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Early Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique

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***Abstract*—One of the robust issues facing the world today is a brain tumor, out of many diseases in the medical sciences. Brain Tumor is a cellular proliferation in the brain that is uncontrolled. Early detection and diagnosis can reduce the mortality rate significantly. In this paper, a tumor detection algorithm has proposed based on support vector machine (SVM) and artificial neural network. The proposed algorithm is divided into gradient intensity smoothing based edge preservation, image enhancement, SVM based segmentation, features extraction, and classification. To measure the performances of the proposed algorithm is tested on the BRATS dataset image. Experimental result has shown that the proposed algorithm achieved 97.7% accuracy, which is better than many existing algorithms.**

Keywords—MRI, Brain Tumor, CLAHE, SVM, Tumor Classification

I. Introduction

A brain tumor is a fast developing and expanding the unwanted mass of the tissues. It develops within the brain, which is called the primary brain tumor and spread to the brain at a later stage. About 120 different types of tumors are existing as benign to cancerous. Tumors, such as extreme headache, blindness, and paralysis, cause severe health concerns [1]. Even the early diagnosis and detection of tumors help clinicians to choose the appropriate treatment. One of the most popular forms of medical imaging is magnet resonance (MRI) to detect brain abnormalities. The imagery used for the treatment of tumors in human brain tissues is not invasive to contrast the softer tissue [2]. By using the radio waves have combined with the strong magnetic field MRI generates image scans to match magnet spins in the body organ around the magnetic field. The Spin Mechanism generates a signal, the free induction decay (FID) signal that re-aligns the water content of brain tissues.

The FID is further processed in order to create a 2D image of the organ tissues. MRI systems may generate images from different parts (slices) of the brain without overlapping other anatomical structures and providing detailed information on tumors of the brain, such as their precise location, shape, and scale. This knowledge will allow physicians and surgeons to correctly identify tumors in the determination of an appropriate treatment/protocol including procedure, chemotherapy, and radiation therapy. The manual retrieval of essential clinical details from the MRI images is not a straightforward process because of the complex nature of the images. In addition, manual segmentation is a very difficult and time-consuming process because of the high number of MRI images collected in hospitals and clinics. Several automated diagnosis and detection techniques were designed to speed up and make the diagnosis trustworthy and accurate [3]. Segmentation of the brain image begins with the preprocessing of images including removal of non-brain tissue from the image through a procedure known as skull striping accompanied by the standardization of intensity and [4, 5] features of the group of pixels. Through the years numerous methods were developed for skull stripping. Hahn et al. presented a skull stripping technique based on the 3D transformation of the wetlands by means of the three-dimensional combination of white matter and a modus tube algorithm combined with pre-segmentation [6]. The literature explained various fully automated techniques of medical image segmentation involving different techniques of machine vision [7]. A wavelet decomposition technique is based upon the color wavelet covariance characteristics of second-order texture in an endoscopic video implemented in Karkanis et al [8]. Logeswari et al. [9] suggested another approach to hierarchical, self-organizing maps created by noise and artifact removal and then defining the principal structures of tissue by fugitive C-mean clustering. Sinha et al. [10] proposed a tumor detection algorithm consist of k-mean watershed segmentation clustering, optimized clustering based on k-mean with genetic algorithms, and optimized C-means with genetic algorithms. The skull stripping and Hop fuzzy combined neural networks is a technique for tumor-region detection developed in Megersa et al [11]. Berkley Wavelet Transform and supporting vector machinery are a technique pioneered by Bahadure et al. [12] and it was used to help segment the process by extracting characteristics from segmented tissues.

This paper proposed an efficient brain tumor detection method that detects and classifies the brain tumor from MRI image. The paper is organized are as follows, section I represent the brief introduction of the brain tumor detection system, the proposed methodology is described in section II, section III represents the results and discussion, finally, some concluding remarks are mention in section IV.

