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Intelligent Brain Tumor Detection and Classification Using Image Processing

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ABSTRACT

The abnormal growths of cells in the brain are called tumours and cancer is a term used to represent malignant tumours. Usually, CT or MRI scans are used for the detection of cancer regions in the brain. Positron Emission Tomography, Cerebral Arteriogram, Lumbar Puncture, Molecular testing are also used for brain tumour detection. In this study, MRI scan images are taken to analyse the disease condition. Objective this research works is i) identify the abnormal image ii) segment tumour region. Density of the tumour can be estimated from the segmented mask and it will help in therapy. Deep learning technique is employed to detect abnormality from MRI images. Multi-level thresholding is applied to segment the tumour region. Number of malignant pixels gives the density of the affected region. The objective of the research is to find the tumour portion of the abnormal MRI brain image using automatic segmentation. The automatic segmentation is accomplished using wavelet transform to extract various features. Then the abnormal images are processed by conventional K means clustering and Fuzzy C means algorithm. But the conventional methods take long iteration and long time to converge. The hybrid clustering method overcomes the long iteration and time.

Keywords: Segmentation; Fuzzy; K-means clustering.

1. Introduction

The main causes of the brain tumour, different types of medical imaging modalities are also discussed. It describes the role of Digital Image Processing (DIP) and Artificial Neural Network (ANN), and how it is helpful to find the area of the tumour for the classification the cancerous and non-cancerous tumour. Yezzi et al. (1997) the clear and accurate visual arrangements of an internal organ of our body have been generated using various medical imaging modalities like CT (Computer Tomography), MRI (Magnetic Resonance Imaging).

The brain images can be captured using a different kind of medical imaging techniques. Mostly the CT, MRI imaging techniques are used in medical image processing. Thev research work performs the segmentation process on MRI brain images.

Image acquisition: The initial step for the segmentation process was image acquisition. The image was obtained through various medical image modalities like MRI, CT. Next, the acquired the image was preprocessed in order to remove the noise.

Image enhancement: This is one of the easiest methods in digital image processing. The word enhancement means to highlight the specific features in ROI or simply provide the hidden information of an image.

Colour image processing: Due to the excellent growth of the communication media now a day's digital images widely used in all areas. This may contain colour modelling and processing in a digital domain etc.

Wavelets and multiresolution processing: With the help of wavelets, the images were expressed in various degrees of resolution. Using wavelet, the images were segmented into smaller sections for data compression.

Basically the most popular and simplest way to find the tumour portion is K, which means Clustering. This method calculates the tumour portion with minimal execution time. But in the case of malignant tumour the k means clustering gives the imperfect detection of tumour. Diagnosis of tumour portion is performed in another way with the help of Fuzzy C means. The accurate segmentation of tumour is possible in the case of noise free images.

Next survey transforms about the use of different wavelet transforms in image denoising and the use of neural network in tumour detection. Salim Lahmiri et al. (2017) proposed a new methodology to perform denoising process by using wiener filtering. It performs the denoising operation until to obtain a certain condition until to obtain a certain condition of an image to be calculated. The performance of the method is measured using PSNR (Peak signal to Noise Ratio). This denoising is one of the important processes, because man electronic sensors may be affected by noise. The author used winer filter to remove the noise from the acquired image.

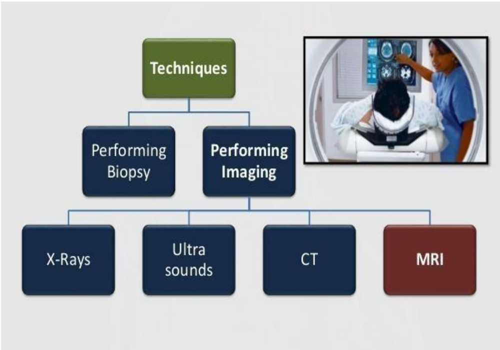

Figure 1. Diagnostic methods

2. Clustering Methodology

This chapter deals with different kinds of available methodologies for segmentation and its advantages and disadvantages. Before the detail discussion on clustering technique, it is necessary to understand the basic concept of segmentation, Role of segmentation in diagnosing a tumour, the necessity of automatic segmentation, the basic process involved in segmentation. Further, it describes the different types of Clustering algorithms for automatic segmentation and the implementation of the same with the help of MATLAB.

