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Brain Image Tumor Detection Using Weiner Filtering and Adaptive Clustering

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ABSTRACT- Image segmentation is one of the challenging tasks to extract information in image processing. To satisfy increasing requirement of image segmentation, many segmentation approaches have been developed over couple of years. Brain tumor, which is one of the most fashioned brain illnesses, has affected and devastated many lives. Proper detection of the brain abnormality is highly essential for cure planning as a way to minimize diagnostic blunders. Therefore, it's highly necessary that segmentation of the MRI image need to be executed properly before asking the computer to do the certain diagnosis. Earlier, a variety of algorithms have been developed for segmentation of MRI images using tools and methods. However, this paper presents a segmentation methodology which is used to observe brain tumor by using adaptive clustering.

KEYWORDS: CBIR, Gabor and Shape based Features, Improving Precision Priority (IPP), Morphological-based Segmentation.

I. INTRODUCTION

Brain tumor detection and segmentation in magnetic resonance imaging (MRI) is foremost in bio medical because it presents information related to anatomical structures as good as advantage abnormal tissues essential to treatment planning and sufferer comply with-up. The segmentation of brain tumors may also be invaluable for common modeling of pathological brains and the development of pathological brain atlases. Despite numerous efforts and promising results in the medical imaging community, accurate and reproducible segmentation and characterization of abnormalities are challenging and difficult tasks because of the type of the feasible shapes, areas and image intensities of quite a lot of types of tumors. Some of them may also deform the encompassing structures or may be associated to edema or necrosis that changes the image depth around the tumor. Current approaches depart large room for accelerated automation, applicability and accuracy.

Today's modern medical imaging research faces the challenge of detecting brain tumor by Magnetic Resonance images (MRI). Normally, to provide images of soft tissue of human body, MRI images are used by professionals. It is used for analysis of human organs to replace surgery. For brain tumor detection, image segmentation is required. For this purpose, the brain is partitioned into two certain regions. That is considered to be one of the fundamental but problematic part of the process of detecting brain tumor. Thus, it's totally essential that segmentation of the MRI images need to be done effectively before asking the computer to do the exact diagnosis. Earlier, a variety of algorithms have been developed for segmentation of MRI images by using different tools and approaches.

Image segmentation may also be defined because the classification of all the image elements or pixels in an image into special clusters that show off identical aspects. Segmentation involves partitioning an image into group of pixels that are homogeneous with respect to some criterion [7]. Different groups must not intersect each and every different and adjacent must be heterogeneous. The groups are known as segments. Image segmentation is regarded as a foremost general approach for meaningful evaluation and interpretation of image acquired. It is a relevant and main component of an image analysis and pattern recognition system, and is one of the most complex tasks in image processing, which determines the quality of the final segmentation. Researchers have greatly worked over this primary problem and proposed various methods for image segmentation.

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II. RELATED WORK

Roshan G. Selka and M. N. Thakare presented an approach [1] which detects and segments the brain image using thresholding and watershed approaches. This system consists of three stages. As a first step they enhanced the input scanned image then morphological operators are applied. Finally edge operators are applied to find the tumor edges in MRI Images.

Mohammed Sabbih Hamoud Al-Tamimi and Ghazali Sulong [2] reviewed on Tumor Brain Detection through MR Images, in this paper they presented a comprehensive review of the methods and techniques used to detect brain tumor through MRI image segmentation. Lastly, the paper concluded with a concise discussion and provides a direction toward the upcoming trend of more advanced research studies on brain image segmentation and Tumor detection. Indah Soesanti et al [3] have presented a methodology for brain image segmentation based on modified fuzzy c-means (FCM) clustering algorithm.

Saeid Fazli and Parisa Nadirkhanlou proposed a novel method for automatic segmentation of brain tumors in MRI images [4]. First in the preprocessing level, the extra parts which are outside the skull and don't have any helpful information are removed and then anisotropic diffusion filter with 8-connected neighborhood is applied to the MRI images to remove noise. By applying the fast bounding box (FBB) algorithm, the tumor area is displayed on the MRI image with a bounding box and the central part is selected as sample points for training of a one class SVM classifier.

