Analytical Approach of Early Detection of Brain Tumor by Fuzzy Based Method

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***Abstract*— Early diagnosis of brain tumor is an complex task, as tumor segmentation studies focused on MRI imaging have drawn growing interest in recent years. The MRI scan can be used for identification of irregular tissue growth and obstruction of blood in the nervous system. The first step in brain tumor diagnosis is to test human brain's symmetric and asymmetric shape that will identify the abnormality. In this next phase segmentation is based on two techniques. 1) Converting the Fuzzy 2) Morphological operations. Such operations are conducted to delineate the borders of brain tumors and quantify the tumor region. The F-Transform is an insightful, competent way of managing unknown details and removing distinctive edges.**

Keywords— MRI image segmentation, brain tumor, fuzzy transform, morphological operation

I. INTRODUCTION

The most difficult and emerging field of medical image processing is. Now one of the aspects of this area is the retrieval of MRI images by a day. MRI brain tumor observable research allows for useful primary markers of disease development to be collected. Brain tumors are classified as irregular tissue growth. Brain tumors may either be primary or secondary to each other. Primary tumors consist of cells just like those which belong to the organ or tissue where they begin. Tumors can disturb any part of the brain, and can affect what areas of the brain it distresses. Brain tumors are known as Gliomas, Medulloblastoma, Ependymomas, CNS, Oligodendroglioma and Lymphoma. Gliomas are the most prevalent primary brain tumors in adults, accounting for 70 per cent of primary brain tumors in adults.

II. RELEVANCE

Brain tumors are the number one cause of deaths from childhood cancer. Early identification of Brain tumor can require life-saving intervention. Clinical and preclinical treatment and evaluation of brain cancer includes many imaging technologies, including magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT), ultrasound (US). At every age, brain tumor can affect every person, and the effect on the body may not be the same for any person. Brain tumor can affect people of all ages

III. LITERATURE REVIEW

1. Automatic Brain Tumor Segmentation and Detection from MRI.

In this paper [1] the author suggested approach for segmenting brain tumors in images of MRIs based on convolutional neural networks. The segmentation of brain tumors is performed manually for cancer diagnosis, from MRI images with large volumes of data produced in clinical procedure resulting in time process. It proposes the use of neural convolution networks (CNN) approach to segment brain tumors in MRI images. In medical imaging technique, the magnetic resonance imaging (MRI) images are used to provide detailed information about the respective image 's internal tissue.

2. MRI Brain Tumor Identification using Vector Support Machines for Cuckoo Search and Particle Swarm Optimization Based Feature SELECTION.

In this paper [2], author proposed an automated diagnostic system based on the classification of human brain images using Magnetic Resonance Imaging (MRI). Wavelet Transform is used for extraction of the functionality. Particle Swarm Optimization (PSO) is used for function discovery to decrease the scale of the applications. Author uses Cuckoo Scan and Support Vector Machine (CS-SVM) model to refine support vector machine (SVM) parameters. The classifier is generated using SVM.

3. HGG and LGG Brain Tumor diagnosis and recognition using Machine Learning.

The experimental system [3] is designed to reliably diagnose and distinguish regular and irregular brain MRIs, and then distinguish irregular MRIs into HGG or LGG glioma tumors. The machine reads the Brain MRI, and Otsu binarization is then applied to transform the signal to a binary image. Before that the clustering of k-means is implemented for segmentation. After, the implementation of DWT and PCA. SVM[4] is primarily used for grouping. Stage 1 classifies the images as normal or abnormal MRI's. Stage 2 classifies the irregular MRI images as HGG or LGG glioma tumor MRI.

4. Hybrid Identification and segmentation method using FCM-based artificial BEE colony Optimisation.
Author suggested a method in this paper [10] to recognize the tumor at a suitable level. The clarification-hence the bunching of the Fuzzy-C-Means (FCM) is integrated alongside Ant Colony Optimization, the FCM which aggregates the tumor district pixels into gatherings / groups. Arrangement is done using the form of change, in order to reduce the time measurement.

