Automatic Classification of MR Brain Tumor Images using Decision Tree

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ABSTRACT
A tumor classification system has been designed and developed. It is used to classify five different types of tumors such as glioblastoma multiforme, astrocytoma, metastatic, glioma and pituitary macro. The magnetic resonance feature images used for the tumor classification consist of T1-weighted images with contrast for each axial slice through the head. The magnetic resonance imaging has become a widely used method of high quality medical imaging, especially in brain imaging where the soft-tissue contrast and non invasiveness is a clear advantage. The proposed method has three stages. They are pre-processing, feature extraction and classification. In the first stage, the noise is removed using a wiener filter. In the second stage, six texture features are extracted using gray level co-occurrence matrix. The features extracted are angular second moment, contrast, inverse difference moment, entrophy, correlation and variance. Finally, a decision tree classifier is used to classify the type of tumor image. The extracted features are compared with the stored features in the knowledge base to classify the type of tumors. Thus, the proposed system has been evaluated on a dataset of 21 patients. Then the system was found efficient in classification with a success of 98%.

Keywords
Tumor, Magnetic resonance imaging, Gray level co-occurrence matrix, Decision tree.

1. INTRODUCTION
Brain tumor is a cluster of abnormal cells growing in the brain. It may occur in any person at almost any age. It may even change from one treatment session to the next but its effects may not be the same for each person. Brain tumours appear at any location, in different image intensities, can have a variety of shapes and sizes. Brain tumours can be malignant or benign. Low grade gliomas and meningiomas [1], which are benign tumors, and glioblastoma multiforme is a malignant tumor and represents the most common primary brain neoplasm. Benign brain tumors have a homogeneous structure and do not contain cancer cells. They may be either monitored radiologically or surgically destroyed completely, and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. They can be treated by radiotherapy, chemotherapy or a combination thereof, and they are life threatening. Therefore, diagnosing the brain tumors in an appropriate time is very essential for further treatments. In recent years, neurology and basic neuroscience have been significantly advanced by imaging tools that enable in vivo monitoring of the brain. Magnetic resonance imaging (MRI) [2] has proven to be a powerful and versatile brain imaging modality that allows noninvasive longitudinal and 3D assessment of tissue morphology, metabolism, physiology, and function [3]. The information MRI provides, has greatly increased the knowledge of normal and diseased anatomy for medical research, and is a important component in diagnosis and treatment planning. MR imaging is currently the method of choice for early detection of brain tumor in human brain. However, the interpretation of MRI is largely based on radiologist's opinion. According to World Health Organization (WHO), there are 126 types of different brain tumors many of which arise from structures intimately associated with the brain such as tumors of the covering membranes (meningiomas) to posterior fossa. In India, totally 80,271 people are affected by various types of tumor (2007 estimates). National Brain Tumor Foundation reported highest rate of primary malignant brain tumor occurred in Northern Europe, United States and Israel. Lowest rate was found to be in India and Philippines.

In the field of brain MRI, Gibbs et al. [4] introduced a morphological edge detection technique combined with simple region growing to segment enhancing tumors on T1-weighted MRI data. Letteboer et al. [5] proposed an interactive segmentation method for three types of tumors: full enhancing, ring enhancing and non-enhancing. Droske et al. [6] proposed a deformable model, implemented with a level set formulation, to divide the MRI data into regions with similar image properties, based on prior intensity based pixel likelihoods for tumor tissues. Fletcher-Heath et al. [7] proposed a combination of unsupervised classification with FCM and knowledge based image processing for segmentation of non-enhancing tumors. Zou et al. has proposed a method for automatic brain tumor segmentation in MRI [8]. Dou et al. [9] have proposed a fuzzy information fusion framework for brain tumor segmentation using T1-weighted, T2-weighted and PD images. In detecting tumor from MRI, mathematical models have been proposed in numerous works [10-14] that extract necessary features from the images to characterize tumors. Ahmed et al. [15] has proposed a method using genetic algorithm and support vector machine for efficient classification of brain MRI with high sensitivity 98%, specificity 97% and accuracy 98%. Baskaran et al. [16] has proposed a method for texture based classification using binary decision tree. Dipali M. joshi et al. [17] has proposed classification method for MR brain cancer using artificial neural network. Fazel Zarandi et al. [18] has proposed a method for classification of different grades in astrocytoma tumor.

The rest of this paper is organized as follows. Section 2, presents the proposed technique, utilized in this work for five types of brain tumor classification. In this section pre-processing, feature extraction and classification are presented. Section 3 experimentally demonstrates the performance of the proposed method. Finally, section 4 describes the conclusion of this paper.

2. PROPOSED TECHNIQUE

Developing an efficient classification method may help physicians to know the type of tumors in an appropriate time. Considering the T1 weighted MR images as an input data, the proposed method has three main steps, pre-processing, feature extraction using Gray Level Co-occurrence Matrix and classification. The proposed technique for automatic MR brain tumor image classification is illustrated in Fig. 1.