3. Segmentation

Segmentation is the process of cuts or splits an image or objects. The entire image is split into smaller regions through segmentation process, which helps extremely to connect with Region of interest of the image. The basic necessity of Segmentation is in order to extract the unique features from an image. It removes the gap between low-level image processing and high-level processing. The level of segmentation mainly depends on the problem being solved. When the desired portion is separated from an object or image, the segmentation process will be stopped. It finds many applications in various fields:

- It is used in recognition of optical characters.
- It helps to examine the desired object from industry.
- It helps to identify the particular objects from the group of images.

Edges are the most important features for segmentation. Edges are generally referring boundaries or borders of an object. The intensity variations on the edges are high compared to other parts. This type of intensity changes can be detected by using thresholding. This method is sensitive to noise. For thresholding method, the region of interest is calculated by comparing each pixel with the threshold value. The value of the threshold is calculated from the overall intensity distribution of the image.

Mean: It is defined as the ratio of the sum of all pixel value of images in a total number of pixels in an image.

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P(i,j)$$

P (i, j) is the pixel value at that point (i, j).

Standard deviation: It is used to represent the probability distribution of a certain object. It gives the measures of inhomogeneity. The high value of standard deviation refers the image has high intensity and high contrast edges of an image.

$$\sigma = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P(i,j)-\mu)^2}$$

Contrast: It is the measure of the difference in intensity contrast between the pixel and its neighbourhood pixels over the whole image. The value is 0 for the constant image.

$$C = |i-j|^2 p(i,j)$$

Correlation: In a whole image how a pixel is correlated with the neighbourhood, a pixel is called as correlation. The range lies between [-1 1]. The correlation value is 1 for the positively correlated image, -1 for the negatively correlated image.

3.1. Hard computing clustering

Clustering is a technique which partitions the input image into different clusters by repeatedly calculating the centroid, and the pixel is forced to move to the nearest cluster centre. This is called as hard clustering. Because it pushes each pixel into particular cluster centre through the continuous iteration. There are three common types of hard clustering:

K- means clustering.

Fuzzy c- means clustering.

Expectation and Maximization (EM Algorithm).

K means clustering

The algorithm is introduced by Macqueen in the year 1997.This is one of the unsupervised algorithms. The algorithm starts by assigning the number of cluster K randomly. The Algorithm steps are explained as follows

Step 1: Randomly choose the C cluster centre.

Step 2: Euclidean distance has evaluated the among each pixel to cluster centre.

Step 3: Every pixel is allotted to the specific cluster, which has shortest distance.

Step 4: The main objective of the algorithm is to reduce the squared error

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$X_i - V_i$ is the Euclidean distance between X_i, V_i

C is the number of clusters.

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

Next, calculate the cluster centre by using the following formula,

$$C = \frac{1}{c_i}\sum_{j=1}^{c_i} X_i$$

It is one of the unsupervised methods performs density operation on pixels. It uses the iterative process to calculate the maximum likelihood. It uses the two steps to perform segmentation. The first step is used to estimate the expectation of the likelihood and second step used to find the maximum likelihood. The selected parameters which are used in E phase can be used as a seed point for the next M phase. This process can be performed until to get the necessary square errors.