5. Usage of ANN and ANFIS for brain tumor diagnosis using texture analysis of the DWT and GLCM.
In this research author integrates numerous methodologies to build computer-aided diagnosis (CAD) algorithms for brain tumors from the axial plane. Both approaches use texture analysis by removing features from raw images, without post-processing based on various techniques, such as Gray Level Co-Occurrence Matrix (GLCM), or Discrete Wavelet Transform (DWT) based on ANN or ANFIS. All proposed methodologies, including 65 percent non-healthy MRIs, are established, validated and tested on different sub data. The cumulative sample used is comprised of 202 MRIs from non-stable patients and 18 from stable, visually segmented by qualified neurosurgeons. Our best results are to merge various subsets of features by using 4 GLCM features with one input and two hidden layers. ANN, providing 100 percent sensitivity, 77.8 percent accuracy 94.3 percent. If the ratio of healthy / unhealthy tissue MRIs is around 35 percent/65 percent respectively, the input data to train such a CAD is called unbiased.

IV. PROPOSED WORK

This thesis "Early detection of brain tumor based on F-Transform" suggests an algorithm for early detection of brain tumour. This program is an important tool for brain tumor diagnosis. The suggested method is comprised of many stages.

A.Objectives:

Objectives of proposed work are as follows:

1. This study is suggested to improve the accuracy and to reduce statistical problems in the algorithms already developed.
2. Using F-transform, the key objective is to monitor the amount of information in the edge picture and to remove noise
3. This improves machine performance.

B. Scope:

MRI-based brain tumor segmentation studies have gained more and more interest in recent years due to non-invasive imaging and strong comparison between soft tissues. It also outlines the theoretical approach to brain tumor diagnosis and retrieval from MRI scans of brain images.

C.Methodology:

For every research initiative the use of an effective, validated technique is an essential move. We'll design a simulation model to test the efficiency of the proposed work. Within the simulation model the architecture phases are as follows:
In Flow Diagram the description of the proposed program is shown.

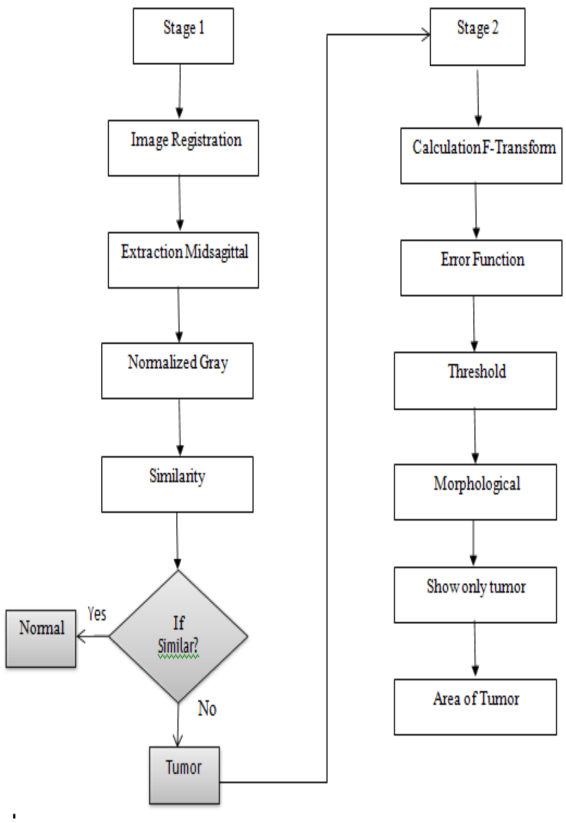


Fig.1. Flow Diagram of proposed work

For every research initiative the use of an effective, validated technique is an essential move. We'll design a simulation model to test the efficiency of the proposed work. Within the simulation model the architecture phases are as follows:

A.Stage-I

1. Image registration-To maintain the representation of the brain in the center. If not then the process of eye orientation was done in order to get brain picture in the centre.
2. Midsagittal extraction-This procedure was used to split the brain between right and left hemispheres. Via this strategy the human brain is separated into two separate sections, left and right.
3. Standardized Gray-It measures the standard gray point histograms of the left and right hemispheres.
4. Resemblance metrics – Five symmetry tests i.e. 2-D correlation, Root Mean Square Error (RMSE), Average Gradient (AV), Entropy, Variance Distance are used to quantify the similarity between two sections.