Mark Schmidt et al [5] described an algorithm for segmenting brain tumor images using Alignment-based features. This work quantitatively evaluates the performance of 4 different types of Alignment-Based (AB) features encoding spatial anatomic information for use in supervised pixel classification. This is the first work to (1) compare several types of AB features, (2) explore ways to combine different types of AB features, and (3) explore combining AB features with textural features in a learning framework. We considered situations where existing methods perform poorly, and found that combining textural and AB features allows a substantial performance increase, achieving segmentations that very closely resemble expert annotations. Hassan Khotanlou et al [6] have proposed 3D brain tumor segmentation method to segment an MRI image. This work consists of two phases such as initialization and refinement; in the first stage they segment the brain image and in second stage they apply morphological operations to segment the proper tumor part.

III. PROPOSED SYSTEM

Proposed work is divided into two categories such as training and testing. In the training phase, tumor images are pre-processed and features are extracted using Gray Level Co-occurrence Matrix. These features are stored in the knowledge base. With the same steps in the testing, query image is tested which includes pre-processing and segmentation. Adaptive clustering is used for segmentation. Features of query image will match the trained image features and detect the tumor part. The Steps used in system can be explained as given below.

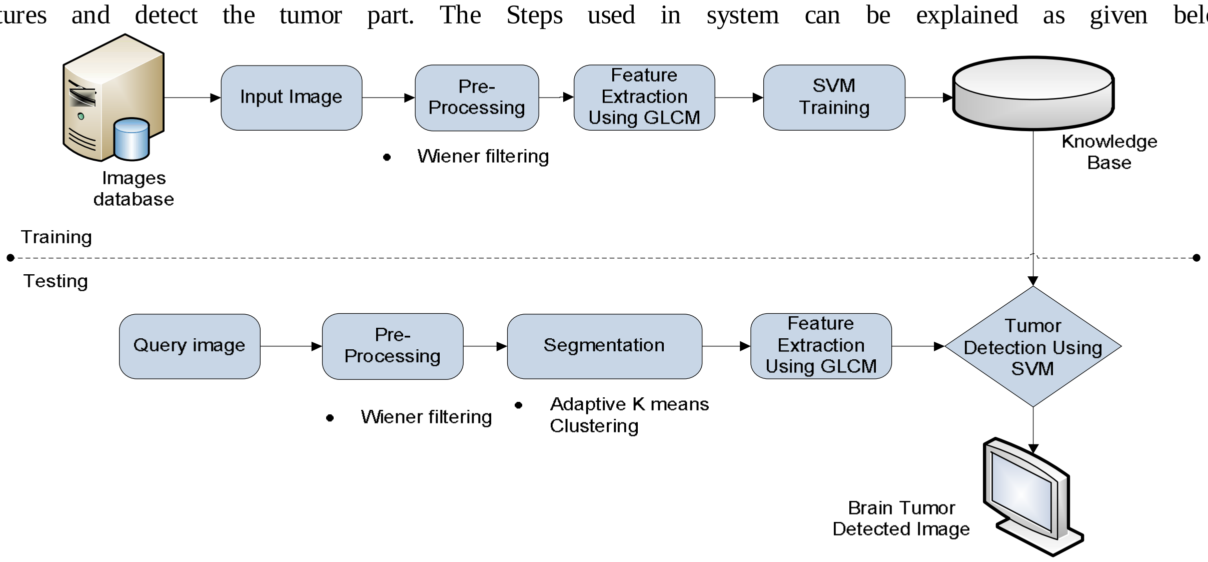

Fig. 1 Block Diagram of Proposed Work

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A. Pre-processing:

Pre-processing is a stage where the input image is read and pre-processed. Pre-processing is stage where we resize the input image, convert color of input image to gray and noise will be removed using wiener filtering. Median filtering follows common prescription. The median filter [8][9] is in general used to reduce noise in an image, reasonably like the mean filter. Nevertheless, it in most cases does a better job than the mean filter of preserving valuable detail in the image. This type of filter belongs to the class of edge retaining smoothing filters which can be non-linear filters. This means that for images $A(x)$ and $B(x)$ can be defined using eq. (1),

$$Median\,[A(x)+B(x)] \neq median\,[A(x)] + median\,[B(x)] \quad (1)$$

These filters smooth's the data while maintaining the small and sharp important points. The median is just the middle value of all the values of the pixels in the neighborhood. Notice that this is not the identical as the average (or mean); instead, the median has half the values in the neighborhood larger and half smaller. The median is an improved "central indicator" than the usual. In particular, the median is hardly ever suffering from a small quantity of discrepant values among the pixels in the neighborhood. Hence, median filtering is very strong at disposing of quite a lot of sorts of noise.