Let the data set is represented by $X = \{x_1, x_2, x_3 \ldots\ldots x_n\}$

Where $x_i \in R^d$ and K components presented in the mixture model. The probability density of mixture is,

$$F(x) = \sum_{i=1}^{k} \alpha_i \; p\left(\frac{x}{\theta_i}\right)$$

$$\sum_{i=1}^{k} \alpha_i \; p = 1$$

Where α_iRefers the probability to select the each cluster. Or It is also called as weight of every cluster,

The Gaussian mixture distribution parameter is,

$$\theta_i = \left(\mu_{i\,,}\, \sigma_i\right)$$

The probability density faction of Gaussian distribution is,

$$f\left(\frac{x}{\mu_{i\,,}}\; \sigma_i^2\right) = \frac{1}{\sqrt{2\pi\sigma_i}}\; \exp\left[-\;\frac{(x-\mu_i)^2}{2\sigma_i^2}\right]$$

Hybrid segmentation

Zhang Xiang al. (2002) Finding the proper choice of the segmentation algorithm for the given applications is a difficult task in medical image segmentation. A novel method is introduced which combines any two segmentation methods to obtain the exact segment of lesion from MRI brain image. The process of combining two segmentation algorithms is called as hybrid segmentation. The main objective of combining the various algorithms is to remove the drawbacks of two different methods and to improve the accuracy of segmentation.

Implementation of clustering techniques

The following topic describes the brief discussion about results for various segmentation algorithms. The algorithms are like K-means clustering, adaptive k-means clustering, spatial fuzzy, c-means clustering using for segmentation of brain image. The performance analysis between the various stages of results of K-means, adaptive k- means algorithms are compared in terms of accuracy, time, PSNR, area.

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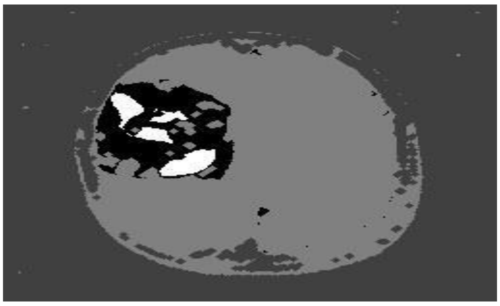

Figure 2. Tumour detection after K means clustering

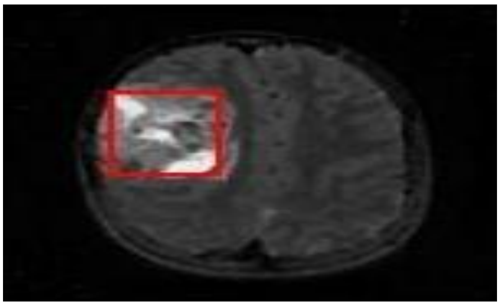

Figure 3. Tumour area calculation after K means clustering

Tumour Area calculation

After the region tumour region is identified, the area of the tumour is calculated in Matlab using command region props. STSTS –region props (BW, properties) which helps to measure the properties of each connected region of an image."Area" which actually provides the number of pixels in the region."Bounding box" which is the smallest rectangle region, which is used to represent the tumour portion in the form of a rectangular box.The tumour area is calculated by counting the number of pixels in a rectangular box.

