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Brain Tumor Detection from MRI Images based on Cellular Neural Network and Firefly Algorithm

Ehsan Sadeghi Pour*[1], Zeinab Bahman Zadeh[2]
*[*1] Department of Electrical and Computer Engineering, Kashan Branch, Islamic Azad University, Kashan, Iran.*
[2] Departments of Civil, Architectural, and Environmental Engineering, College of Engineering, Drexel University, Philadelphia, PA
Corresponding Author: Ehsan61.ai@gmail.com

Abstract
Brain tumor is the most important reason of fatality in today's world. So, proposing a system to detect tumors in early stage can help patients. The importance of MRI image segmentation is due to represent exact place of White Matter, Grey Matter, and Cerebrospinal Fluid which provide an efficient way to detect brain disturbance such as Dementia, Schizophrenia, Schizophrenia, Alzheimer, and etc. In this article, a new MRI image segmentation method proposed for tumor detection. The proposed algorithm consists of four stages. At first pre-processing to equalizing input image specially noise reduction. Then two features such as edges and edema extract in image segmentation with morphology techniques. Then cellular neural network apply to detect exact area of tumor and at last, Firefly Algorithm apply to extract tumor area and detection. BraTS dataset used as input data. Obtained results show that proposed method which named brain tumor detection with cellular neural network and firefly algorithm (BTD-CFA) have better performance in comparison to other techniques based on accuracy evaluation criteria which proposed method obtained 96.30% accuracy and sensitivity is 90.51 %.

Keywords: *Tumor Detection, Tumor Segmentation, Morphology, Cellular Neural Network, Firefly Algorithm (FA)*

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I. Introduction

Brain tumor recognition and detection is critical in health care systems. Identifying type of tumor in early stages can help the patients to live more and cure. Brain have different tissue which tumor created by growing and aggregation of more cells in brain area. The most common brain tumors are Glioma, Meningioma, Schwannoma. Primary CNS Lymphoma, Medulloblastoma, and Hipofiza Adenom [1].

Tumor is not the synonym of cancer, because tumor might be benign or malignant, but cancer define as malignant. One of the difference between benign and malignant tumors are that benign tumor do not grow fast, but malignant tumors can attack to brain tissues and grow so fast. Some of the brain tumors symptoms are headache, seizure, Mood changes and movement disorders. Generally, there are three methods for cure tumor such as surgery, radiotherapy, and chemotherapy which all of these methods have their own complications.

MRI images use widely due to have good spatial resolution and contrast. Brain image segmentation enhance the representation of White Matter, Grey Matter, and Cerebrospinal Fluid and many other diseases. In this article, a new method for segmentation and detection of brain tumors proposed by using MRI images. This approach is combination of cellular neural network for training to detect exact area of tumor and Firefly Algorithm for optimizing segmentation and make optimized class for tumor area extraction. Edema considered as the main features and detects simultaneously which is important for diagnosis, planning, and treatment.

II. Literature Review

In study [2], applied K-Means and FCM clustering algorithms for brain tumor image segmentation proposed. Another method used hybrid clustering method for brain tumor image segmentation which used mean filter as noised reduction and then K-Means and FCM named KIFCM applied for clustering and segmentation [3]. In another method, combination of two algorithms EP and FCM proposed for detecting brain tumor in image which named by EPFCM and used GVF algorithm [4]. Another research used FCM and anisotropic diffusion based on segmentation for brain tumor detection [5]. In anisotropic diffusion part, smoothing operation was based on Support Vector Machine (SVM). Tumor extraction will be done after classification based on FCM method.

In another study [6], used wavelet transform and Gabor filter for detecting brain tumor in MRI images and in contrast of that, statistical features method used such as LSVM, Hybrid SVM-RBF neural network, KNN, Euclidian K-Means, Blocking K-Means, and sparse representation. Result showed that statistical feature methods with hybrid SVM-RBF had the best performance by using BraTS dataset.

In another researches, neural networks used as training parts as hybrid methods [7]. In this research used SOM neural network and Gradient Entropy Clustering for MRI image segmentation. Unsupervised method proposed for MRI image segmentation based on SOM neural network and Genetic Algorithm which used IBSR dataset. In reference [8], proposed SOM and K-Means as unsupervised learning with clustering approach in MRI images. Another study [9], proposed classification analysis for brain tumor recognition and detection by using ANFIS. In this research [10], proposed hybrid ANFIS-DCT for extracting features of brain tumor for MRI images. GLCM used for feature extraction part. The results of these features optimized by Genetic Algorithm and then trained and tested by fuzzy rules and membership functions based on ANFIS for image segmentation [11]. Other methods used evolutionary algorithms and hybrid methods. In reference [12], proposed DCT method for image enhancement and Genetic Algorithm for segmentation for brain tumor detection. In study [13], proposed a new method for optimizing MRI image segmentation by using ACO algorithm and finally Genetic Algorithm by using weighted mean filter for noise reduction proposed. In another optimized approach, LVQ neural network used for clustering and hierarchical Genetic Algorithm used for recognized clusters performance and tumor detection [14]. In another method, MRI image clustering proposed based on region which Genetic Algorithm applied to extract features [15]. Another method used previous approach which had better efficiency by using Genetic Algorithm for dimension reduction and selecting features [16].

