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A comparative study on various brain tumor classification methods

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ABSTRACT

Today, Brain Tumor is one of the major important problem among various other existing life threatening diseases. People at any age, both adult and child are affected by this brain tumor. Brain tumor are classified into two types, primary and secondary .The Primary brain tumors can be either malignant which contain cancer cells or benign which do not contain cancer cells. A primary brain tumor is a tumor which begins in the brain. If a cancerous tumor which starts elsewhere in the body sends cells which end up growing in the brain, such tumors are then called secondary brain tumors. The early detection of brain tumor may lead the affected persons to diagnose it initially, and have a lengthy life .Such brain tumor detection is done mainly using MRI, CT scans and other types of tests. Then this brain tumors' are diagnosed by the doctors on the results of that images .Here some times , in the detection of brain tumors when done manually with that scan images, there exists to a confusion in differentiating normal brain tissues and brain tumors , this may lead to wrong treatments and end in life and financial loss. Hence a brain tumor detection and classification can be done in an effective and efficient way. There are more methods such as SVM, KNN, FUZZY CONNECTEDNESS, ADA BOOST, GCLM are available for this type of brain tumor detection and classification. In this paper, the comparison studies on the SVM & GCLM methods were illustrated in detail.

Keywords: SVM, GCLM, MRI, CT

1. INTRODUCTION

Brain tumor is an abnormal growth of cells inside the skull. Normally the tumor will grow from the cells of the brain, blood vessels, nerves that emerge from the brain. There are two types of tumor which are benign (non-cancerous) and malignant (cancerous) tumors. The former is described as slow growing tumors that will exert potentially damaging pressure but it will not spread into surrounding brain tissue. However, the latter is described as rapid growing tumor and it is able to spread into surrounding brain. Tumors can damage the normal brain cells by producing inflammation, exerting pressure on parts of brain and increasing pressure within the skull. MRI is an imaging technique used primarily in medical settings to produce high quality images of the inside of the human body. There is a horizontal tube running through the magnet from front to back. This tube is called as the bore of the magnet. The patient lying on his or her back slides into the bore on a specific table. Whether or not the patient goes in head first or feet first, as well as how far in the magnet they will go, is determined by the type of exam to be executed. Once the body part to be scanned is in the particular center of the magnetic field, the scan can begin. MRI offers an unparalleled view inside the human body. The level of information we can see is surprising compared with any other imaging modality. MRI is the method of option for the diagnosis of many types of injuries and situations. Radiologists examine the patient physically by using Computed Tomography (CT scan) and Magnetic Resonance Imaging (MRI). MRI images showed the brain structures, tumor's size and location. From the MRI images the information such as tumors location provided radiologists, an easy way to diagnose the tumor and plan the surgical approach for its removal.

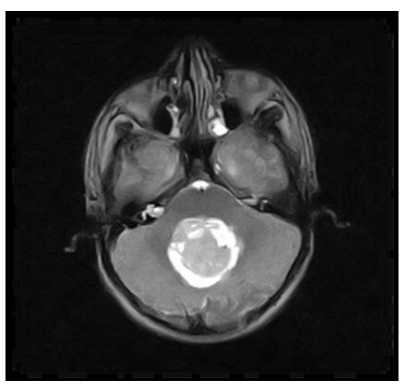


Figure 1 Brain Tumour image

2. CLASSIFICATION METHODS

2.1. GLCM

The various stages of this method are MRI database, pre-processing, feature extraction and classification.

Image preprocessing Image preprocessing consists mainly of following steps

- Image histogram equalization.
- Binarization.

- Thresholding
- Morphological operation.
- Region isolation.

1. Histogram Equalization: The first step is to perform histogram equalization on the MRI image. The given MRI is equalized using histogram. The Histogram of an image shows the relative frequency of occurrences of pixel in a given MRI image. The non-uniform changeable image due to external conditions is equalized to a uniform variation.

2. Binarization: Image binarization converts an image in 0 to 255 gray levels to a black and white image. The easiest way to use image binarization is to select a threshold value, and classify all pixels with values above this threshold as white, and all other pixels as black.For this thresholding technique is used. For the equalized image the pixels are represented in a 0 to 255 gray level intensity.As the method is to extract the affected region or the accumulated region, a 2-level image representation would be satisfactory for better computation.

