International Journal of Recent Trends in Engineering & Research
ISSN(ONLINE) : 2455-1457
IMPACT FACTOR : 3.344

Brain Image Segmentation and Tumour Detection using Adaptive Clustering and RBF-SVM Classifier

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Abstract- Brain tumour is a group of abnormal cells that grows inside of the brain or around the brain. Tumours can directly destroy all healthy brain cells. In order to detect the tumour part, image segmentation plays a significant role in computer vision systems. It aims at extracting meaningful objects lying within the image. Generally, there is no particular system or method for image segmentation. Clustering is a robust approach that has been reached in image segmentation. The cluster analysis is to partition image information set into a number of disjoint groups or clusters. In this work we used adaptive k-means clustering for segmentation, this is one among the standard methods because of its simplicity and computational efficiency, GLDM (Grey Level Difference Method) for features extraction and interpolation for feature selection. RBF-SVM (Radial Basis Function Support Vector Machine) classifier is used for the classification of the brain tumor part in image.
Keywords-Adaptive k-means Clustering, GLDM features, RBF-SVM Classifier.

I. INTRODUCTION

Brain tumour is one of the major causes of death among the people. Brain tumour is a cluster of abnormal cells growing in the brain. It is possible that the chances of survival can be increased if the tumour is detected and labeled properly at its early stage. Detection of these tumours from brain may be very difficult at the areas where a tumour is overlapped with dense brain tissues. Visual detection of these abnormal tissues may just effect in misdiagnosis of volume and location of undesirable tissues because of human errors caused by using visual fatigue. Nowadays, automatic brain tumour detection in MRI images is very important in many diagnostic and therapeutic applications. Automatic classification and detection of tumors in different medical images is inspired with the help of the necessity of high accuracy when dealing with a human existence.

The Magnetic Resonance Imaging (MRI) is a broadly used medical imaging technique which presents particular information of the internal tissue constitutions of the image. In disease analysis, the high resolution and non-invasive MR images have a vital control as a result the image segmentation has more importance. The segmentation process used to detach the smooth brain tissues like White matter (WM), grey matter (GM) and Cerebral Spinal Fluid (CSF) and so on in the type of neuro anatomical structures surrounded by the medical images and these areas are viewed as pathological tissues. There are two types of segmentation approaches current such as, manual and computerized segmentation. Though the manual segmentation procedure depends upon developed into an accredited modality for medical imaging of ailment processes in the musculoskeletal process, especially the foot and mind due to the use of non-ionizing radiation. MRI supplies a digital representation of tissue attribute that may be obtained in any tissue plane. The images produced with the help of an MRI scanner are best described as slices through the brain. MRI has the added advantage of being ready to produce images which slice by way of the brain in both horizontal and vertical planes.Clustering may also be considered as the most important unsupervised learning problem; so, as every different problem of this type, it deals with finding a structure in a set of unlabeled knowledge base. A definition of clustering could be “the process of organizing objects into groups whose members are an identical by some way”. A cluster is for this reason a set of objects which are “identical” between them and are “dissimilar” to the objects belonging to different clusters [3], [4], [5].

The paper is organized as follows: Section 2: explains literature survey, different methodologies on brain tumor detection and classification and; Section 3: contains methodology of proposed system which includes pre-processing, Segmentation, feature extraction and classification to detect the tumor. Section 4: depicts the experimental results obtained from the evaluation of the proposed methods. Section 5: finally, conclusions are drawn in.

II. RELATED WORK

Nagalkar V.J and Asole S.S [6] proposed a system for brain tumor detection in CT scan image, the input image is pre-processed, i.e. convert the input image to gray color which helps us to make other process easier. Extract the features from the gray image and compare the features with the already stored features of non-tumor image. Finally they classified the obtained image as tumor image or non-tumor image using extracted features. Dr. P.V. Ramaraju and Shaik Baji proposed an approach for an automatic detection of brain image using Probabilistic Neural Network and Graphical User Interface. Input image will be pre-processed and segmentation is done for the pre-processed image using k-means clustering [7]. By performing feature extraction and classification using 'PNN', MRI images are classified as benign, malignant or normal. And also they calculated parameters like area, mean, standard deviation and entropy.