In reference [17], used hierarchical clustering methods for brain tumor segmentation and detection which used Watershed algorithm, KNN, KFA, and Minimal Spanning Tree. Result represented that Minimal Spanning Tree had the better performance in comparison to others. Statistical analysis methods used in brain tumor image segmentation and detection, too. In another study [18], proposed a new algorithm named ITGO which was combination of classification method such as SVM and statistical analysis method such as Friedman Test and Wilcoxon-Rank Test. The advantages of this method were high speed of convergence and optimized two methods mean PSO and BCOA. Another method which proposed in reference [19], used fusion MRI image segmentation for brain tumor detection. A new method proposed named Potential Field Segmentation (PFS) and use of ensemble approaches that combine the results generated by PFS and other methods to achieve a fused segmentation. In study [20], proposed fusion based Glioma brain tumor detection and segmentation using ANFIS classification. The aim of this research was to classify the brain image into normal and Glioma brain image. Then, the tumor regions in Glioma brain image was segmented using morphological functions.

A new method proposed in reference [21], which used a distinctive approach in brain tumor detection and classification using MRI images. Support Vector Machine (SVM) classifier applied with different cross-validations on the features set to compare the precision of proposed framework. The proposed method validated on three benchmark datasets such as Harvard, RIDER and Local. In this research [22], used Rough-Fuzzy C-Means and Shape Based Properties for MRI brain tumor segmentation and analysis. Fuzzy boundary and crisp lower approximation in RFCM played an effective contribution in brain tumor segmentation on MR images. Experimental results represented that the proposed method had achieved better performance based on statistical volume metrics than previous state-of-the-art algorithms with respect to ground truth or manual segmentation. In references [23] and [24], the XCSR and XCSLA classification system for diagnosing some of the diseases are that it can also be used to diagnose breast cancer. In [25] discusses machine learning methods (ML) and their application for mental health. A scoping process has been used to discover ML context in mental health. This study identifies the applicable areas of diagnosis and stress prediction as a factor in mental health disorders.

In another study [26], proposed MRI brain tumor segmentation based on texture features and kernel sparse coding. Based on the kernel dictionary learning method, two adaptive dictionaries were constructed, one for healthy tissues and another for pathological tissues. This could be achieved by coding the voxels using a kernel-clustering algorithm based on dictionary learning, followed by classifying the target pixels using a linear discrimination algorithm. As a result, the flood-fill operation was used to improve the quality of the segmentation. In article [27], proposed Glioma detection on brain MRIs using texture and morphological features with ensemble learning. Some method used in this approach such as different segmentation schemes for different pulse sequences, fusion of texture features, and ensemble classifier to perform three levels of classification. Using sparse non-uniform graphs based on uncertainty, another method that represents [28], proposed concurrent tumor segmentation and registration. A unified pairwise discrete Markov Random Field model superimposed on a sparse grid was used to model both segmentation and registration problems. Based on pattern classification techniques, segmentation techniques were used for segmentation, while registration techniques were designed to maximize similarity between volumes and to be modular with respect to the matching criteria. BraTS used as input dataset and result represented maintained performance and strongly reduced complexity of the model. In reference [29] the literature on breast cancer detection and classification based on ML algorithms was reviewed. The detection of breast cancer on mammographic images is carried out in three stages: (1) image preprocessing, (2) feature extraction, and (3) classification and evaluation. A total of 93 works were reviewed, reporting that deep learning techniques account for the majority of the effective methods that are used for cancer detection. This study [30], states that mental stress affects heart rate, hear rate variability, blood pressure, and skin conductance.

In reference [31], proposed a brain tumor segmentation framework based on outlier detection. This article described a framework for automatic brain tumor segmentation from MR images which detected edema simultaneously with tumor segmentation. The method proposed in this research did not require contrast enhanced image channels. In order to segment abnormal brain regions, a registered brain atlas is used as a model for healthy brains. In order to determine the intensity properties of the different tissue types, robust estimates were made of the location and dispersion of the normal brain tissue intensity clusters. In the second stage, T2 image intensities were used to determine whether edema was present along with tumors. As a final step, geometric and spatial constraints were applied to the regions detected to have tumors and edema. In reference [32] A hybrid of the firefly algorithm and artificial intelligence (AI) was employed to detect breast cancer. In another study [33] AI and image processing techniques were employed to detect breast cancer. Furthermore, a new breast cancer detection methodology was introduced using ML algorithms.

