Methodology

3. METHODOLOGY

The proposed algorithm comprises of four stages. The first stage encompasses pre-processing of the given MRI image. The second stage consists of clustering the pre-processed image. The third is the feature extraction stage, followed by segmentation .Steps of the algorithm are described as follows:-

- Pre-processing
  - ✓ Median filter incorporated in this study is used to remove high frequency components and noise.
  - ✓ Thresholding and morphological processes are used to extract the portion of the brain, which being the area of interest in this study.
- Clustering
  - ✓ MRI brain images are clustered by using Fuzzy C-mean.
- Feature Extraction
  - ✓ In the Feature Extraction phase, the Mean Standard Deviation (MSD) is used to extract the intensity based feature.
- Segmentation
  - ✓ In the segmentation process, the HSOM method is to find the abnormality in the portion of the brain engrossed with the size of the tumor and time taken to execute the process
  - ✓ The performance of the proposed method has been evaluated with the help of SVM classifier.

Thus, the HSOM based tumor detection system is in the Figure 3.1.

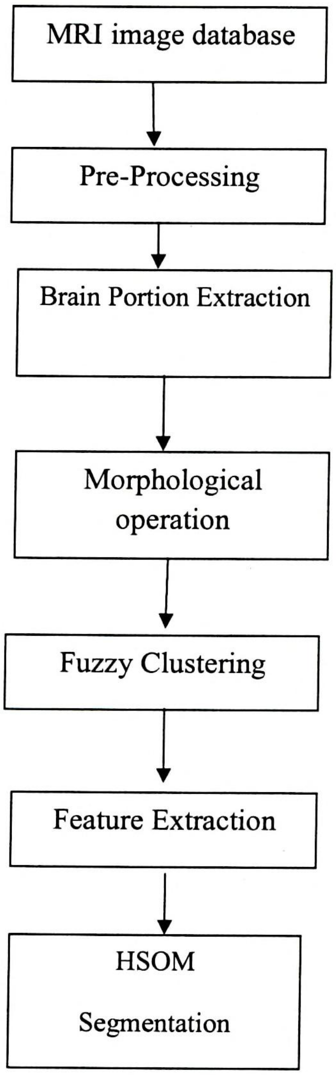


Figure 3.1: Steps in proposed HSOM based brain Tumor Detection

3.1 Preprocessing

Median filter which is used for preprocessing removes noise and other high frequency components from MRI without disturbing the edges. This technique calculates the median of the surrounding pixels to determine the denoising value of the pixel.

The comparative results of mean, median and smoothing filter are summarized in Table 3.1. (M. N. Nobi and M. A. Yousuf, 2011)

Filtering Methods	PSNR	MSE
Smoothing Filter	43.43	18.44
Median Filter	43.64	16.26
Mean Filter	42.08	18.40

Table 3.1. Comparison results of different filtering method

From the above table it can be observed that, smoothing, median, and mean filters are compared by using quantitative parameters like Peak signal-to-noise ratio (PSNR), Mean Square Error (MSE). It can be noted that the Median filter provides better result for MRI.

In the proposed method the high frequency components and noise are removed from MRI using the median filters. Few sample images are given Figure 3.2.

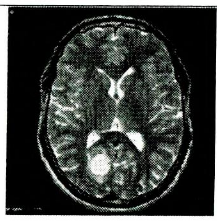
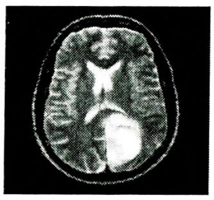
Original image	Noise Removed image
	
	

Figure 3.2: Filtered image

3.1.1 Skull removal from brain MRI

The thresholding and morphological processes are used to separate the brain from non-brain portions. Further an intensity threshold is computed, by means of which a rough binary brain portion is generated. The morphological operations, erosion, connected component analysis and region properties are performed on the rough brain portion to produce the brain mask. Finally the brain mask is used to extract the brain from MRI. In Figure 3.3, the extracted brain portions are shown in column 2.