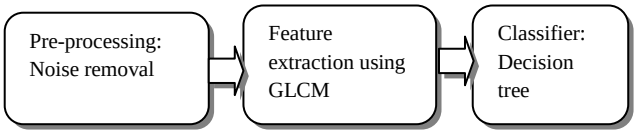

Fig 1: Methodology of the Proposed Technique

2.1 Pre-Processing

In, the literature, there are many pre-processing techniques, which are applicable in different circumstances. Moreover, in the case of inappropriate usage of these methods, the noise may be increased or small details may be eliminated. The noises and artifacts on the image are reduced in pre-processing step by using a wiener filter. The general idea behind the filtering is based on statistics estimated from a local neighborhood of each pixel. By using this, the noises in the pre-processed image are reduced.

2.2 Texture Features From Gray Level Co-occurrence Matrix

Texture is a repeating pattern of local variations in image intensity. It is a statistical method that considers the spatial relationship of pixels is the gray level co-occurrence matrix (GLCM), also known as the gray level spatial dependence matrix. By default, these spatial relationships are defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (*I, J*) in the resultant GLCM is simply the sum of the number of times that the pixel with value *I* occurred in the specified spatial relationship to a pixel with value *J* in the input image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics. The GLCM [19] method is a way of extracting second order statistical texture features. A GLCM is a matrix where the number of rows and colums is equal to the number of gray levels, G, in the image. The matrix element P (i,j |Δx,Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx,Δy), occur within a given neighborhood, one with intensity i and the other with intensity j. One may also say that the matrix element P (i,j |d,θ) contains the second order statistical probability values for changes between gray levels i and j at a particular displacement distance d and at a particular angle(θ). However, the performance of a given GLCM based feature, as well as the ranking of the features, may depend on the number of gray levels used. We use the following notation: μ is the mean value of P. μ_x, μ_y, σ_x $\sigma_x$and σ_y are the means and standard deviations of P_x and P_y The elements of P_d [i,j] can be normalized by dividing each entry by the total number of pixel pairs. Normalized co-occurrence values lie between 0 and 1, and allow them to be thought of as probabilities. The following GLCM features were extracted in our research work: angular second moment, contrast, inverse difference moment, entropy, correlation and sum of variance. Eqs. (1) – (6) are given below for the above features.

1. Angular second moment (ASM)

$$\mathrm{ASM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \qquad (1)$$

ASM is a measure of homogeneity of the image. A homogeneous image will contain only a few gray levels, GLCM gives only a few but relatively high values of P(i,j). Thus, the sum of squares also will be high.

2. Contrast

$$\mathrm{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j) \right\}, |i-j| = n \qquad (2)$$

Contrast is a measure of the local variations present in an image. This measure of contrast will favour contributions from P(i,j) away from the diagonal, i.e. i = j. If there is a large amount of variations in an image, the P[i,j]'s will be concentrated away from the main diagonal, and contrast will be a high value.

3. Inverse difference moment (IDM)

$$\mathrm{IDM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \qquad (3)$$

IDM is also influenced by the homogeneity of the image. Because of the weighting factor $(1+(i-j)^2)^{-1}$ IDM will get small contributions from inhomogeneous areas (i j). The result is a low IDM value for inhomogeneous images, and higher value for homogeneous images.

4. Entropy

$$\mathrm{Entropy} = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times \log\big(P(i,j)\big) \qquad (4)$$

This statistic measures the disorder or complexity of an image. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy.

5. Correlation

$$\mathrm{Correlation} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \qquad (5)$$

Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other. Correlation will be high if an image contains a considerable amount of linear structure.

6. Sum of Squares, Variance

$$\mathrm{Variance} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2 P(i,j) \qquad (6)$$

The variance is a measure of the dispersion of the gray level differences at a certain distance, d. This feature puts relatively high weights on the elements that differ from the average value of P(i,j).

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relatively high weights on the elements that differ from the average value of P (i,j).

2.3 Decision Tree Classifier

This classification algorithm is based on a decision tree. A decision tree is a set of simple rules. Decision trees [16] are also nonparametric because they do not require any assumptions about the distribution of the variables in each class. Every interior node contains a decision criterion depending only on one feature. For the first split into two parts, the feature with the highest relevance is used. This procedure is recursively repeated for each subset until no more splitting is possible. After such a decision, the next feature is determined, this splits the data optimally into two parts. All non terminal nodes contain splits. If followed from a root to a leaf node the decision tree corresponds to a rule-based classifier. An advantage of decision tree classifiers is their simple structure, which allows for interpretation (most important features are near the root node) and visualisation. A decision tree is built from a training set, which consists of objects, each of which is completely described by a set of attributes and a class label. The class that is associated with the leaf is the output of the tree. A tree misclassifies the image if the class label output by the tree does not match the class label. The proportion of images correctly classified by the tree is called accuracy and the proportion of images incorrectly classified by the tree is called error.

