BRAIN TUMOR CLASSIFICATION USING BAT-ANN WITH BWT SEGMENTATION TECHNIQUE

[1]DEEPA A.R, [2]SAM EMMANUEL W.R

[1]Research Scholar, Nesamony Memorial Christian College, Affiliated to Manonmanium Sundaranar University, Abishekapatti, India.
[2]Department of Computer Science, Nesamony Memorial Christian College, Marthandam, India.

Abstract - The segmentation and classification of infected tumor area from magnetic resonance imaging (MRI) are a major concern but a tedious and time consuming task achieved by medical specialists, and their accuracy depends on their knowledge only. Consequently, the utilization of computer aided technology becomes very essential to overcome these restrictions. In this paper, to increase the performance and diminish the difficulty includes in the image segmentation method, we have considered Berkeley wavelet transformation (BWT) based tumor segmentation. Moreover, to increase the accuracy and quality rate, a Bat algorithm based Artificial Neural Network (ANN) classifier by extracting relevant features from each segmented tissue. The results of proposed technique have been assessed and validated for performance on MRI images, based on accuracy, sensitivity, specificity, and so on.

Keywords - MRI, BWT, BAT-ANN, Tumor.

I. INTRODUCTION

Nowadays the introduction of information technology in the medical area supports medical specialists to afford enhanced health care to the patient. This paper talks the difficulties of segmentation of irregular brain and regular tissues such as gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) from MRI utilizing the technique of feature extraction and artificial neural network (ANN) classifier [1].
To identify irregular tumor tissues from MRI, segmentation is applied. Segmentation is essential and significant step in image processing; which is a method of splitting an image into dissimilar Blocks or regions sharing mutual and identical properties, such as texture, color, contrast, boundaries, brightness, and gray level. Segmentation of Brain tumor includes the procedure of splitting the tumor tissues such as dead cells from regular brain tissues and tumors, such as WM, GM, and CSF [2] with the help of MRI [3–6].
In this paper, different MRI images are engaged for analysis, containing T1, T2, and FLAIR weighted MRI. The brain tumor detection at the beginning stage is a significant problem for providing better treatment. Once the tumor is clinically found, radiological assessment is essential to define its size, its location, and impact on the nearby areas. Based on this data the best therapy, radiation, surgery, or chemotherapy, is decided. It is obvious that the probabilities of existence of a tumor affected patient can be improved considerably if the tumor is spotted precisely in beginning stage which results the study of brain tumors using imaging modalities has gained importance in the radiology department [7].

II. BRAIN TUMOR SEGMENTATION AND CLASSIFICATION BY BWT AND BAT-ANN

In this paper, we present a robust segmentation of brain MRI using Berkeley wavelet transformation (BWT) and in order to improve the classification accuracy we use Bat algorithm based Artificial Neural Network (ANN). Our proposed method consists of following stages. Initially, preprocessing of brain MRI is done to improve the quality of image. Then segmentation is done in preprocessed image using BWT method. Secondly, six type of features such as mean, correlation, standard deviation, energy, entropy, and homogeneity are extracted. Finally the features are used to determine the tumor cell by utilizing Bat-ANN classifier. Thus, the proposed methodology can extract brain tissues with a higher accuracy and robustness when compared to other methods. The proposed method will be implemented on Matlab working platform and Brain MRI database used for proposed method will be taken form the "The Cancer Imaging Archive (TCIA)" provided by the Frederick National Laboratory and the experimental results are evaluated.

2.1 Image Preprocessing

In order to improve the quality of images and to make sure that it is in form appropriate for further processing by machine or human, preprocessing is done. Also, it improves certain parameters like visual appearance, signal to noise ratio, removes irrelevant noises and undesired parts in background. In this paper, we apply applied adaptive contrast improvement based on modified sigmoid function [8].

2.2 Image Segmentation

In this paper, we use Berkeley wavelet transformation (BWT) based tumor segmentation. The segmentation of brain MRI is achieved by the following steps.

1. Initially the preprocessed images is transformed into binary image with a threshold value if 128. The values if pixels which are smaller than threshold are mapped to black, and others are

marked as white. By doing this two different types of regions are generated in the preprocessed images which is cropped out.
2. Secondly, a morphology based erosion operation is applied to remove the white pixel.
3. Lastly, the original image and eroded region are separated into equal regions and black pixels are mined from erode operation is counted as brain image mask.
4. In this paper, for effective brain image segmentation we apply Berkeley wavelet transformation [9].

