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A Hybrid Approach for MRI Based Statistical Feature Extraction to Detect Brain Tumor

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Abstract*—Undesired abnormal growth of cells in the brain is a serious neurological problem which is known as brain tumor. Early detection and diagnosis of tumor from an MRI image is a primary task. It is tedious and time consuming task which requires expertise of radiologists. To overcome this limitation, an automated state-of-the-art system is required which can give an estimate about whether the brain MRI image has tumor or not. The literature reveals that feature extraction is a significant step for detection of tumor. In this study, feature extraction is incorporated with significant feature identification so as to minimize the time required for processing the data and to improve the accuracy. This paper presents a technique for statistical feature extraction by hybridization of analytical and algorithmic means and Gray Level Cooccurrence Matrix (GLCM) properties. This gives a contribution in feature extraction which is fundamental for any decision algorithm to give better and accurate results. The experimental results have been evaluated for axial, coronal and sagittal views of brain MRI image. The results show that the proposed method is effective for extracting the significant features.*

Index Terms*—Brain tumor, Magnetic resonance imaging (MRI), feature extraction*

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I. Introduction

Brain tumor or intracranial neoplasm is a mass of involuntary growth of cells which grow in the brain [1]. There are two types of tumor namely benign and malignant tumor. Benign tumor is non-cancerous as it has slow growth and does not spread whereas malignant tumors are cancerous as it can spread fast to other parts of brain and central nervous system [2]. Thus malignant tumors are much more harmful. Meningioma, papilloma, lipoma, adenoma are classified under benign tumors, whereas, sarcoma, carcinoma, lungs tumor comes under malignant tumor. The lifespan of patients with benign tumor is 10 to 12 years. Patients with malignant tumor can survive not more than 14 months even if the treatment is going on. Early detection and diagnosis of brain tumor is not only important for treatment and curing but also for assessment of percentage growth of tumor and follow-ups. Surgical operations, chemotherapy, radiation therapy and so on can be used for the treatment. MRI scan, CT scan, PET scan and various other scans can be used to detect the tumor. MRI is having an additive advantage because it does not emit ionizing radiation rays. As such, no biological hazards have been reported with the use of MRI [3].

Detection of tumor from a brain MRI image is thus a very important step but is complicated because of the complexities in the MRI image arising due to the shape, size, location and distribution of tumor cells. Thus an automatic system will assist the radiologists for easy detection of tumor as well as reduce the complexities. Statistical features like mean, variance, standard deviation, correlation, contrast, energy, entropy, homogeneity etc can be used for feature extraction of brain MRI image and thus can be used to distinguish between a normal brain MRI image and a tumorous image.

Rest of the paper has been organized as follows. Section II describes the Brain tumor and MRI overview which includes types of MRI scans and brain tumor detection factors. Section III describes the process of brain tumor detection using statistical features. Section IV describes Results and Discussion, followed by Conclusion in Section V.

II. Brain Tumor and MRI Overview

A. T ypes of MRI scans

These are T1, T2, Fluid Attenuated Inversion Recovery (FLAIR), Gradient Echo Sequences (GRE), Clinically Isolated Syndrome(CSE), Gradient (allows spatial encoding of MR signal) and so on. Of these, T2 and FLAIR images can detect most of the tumor region as suggested by the doctors. Table 1 gives an overview comparison about the T1, T2 and FLAIR image.

"Time of Echo (TE) is the time between the delivery of the Radio Frequency (RF) pulse and the receipt of the echo signal". "Repetition Time (TR) is the amount of time between successive pulse sequences applied to the same slice".

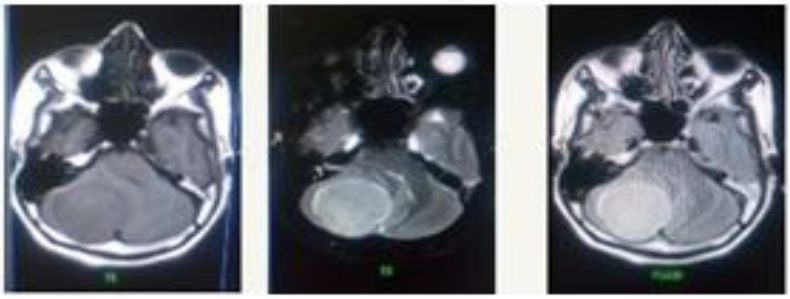

Figure 1. T1, T2 and FLAIR image sequence of brain MRI

Tissue	T1-weighted	T2-weighted	FLAIR
White matter	Light	Dark	Intermediate
Grey matter	Intermediate	Intermediate	Light
CSF	Dark	Light	Dark
Edema	Dark	Light	Light
Tumor	Dark	Light	Light

TABLE 1. COMPARISON OF MRI SCANS APPEARANCE

Third commonly used sequence is the FLAIR [4]. "The FLAIR sequence is similar to T2-weighted image except that the TE and TR times are very long." By doing so, abnormalities remain bright but normal Cerebrospinal Fluid (CSF) is attenuated and made dark. It is very sensitive to pathology and makes differentiation between CSF and abnormality easier [4].