II. Methology

The block diagram of the proposed brain tumor detection system is shown in Fig.1. The descriptions of the proposed tumor detection system are as follows:

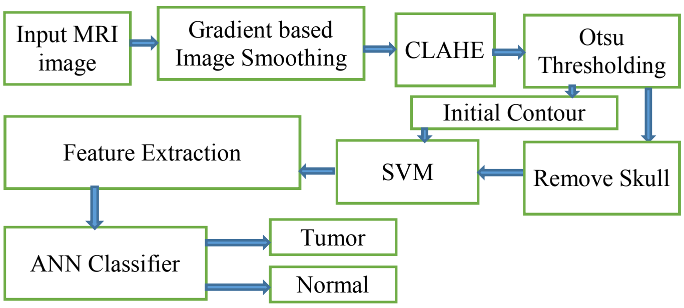

Fig. 1. *Proposed brain tumor detection system from MRI image.*

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A. Gradient Based Image Smoothing

The proposed edge preservation-based image smoothing takes the low contrast noisy image as input. Then, the second-order derivatives for each pixel are calculated by using four directions (horizontal, vertical, left, and right diagonal). Now the maximum intensity in each pixel position is measured by using the 4 different directional images. Then, the isodata [13] based thresholding method is applied to find the edge of the image. The purposes of the edge detection are to preserve in the noise removal steps. Now, a sliding window with size 32x32 is used to smooth the edge free reason. The second-order derivatives called Laplacian operators is introduced to smooth the image. The mathematical expressions of the proposed smoothing algorithm are as follows:

$$\nabla_D^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial x \partial y} + \frac{\partial^2}{\partial y \partial x} \tag{1}$$

$$\frac{\partial^2 I(\mathrm{x},\mathrm{y})}{\partial x^2} = I(\mathrm{x}_0,\mathrm{y}_0-1) + \mathrm{I}(\mathrm{x}_0,\mathrm{y}_0+1) - 2\mathrm{I}(\mathrm{x}_0,\mathrm{y}_0) \tag{2}$$

$$I_{\max}(\mathrm{x},\mathrm{y}) = \max\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial x \partial y} + \frac{\partial^2}{\partial y \partial x}\right) \tag{3}$$

$$I_{edge}(\mathrm{x},\mathrm{y}) = \begin{cases} 1, & |I_{\max}(\mathrm{x},\mathrm{y})| > T \\ 0, & Otherwise \end{cases} \tag{4}$$

This edge is preserved in the smoothing steps. However the order of the edge is depends on the threshold 'T'. The smoothing process is expressed using equation (5).

$$I_{smo}(\mathrm{x},\mathrm{y}) = I(\mathrm{x},\mathrm{y}) - \mathrm{C}(I).div(I) \tag{5}$$

Here, C(I) is the directional gradient sine function, whose value either (-) or (+). If the gradient is negative than the corresponding pixel value of C(I) is a negative sign otherwise represents a positive sign. The function div(I) represent the order of the smoothness. Its value depends on the surrounding image intensity.

$$div(I) = \left| \left(\frac{\partial^2(\mathrm{x},\mathrm{y})}{\partial x^2} - mean(window(I)) \right) \Big/ 2 \right| \tag{6}$$

B. Image Enhancement

The MRI is a low contrast image. To increase the contrast of MRI image, in the proposed algorithm using well-known contrast limited adaptive histogram equalization (CLAHE) [14]. In the CLAHE algorithm, the input image is divided into 64x64 non-overlapping block. Contrast is limited in each block to a selective level and the concatenation of each block represents the enhanced image. The mathematical expression of the following process described as:

$$\Gamma = \Gamma_{\min} - \left(\frac{1}{a}\right) * \ln\left[1 - p(f)\right] \tag{7}$$

Here *p(f)* is the cumulative probability function and followed the Rayleigh distribution.

$$CDF = p\left(f\left(x/b\right)\right) = \int_0^x \frac{x}{b^2} e^{\frac{-x^2}{2b^2}} \tag{8}$$

C. Skull Removal

The Otsu thresholding [15] is applied to the CLAHE enhanced image. The brain's tissues are surrounded by the skull, the Otsu segmentation method segment the high-intensity region from the low-intensity region. The skull is removed by applying some morphological operation; at first, detect the largest surrounding edge and the edge is expanded inward the brain tissue. Then the hole-filling algorithm is applied to it to fill the closed region. The holes filled region contains the cerebral tissue pixels and other objects such as the skull. The 'XOR' of two images represent the skull removal image.