III. Proposed method and simulation

The proposed method shown in in Figure 1., which presented proposed method steps.

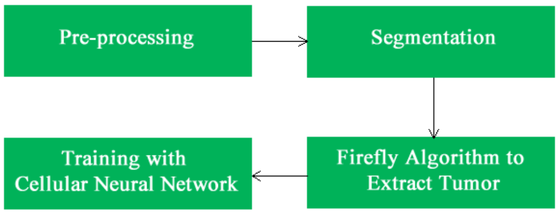

Figure 1: Proposed method main steps such as a) pre-processing for noise reduction, b) segmentation with morphological operators, c) feature extraction with Firefly Algorithm, d) training and testing data with cellular neural network

In pre-processing, simple operation done such as converting image to gray-scale and binary mode, contrast optimization, noise reduction and image filtering. Thresholding apply for image edge detection with the aim of better segmentation results to show brain tumor. Canny operator apply to detect edges.

Input images should be segmented due to tumor detection. Pixel labeling in medical images named segmentation which divide image to separate parts. Image segmentation done in two levels. First, feature extraction of image and second is feature classification with an algorithm for obtaining sufficient information on that region. Each region has uniform brightness level. This paper, use image morphology techniques such as erosion and dilation proposed in [34], due to segmentation. Two features such edges and edema should be extract well. After segmentation, some features extracted specially edges and edema. Then it should train in cellular neural network to learn about features to detect exact area of tumors. Training started in segmented image dataset and it has some advantages such as presenting exact area of tumors and generalized medical system which can find exact area of tumors from other images, because the network, trained and tested more and more. Other features such as texture, light intensity and shape considered in training part, too.

Proposed cellular neural network consist of 9 layers which after the input layer, there are four pairs of layers. The units within each layer are arranged in a number of square arrays. Each unit in every arrays received pixels from small group of previous units. Similarly, it sends pixels to only a few units in the next layer. The input units are arranged in a single 19×19 square array. The first layer above the input layer has 12 arrays, each consisting of 19×19 units. In general, the size of the arrays decreases as we progress from the input layer to the output layer of the network. Each output array is single unit which can see the total of arrays in 6×32 and it's because of total data array is 6×256. Output pixel of one unit in the cells of pair's cells is the function of received transition pixels from previous layer units and received inhibitor pixels of those units. This mechanism described as middle unit named v. The first layer in each pair consists of S cells fits to transmitted pixel Euclidian Weighted Norm from input units. Submitted pixel from inhibitor pixel of v is as equation (1).

$$v = \sqrt{\sum \sum t_i c_i^2} \qquad (1)$$

In equation (1), t_i is the fixed point of C unit to v and v is the output of V. Input layer consider as the surface of C_0. So, one unit of S, form the scalable input as equation (2).

$$x = \frac{1+e}{1+vw_0} - 1 \qquad (2)$$

In equation (2), w_0 is the adjustable weight of V unit to S unit and $e = \sum_i e_i w_i$ is the transitional input of network from C and vw_0 units of V unit. Output pixel will be calculate from equation (3).

$$s = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (3)$$

Inhibitor pixel use ART neural network in references [35] and [36], method for normalization of S answered units. The output of one unit in C layer is the function from input network which received from all units and all S arrays. Network input is as equation (4).

$$C_{in} = \sum_i s_i u_i \qquad (4)$$

In equation (4), s_i is the output from S unit and u_i is the fixed weight from S unit to C unit. Output pixel of segmented part should be as equation (5).

$$\begin{cases} \frac{C_{in}}{a+C_{in}} & \text{if } C_{in} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

In equation (5), a is depending to layers levels, then training process begin based on image pixel. Training process in cellular neural network is layer by layer. Weights of C unit can be changed to S unit and V unit to S unit, but weights of C units to V units are fixed. Weights of layer array of S to corresponding array in C layer are fixed which this weights is stronger for nearest units. Fixed weights from V units to inhibitor units reduce monotonic as a function of distance. Imported weighted to layer units of S trained consecutively. Weights of input units to s_1 units train and then fixed. After that, input units to s_2 train and fixed. Training process continue level by levels in a similar manner to reach to output layer to complete segmentation operation. Figure 2. Represent the structure of used cellular neural network.

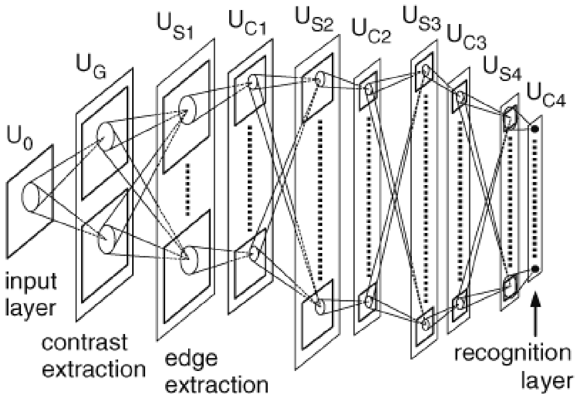

Figure 2: cellular neural network used structure. It consists of input layer, contract extraction, edge extraction and recognition layer.