Upon evaluating these five criteria, evaluate the results according to the quantified resemblance value of each symmetry attribute as normal or with suspect tumours.

The degree of asymmetry as a sign of pathology must be closely regarded.

B.Stage-II

1. F-transform estimation — Calculate F[u] direct picture F-transform and calculate unn — reverse F-transform using F[u] elements.

2. Error Function-Calculate the Rescale error function and round the values of e.

3. Calculate the dividing intent threshold value.

4. Morphology – They have to use morphology to get tumor area after applying threshold.

5. Display just square tumor area, and delete all other components. Tumor area is measured using vertical dimension and horizontal dimension

C.Stage-III

Quality Measurement Criteria

1) Accuracy – We need to test the algorithm on at least ten images to determine accuracy and then jointly say the accuracy.
2) Precision – Same thing about precision, to measure precision, we need to analyze more than ten images.

D.Stage IV

Quality of the planned study is checked using photographs in real time.

E. MRI Brain image database (normal and abnormal)

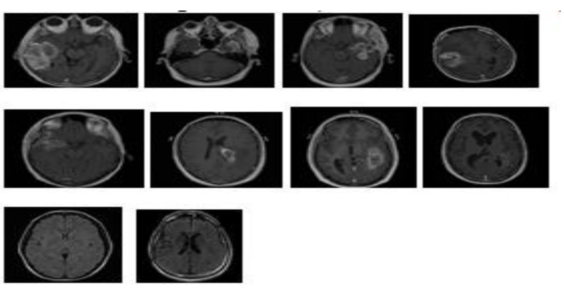


Fig.2 MRI brain image database

V. Similarity measures

By using the five tests of symmetry, i.e. Entropy, 2-D correlation, Root Mean Square Error (RMSE), Average Gradient (AV), Variance Distance is determined for the similitude between two sections.

A.Entropy

Entropy is a statistical randomness measure that may be used to characterize the input image texture.

Entropy is defined as -sum(p.*log2(p)), where p is a normalized count of histograms.

B.2-D correlation

Correlation is a tool for determining the degree of probability that there is a causal relationship between two calculated quantities. In 1895 the Pearson product-moment correlation coefficient r was defined by Karl Pearson. The correlation coefficient of Pearson, r, was the first systematic correlation measure and is commonly used in mathematical analysis, pattern recognition, and processing of images. Coefficient of correlation is defined as where, respectively, xi and yi are intensity values of ith pixels in the first and second images. The mean strength values for the 1st and 2nd image are xm and ym, respectively. If the two images are totally equal, r=0 if they are completely uncorrelated, and r= -1 if they are fully anti-correlated, the correlation coefficient shall have the value r=1.

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}} \tag{1}$$

C.Root Mean Square Error

RMSE is the standard residual deviation (pronounced errors). Residuals are a measure of how far these data points are from the regression line; RMSE is a measure of how those residuals are spread out. That is to say, it shows you how clustered the data is along the best match axis. RMSE (root mean square error):- The square root of a mean square error is known as RMSE.

$$RMSE = \sqrt{MSE} \tag{2}$$

D.Average Gradient

Average Gradient measures an image's gradient magnitude and takes into account the variation of each of its adjacent pixels. The description is the calculated gradient

$$AG = \frac{1}{(H-1)(W-1)} \sum_x \sum_y \frac{|G(x,y)|}{\sqrt{2}} \tag{3}$$

Where H X W is image size and G (.) is image gradient vector.

