Comparative study on Brain tumor detection Techniques

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***Abstract*— Brain tumor detection is an algorithm for identifying the tumor present in the Brain. Brain tumor patients often suffer from blood clot, movement control loss, vision loss, behavioral changes, hormone changes, etc.. The location, type and size of the tumor have an effect on the normal functioning of the individual. MRI images help the doctors for identifying the Brain tumor size and shape of the tumor. But, it consumes the doctor's time. In order to save the time and burden of the doctor, there is a need for the automation of the brain tumor.Here, the proposed algorithm is divided into two parts: preprocessing and segmentation. For preprocessing the Brain MRI images used local binary pattern. For segmentation of the Brain MRI images used different techniques like K-means, edge detectionand Morphological operations like erosion and dilation. Further all these techniques are combined and observed for the segmentation results. Dimensionality reduction was achieved by using K-means algorithm.**

Keywords— Morphological operations; Local binary pattern; K-means algorithm; erosion; dilation; Structure element

I. Introduction

Brain tumor is uneven or uncontrolled growth of the cells in the brain. The growth may be faster or slower based on the type and condition of the patient health. Based on the horizon of tumor, brain tumors are classified into two. Primary tumors and secondary tumors. The tumors which are originate in the brain are called primary tumors (like Glioblastoma Multiforme, Meningioma, Astrocytoma … etc) and the tumors which are spread to the brain from originating another part of the body are called as secondary tumors (like Metastatic tumors). Primary tumors are again divided into two types. They are Benign and Malignant. Benign are non cancerous tumors and they seldom grows back. Whereas, Malignant tumors are cancerous and they grow faster. Whatever the type or category of the tumor, there is a need to identify the tumorin early stages in order start the treatment and for saving the life of the patient [1,2,3].

Segmentation subdivides an image into regions based on the interest of the application. While applying segmentation, two points need to be carried. First, in analysis whether anomaly is present or not and second is to find the location where anomaly is. Most of the segmentation algorithms are categorized based on the intensity values: discontinuity and similarity. The first category deals with the intensity changes like edges in the image and the second category is the partition of the images with predefined criteria's. Examples for the second category are region growing, Thresholding, and splitting and merging. Segmentation using edge detection is an old method. Thresholding is best method for the segmentation where speed is an important factor for the applications. [3,4].

Local binary pattern, K-means clustering are well known methods. They are simple and their computational complexity is low. For bio-medical image segmentation, K-means clustering and Local Binary pattern (LBP) gives the best results. K-means clustering divides the images into different clusters. These clusters are called as features of the image. Local Binary pattern is a simple classifier and it concentration on the minor changes in the images by considering the relationship among the neighboring pixels [5,6,7].

In the Existing system for Brain tumor Segmentation several algorithms are proposed using K-means algorithm, edge detection algorithm, Thresholding algorithms…etc. Every algorithm has their advantages and limitations. By studying all these algorithms, here, in this paper, an attempt is made for the comparing all these algorithms. Illumination plays an important role for the brain MRI images. While Brain tumor segmentation due to the illumination effect, there is a possibility of wrong selection of the tumor location. As a result, the treatment for the patient is given wrong, which further slowly damage the health of the patient. For solving this, Local Binary pattern is considered. In this paper, further all these above methods with LBP are combined for obtaining the location of the tumor region,in the Brain MRI images.

This paper is divided into five sections. In Section 1introduction to the Brain tumor and segmentation was discussed. Literature work was discussed in the section 2. System modeling is mentioned in section 3. Experimental results are shown in section 4 and finally, conclusion and future scope is presented in section 5.

II. Previous Work

Brain tumor segmentation was developed by different member of researchers using various techniques like K-means clustering, water shed segmentation algorithm, global and local thresholding,…etc. Here, presented some of them.