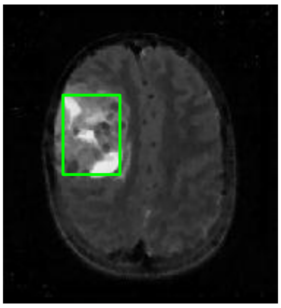

Figure 4. Tumour area calculation by K means and adaptive K means

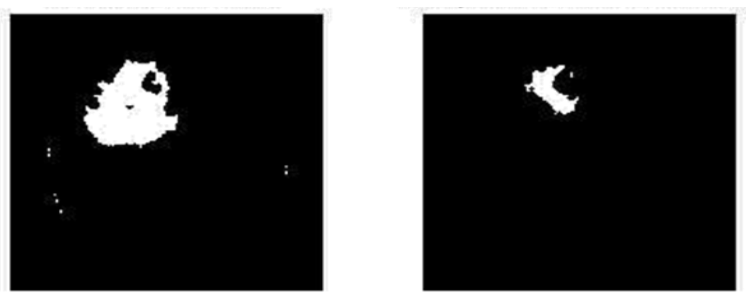

Figure 5. K means and adaptive K means result

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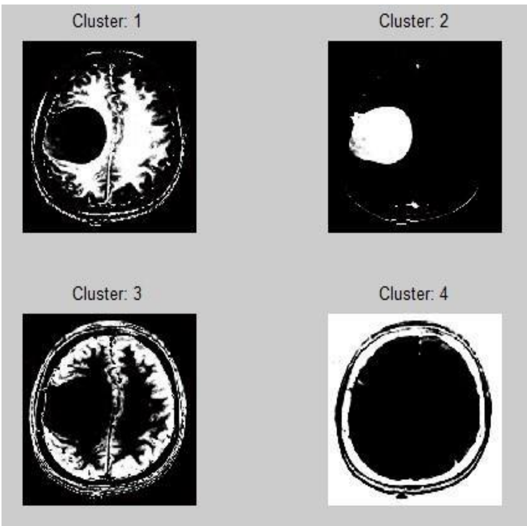

Figure 6. SFCM output

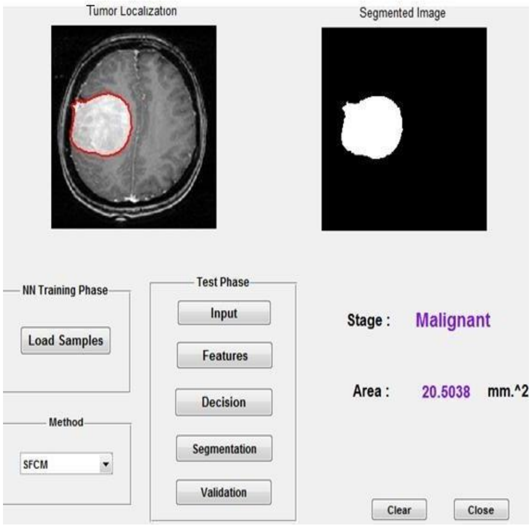

Figure 7. Segmentation of Tumour using SFCM

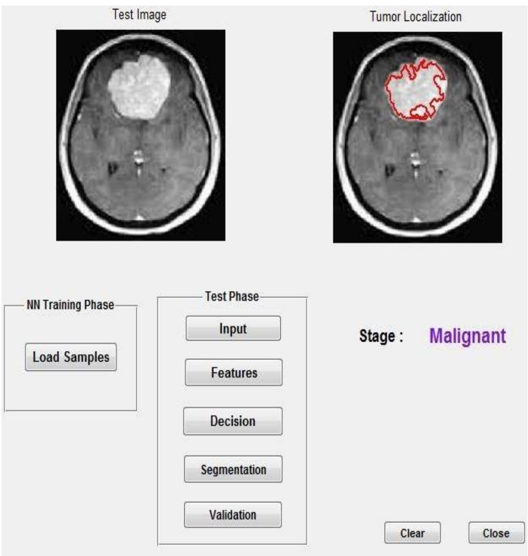

Figure 8. KISFCM Output

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4. Conclusion

The research work is performed using three different types of algorithms. Among the entire algorithm the proposed hybrid segmentation-based algorithm provides the best result and provide the accurate calculation of area and time when compared with other two algorithms. It can be identified that the integration of two algorithms leads good result. K means algorithms detect the tumour as faster than FCM, but it provides good result for only the smaller value of K. The next algorithm FCM is used to find the tumour cells that are not connected by K-means. The classification efficiency of the network is 87%.. This can be improved in this research work with the help of DWT extraction. The extracted features are used by BPNN to provide the improved classification efficiency of 93.28%.

Declarations

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Competing Interests Statement

The authors declare no competing financial, professional, or personal interests.

Consent for publication

The authors declare that they consented to the publication of this study.

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