B. Brain tumor detectionfactors

The important aspects of brain tumor detection are mass effect, signal intensity on T2-weighted images and FLAIR images, the way how it enhances i.e. homogeneous or heterogeneous, whether it is single region or multiple region and location of tumor. MRI scans can have three types of appearances i.e. hypodense, hyperdense and isodense. Hypodense has low density, hyperdense shows high density or high vascularity and isodense has a same density as that of brain. Hence this may create a confusion to detect brain tumor with accuracy. The type of enhancement tells the grade of tumor. The high grade of tumor will enhance more after contrast is given. Table 2 gives comparison of T1 weighted image with T2 weighted image.

T1-weighted images	T2-weighted images
T1-weighted images are produced by using short TE and TR times.	T2-weighted images are produced by using longer TE and TR times.
T1 is longitudinal relaxation time	T2 is transverse relaxation time.

TABLE 2. COMPARISON OF T1 AND T2 WEIGHTED IMAGE OF BRAIN MRI

III. Process of brain tumor detection

A. Image Preprocessing

Image preprocessing is a primary task of improving the quality of the MR image to make it available in a suitable form to be further provided for processing the data. In addition to this, it also helps to enhance the quality of image by removing the noise, enhancing some parameters of the image and to make it clear for the visual appearance of the MRI scan [2]. In this paper, contrast enhancement, histogram equalization, adaptive histogram equalization termed as Contrast-Limited adaptive histogram equalization (CLAHE) are the image enhancement techniques applied to improve the quality of the image.

Contrast enhancement technique uses image adjust by mapping the intensity value of the image into grayscale image. It helps to increase the contrast of the output image so that it can become clear to be viewed. Histogram Equalization (HE) is a technique which generates a gray map image by changing the histogram of an image. All the pixel values are redistributed in such a way that pixel values are made as close as possible to the desired histogram. This technique adjusts the intensity of image to enhance contrast [5]. Contrast-Limited adaptive histogram equalization (CLAHE) was initially developed for biomedical applications. CLAHE divides the input image into contextual regions of equal sized blocks. In each region histogram equalization is applied. This helps in enhancing the low contrast images and thus helps in making the hidden features more visible [5]

B. Feature extraction

The characteristic features of the image can provide a helpful hand to the detection of tumor. Feature extraction involves the process of collecting information such as shape, color, texture, gray level, contrast, etc [2]. Texture analysis gives an idea of the image . Moreover, statistical features can be employed to have an overview of the given MRI image.

C. Statistical features

The pixels or the gray level values of the image gives spatial features and can be used in bio-medical applications to study the image characteristics. Statistical features include mean, variance, standard deviation, entropy, energy, homogeneity, correlation, contrast which are briefly stated as below [1].

- Mean : Mean of an image depends upon the homogeneity of brightness of the MRI image. Mean will have high value if the image is persistently bright [6]. Mean is defined as the sum of all pixel values divided by total number of pixels. It gives the average distribution of the intensity values of an image.

  $M=(\frac{1}{mxn})\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)$

- Variance : Variance characterizes distribution of calculated gray levels. If there is difference between graylevel values of means then the variance will be increased [6]. Variance gives a measure of how each pixel differ from the mean value. It is given as the average of square of the difference between mean and individual pixel.

  $Variance = (\frac{1}{mxn})\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} (f(x,y)-M)^2$

- Standard deviation : Standard deviation defines the difference in set of data values from the mean. It can be expressed as the square root of variance. It is given as follows

  $$SD(\sigma) = \sqrt{(\frac{1}{mxn})\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}(f(x,y)-M)^2}$$

- Entropy : Entropy is used to calculate dissimilarity in MRI image or in the Region of interest (ROI) [6]. Entropy is the statistical measure of randomness that can be used to characterize texture of an image.