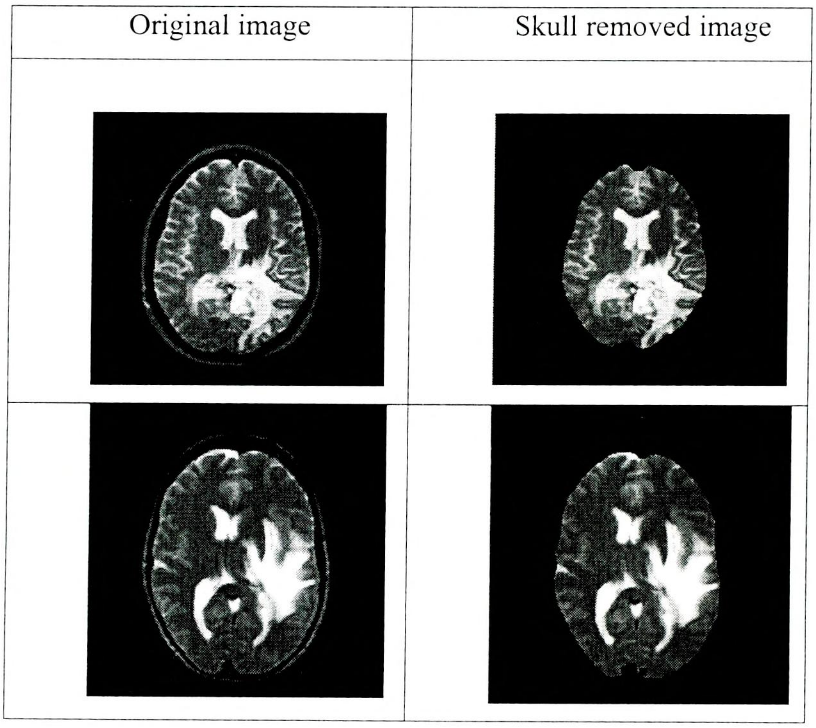


Figure 3.3: Skull removed image

3.2 Fuzzy Clustering

3.2.1 Clustering:

Clustering is the process of grouping feature vectors into classes and this is performed in a self-organized mode. Choosing the cluster centers are crucial to the clustering. Clustering involves the task of dividing data points into homogeneous classes or clusters, so that items in the same class are as similar as possible and items in different classes are as dissimilar as possible. Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification.

3.2.2 Overview of clustering:

- Feature Selection:
  - It is performed by using clusters, to identify the most effective subset.
- Feature Extraction:
  - It is transformation performed on the input features to produce new salient features.
- Interpattern Similarity:
  - It is measured by a distance function defined on the pairs of patterns.
- Grouping:
  - It is a method used to group similar patterns in the identified clusters.

The clustering steps are shown in Figure 3.4

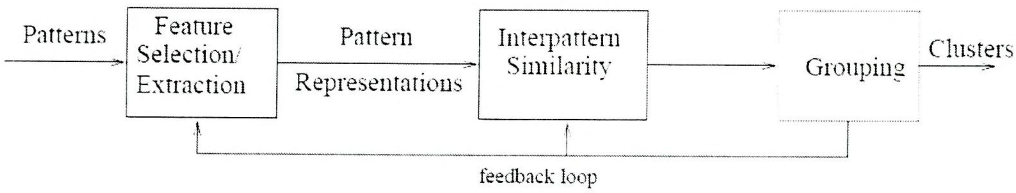


Figure 3.4: Overview of cluster

3.2.3 Cluster analysis:

Cluster analysis is a technique used to find similarities between data according to the characteristics found in the data and thereby grouping similar data objects into clusters.

The different types of clustering techniques are shown in Figure 3.5

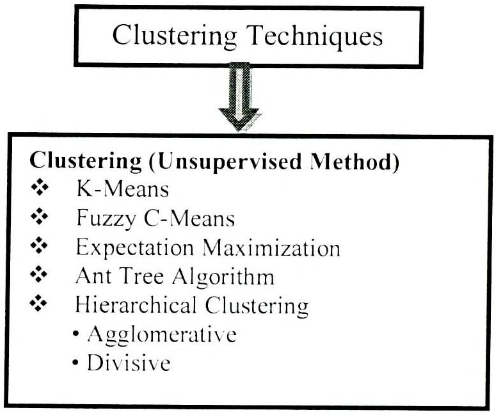


Figure 3.5: Clustering Techniques

3.2.4 Fuzzy C-Mean Clustering (FCM)

The FCM algorithm is one of the most widely used fuzzy clustering algorithms. This technique was originally introduced by Professor Jim Bezdek in 1981.Fuzzy c-mean (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. It is frequently used in pattern recognition. It is based on minimization of the objective function.