D. Tumor Segmentation

The tumor segmentation is done using the Support Vector Machine (SVM). The object detection within the cerebral tissues in the Otsu segmentation is considered as the initial contour of the SVM. image is considered as the initial contour for the SVM. The SVM is the easiest classifier with excellent performances. In the case of linearly separable data, the classification approaches reduce the training error and find the largest margin [16]. These approaches can be expressed with a small margin which has higher expected risk. In the given learning algorithm the machine find the parameters $w=[w_1,w_2,\ldots\ldots w_n]^T$ and the decision function J(x,w,b) given as:

$$J\left(x,w,b\right) = w^T x + b = \sum_{i=1}^{n} w_i x_i + b \tag{9}$$

Here, b is the bias parameter and $x,w,\epsilon R^n$. Based on the above description, the tumor segmentation and localization problems are treated as a binary classification.

E. Feature Extraction

The image statistical information can be expressed by the image histogram. For any gray scale image I(x,y) having intensity level 0,1…,N-1, then the probability and histogram of each intensity expressed as:

$$p(\mathrm{i}) = \frac{h(\mathrm{i})}{nm} \quad for\ i = 0,1,2\ldots N-1 \tag{10}$$

$$h(\mathrm{i}) = \sum_{x=1}^{n} \sum_{y=1}^{m} \psi\left(\mathrm{I}(\mathrm{x},\mathrm{y}),\mathrm{i}\right) \tag{11}$$

Here ψ(i,j) are the Kronecker delta function that can be written as:

$$\psi(\mathrm{i},\mathrm{j}) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \tag{12}$$

To calculate the statistical parameter the mentioned parameter are used as bellows.

Mean: it represent the average intensity value.

$$\mu = \sum_{i=0}^{n-1} i.\mathrm{p}(\mathrm{i}) \tag{13}$$

Variance: it measures the variation around the mean value.

$$\sigma^2 = \sum_{i=0}^{n-1} \left(i-\mu\right)^2 p(i) \tag{14}$$

Skewness: it represents the symmetry around the mean.

$$\mu_3 = \sigma^{-3} \sum_{i=0}^{n-1} \left(i-\mu\right)^3 p(\mathrm{i}) \tag{15}$$

Kurtosis: it measure the fitness in the histogram

$$\mu_4 = \sigma^{-4} \sum_{i=0}^{n-1} \left(i-\mu\right)^4 p(\mathrm{i}) - 3 \tag{16}$$

Entropy: measure the uniformity of the histogram

$$H = \sum_{i=0}^{n-1} p(\mathrm{i}) \log_2 [p(\mathrm{i})] \tag{17}$$

Energy: represents the mean square of each pixel intensity

$$E = \sum_{i=0}^{n-1} [p(\mathrm{i})]^2 \tag{18}$$

Local Binary pattern: the local binary pattern are expressed as

$$LBP = \sum_{x,y}^{n,m} f\{I(x,y) = i\} \qquad i = 1,2,....n-1 \tag{19}$$

The above parameters are used to calculate the texture feature. The gray level co-occurrence matrix (GLCM) represents the probability distribution of each pixel. The total neighboring pixels R(d,θ) is used to divide the image matrix, which represents the joint probability $P_{d,\theta}(x,y)$ of two pixels with distance d. where d=1,2…. and $\theta=0^0$, 45^0, 90^0, 135^0. The GLCM features are as follows