  $Entropy = -\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\, log2f\ (x,y)$

- Energy : Energy is a portion which claims picture similarity. It mirrors pixel pair replications [6]. Gray level is the fundamental unit of each image. Energy is given as the sum of square of all gray levels or

the pixel values.

$$Energy = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x,y)$$

- Homogeneity : Homogeneity gives a measure of value that measures the closeness o distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{x,y} \frac{P(x,y)}{1+|x-y|}$$

- Correlation : Correlation gives a value of how a pixel is correlated with its neighbouring pixel throughout the whole image.

$$Correlation = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x,y) f(x,y) - M\mathrm{x}My}{\sigma \mathrm{x} \sigma \mathrm{y}}$$

- Contrast : Contrast of an image returns the change in the measure of intensity values between a pixel and its neighbouring pixel [1]. If there are many variation in adjacent gray level alterations, it implies high level of dissimilarity [6].

$$Contrast = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x,y)^2 f(x,y)$$

Feature extraction methodologies are applied to extract the prominent features from the image that represents the different classes of objects. Feature extraction forms the input to the classifier. The objective behind feature ex traction is reducing the original data by computing certain properties or features which differentiates one input pattern from another [7].

Extracting features is not only a preliminary step for any decision algorithm, but also, identifying relevant and significant features improves the accuracy of the algorithm and thereby reduces timerequired for processing the data and hence for diagnosis too.

Mean, variance, standard deviation are intensity based features. Entropy, energy, homogeneity, correlation and contrast are texture based features [7]. Statistical features extraction is done using hybridization of analytical and algorithmic means and GLCM properties. The first order statistical features like mean, variance, standard deviation and entropy are derived using algorithmic and arithmetic means. The second order statistical features comprising of energy, homogeneity, correlation and contrast are extracted using Gray Level Co-occurence Matrix (GLCM). Gray Level Co-occurence Matrix is one of the most widely used image analysis application which can be employed to extract textural features [8]. Feature extraction from medical images can be done by following two steps using this technique. The first step gives GLCM computation. Texture features based on GLCM is calculated in second step [8]. GLCM takes gray levels as input. Hence, the given image is checked for a gray scale image. If it is not, RGB image will be converted into gray scale image to take gray levels as input. Textural findings and analysis helps in assessment and diagnosis of tumor and its stages. The steps given below describe the GLCM algorithm.

Steps to create a set of GLCM and deriving statistics from them :

1) Read the image and convert it into a grayscale image if it is not, then display it.
2) Since the image consists of varying shapes and sizes which are arranged in horizontal and vertical direction, offset of varying direction and distance needs to be defined.
3) Create the GLCMs.
4) Derive statistics from GLCMs.
5) Read energy, contrast, correlation and homogeneity as a function of offset.

Brain MRI images fed as an input can be of several data type or format such as jpeg, tiff, png and bitmap. The algorithm implemented in matlab allows to use any kind of image format, hence is an advantage which saves time to convert an image to the required data type. This has been tested with jpeg, tiff, png and bitmap type of images.

IV. Results and Discussion

The statistical features can be extracted using the above mentioned formulae and implementation is done using MAT LAB R2017a. Figure 2. is an MRI scan (T2 axial view) of brain. Tables 3, 4 and 5 give an overview comparison of the extracted features for axial, coronal and sagittal view of brain MRI respectively.

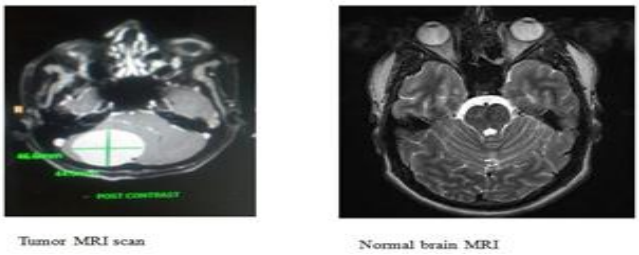

Figure 2. Tumor image and normal image (axial view)

No.	Feature	Range for Tumor (min – max)	Range for normal (min – max)
1	Mean	73.10 – 100.20	45.06 – 54.58
2	Variance	74.09 – 114.46	78.52 – 93.22
3	Standard deviation	8.60 – 10.69	8.86 – 9.65
4	Energy	0.19 – 0.14	0.21 – 0.38
5	Entropy	7.30 – 7.50	5.87 – 6.66
6	Homogeneity	0.94 – 0.88	0.47 – 0.90
7	Contrast	0.11 – 0.46	0.44 – 0.47
8	Correlation	0.98 – 0.94	0.89 – 0.93