The wavelet transformation method is engaged to develop operators, functions, data, or information into components of dissimilar frequency, which allows analyzing each component independently. Generally, all wavelets are developed from basic wavelet ψ(t) which is also called as mother wavelet. By using translation and scaling process given by equation 1.

$$\Psi_{s,\tau} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

wheres demotes scale factor and τ denotes translation factor. Similar to the mother wavelet transformation or other groups of wavelet transformation, the Berkeley wavelet transformation will also perform data exchange from a spatial into temporal domain frequency. The Berkeley wavelet transformation presents an active way of illustration of transformation of image which is a complete orthonormal. The mother wavelet transformation α_θ^φ is constant piecewise function. The substitute wavelets from mother wavelet α_θ^φ are formed at several pixels locations in the two-dimensional plane through translation and scaling of the mother wavelet and it is given in equation 2.

$$\alpha_\theta^\varphi = \frac{1}{s^2}\alpha_x^\varphi\left(3^s(x-i), 3^s(y-j)\right) \quad (2)$$

The single constant term is enough to signify the mean value; the coefficient value of the single term is given by

$$\alpha_0 = \frac{1}{\sqrt{9}}\left[u\left(\frac{x}{3},\frac{y}{3}\right)\right] \quad (3)$$

The morphological operation is utilized for the boundary areas extraction of the brain images. Theoretically, this rearrange the relative order of pixel, not on their mathematical values, hence it is appropriate for only binary images. Dilation and erosion are the two most basic operations of morphology in which performs operation of addition and removing pixels to or from boundary region of the objects which is based on the structuring element of the selected image. Then from the segmented image six different types of features are extracted such as mean, correlation, standard deviation, energy, entropy, and homogeneity are extracted and given to classification.

2.3 Classification using Bat based ANN

A classification method uses ANN for classifying the reviews and opinions. Neural network is a three-layer standard classifier with n input nodes, l hidden nodes and k output nodes. We examined that if two hidden layers are used then a hidden layer is to associate every pair in an important unit and second is regarded to the real hidden layer after classifying the input data in the first hidden layer. For the proposed work, the input layers are the features, HU_a Hidden Units and an output unit, f.

2.3.1. NN Function Steps

1. Set weights for every neuron's except the neurons in the input layer.

2. Generate the neural network with the extracted features $\{A_1, A_2, A_3, A_4, \ldots\ldots\ldots, A_i\}$ as the input units, H Hidden units and f as the output unit.

3. The input layer of the proposed Bias function and output layer of the activation function is calculated as,

$$X = \sum_{n'=0}^{NF-1} w_{1(n')} A_1(n') + w_{2(n')} A_2(n') + w_{3(n')} A_3(n') + \ldots + w_{7(i')} A_7(i') \quad (4)$$

$$Active\,(X) = \frac{1}{1+e^{-X}} \quad (5)$$

4. Identify the learning error as given below

$$E = \frac{1}{NF}\sum_{n'=0}^{NF-1} Y_{n'} - Z_{n'} \quad (6)$$

Where, E - learning rate of FFBNN, $Y_{n'}$ - Desired outputs, $Z_{n'}$ - Actual outputs, NF - Number.

Back Propagation Algorithm in the Feed Forward Neural Network used as the Learning Algorithm and this algorithm is a supervised learning technique and moreover, it is an overview of delta rule. It wants a dataset of the required output to produce the training set for various inputs and basically, Back Propagation Algorithm is helpful for Feed-Forward Networks and these learning algorithm needs that the activation function used by the neurons be differentiable. In the process the weights for the neurons of hidden layer and the output layer were assigned using Bat. The Proposed Bias function and the activation function are calculated using Equation (4) and (5) for the ANN.