The Fuzzy c-mean Algorithm:

Step 1: Initialize $U = [\ u_{ij}]$ matrix, U(0)

Step 2: At k-step: calculate vectors $C^k=[c_j]$ with $U^{(k)}$

$$c_j = \sum_{i=1}^{N} (u_{i,j}^m . x_i) / \sum_{i=1}^{N} u_{i,j}^m$$

Step 3: Update $U_{i,j}$ matrix,

$$u_{i,j} = 1 / \sum_{k=1}^{C} (\| x_i - c_j \| / \| x_i - c_k \|)^{2/(m-1)}$$

Step 4: if $\|U^{(k+1)} - U^k\| < \varepsilon$ then Stop; otherwise return to Step 2.

In the proposed method Fuzzy C Mean is used for clustering. The aim of using FCM is to find a cluster centre that minimizes an objective function.

3.3 Feature extraction

Feature extraction is a general term used for constructing combinations of the variables. It describes the data with sufficient accuracy. Representing an image requires a large amount of data. Handling enormous data will be time consuming and will have an impact on the capacity of the memory. In order to reduce the amount of data, memory and time, it is crucial that the features are extracted from an image. The feature extraction contains the relevant information of an image. The type of features extracted from an image is classified as in Figure 3.6.

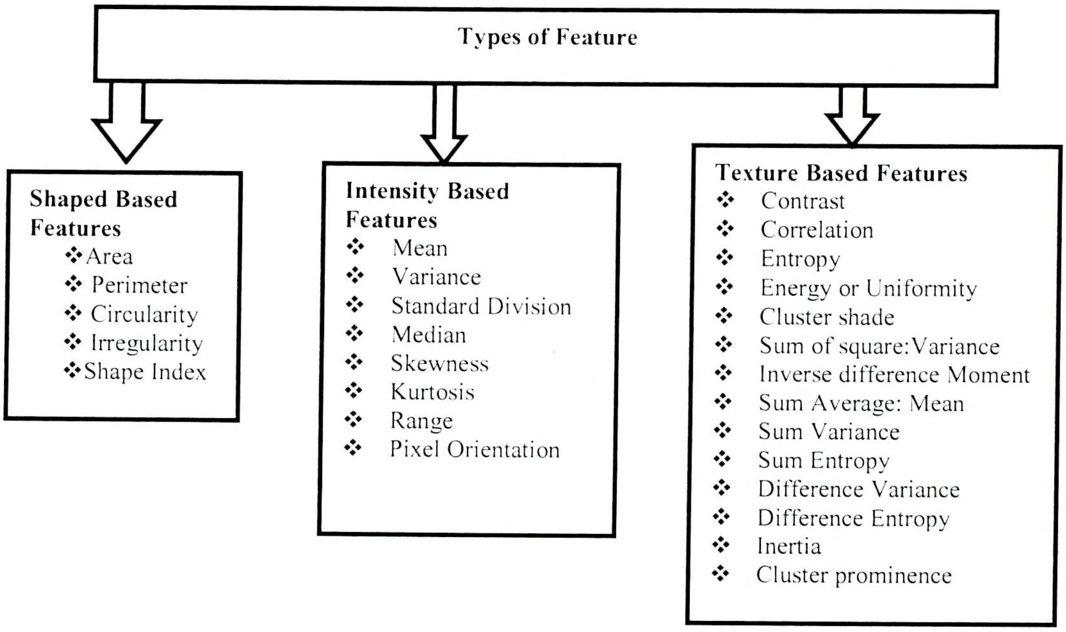


Figure 3.6: Types of features

3.3.1 The Intensity Based Features:

The intensity based feature is one of the most widely used features. In the proposed method Mean Standard Deviation (MSD) is used for feature extraction. It calculates the mean and standard deviation of pixels in each bin. Each bin consists of a range of pixel values. The values in each bin are used to calculate the mean value, which in turn represents an appropriate value of brightness of the image of the bin.

The standard deviation is also calculated by using the mean and pixel values of each bin. The standard deviation also reveals information about the contrast of an image in a particular bin.

