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Brain Tumour Categorization with MRI Representation by Feature Extraction using GLCM and Support Vector Machine

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Abstract: *Cluster of tissue that influence the normal tissue by moderate expansion of irregular cells is known as Brain tumour. It happens when cell get anomalous development inside the brain and this remains the primary reason in increasing the fatality rate among humans. Among a wide range of cancers, brain tumour is incredibly serious and to avoid life threats of an individual, quick diagnosing and treatment must be given. Identifying these cells is a problematic issue, due to formation of tumour cells. It is exceptionally crucial to classify brain tumour from MRI image. In our proposed work, MRI images retrieved by utilizing Content based image retrieval technique are taken as input for classification. To achieve accuracy in classification and for efficient segmentation, pre-processing is carried for color conversion, noise reduction and resizing. Segmentation of tumour cells is done by Expectation and Maximization technique to know about region of affected cells present in that segmented area. This is trailed by statistical and size-based feature extraction by Gray Level Co-Occurrence Matrix from segmented images. The features extracted from segmented portion will be trained to analyze the presence of tumour in given MR images. The brain tumor classification, done in MATLAB environment allows localizing a mass of abnormal cells in a slice of MRI image using SVM Classifier, which is quickest method and furthermore give the great accuracy in classification. Experimental results accomplished accuracy of 100% in distinguishing the tissues as normal or abnormal from MR images exhibiting the viability of proposed method.*

Keywords: Expectation Maximization, Segmentation, GLCM, SVM, Statistical feature

I. INTRODUCTION

In medical field, technology innovations and techniques in image processing supports specialists to provide and look after their patients from various defections, in recent times. Among this, brain tumor is a most deadly disease that leads human life fatal. This research work concentrates on classifying brain tumor existence by using patients MRI images [1]. It solves the issues in segmenting normal and affected tissues in Magnetic Resonance Imaging by statistical and size based features are extracted using Gray Level Co-occurrence Matrix (GLCM). And at last classification of normal cell image and abnormal cell image is done by Support Vector Machine classifier [2].Irregular growth of cancerous tissues in human brain that affects the regular functioning of brain is known as brain tumor. It can be malignant or benign, in which benign has non active cancer cells and malignant has active cancer cells that remains as threat and spreads all over.

Thus, detection of affected area, identifying and classifying them in initial stage is tiresome issue in restorative science. By upgrading the techniques of image processing, it encourages the specialists to examine and analyze the presence and advancement of tumor at different stages so they can contribute reasonable analysis with these scanning images.

In our work, to identify tumor tissues from MRI image, segmentation is done and these MRI images are retrieved efficiently by Content Based Image Retrieval (CBIR) technique [3]. Segmentation is a fundamental and significant process in classifying brain tumor; it is a procedure of segmenting images into various blocks that shares identical or common properties, for example, contrast, color, brightness, gray level, boundaries and texture [4]. In brief, it can be said that segmentation is separating dead and tumor cells from unaffected tissues and here, it is done with Expectation and Maximization algorithm by Maximum Likelihood computation [5]. Before segmentation, the retrieved images are preprocessed for changing size, color conversion and to remove unwanted noise which helps for accurate classification. The significant process in detecting brain tumor and classifying them is feature extraction. Here in our research, statistical feature and size based feature is considered to maintain the efficiency of the system and to achieve 100% accuracy. Gray Level Co-Occurrence Matrix is utilized for analyzing textures that regards pixels spatial relationship [6]. Finally, classification is done using supervised learning method called Support Vector Machine classification that analyze the data and classify as normal or abnormal for the inputted MRI images [7].

Following of this research paper holds: Section 2 discusses the previous workdone by various authors to perceive the background of research, Section 3 explains the methods proposed with process involved in it, Section 4 discusses the simulation outcomes obtained and finally this paper is concluded in Section 5 and provides scope for future.

II. LITERATURE SURVEY

Processing and classifying MRI image of patients affected by brain tumor is forth coming field with many challenges. MR imaging is propelled imaging method used to create images of human parts with high quality and it is significant procedure for choosing the right treatment at right stage for tumor affected person.