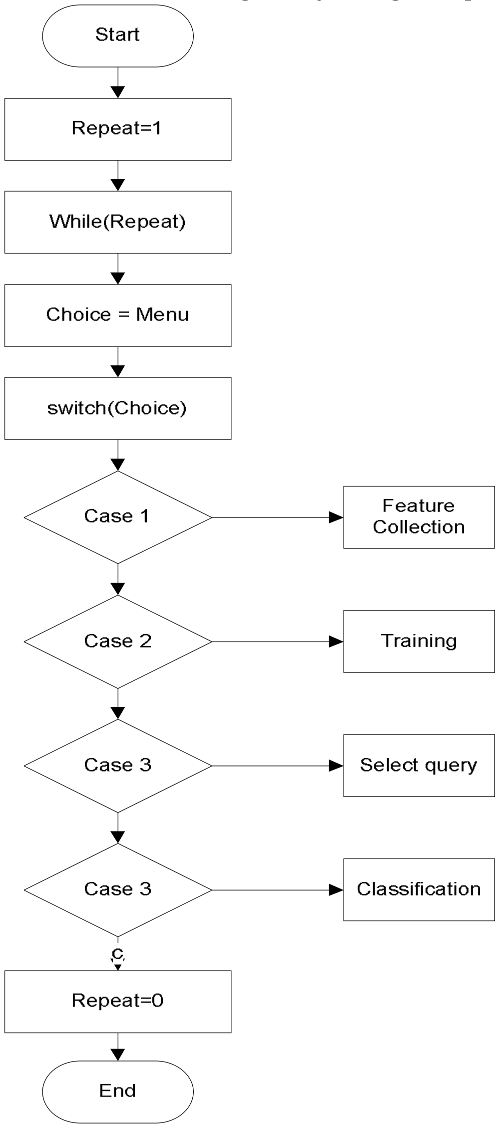

Fig 2.Flow Diagram of Proposed Work

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B. Segmentation: Adaptive Clustering

The aim of image segmentation is to cluster pixels into salient image regions, i.e. regions corresponding to individual surfaces, objects, or ordinary constituents of object, segmentation could be used for object recognition, occlusion boundary estimation inside motion or stereo methodologies and image modifying.

The work can be explained in stepwise as below,

- Either randomly or based on some heuristic, pick K cluster centers,
- Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
- Re-compute the cluster centers by averaging all of the pixels in the cluster.

Repeat last two steps until the convergence is attained.

Given a set of observations, $(X_1, X_2, \dots, X_n)$ where each observation is a d-dimensional real vector, k-means clustering aims to cluster the n observations into *k* sets $(k < n) S = \{S_1, S_2, \dots, S_n\}$, so as to minimize the within-cluster of squares, and is given by eq. (2);

$$arg_S min \sum_{i=1}^{k} \sum_{x_j \in S_i} \left\| X_j = \mu_i \right\|^2 \qquad (2)$$

Where μ_i is the mean of point in S_i.

Essentially the most common algorithm makes use of an iterative refinement procedure. Because of its ubiquity it is often known as the k-means algorithm; additionally it is referred to as Lloyd's algorithm, specifically in the computer science group. Given an initial set of k means $\mathrm{m}_1^{(1)}, \dots, \mathrm{m}_\mathrm{k}^{(1)}$, which may be precise randomly or by some heuristic, the algorithm proceeds by alternating between two steps.

Allot each observation to the cluster with the closest mean by eq. (3),

$$S_i^{(t)} = \{X_j : \left\| X_j - m_i^{(t)} \right\| \le \left\| X_j - m_{i^*}^{(t)} \right\|\} \quad for\ all\ i^* = 1, \dots, k \qquad (3)$$

Then calculate the new means to be Centroid of the observation in the cluster,

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \in S_i^{(t)}} X_j \qquad (4)$$

