AUTOMATIC BRAIN TUMOR SEGMENTATION WITH K-MEANS, FUZZY C-MEANS, SELF-ORGANIZING MAP AND OTSU METHODS

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Abstract

The human brain is an amazing organ of the human nervous system and controls all functions of our body. Brain tumors emerge from a mass of abnormal cells in the brain, and catching tumors early often allows for more treatment options. For diagnosing brain tumors, it has been benefited mostly from magnetic resonance images. In this study, we have developed the segmentation systems using the methods as K-Means, Fuzzy C-Means, Self-Organizing Map, Otsu, and the hybrid method of them, and evaluated the methods according to their success rates of segmentation. The developed systems, which take the brain image of MRI as input, perform skull stripping, preprocessing, and segmentation is performed using the clustering algorithms as K-Means, Fuzzy C-Means, Self-Organizing Map and Otsu Methods. Before preprocessing, the skull region is removed from the images in the MRI brain image data set. In preprocessing, the quality of the brain images is enhanced and the noise of the images is removed by some various filtering and morphological techniques. Finally, with the clustering and thresholding techniques, the tumor area of the brain is detected, and then the systems of the segmentation have been evaluated and compared with each other according to accuracy, true positive rate, and true negative rate.

Keywords: Brain Tumor Segmentation, Medical Imaging, Fuzzy C-Means, K-Means, Self-Organizing Map, Otsu Method

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BULANIK C-ORTALAMALAR, K-ORTALAMALAR, ÖZDÜZENLEMELİ AĞ VE OTSU METOT İLE BEYİN TÜMÖRÜ SEGMENTASYONU

Özet

İnsan beyni, insan sinir sisteminin en önemli organıdır ve vücudumuzun tamamını kontrol eder. Beyin tümörleri beyindeki normal olmayan hücrelerden oluşur ve tümörleri erken tespit etmek birçok tedavi seçeneklerinin uygulanmasına olanak sağlar. Beyin tümörlerinin teşhisi için çoğunlukla manyetik rezonans görüntülerinden yararlanılmıştır. Bu çalışmada, Bulanık C-Ortalamalar, K-Ortalamalar, Özdüzenlemeli Ağ, Otsu Metot ve bu metotların birleşiminden oluşan hibrid metotlar kullanılarak beyin tümör segmentasyon sistemleri geliştirilmiştir. Bu metotların segmentasyon başarı oranları tespit edilmiş ve birbirleriyle karşılaştırılmıştır. Geliştirilen sistemlerde, ilk olarak MRI beyin görüntülerini girdi olarak alınır, sonra kafatası bölgesinin görüntüden ayrılması, önişleme ve Bulanık C-Ortalamalar, K-Ortalamalar, Özdüzenlemeli Ağ, Otsu metot gibi algoritmalarla segmentasyon işlemleri uygulanır. Önişlemden önce, kafatası bölgesi, MRI beyin görüntüsü veri setindeki görüntülerden çıkarılır. Ön işlemede, beyin görüntülerinin kalitesi iyileştirilir ve görüntülerin gürültüsü, çeşitli filtreleme ve morfolojik tekniklerle kaldırılır. Son olarak, kümeleme ve eşikleme teknikleri ile beynin tümör bölgesi tespit edildi. Daha sonra, segmentasyon sistemleri değerlendirildi ve doğruluk, gerçek pozitif oranı ve gerçek negatif oranına göre birbirleriyle karşılaştırıldı.

Anahtar Kelimeler: Beyin Tümörü Segmentasyonu, Tıbbi Görüntüleme, Bulanık C-Ortalamalar, K-Ortalamalar, Özdüzenlemeli Ağ, Otsu Metot

1. Introduction

Brain tumors consist of the growing abnormal cells which cannot be controlled by the body. The cell proliferation in brain tumors remains out of control. In general, tumors are diagnosed as benign or malignant tumors.

The skull is a bone structure that has no moving joints. Hence, the skull cannot expand and the tumor starts to press in the brain after occurring inside the brain.

If the brain tumors begin in the brain, it is called primary brain tumors. However, if cancer occurs in the other parts of the body and extends to the brain, it is named as secondary or metastatic. Brain tumors can spread at various speeds in the brain. Its growth speed depends on the location of the brain tumor. The location of the tumor is also important in terms of damage to the human nervous system. At the same time, the treatment of the tumor relies on tumor size, location, and type.

The diagnosis of brain tumors begins with the patient's different complaints. Then, a doctor estimates how well the reflexes, strength, senses, balance, and nerves are working. If the doctor suspects it as a tumor, other examination techniques are applied to reach the diagnosis of the brain tumors.

The definitive diagnosing of a brain tumor usually starts with magnetic resonance imaging (MRI). After determining the tumor in the brain, the commonly conducted process is to decide the type of the brain tumor with a biopsy or surgery. Namely, a part of the brain tissue is extracted from the brain tumor and inspected by the experts.

Brain tumors are displayed with different imaging methods. The major imaging methods are CBT (Computerized Brain Tomography), MRI (Magnetic Resonance Imaging), PET Scan (Positron Emission Tomography), and SPECT (Single Photon Emission Computed Tomography).

In medical image processing, brain tumor segmentation is an important task of segmenting brain tumors in the MRI image of the brain.

For brain tumor detection and segmentation, the systems are developed using the methods as expectation maximization (EM) algorithm [1], multiresolution-fractals modes [2], generative model technique [3], modified fuzzy algorithm [4], deep learning algorithm [5], convolutional neural networks [6], Fuzzy C Means [7], genetic algorithms [8], Artificial Neural Network Fuzzy Inference System (ANFIS) [9]-[10], Support Vector machines [11]-[12], Random Forests [13], Bayesian classifier [14], fractal features [15], Outlier detection [16], Markov Random Fields [17], K-Means [18]-[20], Self-Organizin Map (SOM) [21]-[22] and Otsu method [23]-[24].