Joseph et al. [8] segmented MRI images of brain by K-means clustering in parallel with morphologic filtering for tumor detection. Zanaty [9] introduced a method with hybrid type by combining FCM, Jaccard similarity coefficient and seed growing with the proportion of white and gray fragmented tissue from images. By this, 90% of avg. value of S was accomplished with 9–3% noise level. Yao et al. [10] proposed a strategy that includes texture and feature extraction with SVM and wavelet transforms with 83% of accuracy for managing and addressing protocols of various images and efficient classification that relies on different enhanced MRI images i.e., non-linearity of real data .For medical image segmentation, local fuzzy based clustering by spatial data extraction of was introduced by Cui et al. [11]. Jaccard similarity index was utilized by author as a proportion of segmentation with 83–95% accuracy and separating into gray, white and cerebro-spinal fluid.

The survey done gives a fine perspective on the techniques that were proposed distinctly for acquiring specific region by segmenting, some strategies for feature extrication and some to test and train by using SVM for just classifying. Much reasonable segmentation with blend of feature extraction can't be directed, and simply a few features were removed with low accuracy in identifying and detecting tumor. And also, the classifiers utilized for training the features were not effective.

This research deals with feature extraction from segmented image for detecting and classifying the given MRI images as normal or abnormal for large database. Our result concludes that with this proposed technique, it makes the job of clinical specialists easy for decision making regarding scanning and diagnosing.

III. PROPOSED METHOD

This section discusses the method, brain image is obtained and algorithms implemented for segmenting and feature extraction from MRI images. The proposed methodology incorporates MRI images of different pixel size for classifying. It is preprocessed into gray image for further improvement in classifying result. The further section discusses the proposed process execution.

3.1 Preprocessing

Preprocessing process is done to enhance MR images quality and modifies these images into appropriate need for further classification by imaging modalities or clinical specialists. It in like manner helps in improving MR images parameters. The inclusion of parameters are improvement in SNR, upgradation in visual view of images, clearing of unessential commotion and removing unwanted backgrounds, and edge corrections[12].

3.2 Segmentation

It is the process of partitioning images into various regions. Assume the complete image is represented as S. Segmentation divides this region S into sub regions such as S1, S2, S3, and so on. Specified conditions must be satisfied, for example, the segmentation should be unblemished i.e., every pixel should be within region and each point in the regions ought to be associated by some parameter, regions ought to be disjoint, and so on.

