Zhu, C. Ni, Y. Li, G. Gu, “General Tendencies in Segmentation of Medical Ultrasound Images”, International Conference on ICICSE, 2009, pp. 113-117.

82. D. Selvaraj, R. Dhanasekaran, “Combining Tissue Segmentation and Neural Network for Brain tumour Detection”, IAJIT, Vol.12. No.1, In press.

83. Sandeep chaplot, Patnaik, L.M., Jagannathan, N.R., “Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network,” BSPC, 2006 pp. 86-92.

84. Mehdi jafari, shohreh kasaei, “Automatic brain tissue detection in MRI images using seeded region growing segmentation and neural network classification,” AJBAS, vol. 5, 8, 2011, pp.1066 – 1079.

85. Eltaher mohammed Hussein, Dalia mahmoud adam mahmoud, “Brain tumour detection using artificial neural network,” 2012, Journal of science and Technology, vol. 13, no.2, pp.31 – 39.

86. Venkateswara Reddy. B, Satish kumar. P., Bhaskar reddy, P., Naresh kumar reddy, “ Identifying brain tumour from MRI image using modified FCM and SVM,” IJCET, 2013, vol. 4, 1. pp. 244 – 262.