Segmentation results by morphological operators and training in cellular neural network represented in Figure 3. from BraTS dataset.

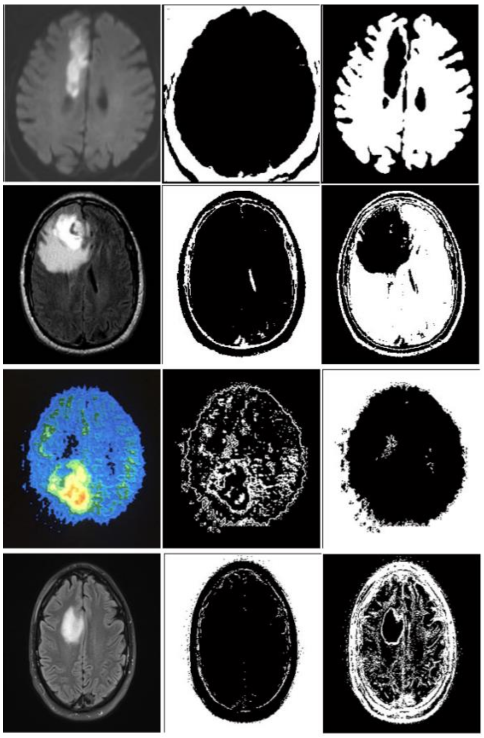

Figure 3: Segmentation results by morphological operators and training with cellular neural network. From left to right: raw input image, binary conversion and then dilation and erosion from morphological operators.

As it can be seen in Figure 3. MRI tumor segmentation done as well with morphological operators, but by using another extraction method, the results can be more accurate. After segmentation by morphological operators and training segmented parts with cellular neural network which represent exact area of tumors, Firefly Algorithm will be used for optimizing segmentation and optimized class selection for correct detection of tumor area in image and extract true parts of tumors. Firefly Algorithm use texture of image pixel for appropriate features selection. In fact, the output of cellular neural network is the input of Firefly Algorithm. In Figure 4., Firefly Algorithm steps shown for optimizing image segmentation.

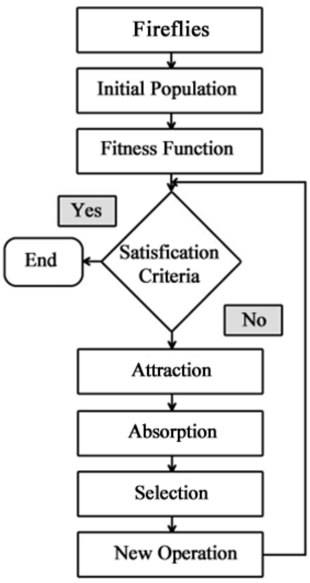

Figure 4: Firefly Algorithm steps for image segmentation optimization. Creating initial population of fireflies, defining parameters of attraction, absorption, selection and then creating new population and then determine fitness function. After some many iteration, satisfaction criteria check and if it satisfied, ending or go to previous steps.

3.1 Firefly Algorithm for Selecting Proper Features

The firefly algorithm apply to find precise area detection than cellular neural network and extract tumors area. A variation in light intensity or brightness and a formulation of attractiveness play an important role in the development of this algorithm. For simplicity, the assumption is always based on the fact that the attractiveness of the firefly is determined by its brightness, which in turn is associated with the coding target function. In order to maximize the effectiveness of the optimization process, the brightness with the variable I for fireflies is selected in the special position x as $I(x)\infty f(x)$. Other luminous worms have recognized β's attractiveness. Therefore, there will be a difference between the distance r_{ij} between the fireflies i and j. A note should be made regarding the fact that light intensity decreases with distance from its source. As a simple example, the intensity of light $I(r)$ differs according to the inverse square law and is defined as equation (6).

$$I(r) = \frac{I_S}{r^2} \quad (6)$$

Where I_s are intense in the source. For a given medium, γ represents a constant light absorption coefficient. There is a difference between the intensity of the brightness I and the brightness r, which can be calculated using equation (7).

$$I = I_0 e^{-\gamma r} \quad (7)$$

Based on equation (5), I_0 is the intensity of the main brightness. In order to avoid the singularity mode at $r = 0$ in equationI_S/r^2, the effect of the inverse square law approximation and Gaussin absorption is defined in equation (8).

$$I(r) = I_0 e^{-\gamma r^2} \quad (8)$$

The firefly attractiveness is proportional to the light intensity observed by the fireflies. One can define the attraction β of fireflies by equation (9).