E.Variance distance

The variance (σ2) is a function of how different the mean is from each value in the data set. The meaning here is: Subtract the mean from each value in the results. This gives you a measure of the distance from the mean of a value. Square any of these intervals (so that all of them are positive values), and add all the squares. Divide the squares sum by the specified number of values.

$$\sigma^2 = \frac{\sum X^2}{N} - \mu^2 \tag{4}$$

μ- Mean

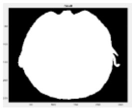
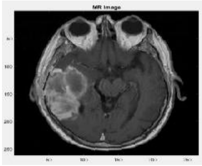
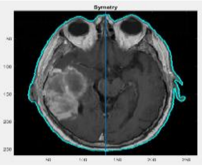
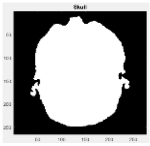
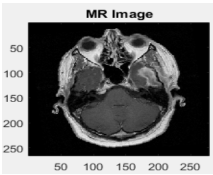
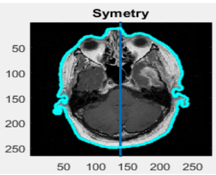
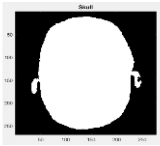
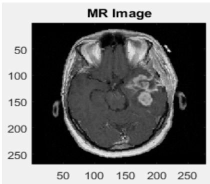
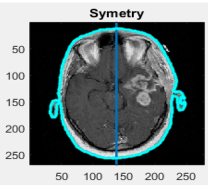
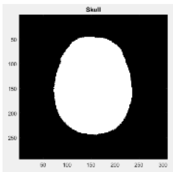
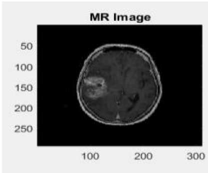
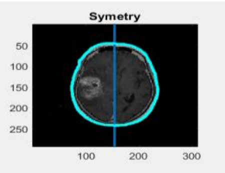
N - Number of terms in the distribution

The results will be assessed as normal or with suspected tumors after review of above five parameters.

VI. RESULT

A. Extraction of midsagittal plane

Skull identification is an effective method for brain segmentation. The skull identification consists of sequence of sequential steps including enhancement of the image to increase efficiency, elimination of context, thresholding based on histograms and morphological activity. In the human body the brain is the most complex organ and can be separated into two roughly symmetrical hemispheres using a plane. This plane is called midsagittal plane.
This divides brain into hemispheres on the left and right. By this approach the human brain is separated into two separate sections, left and right.

Skull detect	MRI IMAGE	SYMMETRY
		
		
		
		

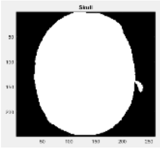
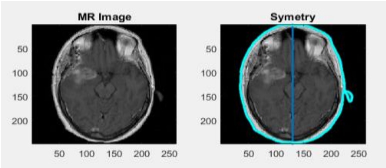
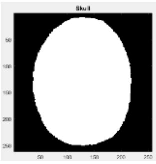
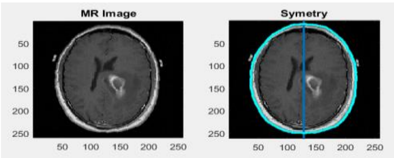
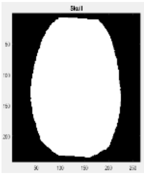
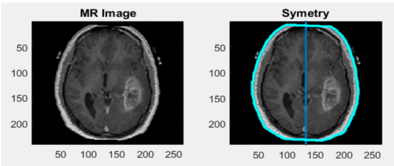
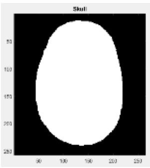
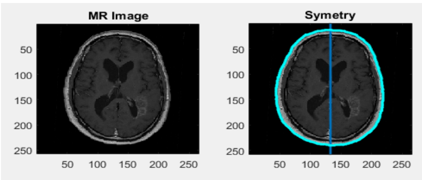
Skull detect	MRI IMAGE
	
	
	
	

Table.1 Extraction of midsagittal plane

B. Brain tumor detection

Detection as a brain tumor is the final stage of the simulation outcome as seen in table below:

