Detection and Classification of Brain Tumors

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ABSTRACT
The incidence of brain tumors is increasing rapidly particularly in the young generation. Tumors can directly destroy all healthy brain cells. Manual (Physical) classification can cause human error. Automatic classification method is required because it reduces the load on the human observer, accuracy is not affected due to large number of images. This paper elaborates attempt to detection & classification of tumor in benign stage. The proposed method consists of two stages namely feature extraction and classification. In the first stage, obtained the features related to MRI images using Gray Level Co-occurrence Matrix (GLCM) based methods, this is one of the tools for extracting texture features and second stage, the classifier is classified images using K-nearest neighbour (K -NN) classifier.

Keywords
MRI Images, Image Pre-processing using Gaussian filter, Tumor segmentation, Feature Extraction, Gray Level Co-occurrence Matrix (GLCM), K-NN (Supervised classification).

1. INTRODUCTION
Magnetic resonance imaging (MRI) is an advanced medical imaging technique that has proven to be an effective tool in the study of the human brain [3]. The rich information that MR images provide about the soft tissue & anatomy has dramatically improved the quality of brain pathology diagnosis and treatment. The most important advantage of MR imaging is that it is a non-invasiveness are clear. An important use of MRI data is tracking the size of brain tumor as it responds to treatment [1]. MRI is a medical imaging technique used to visualize the internal structure of the body & provide high quality images. MRI images do not involve exposure to radiation or emission. So, they can be safely used in people such as pregnant women & babies [10].

The use of computer technology in medical decision support is now wide spread and pervasive across a wide range of medical area, such as cancer research, heart diseases, brain tumors, etc. [2]. Fully automatic normal and a pathological brain, suffering from brain lesion. Classification can be obtained from magnetic resonance images, which is a great importance for research and clinical studies. Recent work has shown that classification of human brain in magnetic resonance (MR) images is possible via supervised techniques such as artificial neural networks and support vector machine (SVM) [13], and unsupervised classification techniques such as self-organization map (SOM) and fuzzy c-means [5]. Other supervised classification techniques, such as k-nearest neighbour (k-NN) can be used to classify the normal/pathological MRI images (abnormal images).

In this proposed method, first segment the input images using image processing technique. The feature extracted gives the property of the text character [7]. Feature extraction means to get the information of image in the form of numerical data. Gray Level Co-occurrence Matrix (GLCM) is used for features extraction. Proposed method is describe the modes of this technique in two stages –Training /Learning & Testing/Classification. Supervised machine learning algorithms (k-NN) is used to obtain the classification of images under two categories, either normal or a pathological brain (abnormal images)[4].

2. METHODOLOGY

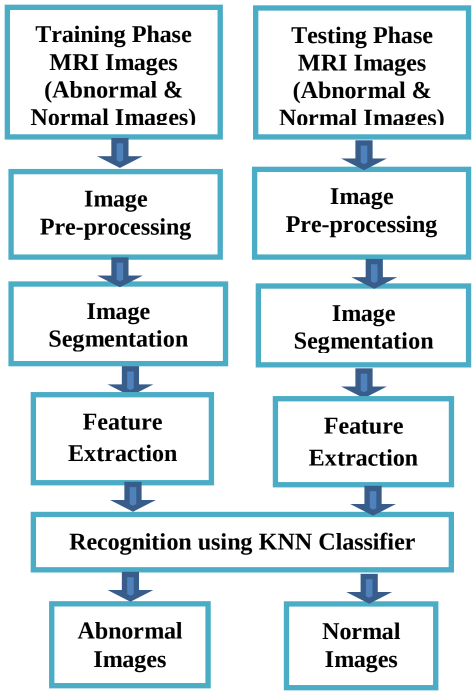

Figure 1. Block diagram of the system

The methodology used for "Detection & Classification brain tumor images is divided in to four parts as shown in fig. 1[1]. The method involves processing of MRI images that are affected by brain tumor for detection and classification of brain tumors. The image processing techniques like Pre-processing, Image Enhancement are used for the detection of tumor and then texture feature extraction method is used for extracting features from the MRI images. Features are extracted using Gray Level Co-occurrence Matrix. After feature extraction K- NN Classifier is used for the classification of brain into normal and abnormal images