In paper [8], S. Murugavalli and V. Rajamani studied the computation speed of the proposed approach. The multilayer segmentation results of the neuro fuzzy are shown to have interesting consequences from the viewpoint of clinical diagnosis. Neuro fuzzy technique shows that MRI brain tumor segmentation using HSOM-FCM also perform more accurate one. B. Sathya and R. Manavalan have compared different images with various segmentation approaches such as improved k-means algorithm, FCM and IFCM. The rand index (RI), global consistency error (GCE), boundary displacement error (BDE), and variations of information (VOI) [10] are used to evaluate the performance. The detailed description with formulae of RI, GCE, BDE, VOI parameters are explained in this paper [9]. Rajesh C. Patil and Dr. A. S. Bhalchandra proposed a methodology to detect the brain tumor in an MRI image. This paper proposed an approach to detect & extraction of brain tumour in MRI scan images. This methodology incorporates with some noise elimination features, segmentation and morphological operations that are the fundamental standards of image processing.

III. PROPOSED SYSTEM

In our approach, we divided the work in 2 phases, i.e. testing and training phase. In the first phase, that is training phase we take segmented tumour part of images like benign, malignant and normal image and we pre-process those images which includes re-sizing, gray conversion and then features of the image will be extracted followed by feature selection. Save those trained images in knowledge base. In the second phase, i.e. testing phase, we take an MRI image and pre-process the image, in order to detect the tumour region we apply segmentation, for this we use adaptive clustering. Extract the region of interest from the image followed by feature extraction and feature selection, and then classify the images using RBFSVM Classifier. Figure 1 shows the architecture of proposed work.

A. Pre-Processing:

Pre-processing is an initial stage where the input MRI image will be taken and resized to 256X256 and convert it to gray image for further processing.

B. Segmentation: Adaptive Clustering

The aim of image segmentation is to cluster pixels into salient image regions, i.e. regions corresponding to individual surfaces, objects, or ordinary constituents of object, segmentation could be used for object recognition, occlusion boundary estimation inside motion or stereo methodologies and image modifying.

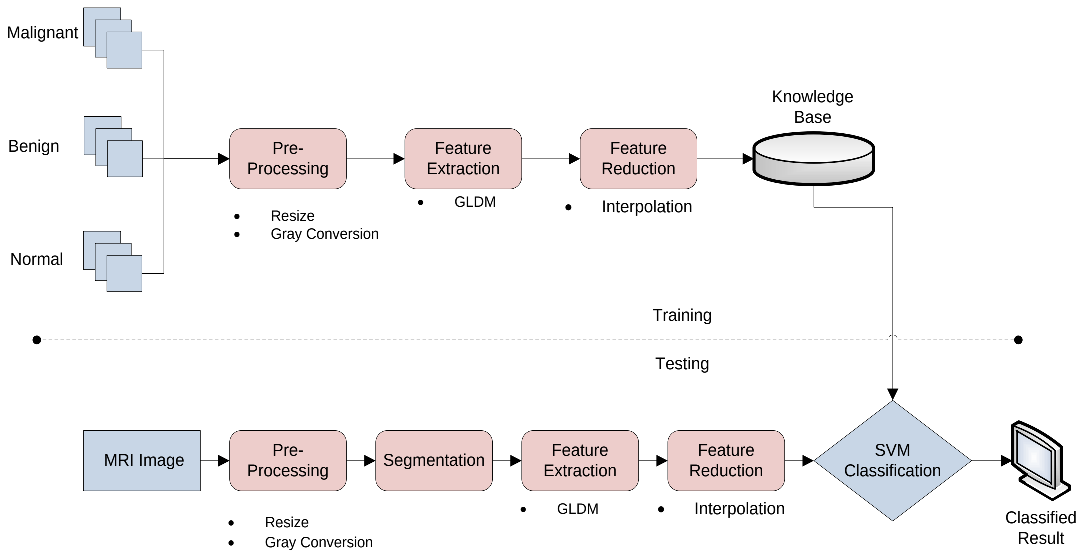


Figure 1: Proposed Architecture

The work can be explained in stepwise as below,

- Either randomly or based on some heuristic, pick K cluster centers,
- Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
- Re-compute the cluster centers by averaging all of the pixels in the cluster.