TABLE 3. COMPARISON OF FEATURES OF TUMOR IMAGE AND NORMAL IMAGE (AXIAL VIEW)

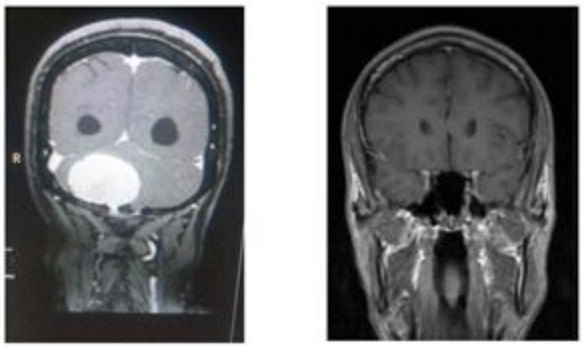

Figure 3. Tumor image and normal image (coronal view)

No .	Feature	Range for Tumor (min – max)	Range for normal (min – max)
1	Mean	99.81 – 108.80	32.27 – 63.59
2	Variance	98.92 – 117.39	105.50 – 107.22
3	Standard deviation	9.94 – 10.83	10.24 – 10.35
4	Energy	0.09 – 0.11	0.17 – 0.33
5	Entropy	7.58 – 7.63	5.28 – 6.96
6	Homogeneity	0.72 – 0.85	0.90 – 0.94
7	Contrast	0.50 – 1.74	0.11 – 0.20
8	Correlation	0.81 – 0.93	0.91 – 0.94

TABLE 4. COMPARISON OF FEATURES OF TUMOR IMAGE AND NORMAL IMAGE (CORONAL VIEW)

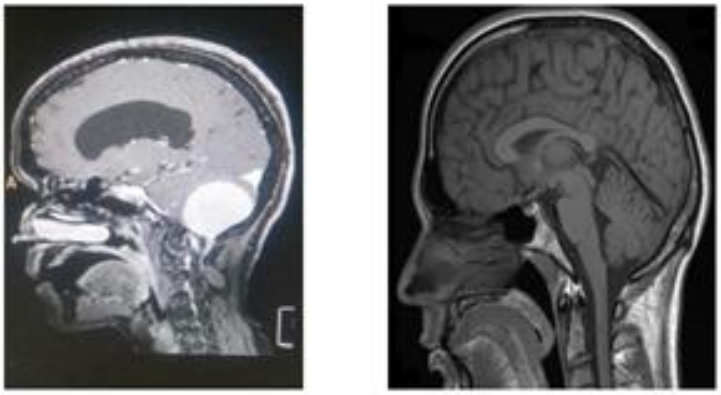

Figure 4. Tumor and normal image (sagittal view)

No .	Feature	Range for Tumor (min – max)	Range for normal (min – max)
1	Mean	99.81 – 108.80	32.27 – 63.59
2	Variance	98.92 – 117.39	105.50 – 107.22
3	Standard deviation	9.94 – 10.83	10.24 – 10.35
4	Energy	0.09 – 0.11	0.17 – 0.33
5	Entropy	7.58 – 7.63	5.28 – 6.96
6	Homogeneity	0.72 – 0.85	0.90 – 0.94
7	Contrast	0.50 – 1.74	0.11 – 0.20
8	Correlation	0.81 – 0.93	0.91 – 0.94

TABLE 5. COMPARISON OF FEATURES OF TUMOR IMAGE AND NORMAL IMAGE (SAGITTAL VIEW)

Figure 5. shows a comparison of the features mean, energy and entropy of a tumor and normal image (axial view) in the form of a bar graph. Figures 6, 7 and 8 resembles the investigation of mean, energy and entropy of a tumor and a normal brain MR image in axial view respectively.