$$\beta = \beta_0 e^{-\gamma r^2} \quad (9)$$

In equation (7), β_0 is attractiveness in $r = 0$. The equation $1/(1 + r^2)$ is faster than the power function in terms of computation, which is generally defined in the form of equation (10).

$$\beta = \frac{\beta_0}{1+\gamma r^2} \quad (10)$$

The charming function β (r) can be as a uniformly reducible function such as equation (11) and the distance between the fireflies i and j in x_i and x_j is a Cartesian distance such as equation (12).

$$\beta(r) = \beta_0 e^{-\gamma r^m},\ (m \geq 1) \quad (11)$$

$$r_{ij} = \left\|x_i - x_j\right\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (12)$$

In the equation (12), $x_{i,k}$ is the k'th spatial coordinate component x_i and the i -th firefly. In a two-dimensional mode, this is expressed in the form of equation (13), which is in fact similar to Euclidean distance.

$$r_{ij} = \sqrt{\left(x_i - x_j\right)^2 + (y_i - y_j)^2} \quad (13)$$

The motion of the fireflies are a kind of attractiveness for the firefly j, which is expressed by equation (14) and can be observed with repeating signals, which are characterized as tumor classification and precise area detection in the input signals.

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha \in_i \quad (14)$$

The second part of equation (14) is due to the attraction of the firefly. The value of α is a random parameter, and ϵ_i is the vector of random numbers drawn from the Gaussian distribution or uniform distribution. Each worm's amount of light is determined by the amount of fitness at its location at each recurrence. Light is added in accordance with the amount of fitness in each iteration. Equation (15) describes the correlation between the light firefly correction and each use.

$$\varphi_i(t) = (1 - p)\varphi_i(t - 1) + \gamma j\left(x_i(t)\right) \quad (15)$$

In the equation (15), $j(x_i(t))$ is the new value of the light-emitting of the firefly at reuse time and $(1 - p)\varphi_i(t - 1)$ is the fitness location of the worm i in the repetition t of the algorithm in which p And φ are fixed numbers for modeling the gradual drop and its effect on light. Equation (16) are used to detect the position of other worms in the vicinity or to precise area detection.

$$p_{ij}(t) = \frac{\varphi_j(t)-\varphi_i(t)}{\sum_{k\in N_i(t)}\varphi_k(t)-\varphi_i(t)} \quad (16)$$

In equation (16), $N_i(t)$ is the set of fireflies from firefly neighboring at time t. There is a gap between the firefly i and j at time t which fundamentally use Euclidean distance as $d_{ij}(t)$. There is a probability p that can be used to estimate the discretionary time shift of the firefly in equation (17).

$$x_i(t + 1) = x_i(t) + s\left(\frac{x_j(t)-x_i(t)}{\left\|x_j(t)- x_i(t)\right\|}\right) \quad (17)$$

In the equation (15), the operator ‖…‖ shows the Euclidean soft function and s is the step of motion. $x_t(t)$is the m-dimensional vector of the firefly location in the time unit t. The need to update neighbor ranges is also felt when updating data neighbors with duplicate phrases. In the case of any firefly, a neighbor is assigned to it, whose radial range r_d^i is naturally dynamic. According to equation (18), neighboring update operations are obtained.

$r_d^i\,(t+1) = min\{r_s, max\{0, r_d^i(t) + \beta(n_t - |N_i(t)|\}\}$ (18) In equation (18), β is a constant parameter and n_t is a parameter to control the number of neighborhoods or to identify the exact areas with classification and precise area detection. The value of Firefly Algorithm Operator defined as Table 1.

Table 1: Value of Firefly Algorithm operators

Firefly Algorithm Operators	Defined Value
Population	128
Attraction	0.4
Absorption	0.2
Iteration Number	100

IV. Results

After obtaining results from segmentation by morphological operators and training segmented parts with cellular neural network, Firefly algorithm use image texture for appropriate features selection and optimize segmentation and even can detect tumor area precisely than cellular neural network. Even it can be extract the tumor area. Figure 5., shown the obtaining results of proposed method.

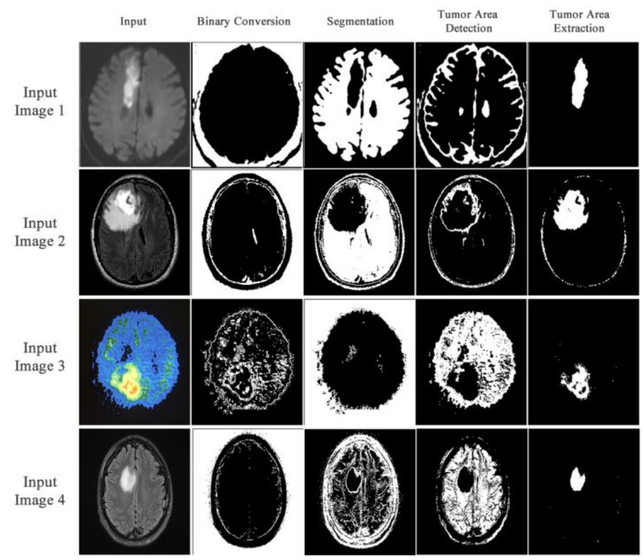

Figure 5: Proposed method output to detect brain tumor. From left to right: 1) raw input image, 2) binary conversion, 3) dilation and erosion of morphological operators, 4) tumor area detection, and 5) tumor area extraction.