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In usman et al., proposed a automatic brain tumor diagnostic system. They developed the system by three stages: Preprocessing for removing the noise and sharpening the brain image, threshold segmentation for segmenting the tumor and Morphological operations for removing the false segmentation locations. They mentioned that the developed technique for brain tumor detection identifies and segments the tumor accurately. In Neda et al., presented automatic method for segmentation of brain tumors in MRI. They applied preprocessing and removed the unnecessary regions like eyes and scalp in the first step. Then, they determined the primary location of the tumor. Finally, they segmented the tumor in brain images. It has given excellent correlation as R^2= 0.97 [8, 9].

Grosso et al, "developed a supervised learning algorithm with the pattern recognition method. They assessed the decision support system for diagnosis of brain cancer. This system is helpful for the early identification of the cancer and also for the classification of the disease level". Sridhar et al., "proposed a new method for the brain tumor classification using DCT and probabilistic neural network. Experimentation was done on the database having 20 brain tumor images. The developed method gives the fast and better recognition rate compared to the previous tumor detection methods [10, 11].

Angel et al., "developed a method for brain tumor detection. They developed this method using three stages. They are acquisition, preprocessing and enhancement and in the last stage feature extraction, feature selection, classification and segmentation. For segmentation they used the watershed algorithm. They found that the proposed method given the exact location of the tumor in the brain. Salai et al., presented a method for brain tumor detection using the scalp EEG and modified Wavelet-Independent Component Analysis and with multi-layer feed forward neural network. This proposed method does not have any side effects and it is having low cost for identifying the presence of the brain tumor. Based on the risks and cost of the CT scan and MRI, the presented method proved to be the best method [12, 13].

"One class support vector machine was used for the detection of brain tumor detection by Zhou et al., Proposed method deals with the learning of the nonlinear image data distribution. It performs two steps learning and segmentation. Experimentation was done by considering the 24 MR images. They found the expected accuracy rate in finding the brain tumor. A 3D Bayesian level set method and volume rendering method was used by yao et al., they probability estimation was done for this 3D segmentation. Using this segmentation, rendering and surface reconstruction, they segmented the tumor, tissue and whole brain [14, 15].

Data processing techniques and probabilistic neural network was used by mohd et al., for brain tumor classification. Feature extraction is done by Principal Component Analysis and classification is done by probabilistic neural network. This classifier gives the fast and accurate classification of the tumor in brain. Brain tumor detection is done based on the size, location and shape of the tumor. In sahar et al., they proposed the brain tumor detection classifier using the AdaBoost. The intensity, deformation, shape, symmetry and texture features are considered from each image and applied AdaBoost classifier. They found the recognition rate is 90.11%. Hongming et al., proposed an automatic brain tumor detection segmentation using the support vector machine classification of vowel-wise features. This method achieved better results [16, 17, 18].

III. MODELLING

A. Preprocessing

Local Binary pattern is a non parametric method for texture analysis, which is defined from the texture measure in a local neighborhood. Mirco patterns plays important role in the identification and detection of tumor in Brain MRI images. LBP concentrate on the micro level information in the images. It is proved computationally efficient and invariance to monotonic gray level changes for face images. For effective results, selection of LBP is the best idea for tumor segmentation [19, 20].

The basic logic behind the LBP is:

1. Consider 3x3 pixel square from the Brain MRI images. If neighboring pixel value is less than center pixel value then give the value as 0, otherwise give the value as 1. Obtain the center pixel value, by considering these binary numbers which is obtained by clockwise direction around the neighboring pixels.
2. Step 1 is repeated until reach the size of the brain image. The obtained resultant image is called as LBP image.

LBP concentrates on the local descriptors of the brain image, which are not desirable for identifying the global description of the image. For efficient results, we have combined the LBP with other segmentation techniques. So that, it balance both local and global level information in the brain images [21, 22].

B. Segmentation

Several techniques are available for segmenting the texture in images like K-means algorithm, Edge detection techniques, and Morphological operations

K-means clustering is clustering or segmenting the images into K-regions. That means it classify the data based on the features of the image. Each cluster is having the image pixels of similar measures. Initially, objects of the images are randomly distributed and divided into K groups. Centroids for these clusters calculated. Euclidian distance between the cluster center points and the individual object in the group is calculated. Finally, objects are assigned to the certain cluster based on the minimum distance. Here, centroid position was estimated by random distribution of the data in the images.