2.3.2 Weight Optimization Using Bat Algorithm

The original bat algorithm was introduced by [11]. The advantage of the bat algorithm lies in the combination of a population-based algorithm and local search which is one step toward balancing exploration and exploitation. The steps in involved are given below

Step 1. Bat Population

The initialization of Bat population is done randomly. For each solution the pulse frequency (p) is defined as,

$$P_i = P_{\min} + (P_{\max} - P_{\min})\beta \quad (7)$$

Where 'β' has the random value in the range of [0, 1]. Initial pulse rates Riand loudness Li are also defined.

Step 2. Velocities, positions and solutions

A new solution is produced by adjusting the frequencies. The velocities and the positions are updated as

$$v_i^{\,t} = v_i^{\,t-1} + (x_i^{\,t-1} - x^*)P_i \quad (8)$$

$$x_i^t = x_i^{t-1} + v_i^{\,t} \quad (9)$$

Where x* = the current global best solution at iteration time t. The updation of velocities and positions is required for the next iteration.

Step 3. Local search

A random number has been generated and compared with the pulse rate in that iteration. A best solution is chosen among the solutions randomly. Now a local search is carried out around the solutions. Here € is selected in random manner from [-1, 1] and Lt is the avr_loudness of all the bats in the present iteration.

$$x_{new} = x_{old} + \in L^t \quad (10)$$

Step 4. Comparison of the pulse rate and loudness

A comparison between loudness, the generated random value and the fitness is carried out. Accordingly the best solutions were accepted for the nest iteration. The pulse rate and loudness of the bats have been adjusted as follows.

$$L_i^{t+1} = \alpha\, L_i^t \quad (11)$$

$$R^{t+1} = R_i^o\,\left[1 - \exp(-\gamma t)\right] \quad (12)$$

'α' and 'γ' are constant with the numerical value equals to 0.9 for the presented work.

Step 5. Ranking of bats according to the Best Solution

The process is repeated until the BP error gets minimized. i.e. If the minimum value is obtained, then the FFBNN is well trained for performing the testing phase. Accordingly, ANN classifier is well trained and the features are tested. In the testing phase, a query image is given by performing all the initial process mentioned and the tumor image associate to the query image are classified.

III. EXPERIMENTAL RESULTS & DISCUSSIONS

The proposed system for the segmentation of images is implemented in the working platform of MATLAB with the following system configuration. This method is implemented in MATLAB R2013a using Intel i5 environments under a Personal Computer with 2.99 GHz CPU, 8GB Ram with Windows 8 system. In this proposed methodology we have used Brain MRI database used for proposed method will be taken form the "The Cancer Imaging Archive (TCIA)" provided by the Frederick National Laboratory and the experimental results are given below.

3.1. Segmentation Results

A healthy brain matter can be classified into three tissues, white matter (WM), cerebrospinal fluid (CSF) and gray matter (GM). The parameters of the algorithm, namely the values of m, the number of clusters c, and finally the vectors form representing the image pixels are defined. The number of clusters is set to 4: cerebrospinal fluid, white matter, gray matter and tumor region. In our proposed method initially we have considered two types of images one without tumor and other one is with tumors region which is shown in figure 1.

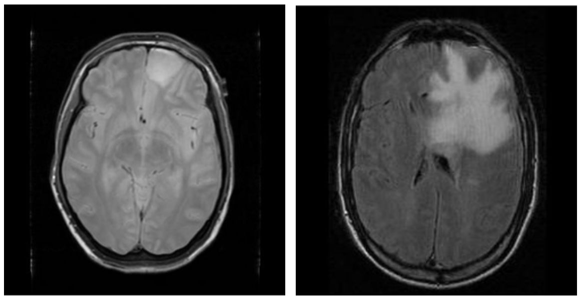
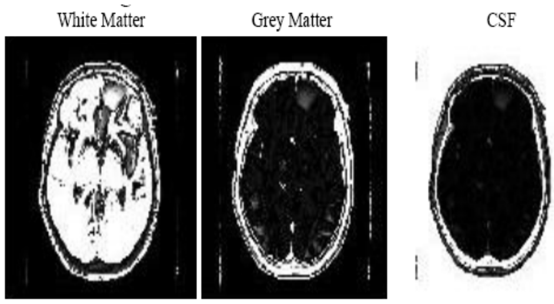
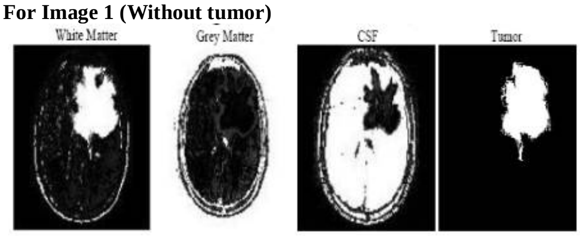


Figure 1: Input Image

The results obtained from the segmented method is shown in figure 2.