Angular Second Moment (ASM): represent uniformity

$$ASM = \sum_{x=1}^{n-1} \sum_{y=1}^{m-1} [p(x,y)]^2 \tag{20}$$

$$Contrast = \sum_{\mathrm{x,y=0}}^{n-1} p_{ij} (x-y)^2 \tag{21}$$

$$Absolute \quad Value = \sum_{x=0}^{n-1} \sum_{y=0}^{m-1} |x-y| \, p(ix,y) \tag{22}$$

$$Inverse \quad Difference = \sum_{x=0}^{n-1} \sum_{y=0}^{m-1} \frac{p(x,y)}{1+(x-y)^2} \tag{23}$$

$$Entropy = -\sum_{x=0}^{n-1} \sum_{y=0}^{m-1} p(x,y) \log_2 [p(x,y)] \tag{24}$$

$$\mathrm{Homogeneity} = \sum_{x,y=0}^{n-1} \frac{p_{xy}}{1+(\mathrm{x}-y)^2} \tag{25}$$

$$Correlation = \sum_{x,y=0}^{n-1} p_{x,y} \frac{(\mathrm{x}-\mu)(\mathrm{y}-\mu)}{\sigma^2} \tag{26}$$

$$Shade = sign(\mathrm{A})|A|^{1/3}, \; A = \sum_{x,y=0}^{n-1} \frac{(\mathrm{x}+y-2\mu)^3 p_{xy}}{\sigma^3(\sqrt{2(1+C)})^3} \tag{27}$$

$$prominence = sign(\mathrm{B})|B|^{1/4}, \; B = \sum_{x,y=0}^{n-1} \frac{(\mathrm{x}+y-2\mu)^4 p_{xy}}{4\sigma^3(1+\mathrm{C})^2} \tag{28}$$

F. Tumor Classification

To classify the tumor, in this proposed algorithm the fully connected back propagation artificial neural network (ANN) is introduced. The feature vector (40 total features) is used to train and test for tumor classification. This network fits the classifier using the gradient descent algorithm. The initial weight vector is to select small random values. The weight and the bias variable is an update by calculation the cost and feed the error back into the network. This algorithm has three layers, one input, one output, and one hidden layer. In the hidden level, the tanh activation is used, while the Sigmoid feature in the output layer is used. The tanh activation function in the hidden layer makes the network nonlinear. Where the sigmoid function has linearity property. The total number of neurons in the hidden layer is 40 and the proposed algorithm use learning rate 0.001 and the gradient is set as 10^{-10} for stopping the training.

III. Result and Discussion

To examine the performance of the proposed brain tumor detection model used the BRATS dataset [17]. Which consist of 217 MRI image and all images have different modalities like FLAIR T1 and T2. Among the 217 images, 187 images contain tumor and 30 MRI images contains no tumor. The performance parameters are sensitivity, specificity and accuracy. 80 percent of image are used for training, where for validation and testing has been used the other 20 percent images.

The proposed algorithm uses 40 different types of features. The step by step outputs of the proposed tumor detection system is shown in Fig. 2. Where the first image is the input image and the last one is the possible tumor. The training, testing, and validation performances are shown in Fig.3. It is shown that the cross-entropy for the training, testing, and validation are very close, which means that the network is trained perfectly. That is the regression line well fit and has low bias and variance. The testing performance is shown in Fig 3(a), in case of BRATS image with 80% training, 10% validation and 10% testing have achieved 97.7% accuracy.

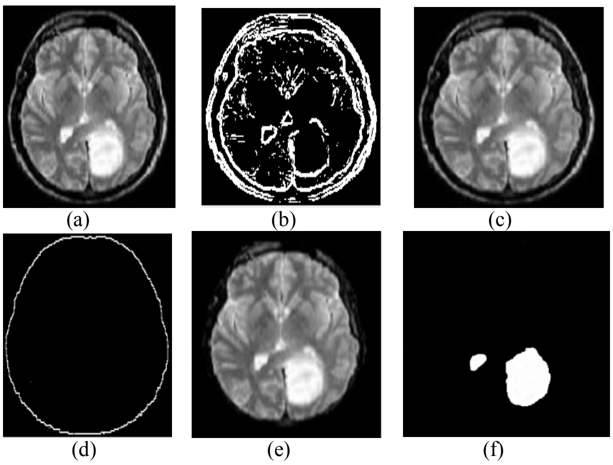

Fig. 2. Step by step output of the proposed algorithm. (a) input MRI image, (b) Edge finding using maximum gradient approaches. (c) Smoothing image, (d) largest boundary objects (skull border), (e) skull removed image, (f) segmented possible tumor region.