3. RESULT AND DISCUSSION

This section portrays some experimental results on real data on brain MRI. All the input data set used for tumor detection consists of T-weighted 256x256 pixel MR brain images. The MR brain images collected from patients was acquired on 1.5 Telsa, Intera MR Scanners from Department of Radiology, Rajah Muthiah Medical College Hospital (RMMCH). The number of MR brain images in the input dataset is 110 abnormal brain images of astrocytoma, glioblastoma, glioma, metastatic and pituitary macro. The abnormal brain image set consists of images of brain affected by brain lesion. The original T1-weighted MR brain image which is stained with tumor is shown in fig.2. In the first stage, we have suppressed the noise using a winner filter. In the second stage features are extracted using GLCM. In our research work, six features are extracted, they are angular second moment, contrast, inverse difference moment, entropy, correlation and variance. Finally, decision tree classifier is used to classify the type of brain tumor images. We evaluate the performance of the classifiers in terms of sensitivity, specificity and accuracy. The formulas are given in eqs.(7)-(9). True positive (TP) is correctly classified positive cases; false positive (FP) is incorrectly classified negative cases; true negative (TN) is correctly classified negative cases, and false negative (FN) is incorrectly classified positive cases. The three terms are defined as follows:

Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the tumor disease.

$$Sensitivity = \frac{TP}{TP+FN} \qquad (7)$$

Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \qquad (8)$$

Accuracy is the probability that a diagnostic test is correctly performed.

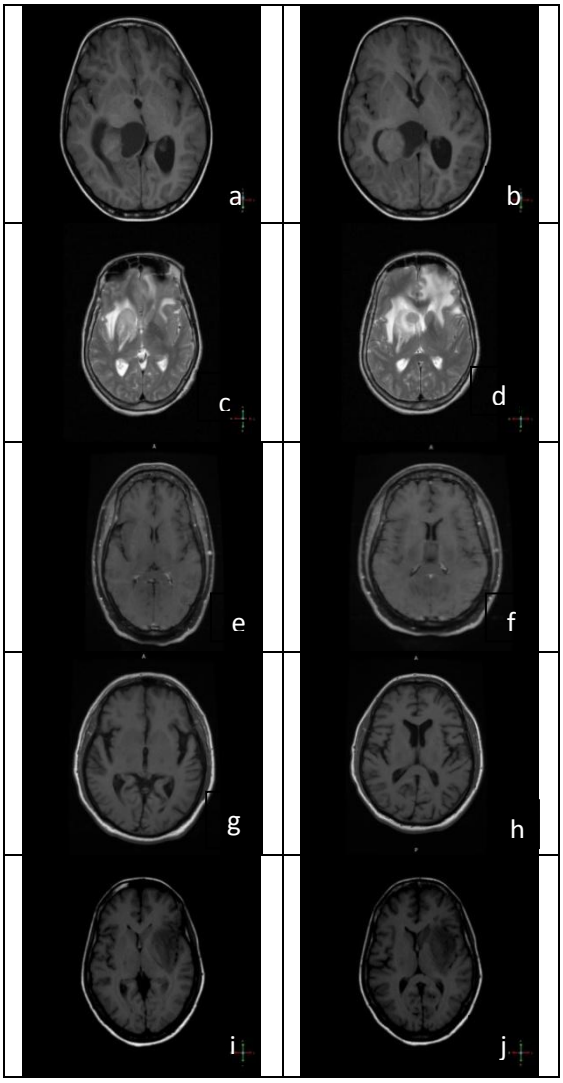

Fig 2: Original MR T1-weighted brain images. a, b-Astrocytoma; c, d-Glioblastoma; e, f- Metastatic; g, h-Pituitary macro; i, j-Glioma

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (9)$$

The tree structure of the classifier is given in fig. 3. The performance of the decision tree classifier is given in table 1. A classification with a success of 98% has been obtained by decision tree.

Table 1. Classifcation rates for decision tree classifier

Types of tumor	Sensitivity	Specificity	Accuracy
Astrocytoma	100	100	100
Glioblastoma multiforme	90	100	98
Glioma	100	100	100
Pituitary macro	100	100	100
Metastatic	90	100	98

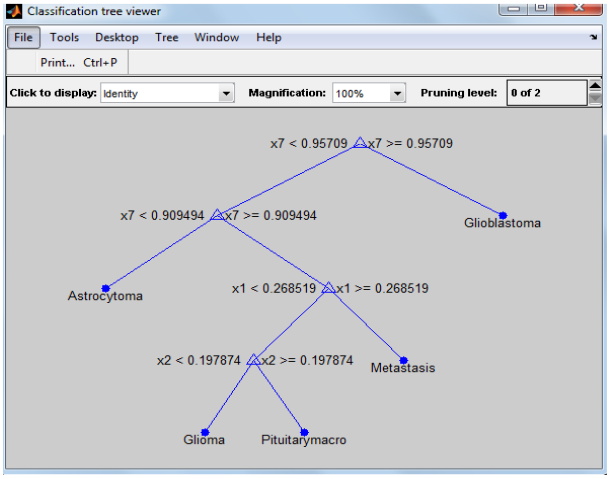

Fig 3: Tree structure of the classifier for five different types of tumors.

4. CONCLUSION

We have developed an automated method for the classification of five different types of tumours in brain MR images using decision tree classifier. The proposed system can help the physicians to know about the type of brain tumours, for further treatment. Our system has been successfully tested on large brain images causing brain tumour. The classification accuracy for decision tree classifier is 98%.

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