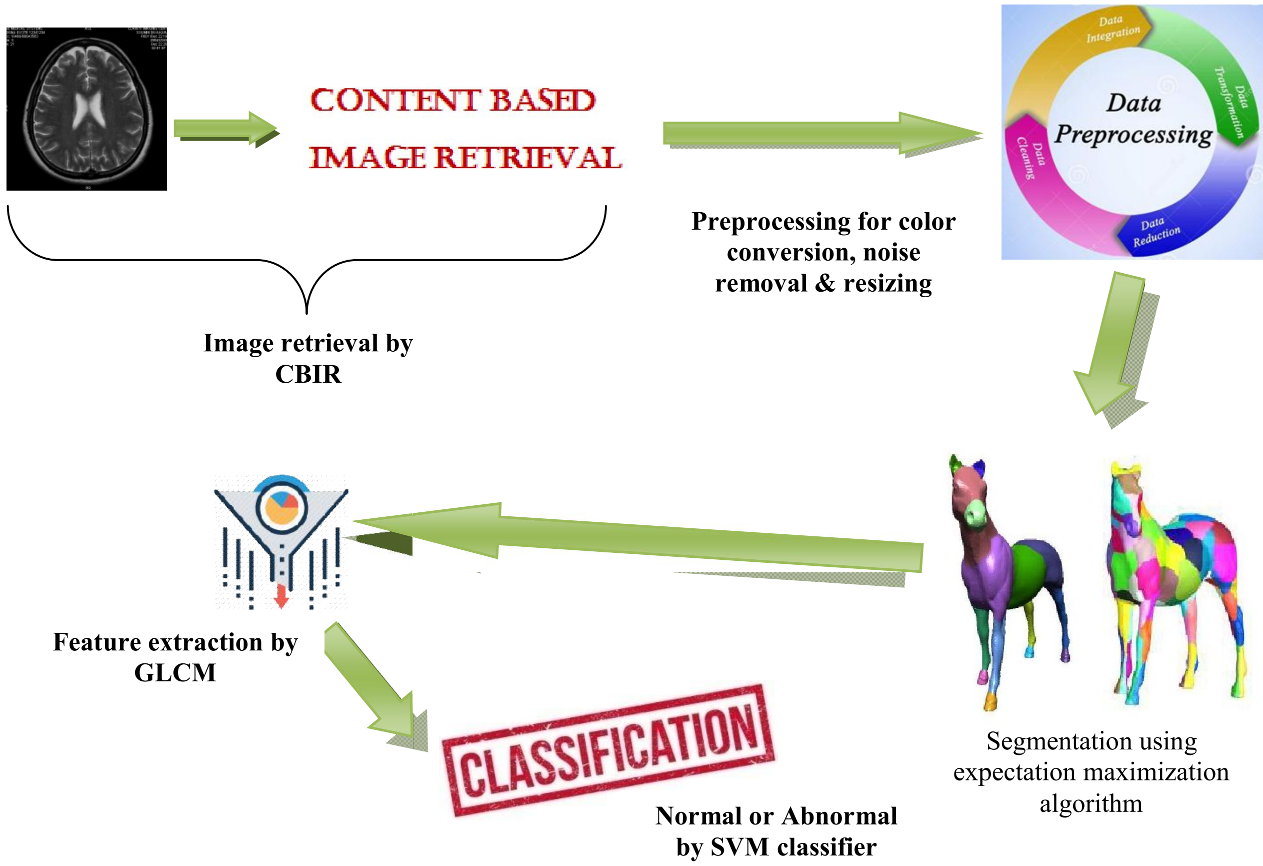

Figure 3.1 Architecture of proposed work

3.2.1 Expectation Maximization algorithm

EM algorithm is utilized to discover (nearby) maximum likelihood parameters of a factual model where the equations are unable to solve directly. Normally these models include latent factors along with known observations and unknown parameters i.e., either values missed are present in data or model can be planned simply by expecting the presence of more unobserved data. For instance, combination model can be portrayed in simple manner just by accepting that each observed data point has specific unobserved data point, or inactive variable, determining the mixture part to which every datum point belongs.

Algorithm: Expectation Maximization

- Initialize: Set i = 1 &select an initial θ_1
- While not converged do:

  Expectation step: Calculate

  $$Q(\theta, \theta_i) = E_{\theta_i}[\ln p_\theta (Z, X|X)]$$
  $$= \int \ln p_\theta(Z, X) p_{\theta_i}(Z|X) dZ$$

- Maximization step: Calculate

  $$\theta_{i+1} = \arg\max \theta \; Q(\theta, \theta_i)$$

- $i \leftarrow i + 1$

3.3 Feature Extraction

This is the procedure of extricating quantitative data from image like texture, color, contrast, and shape. Here, Gray Level Co-occurrence Matrix is implemented for extraction of both statistical and size based features from image.

3.3.1 GLCM Feature extraction

Analyzation of features helps in classifying brain images as normal or abnormal tissues effectively for machine learning and human visual discernment. It likewise gives variation among harmful and ordinary tissues which is invisible to humaneye. Accuracy is enhanced here by picking powerful quantitative features for early analysis. At initial step, the primary request statistical textural feature data's from image intensities histogram were extracted and gray level frequencies at an arbitrary image positions were estimated. Co-occurrences and correlation among pixels were not considered. In subsequent step, extraction of 2nd order textural features is done by considering gray level probability at irregular distances and over whole image directions.

Statistical features were extricated utilizing GLCM, likewise known gray level spatial dependence matrix. Haralick [12] presented GLCM, this is a methodology that portrays spatial connection among pixels of different level of gray values [13]. GLCM is 2-Dimensional histogram where $(p,q)^{th}$ components is event p frequency that exist along with q. It is distance function S = 1, angles, 0°, 45° (+ve), 90°and 135° (-ve) and grayscale p & q, and figures how frequently a pixel with force p, happens in connection with other pixel q at particular distance S and direction. In this technique, GLCM was started and textural features, for example, homogeneity, correlation, energy, variance, contrast and entropy were received from LL & HL sub bands of initial four degrees of wavelet decay [14]. Extracted features are recorded beneath:

Homogeneity is estimating image uniformity locally. It is generally called as inverse distinction moment and has single or more extensive scope of values to differentiate textured images and non-textured one.

$$HOM = \sum_{p=0}^{i-1}\sum_{q=0}^{j-1}\frac{1}{1+(p-q)^2}f(p,q)$$

Correlation is estimation of spatial features conditions among pixels.