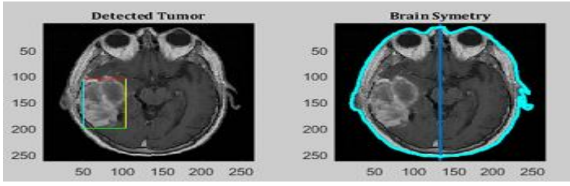
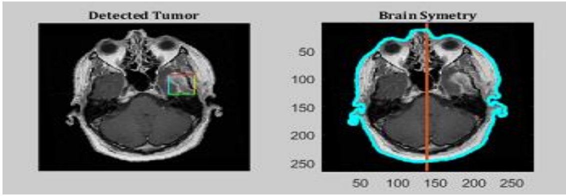
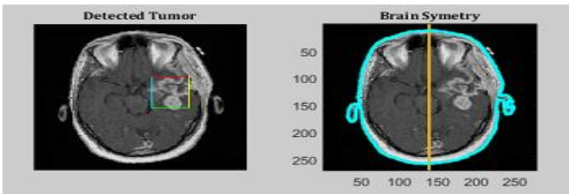
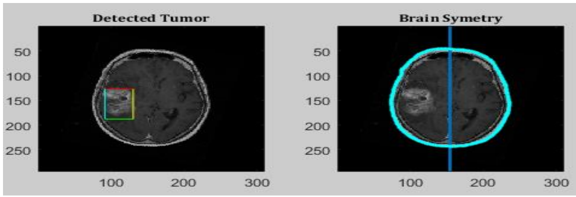
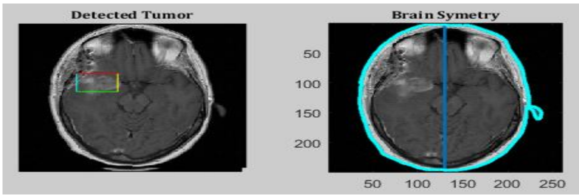
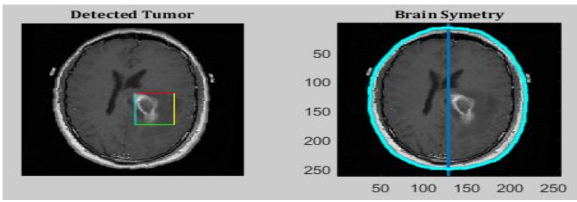
Detected Tumor	Brain Symmetry
	
	
	
	
	
	

Table.2 Detection of brain tumor

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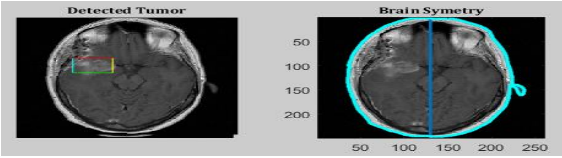
<tr><th>Detected Tumor</th><th>Brain Symmetry</th></tr>
<tr><td colspan="2">
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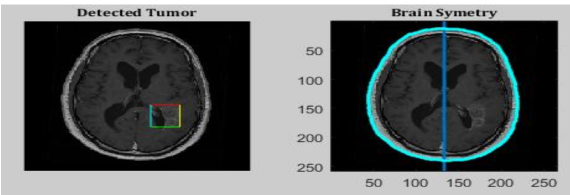
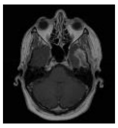
<tr><td colspan="2">
</td></tr>
</table>

IMAGE	Contrast	Correlation	Energy	Homogeneity
	7.61308	-0.03598	2.8739	0.03462
	7.41159	-0.05637	3.65102	0.03587

C. Quality parameter result

Depending on their satisfaction, the image quality evaluation (QA) was conducted subjectively using human observers. This depends on the form, scale, image spectrum, context and motivation of the viewer, and the conditions of experimentation such as illumination, show quality etc. The human visual system (HVS) is incredibly diverse with anomalies such as optical, perceptual, photochemical and electronic. A good objective measure is representative of image distortion due to insufficient blurring, vibration, compression and sensor. Objective analysis involves the use of image quality / distortion metrics to perceive the image quality automatically; the most widely used are contrast, correlation, energy, homogeneity.