The histogram is summary graph showing a count of data features falling in quite a lot of stages. The effect is rough approximation of the frequency distribution of data. The group of knowledge is referred to as classes, and in context of histogram they are referred to as bins, because one can think of them as containers that accumulate data and refill at a rate equal to the frequency of that class. The shape of the histogram sometimes is particularly sensitive to the quantity of bins. If the containers are too wide, essential information would get omitted. Through reducing the number of bins and increasing the number of classes in the k-means algorithm, the detection accuracy is discovered to be increasing. Quantization in terms of colour histograms refers to the approach of reducing the quantity of bins taking colors which are very similar to every different and placing them in the same bin. By default the maximum number of bins, one may acquire using the histogram function is 256. For the motive of saving time when trying to evaluate colour histograms, we can quantize the quantity of bins. Absolutely quantization reduces the information involving the content of images however as was stated that is the trade-off when one desires to scale back processing time.s

C. Feature Extraction: GLCM

In this module, Texture feature is defined by using grey level Co-occurrence Matrix (GLCM). Grayscale image from the segmentation phase is bought from the colour image, after which the image co-occurrence matrix is generated. As already known the features are the specified characteristics of in an image or object. To extract these features, various feature extraction methods is proposed in such a way that the within-class similarity is maximized and between-type similarity is minimized. In this work, the GLCM [10] feature extraction is used. The work involves extraction of the principal features for brain tumor recognition. The features extracted offers the property of the texture, and are stored in

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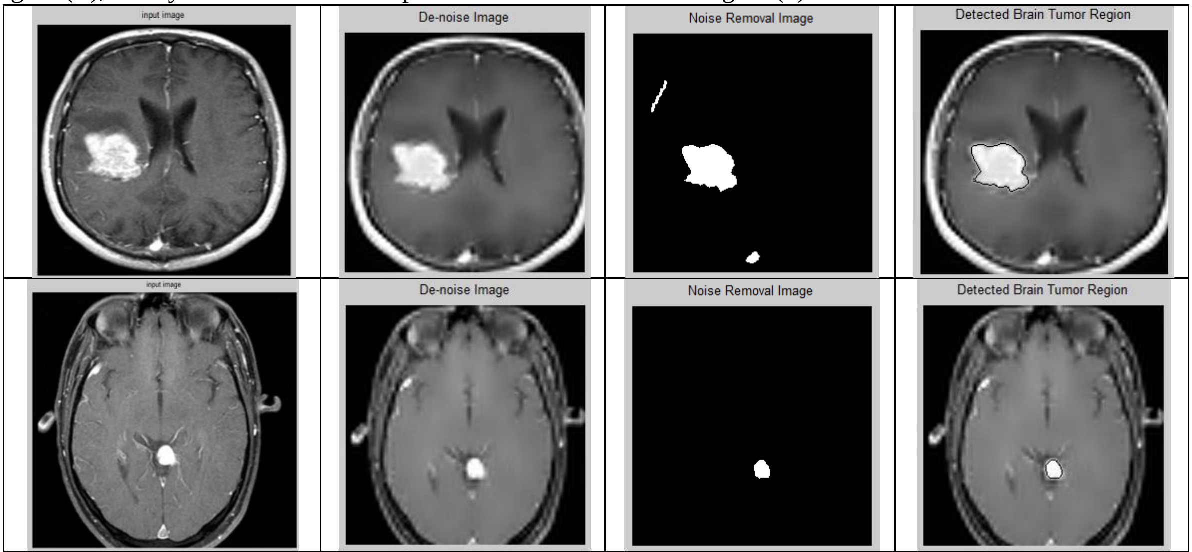
knowledge base and further compared with the features of unknown sample image for classification. Accordingly, texture elements are used to differentiate between common and irregular brain tumors. The major texture aspects are Autocorrelation, contrast, Correlation, Cluster Prominence, Cluster shade, Dissimilarity, Energy, Entropy, Homogeneity, maximum probability , Sum of squares, Sum average, Sum variance, Sum entropy, difference variance, difference entropy, information measure of correlation, Inverse difference moment.

IV. Results and Discussion

Below Figures show results of our proposed work. Figure 2 (a) is the input image and (b) is the De-noised image using Wiener DWT filter. Then we apply segmentation in order to detect the tumor part in an image, and that is shown in the figure (C), finally we detect the tumor part and that is shown in the figure (d).



(a) Input Image	(b) De-Noised Image	(c) Noise Free Image	(d) Detected Tumor

Fig.2 Outcome of Proposed System

V. Conclusion

We have proposed a novel methodology to detect the tumor part an MRI image. Advanced algorithms have been adapted to increase the detection accuracy. As an initial stage noise of an input image is removed using Weiner filtering followed by segmentation to get the tumor part. Features are extracted using GLCM.

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