As it can be seen in Fig. 5, in four part, tumor area detect and extracted correctly. This proposed method show the high performance which will compare to other methods.

4-1 Evaluation methods and comparison

Due to evaluating obtaining results, some methods used such as Accuracy, Sensitivity, Specificity, MSE, SNR, and PSNR. Equation (19) shown the accuracy formula which defined as percentage.

$$Accuracy = 100 \times \frac{TP+TN}{TN+TP+FN+FP} \qquad (19)$$

In equation (19), TP is True Positive which determined there is tumor in results of segmentation there is tumor. TN is True Negative which determined there is no tumor in results of segmentation. FP is False Positive which determined there is no tumor in results of segmentation, and FN is False Negative which determined there is no segmentation process correctly. Sensitivity calculated as equation (20) and equation (21) shown the specificity. Also equation (22) represent the SNR formula.

$Sensitivity = \frac{TP}{TP+FN}$ (20)

$Specificity = \frac{TN}{TN+FP}$ (21)

$SNR = \frac{P_{signal}}{P_{noise}}$ (22)

The value less than 12 dB show the serious problem of noise in segmentation. The value more than 20 dB is satisfying and higher than 30 dB is so suitable. Actually, how more is this index is better and show more useful signal in pixels. The most signals defined as dB because they have dynamic range which calculated as equation (23) for power signal and equation (24) for noise signal in terms of dB.

$P_{signal,dB} = 10log_{10}(P_{signal})$ (23)

$P_{noise,dB} = 10log_{10}(P_{noise})$ (24)

MSE used as evaluation of dataset after segmentation which needs training data for parameter recognition that defined as equation (25).

$\{(u_i; y_i), i = 1, \ldots, m\}$ (25)

Another criteria for evaluation is PSNR which calculated as equation (262) In terms of dB.

$PSNR = 10. log_{10}(\frac{MAX_I^2}{MSE})$ (26)

In equation (26), $\mathrm{MAX}_\mathrm{I}^2$ is the great possible of signal. Table 2. represents the obtained results of each evaluation method by processing in BraTS dataset for tumor area detection with cellular neural network and Table 3., represent more accuracy to detect and extract tumor area. Actually, Firefly Algorithm optimized cellular neural network, too.

Table 2: Obtained results of evaluation for cellular neural network

Accuracy	91.24 %
Sensitivity	50.81 %
Specificity	51.84 %
MSE	0.39
SNR	27.72 dB
PSNR	20.82 dB
Average of Runtime	3.60 sec

Table 3: Obtained results of evaluation for Firefly Algorithm

Accuracy	96.30 %
Sensitivity	90.51 %
Specificity	90.00 %
MSE	0.10
SNR	30.17 dB
PSNR	25.89 dB
Average of Runtime	2.63 sec

By comparing Table 2. and 3., it is obvious that Firefly Algorithm optimized cellular neural network results, too. Table 4. show the comparison of proposed method with others which used BraTS dataset in accuracy and sensitivity.

Table 4: Methods comparison

Methods	Accuracy	Sensitivity
Linear SVM	82.20 %	48.21
SVM-RBF	90.09 %	48.85
KNN-SVM	83.10 %	47.18
Proposed Method (BTD-CFA)	91.2452 %	50.5184

It can be seen that proposed method has the better accuracy and sensitivity in comparison to other methods such as Linear SVM, SVM-RBF, and KNN-SVM.

V. Conclusion

One of the concerns of image processing in medical field is recognition and detection of brain tumors in early stages. In this article, a new model for detect and extract tumor area from MRI images proposed. At first, some pre-processing method applied due to enhancing input image which selected from BraTS dataset. Then, segmentation of MRI images applied by morphological operators which represented image edges and edema as two main features beside texture, light intensity and shape. Then cellular neural network training started to learn features from segmented part which could detect exact area of tumors.

Because there was much more search spaces to increase accuracy and finding exact area and extract tumor area, Firefly Algorithm applied for optimizing segmentation with more precision. Obtained results represented that the accuracy of proposed method had the most performance in comparison to others. It proved by using some evaluation methods such as accuracy, sensitivity, specificity, MSE, SNR, and PSNR. The method named BTD-CFA obtained 96.30 % accuracy.