Repeat last two steps until the convergence is attained.
Given a set of observations,$(X_1, X_2, \ldots, X_n)$ where each observation is a d-dimensional real vector, k-means clustering aims to cluster the n observations into k sets$(k < n)S = \{S_1, S_2, \ldots.., S_n\}$, so as to minimize the within-cluster of squares (WCSS);

$$arg_S min \sum_{i=1}^{k} \sum_{x_j \in S_i} \left\| X_j = \mu_i \right\|^2 \qquad (1)$$

Where μ_i is the mean of point in S_i.

Essentially the most common algorithm makes use of an iterative refinement procedure. Because of its ubiquity it is often known as the k-means algorithm; additionally it is referred to as Lloyd's algorithm, specifically in the computer science group. Given an initial set of k-means $m_1{}^{(1)}, \ldots, m_k{}^{(1)}$, which may be precise randomly or by some heuristic, the algorithm proceeds by alternating between two steps [14].

Allot each observation to the cluster with the closest mean by,

$$S_i{}^{(t)} = \{X_j : \|X_j - m_i{}^{(t)}\| \le \|X_j - m_{i^*}{}^{(t)}\|\} \quad for\ all\ i^* = 1, \ldots.., k \qquad (2)$$

Then calculate the new means to be centroid of the observation in the cluster,

$$m_i{}^{(t+1)} = \frac{1}{|S_i{}^{(t)}|} \sum_{x_j \in S_i{}^{(t)}} X_j \qquad (3)$$

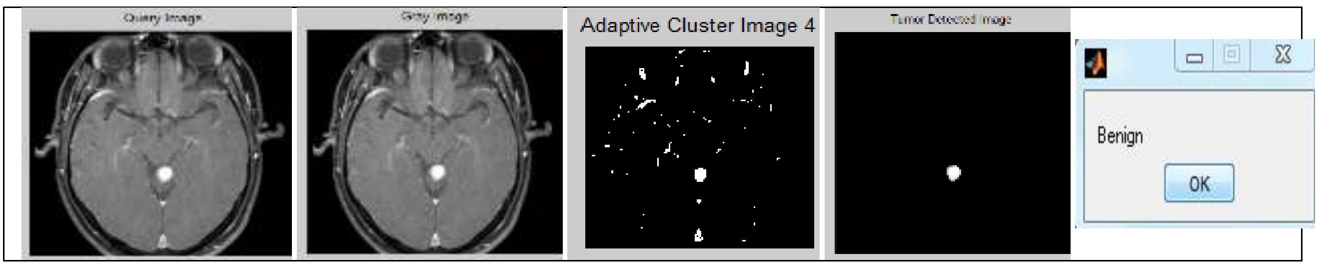
The histogram is summary graph showing a count of data features falling in quite a lot of stages. The effect is rough approximation of the frequency distribution of data. The group of knowledge is referred to as classes, and in context of histogram they are referred to as bins, because one can think of them as containers that accumulate data and refill at a rate equal to the frequency of that class. The shape of the histogram sometimes is particularly sensitive to the quantity of bins. If the containers are too wide, essential information would get omitted. Through reducing the number of bins and increasing the number of classes in the k-means algorithm, the detection accuracy is discovered to be increasing. Quantization in terms of colour histograms refers to the approach of reducing the quantity of bins taking colors which are very similar to every different and placing them in the same bin. By default the maximum number of bins, one may acquire using the histogram function is 256. For the motive of saving time when trying to evaluate colour histograms, we can quantize the quantity of bins. Absolutely quantization reduces the information involving the content of images however as was stated that is the trade-off when one desires to scale back processing time.