2.1 MR Image Database

MRI image database consists of tumor brain images and normal brain images. These images are collected from WHO (World Health Organization), WBA (World Brain Atlas) Website. The samples of MRI brain images are shown in following Figure 2

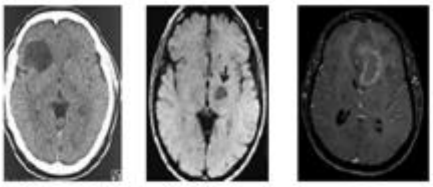

Figure 2. Sample Data Set

2.2 Image Pre-Processing

Medical image analysis requires the pre-processing, because of the noise may be added to the MR images due to imaging devices. The proposed method is used Gaussian filter to improve the quality of the Image by Noise suppression. Gaussian filter reduces effect of noise.

$$w(T) = C(\sigma)\exp\left(-\frac{T^2}{2\sigma^2}\right);\ T = -1,0,+1\ldots\ldots(1)$$

Where,

T- is the distance in time from the current moment

σ- Standard deviation (sigma) is the parameter of the Gaussian filter, by default sigma is 0.5.

$C(\sigma)$- is the normalization constant chosen to make the sum of all weights equal to the unit value.

2.3 Image Enhancement

The major problem in the process of detection of edge of tumor is that the tumor appears very dark on the image which is very confusing or unclear. To solve this problem, Histogram Equalization was performed. Histogram equalization performed on the MRI image, which improve contrast of MRI image to improve quality.

a) Histograms of basic images :

If image is dark image, histogram values will cluster towards low intensities. If image is bright image, histogram values will cluster towards high intensities. If image is a low contrast image, histogram values will cluster towards the centre of intensity range. If image is high or greater contrast image, histogram values will spread over all intensities.

b) How to improve the contrast:

Low contrast image has a histogram clustered over a small range of intensity values. To improve the contrast stretches the histogram so that it will spread over the entire range. The image will now have a large dynamic range

c) Histogram modification:

It is possible to develop a transformation to stretch the histogram. Transformation design is called as histogram equalization.

d) Histogram equalization:

First normalize the intensity values between 0 to 1.Map the intensity values using a monotonically increasing function S given by,

$$S_k = T(r_k) = (L-1)\sum_{j=0}^{k} Pr(r_j)$$

$$= (L-1)\sum_{j=0}^{k} n_j / MN \ \ldots\ldots k = 0, 1, \ldots L-1$$

$$= (L-1)/MN \sum_{j=0}^{k} n_j \ldots\ldots\ldots\ldots (2)$$

Where, s_k= output image, r_k =Input image with intensity &T (r_k) = Transformation function.

Using the Histogram equalization, transform the original image to a histogram equalized image using the intensity r_k into a corresponding pixel with level s_k in the output image.

2.4 Image Segmentation

Segmentation refers to partitioning an image into meaningful regions, in order to distinguish region of interest or concentration [6] [11]. In order to obtain segmentation of the simple image processing techniques such as image enhancement, binarization and morphological operation can be used.

2.4.1 Binarization:

Image binarization is used as pre-processor which converts gray scale image in to a binary image (either black or white) base on some threshold value. The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity $I_{i,j}$ is less than some fixed constant T (that is $I_{i,j} < T$), or a white pixel if the image intensity is greater than that constant. Thresholding has been used for segmentation as it is most suitable for the present application in order to find a binarized image with gray level 1 representing the tumor region and gray level 0 representing the background.

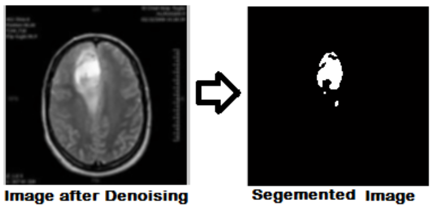

Figure 3. Brain tumor Segmented Image

2.5 Feature Extraction

Features are said to be properties that describe the whole image. The purpose of feature extraction is to reduce the original dataset by measuring certain features. GLCM matrix features are used to distinguish between normal and abnormal brain tumors. GLCM is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, in the image [8].