After distribution of the data to the clusters, centroid location was adjusted. This process is repeated until there is no change of the cluster points. K-means clustering is used in many applications like artificial intelligent, image processing, clustering, etc… Digital image is represented using the pixels values. Normally, images are having huge data. K-means algorithm is simple and efficient method for classifying the data for the images which are having the huge amount of data. Based on its simplicity and less computational time used the K-means algorithm for segmenting the brain tumor [7, 23, 24].

The purpose of using K-means is for Dimensionality reduction and accurate segmentation of the brain tumor. Dimensionality reduction is achieved by using K-means algorithm. Here, in K-means we are dividing the image into K regions. By which we can consider only the N/K pixels for calculation to obtain the brain tumor segmentation. Where, N is the total no of pixels in the image.

In image processing, identification of features is an important criterion's for analyzing the images. With these features structure, local changes and properties of the objects in images are estimated. For segmenting the image features, edge detection plays vital role. It identifies the local changes and boundaries of the edges in the images. Edges are identified and detected by applying filtering, enhancement, detection and localization. Filtering is used for improving the strength of the edges and for removing the noise in images. In enhancement, intensity changes are identified for local pixels using the gradient magnitude. Edge points are identified by the threshold, in detection step. Finally edge location and orientation estimated by using the localization step [4].

Generally, edge detection is done by gradient and laplacian operators. By considering the first derivative of the images, gradient is calculated and using the second derivative of the image laplacian method is derived. Many edge detection techniques are developed by several researchers by using these methods like Robert, sobel, prewitt etc... Canny edge detection is expensive compared to prewitt, sobel and Robert edge detection algorithms. For noisy conditions prewitt, Sobel and Robert are giving the better results [25].

Morphological operations are used to identify the shape, structure, edges, holes…etc. in the images. Several techniques are derived for identifying or segmenting the features in the images. Water shed segmentation, threshold segmentation, region growing and splitting etc. Dilation and erosion are two important morphological operations that are used for eliminating the irrelevant cells and for filling the gaps from the brain image. The relevant and broken segments are easily joined by this dilation. Using erosion, the interested portion of the image is displayed by using the structuring elements. With this, the unwanted portion is removed and only the tumor affected part is displayed. The equations for the dilation and erosion were shown below [4, 26, 27].

Dilation:

$$A \oplus B = \{z \mid (\hat{B}): \cap A \neq \emptyset\} \tag{1}$$

Erosion:

$$A \ominus B = \{z \mid (B^{\hat{}})_z \subseteq A\} \tag{2}$$

Where, A and B are sets in Z^2

IV. Experimental results

Brain tumor segmentation is done by using several techniques like K-means algorithm, LBP, Morphological operations and edge detection techniques. Here, a comparative study was done by applying these techniques combining and individually. Initially, the Brain MRI image is considered as input. Experimentation was done using MATLAB. Sample of brain MRI images are shown in Fig.1.

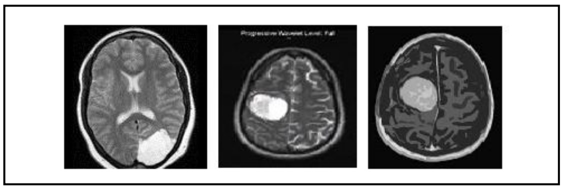

Fig.1: sample of input Brain MRI images.

Fig.2 shows the results after applying the K-means algorithm for the input brain MRI image. I have considered K=3 and divided into three clusters. In Fig.2, first image shows the original input brain image and the remaining three are three cluster images. Here, we have considered only one cluster image for the identifying the tumor in brain images which reduces the no of pixels for the calculation in next step. This has a effect on the dimensionality and takes less time for execution. Fig.3 shows the original and resultant image by applying only morphological operations. For displaying tumor part in this fig.3, we have considered the techniques erosion, dilation and structuring element.