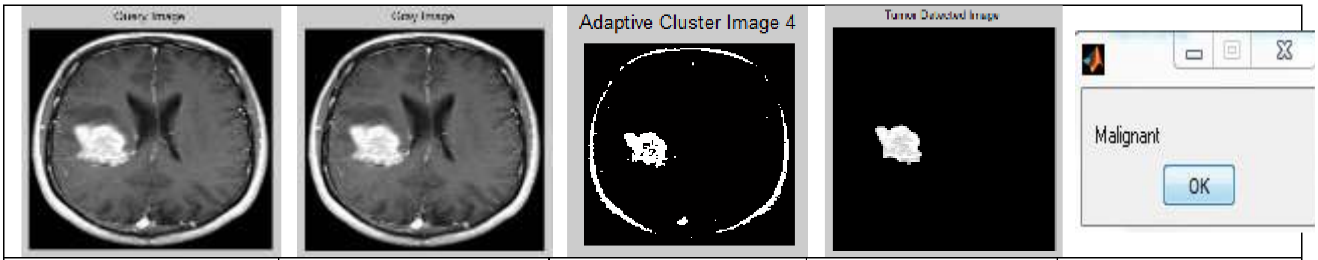
C. Feature Extraction: GLDM

The GLDM process calculates the grey level difference method probability density functions for the pre-processed gray image. This method is used for extracting statistical texture features of a digital image. From each density functions five texture aspects are outlined: contrast, Angular second moment, Entropy, mean and Inverse difference moment. Contrast is defined as the change in intensity between highest and lowest intensity stages in an image for that reason measures the local variations in the gray level. Angular second moment is a measure of homogeneity. If the difference between grey levels over an area is low then these areas are stated to be having better Angular second moment (ASM) values. Mean it offers the average intensity value. Entropy is the average understanding per intensity source output. This parameter measures the disease of an image. When the image is just not texturally uniform, entropy could be very large. Entropy is strongly, however inversely, correlated to energy. Inverse difference moment IDM measures the closeness of the distribution of elements in the gray stage Co-occurrence Matrix (GLCM) to the GLCM diagonal. To describe the gray level difference process, let $g(n,m)$ be the digital picture function. For any given displacement $\delta = (\Delta n, \Delta m)$, where Δn and Δm are integers, let$g\delta(n,m) = |g(n,m) - g(n+\Delta n, m+\ \Delta m)|$. Let $f(|\delta)$ be the estimated probability density function associated with the possible values of $g\delta$ i.e. $f(i|\delta) = P(g\delta(n,m) = i)$ herein our possible forms of vectors δ will be considered. $(0,d), (-d,d), (d,0), (-d,d)$, where d is inter sample distance. We refer $f(|\delta)$ as gray level difference density functions.

IV. RESULTS AND DISCUSSION

In this work we have proposed a methodology which integrates segmentation, feature extraction and classification to recognize and classify the tumor part in an MRI image. As we mentioned we divided the work in two phases, i.e. training and testing phase. Theoretical explanation each algorithm used in our work is given above. Figure 2 depicts the results of our proposed work. (a) is input image, (b) is gray scale image, segmented image is depicted in the figure (c), after removing the noise which is present in the segmented image we will detect the tumor part and is shown in the figure (d), based on the features extracted from the tumor region we classify the as Benign or Malignant.





(a) Input Image	(b) Gray Scale Image	(c) Segmented Image	(d) Tumour Detected Image	(e) Classified Tumour

Figure 2: Results of Proposed Work

V. CONCLUSION

In this paper we proposed an efficient methodology to detect and classify the tumour part in an MR image. Here we used adaptive k-means clustering for detecting region of interest, i.e. tumour part in an image. Then we extract the features using Gray Level Difference Method (GLDM). The obtained features are stored in a knowledge base and compare the features using RBF-SVM classifier, SVM will classify the image as Benign or Malignant based on the features extracted.

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