2.5.1 Gray level co-occurrence matrix (GLCM):

A gray-level co-occurrence matrix (GLCM) is essentially a two-dimensional histogram. The GLCM Method considers the spatial relationship between pixels of different gray levels. The method calculates a GLCM by calculating how often a pixel with a certain intensity i occurs in relation with another pixel j at a certain distance d and orientation ϴ. A co-occurrence matrix is identified by the relative frequencies P (i, j, d, ϴ). A co-occurrence matrix is therefore a function of distance d, angle ϴ and grey scales i and j [11].

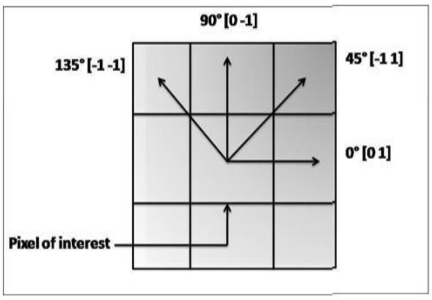

Figure 4. Direction for generation of GLCM

2.5.2 Texture Features:

Texture features used in the analysis and interpretation of images. When the gray-level co-occurrence matrix (GLCM) is generated, the textures feature could be computed from the gray-level co-occurrence matrix (GLCM). GLCM are extracted from each image. Co-occurrence matrices are calculated in four directions: 0, 45, 90 and 135 degrees.

Following statistical texture features are calculated:

1] Entropy - Measure the randomness that can be used to characterize the texture of the input image. The entropy is 0 when all Pij are 0.

Entropy=$\sum - pi,j * \log_2(pi,j)$……. (3)

2] Correlation -A measure of how correlated a pixel to its neighbour over the whole image, Range [-1 1].Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

Correlation=$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p\,(i,j)}{\sigma i\ \sigma j}$ …….(4)

3] Energy -Returns the sum of squared elements in the GLCM, Range [0 1].Energy is 1 for a constant image.

Energy =$\sum_{i,j} p\,(\,i\,,\,j)^2$........ …………. (5)

4] Homogeneity - Measures the spatial closeness of the distribution of elements in the GLCM to the GLCM diagonal, Range [0 1] Homogeneity is 1 for a diagonal GLCM.

Homogeneity =$\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$. …. ……. (6)

5] Contrast – A measure of the intensity contrast between a pixel and its neighbour over the whole image. Contrast is 0 for a constant image.

Contrast=$\sum_{i,j} |i-j|^2$ p (i, j)........ …... (7)

2.6 Classification

Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. Its task is to assign an input pattern represented by a vector to one of many pre-specified classes. In this paper K- NN classifier is used for the classification of brain MRI image into healthy brain or Tumour brain.

2.6.1 K-nearest Neighbour Classifier:

KNN classifier is non-parametric method used for classification. It does not need any prior knowledge about the structure of the data in training set. If the new training pattern is added to existing training set. It does not need any retraining. The output of the KNN algorithm can be interpreted as a posterior probability of the input pattern belonging to a particular class. As the k increases the confidence in prediction improves [9].

2.6.2 KNN Classifier Consist of Two Phase

(A) Training Phase- In this phase, Data points have labels with their class.

(B) Testing Phase- In this phase, Data points are unlabelled & algorithm generates the list of k nearest data point (training data point) to unlabelled point & classifies their class.

2.6.3 KNN Rules

Requires three things:

(i) The set of stored records.

(ii) Distance Metric to compute distance between stored records & unknown record to classify.

(iii) Identify *k* nearest neighbors & use class labels of nearest neighbors to determine the class label of unknown record by taking majority vote.

Store all input data in the training set

↓

In test set, each (unknown) pattern in the test set

↓

Search K-nearest patterns to the input pattern using a Euclidean distance measure.

↓

For, Classification, Compute the confidence for each class as C_i /K, (Where C_i is the number of patterns among the K nearest patterns belonging to class i).

Figure 5. Algorithm of KNN

2.7 Performance Measure

Accuracy is the probably that a diagnostic test is correctly performed [12].

$$\text{Accuracy - } \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 \text{……(8)}$$

Where,

TP - Both proposed segmentation algorithm & radiologist results are positive.

TN - Both segmentation algorithm & radiologist results are negative.

FP - Proposed segmentation algorithm result is positive & radiologist results are negative.