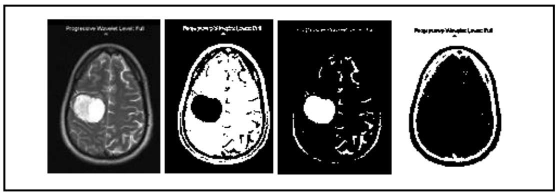

Fig.2: K-means clustering figures

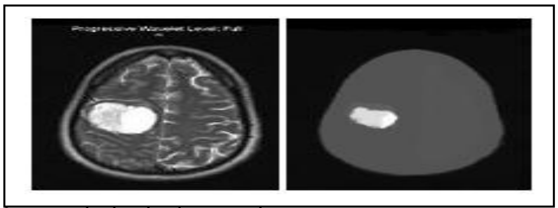

Fig.3: morphological operations

Fig.4: K-means + Morphological operations

The techniques K-means algorithm and Morphological operations discussed in section.3, i segmented the tumor. The results are shown in Fig.4. This Fig.4 shows the segmented image after applying the K-means and Morphological operations. First image is the original image. Second one is after applying K-means algorithm and finally segmented image is shown at last. Only tumor part is displayed in the last image. Fig.5 shows the results for the techniques of edge detection and morphological operations. Second image in Fig.5 is after applying the edge detection and final image is the resultant image after both operations. Here, there is no proper segmentation of the tumor. For proper segmentation we have applied first the K-means and then the edge and morphological operations. The results are shown in Fig.6. Using this logic we have properly segmented the tumor in brain MRI images.

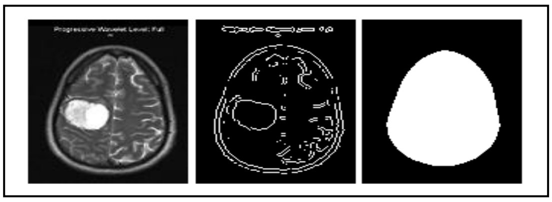

Fig.5: Using edge detection+ morphological

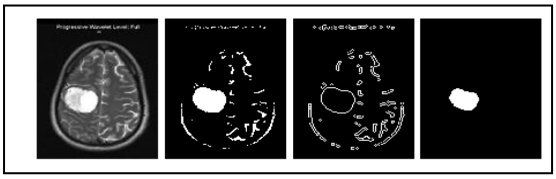

Fig.6: K-means + edge + morphological operations

LBP also plays vital role for finding the relationships between the neighboring pixels and to find the minor changes in the pixel intensities. So, for segmenting the tumor LBP and morphological operations are applied in fig. 7. Next, we experimented to apply edge, K-means and both edge and K-means for the LBP image and tried for segmenting the tumor in the Brain MRI image. But, tumor was not segmented properly. Results are shown simultaneously in Fig.8, Fig.9 and Fig.10.

Fig.7: LBP + morphological

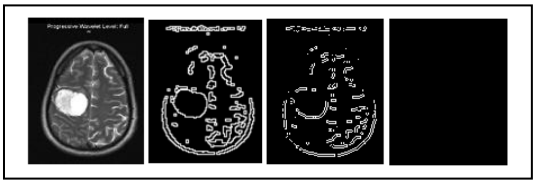

Fig.8: LBP+ edge +Mophological

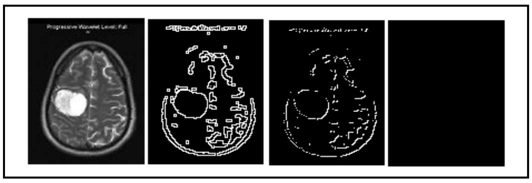

Fig.9: LBP +K-means+Mophological

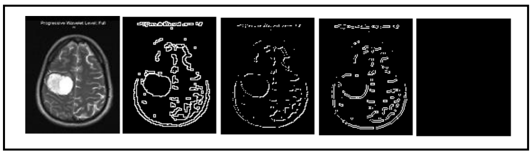

Fig.10: LBP +K-means+edge + Mophological

Here, first applied the K_means and then the LBP for segmenting the image, which properly segmented the tumor. Second image in Fig.11 shows the result after applying the K-means, third one is after applying the LBP and final image is the tumor segmented image. In Fig.12, we have shown the results of applying the techniques K-means, LBP, edge and Morphological operations simultaneously. Finally in Fig.13, we have shown the results of applying the techniques K-means, edge, LBP and Morphological operations simultaneously.