$$COR = \frac{\sum_{p=0}^{i-1}\sum_{q=0}^{j-1}(p,q)f(p,q) - M_p M_q}{\sigma_p \sigma_q}$$

Energy determines the quantitative measure of monotonous pixel sets. It is proclivity measure of image, computed as:

$$ENG = \sqrt{\sum_{p=0}^{i-1}\sum_{q=0}^{j-1}f^2(p,q)}$$

Entropy figures the assigned textural image interference and computed as:

$$ENT = -\sum_{p=0}^{i-1}\sum_{q=0}^{j-1}f(p,q)log_2 f(p,q)$$

Contrast is the estimation of pixel intensities and measuring its neighbors and computed as:

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

To get better analysis of brain images, feature assessment parameter is also needed once the textural extraction of features is done.

Mean Square Error is estimation of image or signals fidelity. It was utilized for comparing images by giving quantitative or likeness scores.

$$MSE = \frac{1}{PXQ}\sum\sum(f(i,j) - f^R(i,j))^2$$

Peak SNR is estimated to assess the trademark features of re-built image from image processed and computed as:

$$PSNR = 20\,log_{10}\frac{2^m - 1}{MSE}$$

Low mean square error and high PSNR ratio indicate better SNR ratio.

These extricated measurable features were given as input into Support Vector Machine (SVM) classifier for training and analysing the exhibition of classifier to classify given brain image as normal and abnormal.

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3.4 Classification

3.4.1 SVM Classification

SVM classifier is a discriminative one that officially characterized by separating hyper plane. In 2D space, this hyper plane is a line separating a plane in two sections where in each class present in either side as appeared in figure beneath.There is particular cost function for this sort of model which modifies the plane until errors are limited.

Whendata is with two classes exactly, SVM is utilized. SVM describes data by finding excel hyperplane that separates data point of one class from others. The appropriate hyperplane for SVM infers the one with wide edge when looking at two classes. Slab's maximal width that is parallel to hyperplane which has no internal datapointis said as Margin. Support vectors are only data points which are closest toward isolating hyperplane which is present in slab boundary. The accompanying figure outlines these with + demonstrating type 1 data points, and – showing type – 1 data points.

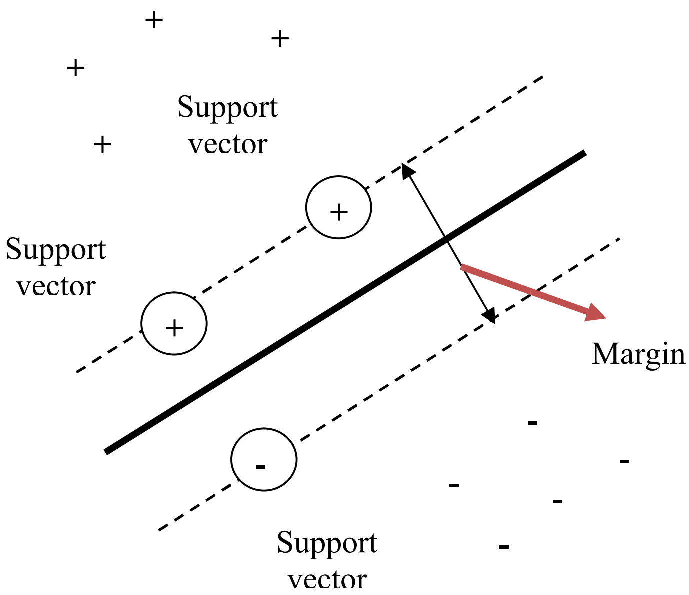

Figure 3.2: Illustration of SVM

IV. RESULTS AND DISCUSSIONS

Initially, the brain tumor images were retrieved from the total number of images by Content Based Image Retrieval technique that is fed as input for classification process. To analyze the classification performance normal and tumor image are considered here as shown below. This classification process provides 100 % accuracy that is explained in the performance analysis in next section.