FN - Proposed segmentation algorithm result is negative & radiologist results are positive.

3. RESULTS

3.1 Astrocytomas type of Tumor - Image Pre-Processing

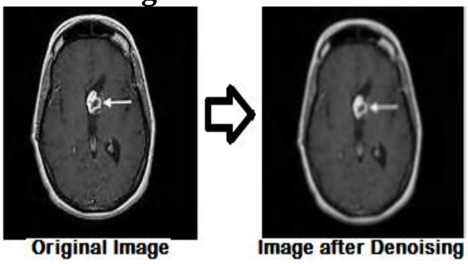

Figure 6 Image Pre-processing of Astrocytomas type of Brain tumor image

3.1.1 Histogram Enhancement -Astrocytomas type of Tumor

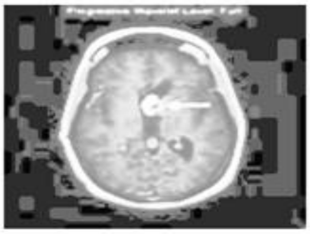

Figure 7. Image Enhancement using Histogram Equalization

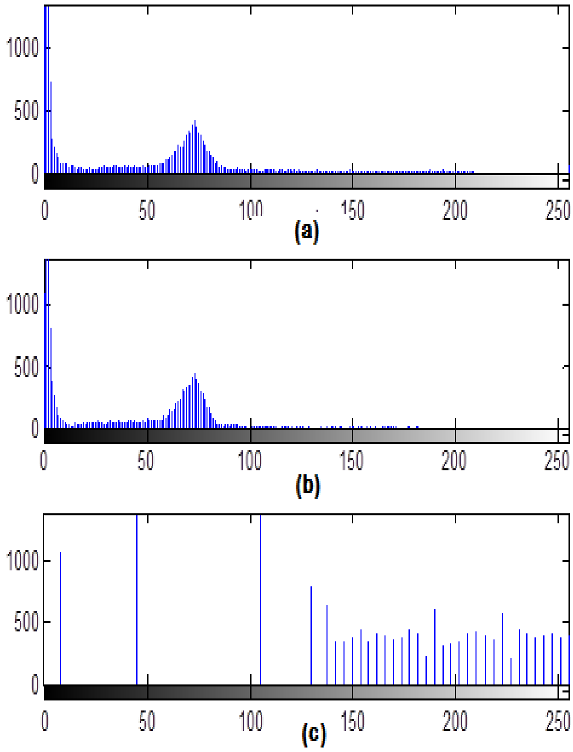

Figure 8. Histogram result:

(a) Original image

(b) Gaussian filter image

(c) Histogram equalizer image

3.1.2 Image segmentation -Astrocytoma type of tumor

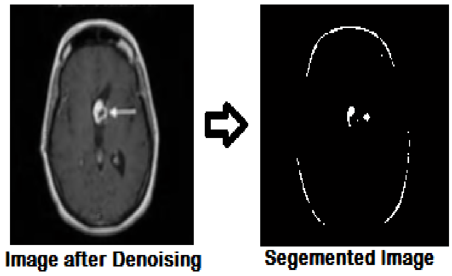

Figure 9. Image Segmentation of Astrocytomas type of Brain tumor image

3.1.3 Feature extraction-Astrocytomas type of tumor

Table 1. GLCM Extracted features

GLCM Extracted Features	Abnormal image value (Astrocytomas)	Normal image value
Entropy	0.33729	0.11612
Correlation	0.47242	0.00000
Energy	0.96758	1.00000
Homogeneity	0.99016	1.00000
Contrast	0.55086	0.00000

Extracted feature is used to train the KNN by 59 image (Abnormal) are used to train the KNN, which classify the MRI brain images into Normal & Abnormal images.