3.3.1.1Mean:

The mean defines the average level of intensity of the image or texture.

$$\mu = \sum_{i=0}^{N_g-1} i.p(i)$$

Where,

$$p(i) = \frac{h(i)}{N_x N_y}, i = 0, 1, 2, \ldots \ldots . N-1$$

$$h(i) = \sum_{x=0}^{N_g-1} \sum_{y=0}^{N_g-1} \delta(f(x,y), i), \; i = 0, 1, 2, \ldots \ldots . N-1$$

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & f(0,2) & \ldots\ldots\ldots\ldots & f(0, N_y-1) \\ f(1,0) & f(1,1) & f(1,2) & \ldots\ldots\ldots\ldots & f(1, N_y-1) \\ f(0,0) & f(0,1) & f(0,2) & \ldots\ldots\ldots\ldots & f(0, N_y-1) \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ f(N_x-1,0) & f(N_x-1,1) & \ldots\ldots\ldots & & f(N_x-1, N_y-1) \end{bmatrix}$$

$$\delta(i,j) = \begin{cases} 1 \; ; \; i=j \\ 0 \; ; \; i \neq j \end{cases}$$

Where, f(x,y) be a two dimensional function of an image.

h(i) be the intensity level of an image.

p(i) be the probability density.

3.3.1.2 Standard Deviation: (SD)

$$SD \text{ or } \sigma = \sqrt{\sum_{i=0}^{N_g-1} (i-\mu)^2 . p(i)}$$

Where, N_g be the total number of gray levels in the entire image.

μ is the mean.

p(i) be the probability density.

σ_j is the standard deviation.

3.4. HSOM Segmentation

The SOM is usually used for mapping high-dimensional data into one, two, or three dimensional feature maps. The basic idea of a SOM is to map the data patterns onto a dimensional grid of units or neurons, and the mapping tries to preserve topological relations. SOM is nowadays used for anomaly detection, data mining, pattern recognition, vector quantization, image analysis, speech recognition, signal processing, medical applications, electronic-circuit design, robotics, and many other applications.

The advantage of SOM to other types of Artificial Neural Networks is their unsupervised aspect of not depending on knowing the input space in advance. In spite of its high popularity, SOM encounters several drawbacks, such as being computationally expensive, needing much learning time, being memory opulent, and search drive being comparatively low. These disadvantages are overcome by various other methods. One of the first revisions of the original algorithm was the Hierarchical SOM (HSOM). HSOM differs from the original SOM algorithm. HSOM is the combination of self-organization and topographic mapping technique.

Hierarchical SOMs share many characteristics with other methods such as the multilayer SOMs, multi-stage SOMs, multi-resolution SOMs, fusion SOMs or Tree-SOMs. All these methods share the idea of constructing a system using SOMs as building blocks. They vary in the way these SOMs interact with each other, and with the original data.

The significance in using Hierarchical SOM (HSOM) are,

- HSOM need less computational effort compared with standard SOM
- HSOM can be better matched to model a problem.

3.4.1 HSOM Taxonomy:

The following taxonomy to classify the HSOM methods shown in Figure 3.7

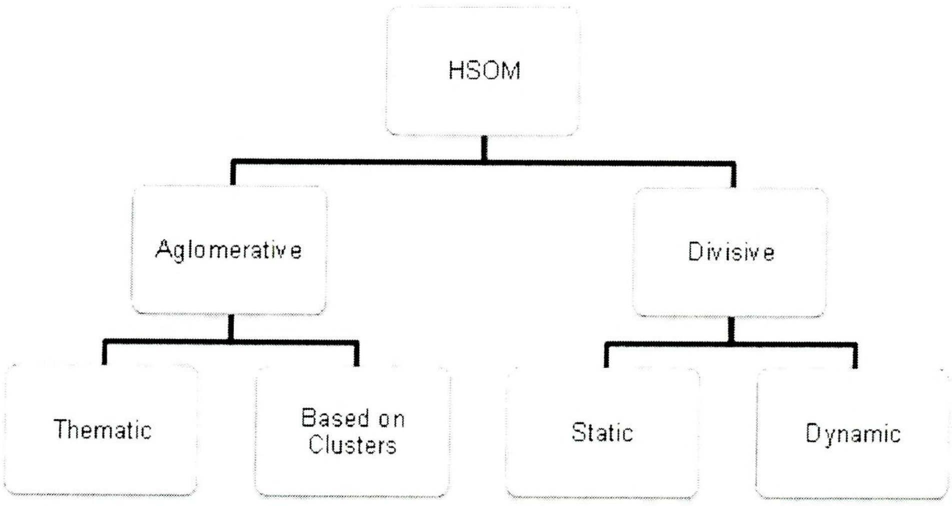
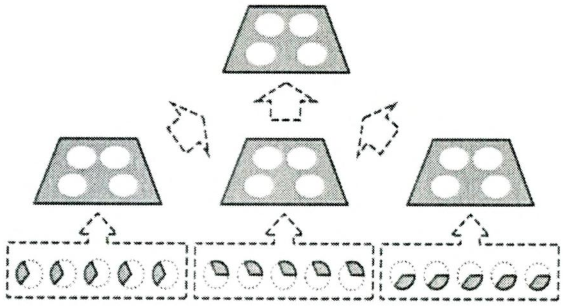