References

[1]. Domingues, Patrícia, González-Tablas, María, Otero, Álvaro, Pascual, Daniel, Miranda, David, Ruiz, Laura, Sousa, Pablo, Ciudad, Juana, Gonçalves, Jesús María, Lopes, María Celeste, Orfao, Alberto, Tabernero, María Dolores, 2015. Tumor infiltrating immune cells in Gliomas and Meningiomas. Brain, Behavior, and Immunity, Vol. 53, pp. 1-15.

[2]. Selvakumar, J., Lakshmi, A., Arivoli, T., 2012. Brain Tumor Segmentation and Its Area Calculation in Brain MR Images using K-Mean Clustering and Fuzzy C-Mean Algorithm. IEEE International Conference on Advances in Engineering, Science and Management (ICAESM), pp. 186-190.

[3]. Abdel-Maksoud, Eman, Elmogy, Mohammed, Al-Awadi, Rashid, 2016. Brain tumor segmentation based on a hybrid clustering technique. Cairo University, Egyptian Informatics Journal, Vol. 16, pp. 71-81.

[4]. Rajandran, A., Dhanasekaran, R., 2012. Fuzzy Clustering and Deformable Model for Tumor Segmentation on MRI Brain Image: A Combined Approach. International Conference on Communication Technology and System Design, 2011, Procedia Engineering. Vol. 30, pp. 327-333.

[5]. Ain, Quratul, Jaffar, M. Arfan, SunChoi, Tae, 2014. Fuzzy anisotropic diffusion based segmentation and texture based ensemble classification of brain tumor. Applied Soft Computing, Vol. 21, pp. 330-340.

[6]. Nabizadeh, Nooshin, Kubat, Miroslav, 2015. Brain tumors detection and segmentation in MR images: Gabor wavelet vs. statistical features. Computers and Electrical Engineering, Vol. 45, pp. 286-301.

[7]. Ortiz, A., Gorriz, J. M., Ramirez, J., Salas-Gonzalez, D., 2014. Improving MR brain image segmentation using self-organizing maps and entropy-gradient clustering. Information Sciences, Vol. 262, pp. 117-136.

[8]. Vishnuvarthanan, G., Rajasekaran, M. Pallikonda, Subbaraj, P., Vishnuvarthanan, Anitha, 2015. An unsupervised learning method with a clustering approach for tumor identification and tissue segmentation in magnetic resonance brain images. Applied Soft Computing.

[9]. Shanthakumar, P., Ganeshkumar, P., 2015. Performance analysis of classifier for brain tumor detection and diagnosis. Computers and Electrical Engineering, Vol. 45, pp. 302-311.

[10]. El-Dahshan, El-Sayed A., Mohsen, Heba M., Revett, Kenneth, Salem, Abdel-Badeeh M., 2014. Computer-Aided Diagnosis of Human Brain Tumor through MRI: A Survey and a New Algorithm. Expert System with Application, Vol. 41, Issue 11.

[11]. Sharma, Minakshi, Mukharjee, Sourabh, 2013. Brain Tumor Segmentation Using Genetic Algorithm and Artificial Neural Network Fuzzy Interference System (ANFIS). Advances in Computing and Information Technology, Vol. 177, pp. 329-339.

[12]. Chandra, G. Rajesh, Rao, Kolasani Ramchand H., 2016. TUMOR DETECTION IN BRAIN USING GENETIC ALGORITHM. 7th International Conference on Communication, Computing and Virtualization, Procedia Computer Science, Vol. 79, pp. 449-457.

[13]. Karnan, M., Selvanayaki, K., 2010. Improved Implementation of Brain MR Image Segmentation Using Meta Heuristic Algorithms. IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), pp. 1-4.

[14]. Yeh, Jinn-Yi, Fu, J. C., 2008. A Hierarchical Genetic Algorithm for Segmentation of Multi-Spectral Human-Brain MRI." Expert System with Application, Vol. 34, Issue 2, pp. 1285-1295.

[15]. Shah, Dipali B., Modi, Nimit S., 2015. Optimized Optics Method for Tumor Detection in Brain. International Journal of Innovative Research in Computer and Communication Engineering. Vol. 3, Issue 5.

[16]. Kaur, Amanpreet, Jindal, Gagan, 2016. Tumor Detection Using Genetic Algorithm. Procedia Computer Science, Proceedings of International Conference on Communication, Computing and Virtualization (ICCCV), Vol. 79, pp. 449-459.

[17]. Rajeswari, R., Gunasekaran, G., 2014. Tumor Detection and Segmentation Using Watershed and Hierarchical Clustering Algorithms. International Journal of Innovative Research in Computer and Communication Engineering, Vol.2, No. 5.