D.Comparison Parameter Result

Comparative analysis plays an important role in evaluating the output of modified algorithms. We analyze the experimental findings using three numerical parameters i.e. entropy, mean gradient and variance. We equate these three dimensions with part of the brain left and part right.Table 4 shows that values for the tumor side of the brain are maximum for abnormal images and values for the non tumor side of the brain are minimal. This also indicates that the values of both pieces are relatively identical in regular images

Table.3 Quality Parameter Result

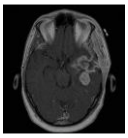
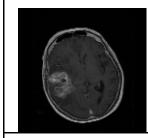
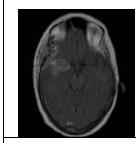
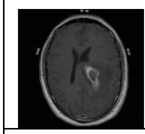
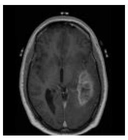
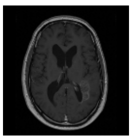
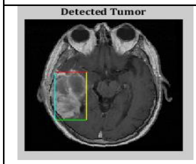
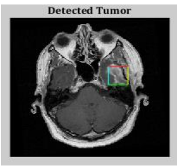
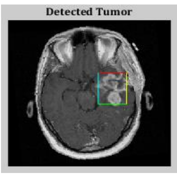
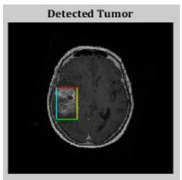
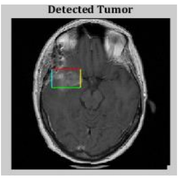
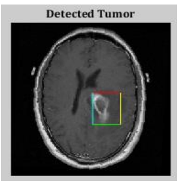
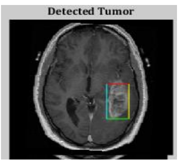
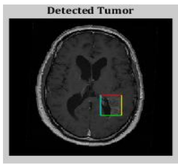
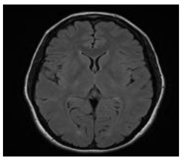
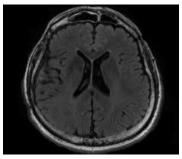
IMAGE	Contrast	Correlation	Energy	Homogeneity
	7.79567	-0.076690	3.65102	0.035878
	4.65603	0.086762	4.69908	0.045603
	7.09955	-0.01623	3.2361	0.037625
	6.41287	0.022087	3.21765	0.040631
	6.66014	0.010747	3.37539	0.040073
	6.22147	0.020588	4.09364	0.041109

Table.4 Comparison Parameter Result

Input Image	Entropy Left	Entropy Right	Average Gradient Left	Average Gradient Right	Variance Left	Variance Right
	0.353309	0.29675	37.3456	30.9868	8546.7	7965.3
	0.29	0.34350	31.3568	36.2178	6154.4	6645.3
	0.56785	0.61345	41.6754	49.5643	6754.5	7656.76
	0.857182	0.79253	25.7867	21.8753	45854	3109.3
	0.491655	0.41245	29.2627	22.2342	6003.2	4921.9
	0.308864	0.358159	27.2166	32.1371	5835.58	7458.15
	0.758933	0.81998	31.6755	38.2735	10008.5	10500.1

Input Image	Entropy Left	Entropy Right	Average Gradient Left	Average Gradient Right	Variance Left	Variance Right
	0.856164	0.896755	28.2284	34.2346	3287.3	4945.3
 (Normal Image)	0.015623	0.015656	34.0312	34.0312	4789.24	4788.34
 (Normal Image)	0.923141	0.923149	42.1487	42.1487	4595.41	4592.2

VII.CONCLUSION

This article addresses the identification of brain tumors using Fuzzy Transform dependent segmentation. The silent edges are identified by transform element F. Detection speed is enhanced with the use of brain asymmetry. The primitive techniques are based on time-consuming, manual segmentation operation. With its high speed and strong accuracy, the algorithm can be used for storing large brain images.

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