Figure 3.7: HSOM Taxonomy

3.4.1.1 Agglomerative:

In the agglomerative HSOM (Figure 3.8), the level of data abstraction increases with hierarchy. The level of HSOM is a more detailed representation. The main objective is to create clusters that will be more general and provide a simple data. Agglomerative HSOMs can be divided into,

- Thematic
- Based on clusters



A

Figure 3.8: Agglomerative

3.4.1.3 Thematic agglomerative HSOM:

In a thematic HSOM, the variables of the input data are gathered according to some criteria in order to form teams. Each of these themes form a subspace, which are then presented to the SOM, and the output will be used to train a final merging SOM. The advantage of thematic agglomerative HSOM lies in the reduction of computation caused by the partition of the input data into several themes. Following Figure 3.9 show the HSOM structured method.

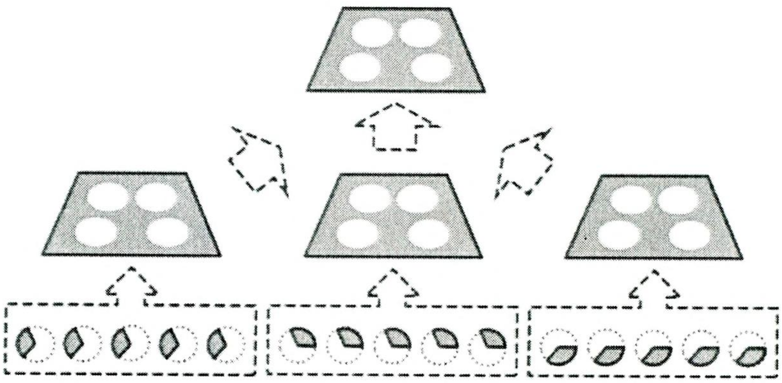


Figure 3.9: Thematic agglomerative

3.4.1.4 Agglomerative HSOM based on clusters:

The Agglomerative HSOM is composed of two levels. Each level is processed by standard SOM. The first level SOM will learn from the original input data and that data is used as an input for second level SOM. The second level SOM is smaller than the first level SOM, but the segmentation is quite easier when compared to first level SOM.

In (Figure 3.10), first level SOM contains the original input data, the data which is synchronized will be passed to second level SOM. The data which is available in second level SOM is represented as Best Match Unit (BMU). The second level SOM will segment the units of first level SOM and the result that obtain will be similar to small standard SOM.

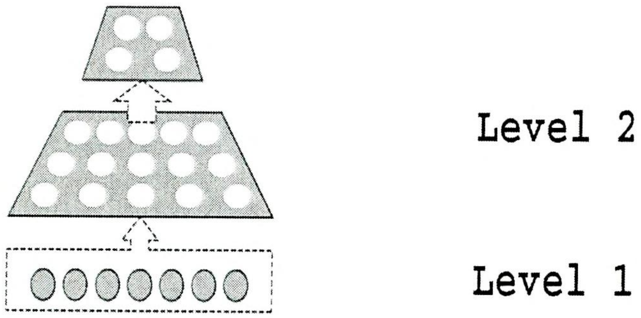


Figure 3.10: HSOM based on clusters

In the proposed work, HSOM segmentation is based on Agglomerative HSOM based on clusters which in turn solely depended on clusters. This method is used to segment the brain tumor from the fuzzy c mean output image, with less execution time and to detect the size of the tumor accurately. The agglomerative HSOM has the advantage of mapping the same data twice using SOM, which is performed at a different level.