[18]. Tang, Deyu, Dong, Shoubin, Jiang, Yi, Li, Huan, and Huang, Yishuan, 2015. ITGO: Invasive Tumor Growth Optimization Algorithm. Applied Soft Computing, Vol. 36, pp. 670-698.

[19]. Cabria, Iván, Gondra, Iker, 2017. MRI segmentation fusion for brain tumor detection. Information Fusion, Vol. 36, pp. 1-9.

[20]. Selvapandian, A., Manivannan K., 2018. Fusion based Glioma brain tumor detection and segmentation using ANFIS classification. Computer Methods and Programs in Biomedicine, Vol. 166, pp. 33-38.

[21]. Amin, Javeria, Sharif, Muhammad, Yasmin, Mussarat, Fernandes, Steven Lawrence, 2017. A distinctive approach in brain tumor detection and classification using MRI. Pattern Recognition Letters, In press, corrected proof, Available online 31 October 2017.

[22]. Bal, Abhishek, Banerjee, Minakshi, Chakrabarti, Amlan, Sharma, Punit, 2018. MRI Brain Tumor Segmentation and Analysis using Rough-Fuzzy C-Means and Shape Based Properties. Journal of King Saud University - Computer and Information Sciences, In press, accepted manuscript, Available online 15 November 2018.

[23]. E. Sadeghipour and A. Hatam, "An Expert Clinical System for Diagnosing Obstructive Sleep Apnea with Help from the XCSR Classifier."

[24]. E. Sadeghipour and A. Hatam, "Designing an Intelligent System for Diagnosing Diabetes with the Help of the XCSLA System."

[25]. Razavi, M., Ziyadidegan, S., & Sasangohar, F. (2022). Machine Learning Techniques for Prediction of Stress-Related Mental Disorders: A Scoping Review. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 66(1), 300–304. https://doi.org/10.1177/1071181322661298

[26]. Tong, Jijun, Zhao, Yingjie, Zhang, Peng, Lingyu, Chen, Lurong Jiang, 2019. MRI brain tumor segmentation based on texture features and kernel sparse coding. Biomedical Signal Processing and Control, Vol. 47, pp. 387-392.

[27]. Gupta, Nidhi, Bhatele, Pushpraj, Khanna, Pritee, 2019. Glioma detection on brain MRIs using texture and morphological features with ensemble learning. Biomedical Signal Processing and Control, Vol. 47, pp. 115-125.

[28]. Parisot, Sarah, Wells, William, Chemouny, Stéphane, Duffau, Hugues, Paragios, Nikos, 2014. Concurrent tumor segmentation and registration with uncertainty-based sparse non-uniform graphs. Medical Image Analysis, Vol. 18, Issue 4, pp. 647–659.

[29]. Sadeghi pour, E., Esmaeili, M,. Romoozi, M,. "Breast cancer diagnosis: a survey of pre- processing, segmentation, feature extraction and classification" International Journal of Electrical and Computer Engineering (IJECE), Vol. 12, No. 6, December2022, pp. 6397~6409;ISSN: 2088-8708, DOI: 10.11591/ijece.v12i6.pp6397-6409

[30]. Ziyadidegan, S., Razavi, M., & Sasangohar, F. (2022). Analyzing physiological responses to quantify anxiety disorders: A scoping review. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 66(1), 2183–2187. https://doi.org/10.1177/1071181322661304

[31]. Prastawa, Marcel, Bullitt, Elizabeth, Ho, Sean, Gerig, Guido, 2004. A brain tumor segmentation framework based on outlier detection. Medical Image Analysis, Vol. 8, Issue 3, pp. 275–283.

[32]. E. Sadeghipour, N. Sahragard, M.-R. Sayebani, and R. Mahdizadeh, "Breast cancer detection based on a hybrid approach of firefly algorithm and intelligent systems," Indian Journal of Fundamental and Applied Life Sciences, vol. 5, p. S1, 2015.

[33]. A. Nomani, Y. Ansari, M. H. Nasirpour, A. Masoumian, E. S. Pour, and A. Valizadeh, "PSOWNNs-CNN: A Computational Radiology for Breast Cancer Diagnosis Improvement Based on Image Processing Using Machine Learning Methods," Computational Intelligence and Neuroscience, vol. 2022, 2022.

[34]. Devkota, B., Alsadoon, Abeer, Prasad, P. W. C., Singh, A. K., Elchouemi, A., 2018. Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Science, Vol. 125, pp. 115-123.

[35]. Carpenter, G. A., Grossberg, S., 1987. ART 2: Self-organization of stable category recognition codes for analog input patterns, Applied Optics, Vol. 26, No. 23, pp. 4919-4930.

[36]. Carpenter, G. A., Grossberg, S., 2003. Adaptive Resonance Theory. In Michael A. Arbib (Ed.), the Handbook of Brain Theory and Neural Networks, Second Edition. Cambridge, MA: MIT Press, pp. 87-90.

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