3.1.4 Classification using K-NN classifier

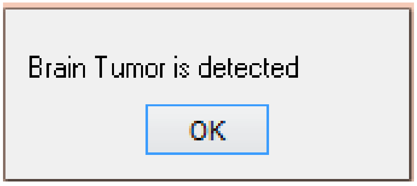

Figure10. Classification of Astrocytomas type of Brain tumor image

3.2 Normal type of Brain Image -Image Pre-Processing

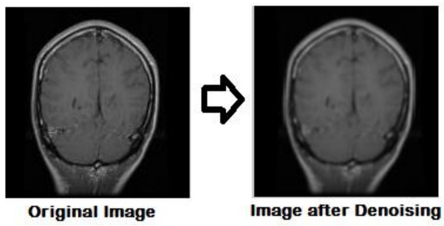

Figure 11 Image Pre-processing of Normal type of Brain image

3.2.1 Histogram enhancement - normal type of brain image

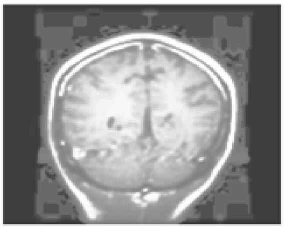

Figure 12. Image Enhancement using Histogram Equalization

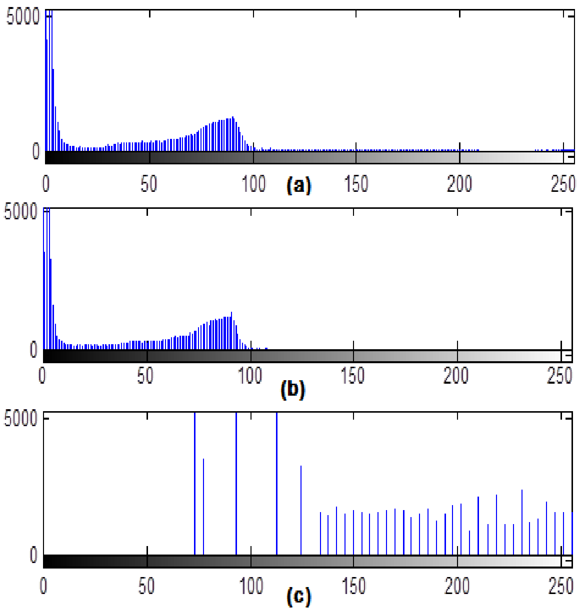

Figure 13. Histogram result :(a) Original image(b) Gaussian filter image(c) Histogram equalizer image

3.2.2 Image Segmentation - normal type of brain image

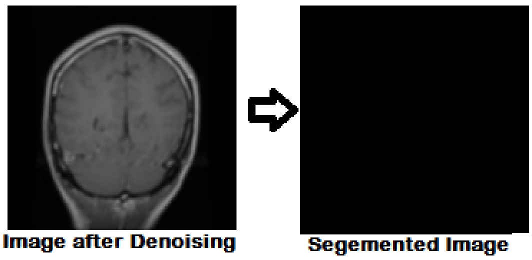

Figure 14. Image Segmentation of Normal type of Brain image

3.2.3 Classification using K-NN classifier

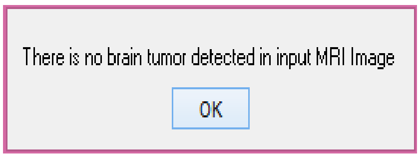

Figure15. Classification of Normal type of Brain image

3.3 Accuracy

Table 2. Comparison of accuracy with various classifiers

Sr. no.	Methods	Accuracy (%)
1	BNN (Back-propagation neural network)	76.19
2	RBFN(Radial basis function neural network)	85.71
3	DWT(Discrete wavelet transform)	89.54
4	PCA-ANN(Principal component analysis)	91.97
5	K-Nearest Neighbor (KNN) (Proposed method)	96.15

The accuracy by using K-NN classifier based on searching for the different K closest (nearest) samples. Performance & accuracy of the designed system is 96.15% found & provide precision detection of the class of the Brain Tumor.

4. CONCLUSION

MRI image is one of the best methods in brain tumor detection, by observing only MRI images the specialists are unable to keep up with diagnosing. Hence, the computer based diagnosis is necessary for the correct brain tumor classification. For such implementation, GLCM texture feature extraction method is used. The extracted features are used to recognize the class of the tumor as normal & abnormal. The overall recognition rate or classification accuracy is achieved up to 96.15% which is more than existing methods in literature survey. In future the classification accuracy can be calculated by using supervised techniques such as Support vector Machine (SVM) & unsupervised techniques such as self-organization map (SOM).

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