3. Thresholding: In various vision applications, it is helpful to be able to separate out the regions of the image corresponding to objects in which we are interested, from the regions of the image that correspond to background. Thresholding often gives an easy and convenient method to achieve this binarization on the basis of the dissimilar intensities or colors in the foreground and background regions of an image.For the binarization of equalized image a thresholding technique is used as shown below:

Binarized Image $b_{i,j} = 255$ if $e(i, j) > T$
Else $b_{i,j} = 0$

Where e (i, j) is the equalized MRI image and T is threshold resultant for the equalized image.

4. Morphological Operations: This is used as a image processing tools for sharpening the regions and filling the gaps for binarized image. The dilation operation is performed by imdilate command in matlab. This is applied for filling the broken gaps at the edges and to have continuities at the boundaries. A structuring element of 3x3 square matrix is applied to complete dilation operation.

5. Region Isolation: After the dilation operator, a filling operator is used to fill the close contours. Then centroids are calculated to localize the regions as shown beside. The last extracted region is then logically operated for extraction of Massive region in given MRI image.

Feature Extraction

Feature extraction is the procedure of data reduction to find a subset of helpful variables based on the image. In this work, seven textural features based on the gray level co-occurrence matrix (GLCM) are extracted from each image. Co-occurrence matrices are calculated for four directions: 0°, 45°, 90° and 135° degrees. The seven Haralick texture descriptors are extracted from each co-occurrence matrices which are computed in each of four angles.

- Angular Second Moment (ASM) / Energy.
- Contrast.
- Inverse Difference Moment (IDM) / Homogenety.
- Dissimilarity.
- Entropy
- Maximum Probability
- Inverse

Classification Using ANNs

The purpose of image classification scheme is to assign each input to one of 'Astrocytoma type of brain cancer' pattern classes. It is the process of assigning a label to each unknown input image. In this method, the artificial neural network approach namely, Back propagation network (BPNs) is used to classify the images.

Back propagation algorithm is applied for learning the samples, Tan-sigmoid (tansig) and logsigmoid (logsig) functions are applied in hidden layer and output layer respectively, Levenberg-Marquardt optimization (trainlm) is used for adjusting the weights as training methodology. Here, each pixel together with a small square neighborhood is defined as a structure element, which is known as 'block'. Further are all based on the blocks. For training process, firstly altered features are extracted block by block in one image. When we use a new image for classification, only those selected features are extracted and the trained classifier is used to classify the tumor in the image

2.2. SVM-RFE

2.2.1. Feature selection

First the number of features is reduced by eliminating the less relevant features using a forward selection method based on a ranking criterion and then backward feature elimination is applied using a feature subset selection method, as explained next.

1) Ranking-based criterion: We use a simple ranking based feature selection criterion, a two-tailed *t-test*, which measures the significance of a difference of means between two distributions, and therefore evaluates the discriminative power of each individual feature in separating two classes. The features are assumed to come from normal distributions with unknown, but equal,variances. Since the correlation among features has been completely ignored in this feature ranking method, redundant features can be inevitably selected, which ultimately affects the classification results. Therefore, we use this feature ranking method to select the more discriminative features, e.g. by applying a cut-off ratio ($pvalue < 0.1$), and then apply a feature subset selection method on the reduced feature space, as detailed next.

Features subset selection method based on SVM:

The support vector machine recursive feature elimination (SVM-RFE) algorithm is applied to find a subset of features that optimizes the performance of the classifier. This algorithm determines the ranking of the features based on a backward sequential selection method that removes one feature at a time. At each time, the removed feature makes the variation of SVM-based leave-one-out error bound smallest, compared to removing other features.

Classification is performed by following a leave-one out strategy on the training samples. For each leave-one-out experiment, feature ranking is performed using data only from the training samples. The feature selection method is implemented in each training subset in order to correct for the selection bias. It is important that cross-validation is external to the feature selection process in order to more accurately estimate the prediction error. Evidently, there is no guarantee that the same subset of features will be selected at each leave-one-out experiment. We combine the rankings of all leave-one-out experiments and report the total rank of features according to the frequency of a feature appearing in a specific rank.