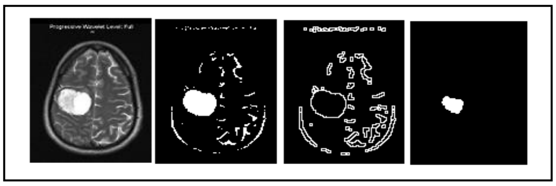

Fig.11: K-menas +LBP + Morphological

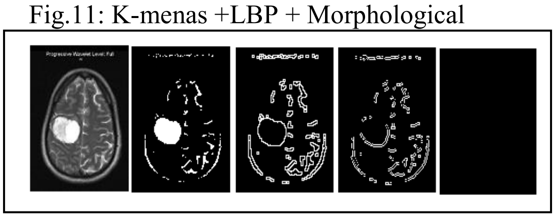

Fig.12: K-menas + LBP + edge + Mophological

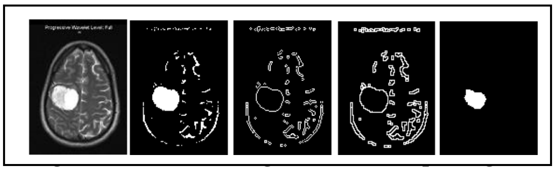

Fig.13: K-menas + edge + LBP+ Mophological

By the experimentation using different techniques, i found that using LBP and Morphological operations, K-means + Morphological operations, K-means + edge + Morphological operations, K_means + LBP + Morphological operations and K-menas + edge + LBP+ Mophological operations are segmenting the tumor exactly. Combining of these K-means, edge and LBP has an effect on the segmentation of the tumor. Here, we are concentrating on the tumor area using K-means and edge detection and minor changes of neighboring pixels are effectively considered by the LBP. Applying K-means first and then the edge or LBP was segmenting the tumor 100% accurately compared to applying first LBP and then the remaining techniques.

TABLE I. TIME MEASURE FOR VARIOUS TECHNIQUES FOR SEGMENTING THE TUMOR

Technique	***Time measure***
Morphological operations	0.296795
K-means+Morphological operations	0.404556
Using edge detection+ morphological	0.393603
K-means + edge + morphological operations	0.490635
LBP + morphological	0.302135
LBP+ edge +Mophological	0.460620
LBP +K-means+Mophological	0.451203
LBP +K-means+edge + Mophological	0.394690
K-menas +LBP + Morphological	0.443603
K-menas + LBP + edge + Mophological	0.590415
K-menas + edge + LBP+ Mophological	0.581035

Dimensionality reduction is achieved by using K-means algorithm. Here, in K-means we are dividing the image into K regions. By which we can consider only the N/K pixels for calculation to obtain the brain tumor segmentation. Where, N is the total no of pixels in the image. Here, excluded (K-1)*N/K pixels from the calculation. This reduces the time complexity and as an effect on the dimensionality.

V. CONCLUSION AND FUTURE SCOPE

Applied different techniques for segmenting the tumor in the brain MRI images and compared these techniques. For segmentation used different techniques like K-means, LBP, Morphological operations and edge detection techniques. We found that using LBP and Morphological operations, K-means + Morphological operations, K-means + edge + Morphological operations, K_means + LBP + Morphological operations and K-menas + edge + LBP+ Mophological operations are properly segmenting the tumor. Applying K-means first and then the edge or LBP was segmenting the tumor 100% accurately compared to applying first LBP and then the remaining techniques. Further this experimentation can be extended by using hierarchical clustering instead of K-means clustering for clustering the image.

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