For Image 1 (Without tumor)



For Image 2 (With tumor)

Figure 2: Segmented Results

3.2Classification Results

The performance of the proposed method is evaluated based on results obtained from the classification. All classification result have error rate and on event which either fail to identify the tumor or identify the tumor which is not present. So, this can be described based on true and false positive and true and false negative. If the classification result is positive in the presence of tumor then it is True Positive (TP). In True Negative (TN), the classification result is negative in the absence of tumor region. In False Positive (FP), the classification result is positive in the absence of tumor and finally in False Negative (FN), the classification result is negative in the presence of tumor. The parameters used for analysis of classification are sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False positive rate (FPR), False Discovery Rate (FDR), and accuracy. Table 1 represents the statistical measures of the proposed system for the given brain MRI images datasets.

S. No	Measures	Result
1	Sensitivity	96%
2	Specificity	100%
3	PPV	100%
4	NPV	90%
5	FPR	0%
6	FDR	8.2%
7	Accuracy	99.09%

Table 1: Statistical measures of the proposed system

Sensitivity value represents the percentage of recognition of actual value and Specificity value represents the percentage of recognition of actual negatives. Accuracy is the degree of closeness of measurements of a quantity to its actual (true) value. From the table 1 we can see that our proposed method has obtained better results which shows this is a promising method in the medical field for the identification of brain tumor.

CONCLUSIONS

The proposed Bat-ANN classification system with the efficient segmentation technique classifies the normal and abnormal MRI brain. It is implemented in MATLAB R2013a. The performance of the classifier system in terms of statistical measures such as sensitivity, specificity and classification accuracy is analyzed. The results indicated that the proposed system yielded superior performance also it further suggests that the proposed classifier is a promising technique for image classification in a medical imaging application and it can be used in computer aided intelligent health care systems. This automated analysis system could be further used for the classification of images with different pathological condition, types and disease status.

REFERENCES

[1] Amato, Filippo, Alberto López, EladiaMaría Peña-Méndez, Petr Vaňhara, AlešHampl, and Josef Havel, "Artificial neural networks in medical diagnosis", pp.47-58, 2013.

[2] Demirhan, M. Toru, and I. Guler, “Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks,” IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1451–1458, 2015.

[3] Madhukumar and N. Santhiyakumari, “Evaluation of kMeans and fuzzy C-means segmentation on MR images of brain,” Egyptian Journal of Radiology and Nuclear Medicine, vol. 46, no. 2, pp. 475–479, 2015.

[4] Y. Kong, Y. Deng, and Q. Dai, “Discriminative clustering and feature selection for brain MRI segmentation,” IEEE Signal Processing Letters, vol. 22, no. 5, pp. 573–577, 2015.

[5] M. T. El-Melegy and H. M. Mokhtar, “Tumor segmentation in brain MRI using a fuzzy approach with class center priors,” EURASIP Journal on Image and Video Processing, vol. 2014, article no. 21, 2014.

[6] G. Coatrieux, H. Huang, H. Shu, L. Luo, and C. Roux, “A watermarking-based medical image integrity control system and an image moment signature for tampering characterization,” IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 6, pp. 1057–1067, 2013.

[7] S. Lal and M. Chandra, “Efficient algorithm for contrast enhancement of natural images,” International Arab Journal of Information Technology, vol. 11, no. 1, pp. 95–102, 2014.

[8] B. Willmore, R. J. Prenger, M. C. Wu, and J. L. Gallant, “The Berkeley wavelet transform: a biologically inspired orthogonal wavelet transform, “Neural Computation, vol.20, no.6, pp.1537-1564, 2008.

[9] X.-S. Yang, A new metaheuristic bat-inspired algorithm, in: Nature Inspired Cooperative Strategies for Optimization (NISCO 2010), Springer, 2010, pp. 65–74.

★★★