2.2.2. Classification

Classification is performed by starting with the more discriminative features and gradually adding less discriminative features, until classification performance no longer improves. Non-linear Support Vector Machines with Gaussian kernel is used as classifier. Since the data are highly unbalanced and the sample size is rather small to produce balanced classes by subsampling the largest class, we used a weighted SVM to apply larger penalty to the class with the smaller number of samples. If the penalty parameter is not weighted, there is an undesirable bias towards the class with the large training size; and thus we set the ratio of penalties for different classes to the inverse ratio of the training class sizes.

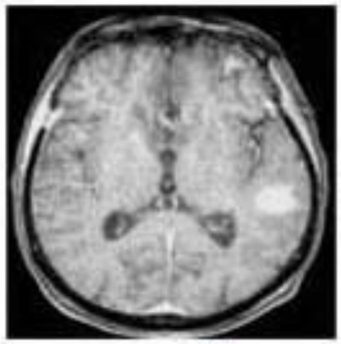
Moreover, the parameter (γ) that controls the size of the Gaussian radial basis function is chosen as

$$\gamma = 1/NF,$$

where NF is the number of features. Therefore the maximum kernel size is 1.0 and decreases with increasing number of features during feature selection.The multi-class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme. We apply majority voting from all one-versus-all binary classification problems. The predictive ability of the classification scheme is assessed by leave-one-out cross validation.

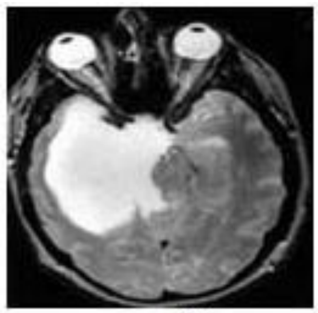
3. EXPERIMENTAL RESULTS

3.1. GCLM images



(a)

GRADE I

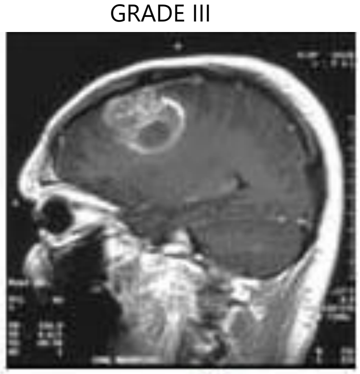


(b)

GRADE II

(c)

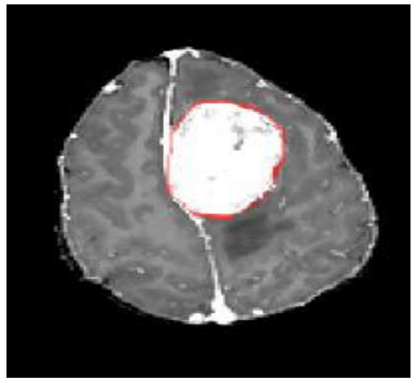
GRADE III



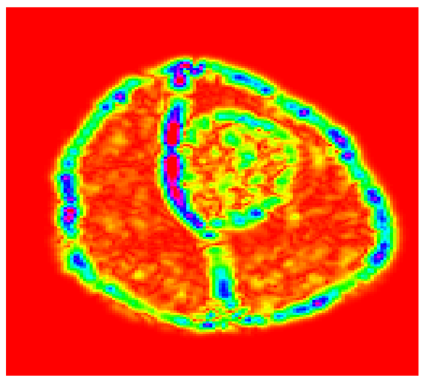
(d)

GRADE IV

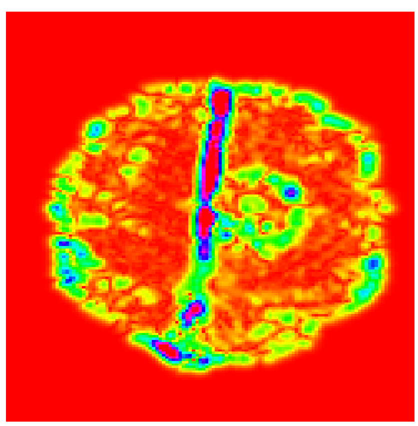
3.2 SVM-RFE images



GRADE II



GRADE III



GRADE IV

4. CONCLUSION

In this paper, the comparison on the classification methods GCLM which describes Classification of Brain Cancer Using Feature Extraction in Artificial Neural Network and SVM, a computer-assisted classification method by combining conventional and perfusion MRI for differential tumor diagnosis, were studied.

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