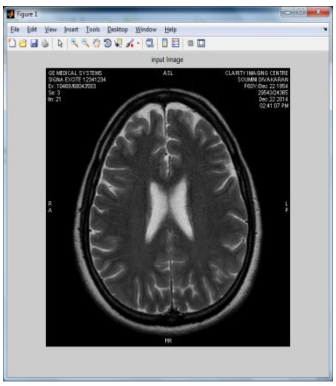

Figure 4.1: Normal brain image

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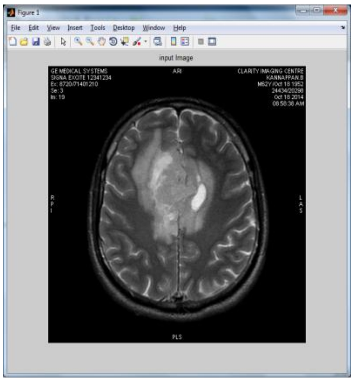

Figure 4.2: Tumor brain image

After this, image is preprocessed to remove noise, for resizing and color conversion of images as mentioned earlier.

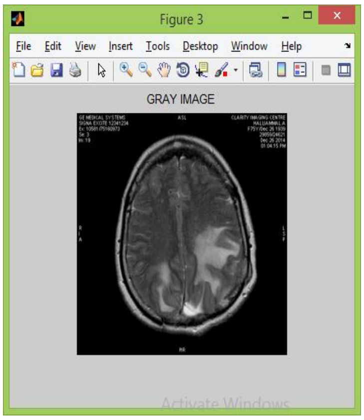

Figure 4.3: Image Preprocessing result

Segmentation result obtained by Expectation Maximization algorithm is depicted in the figure 4.4. The figure shows segmentation of normal image and tumor image.

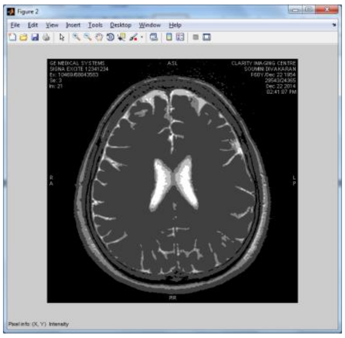

Figure 4.4: EM segmentation of normal brain image

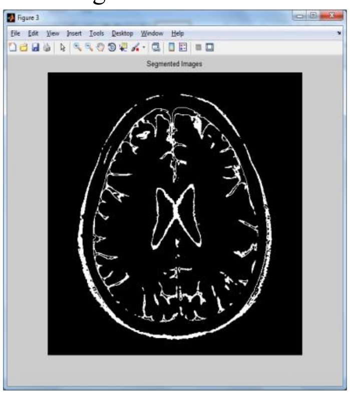

Figure 4.5: Segmented result for normal brain

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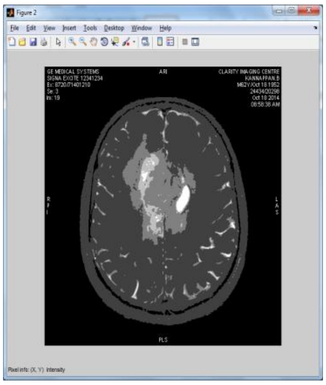

Figure 4.6: EM segmentation of tumor brain image

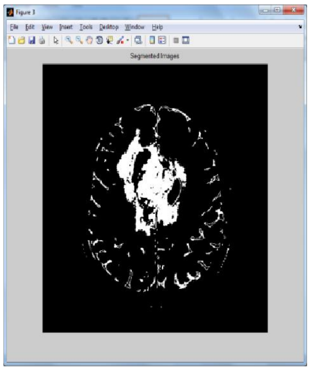

Figure 4.7: Segmented result for tumor brain

Finally after feature extraction, classification is done using SVM classification method, which gives the result as normal or abnormal as shown below.

Figure 4.8: Classification result

V. CONCLUSION AND FUTURE SCOPE

In our research work, we considered normal and tumor images for classification process. To evacuate a commotion and smoothen the picture, preprocessing is utilized which additionally brings about the enhancement in color and resizing. Next, we have segmented the images to point the defected areas accurately using expectation maximization algorithm. And after that features were extracted by considering size and statistical features utilizing gray-level co-occurrence matrix (GLCM). Support Vector Machine (SVM) is utilized for the characterization of tumors from MRI. From the results, it very well may be obviously communicated that the classification of brain tumor is quick and precise when contrasted with the manual identification by clinical specialists. Proposed technique brings about exact and quick recognition of tumor in brain by classification process. In retrieving and classifying brain tumors from MR images, accuracy of about 100% was accomplished in our work.

Future work can be done using various classifiers to enhance the accuracy by combining progressively proficient segmentation and strategies of feature extraction with clinical and real-time cases by utilizing huge dataset covering various parameters.

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