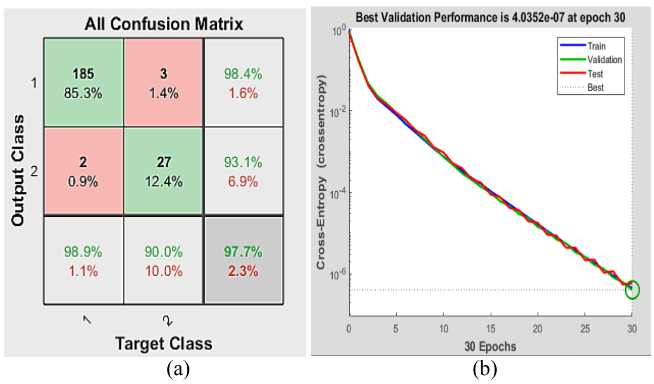

Fig. 3. (a) Confussion matricx for the proposed training algorithm, (b) Cross entropy representtion of the proposed classifier algorithm.

TABLE I. SOME EXTRACTED FEATURES FROM SEGMENTED TUMOR.

Image No.	*ASM*	*Contrast*	*Homogenity*	*Energy*	*Corellation*	*Label*
1	0.82	278.24	0.98	0.91	0.98	1
2	0,97	98.43	0.98	0.97	0.95	1
3	0.94	341.73	0.97	0.98	0.85	1
4	0.86	354.25	0.95	0.92	0.89	1
5	0.94	152.34	0.98	0.95	0.95	0

TABLE II. PERFORMENCED OF THE PROPOSED TUMOR DETECTION ALGORITHM.

no.	*Training Image*	*Testing Image*	*Validation image*	*Accuracy (%)*
1	70%	15%	15%	97.4
2	75%	15%	10%	97.3
3	80%	10%	10%	97.7

TABLE III. COMPARISON OF ACCURACY WITH THE EXISTING ALGORITHM.

References	*year*	*Accuracy (%)*
SEETHA ET AL [18]	2018	97.5
HOSSAIN ET. AL.[19]	2019	97.87
KUMAR ET. AL. [20]	2019	91.17
PROPOSED METHOD		97.7

Table 1 shows some feature of the corresponding image and the label indicate the presence of a tumor. Table 2 displays the efficiency of the proposed algorithm. Here the data are shown for three different types of evaluation. The first row indicates that the 70% image is used for training, 15% image is used for validation and the other 15% image is used for testing. The maximum performance is achieved when 80%image is trained and the other 20% image is used for validation and testing. The comparison of the proposed algorithm is compared with the existing methods. Table 3 shows comparisons with existing methods. The proposed alGORITHM HAS BEEN SHOWN TO BE 97.7% accurate, which is better than 97.5%and 91.17% [18.20] and compliable with 97.87% [17].

IV. CONCLUSION

The brain tumor is one of the deadliest diseases. Early detection and diagnosis can reduce the mortality rate significantly. The MRI image is used to analyze and detect brain tumors. Appropriate detection and classification are essential in brain tumor diagnosis. This paper proposed an algorithm that efficiently detects and classifies the brain tumor. The algorithm consists of gradient intensity-based image smoothing, image enhancement, skull removal, segmentation, feature extraction, and classification steps. The proposed algorithm is tested on the publicly available BRATS dataset. The experimental result has shown that the proposed algorithm provides better accuracy than the existing methods. If the collection of MRI image is large, then the convolutional neural network can be incorporated for better performances.

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