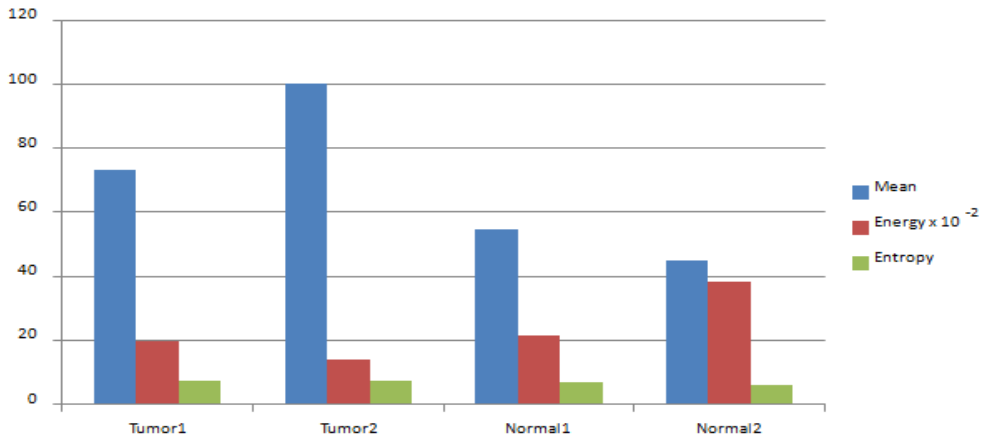

Figure 5. Comparison of features of tumor image and normal image axial view (bar graph)

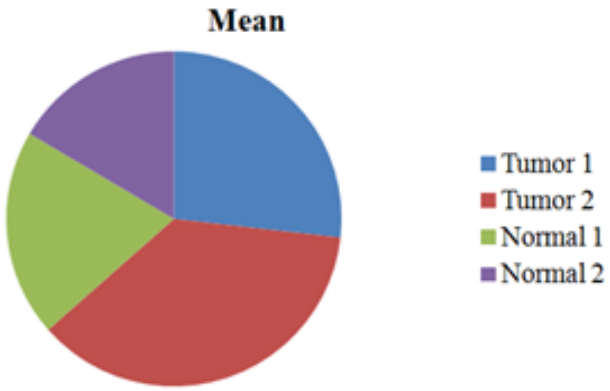

Figure 6. Comparison of mean of tumor image and normal image axial view (pie chart)

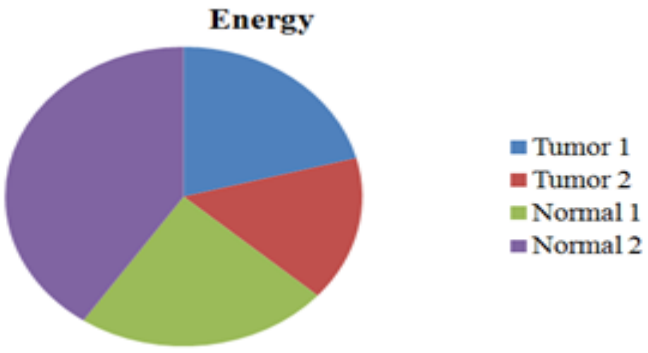

Figure 7. Comparison of energy of tumor image and normal image axial view (pie chart)

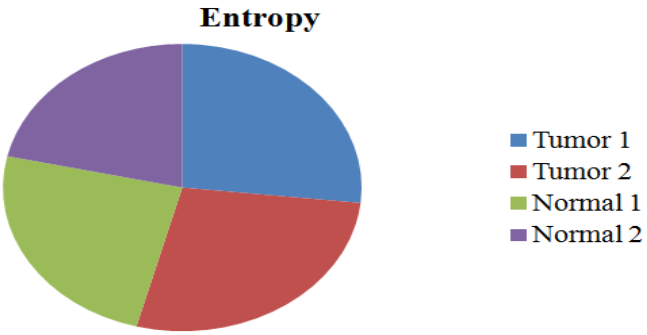

Figure 8. Comparison of entropy of tumor image and normal image axial view (pie chart)

This paper thus gives a comprehensive overview of the features for normal brain image and a tumor image for axial view, coronal view and sagittal view using T2 MRI scan images. Figure 6, 7 and 8 shows the pictorial view of mean, energy and entropy of tumor image and normal image. As seen from the bar graph in figure 5, mean of normal image varies from range 45 to 54 whereas for a tumor image, it is above 70 for axial view. Energy for tumor image is in range 0.14 to 0.2 whereas for normal image it is above 0.2. Mean for coronal view of tumor image is above 90, whereas for normal it is 32 to 63. Mean for sagittal view is above 90 for tumor image and for normal it is 32 to 63. Note that, all the tumor images taken in this study were of the case Meningioma tumor.

V. Conclusion

In this paper, we propose a hybrid technique for feature extraction by analytical and algorithmic means and GLCM properties to learn features from tumor image and normal image of brain MRI. The results have been evaluated for axial, coronal and sagittal view of brain MRI. Statistical features for considered for feature extraction which gives an investigation of a normal image and image containing tumor. Software used is MATLAB R2017a. The algorithm has been tested via extensive experiments and prove relevant for significant feature extraction.

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