As shown in Figure 1, the brain tumor MRI images are presented to the segmentation system. First, in the skull stripping phase, the skull is detected and removed from the brain region in the image. After that, in the preprocessing phase, some noise reduction operations as gaussian and wiener filters are applied to the remaining part of the brain in the image. Finally, the segmented brain tumor image is attained with the methods as K-Means, Fuzzy C-Means, SOM, and Otsu method.

The most successful method is K-Means among these methods with results 93% of Accuracy, 92% of TPR, and 93% of TNR. However, our developed system, a hybrid method that integrates K-Means and Otsu method, has 94% Accuracy, 94% TPR, and 93% TNR values and outperforms the other segmentation methods.

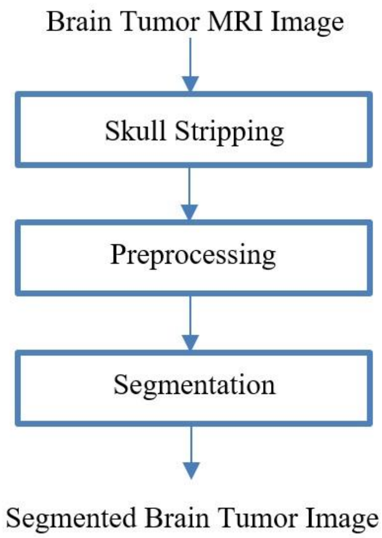

Figure 1. General diagram of brain tumor segmentation

The rest of the paper is organized as the following. In the next section, the methods as K-Means, Fuzzy C-Means, Self Organizing Map and Otsu method are mentioned briefly. In the third section, the experiments and test results have been presented and the success of the methods is evaluated. The main points of the work are expressed in the conclusion.

2. Methods

In this paper, the methods as K-Means, Fuzzy C-Means, Self-Organizing Map and Otsu methods have been used for the segmentation of the brain tumor MRI images and described in the following subsections shortly.

2.1 K-Means Clustering

K-Means clustering [18]-[20] is a vector quantization method that divides samples into k clusters with the nearest cluster centroid.

Assume that $x_1, x_2, \dots, x_n$ are real-valued d-dimensional n input vectors. These sample vectors are partitioned into k clusters as $C_1, C_2, \dots, C_k$. The purpose of this method is to minimize the cluster sum of the square as shown in Equation 1. Let μ_i be the mean of the samples in C_i.

$$arg \min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{1}$$

Equation 1 is equivalent to Equation 2.

$$arg \min_{C} \sum_{i=1}^{k} \frac{1}{2|C_i|} \sum_{x,y \in C_i} \|x - y\|^2 \tag{2}$$

The standard K-Means algorithm uses the iterative refinement approach. The algorithm consists of two steps: Initial step and update step. Let $m_1(1), m_2(1), \dots, m_k(1)$ be an initial set of k means.

Initial step: Using the least squared Euclidean distance, calculate the distances between the samples and the means and assign each sample to the nearest cluster. The sample x is assigned to exactly one cluster $C_i(t)$. t is an iteration number, and i is cluster number.

$$C_i(t) = \left\{x: \|x - m_i(t)\|^2 \le \left\|x - m_j(t)\right\|^2, 1 \le j \le k \right\} \tag{3}$$

Update step: Compute the means, m_i, of samples for all clusters as shown in Equation 4.

$$m_i(t+1) = \frac{1}{|C_i(t)|} \sum_{x_j \in C_i(t)} x_j \tag{4}$$

2.2 Fuzzy C-Means Clustering

Fuzzy C-Means [7] is an unsupervised clustering method that partition samples into k clusters. This method, which is developed by Dunn in 1973 and improved by Bezdek in 1981, aims to minimize an objective function as shown in Equation 5.

$$arg \min_{C} \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \left\|x_i - c_j\right\|^2 \tag{5}$$

where m is a real number greater than 1, x_i is the jth of d-dimensional measured data, c_j is the d-dimension center of the cluster, and u_{ij} is the degree of membership of $x_i$in the cluster j.

In each iteration, membership u_{ij} and cluster centers c_j are updated as shown in Equations 6 and 7.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{2/m-1}} \tag{6}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{7}$$

If $\max_{ij}\left|u_{ij}(t+1) - u_{ij}(t)\right| < \delta$, then the iteration will be finished. t is the iteration number and δ is the termination value which is a real number between 0 and 1.

2.3 Self-Organizing Map

Self-Organizing Map (SOM) [21]-[22] is an artificial neural network that is trained with the unsupervised approach. Besides, SOM applies competitive learning and does dimensionality reduction. As shown in Figure 2, it constructs a map that is a low-dimensional representation of the input space. This method was developed by Kohonen in the 1980s. That's why sometimes it is called Kohonen Map.

SOM Algorithm:

1) All weights of SOM neurons are initialized randomly.
2) An input vector, x, in the training data set is selected randomly.
3) All distances between the input vector and the neurons or units are computed with the Euclidean metric. The neuron which has the smallest distance is the winning neuron.
4) The neighborhood of the winning neuron is calculated.
5) Update the weights of the neurons in the neighborhood of the winning neuron (including the winning neuron). Namely, the neurons come closer to the input vector.

$$W_v(t+1) = W_v(t) + \beta(u,v,t).\alpha(t).\left(x - W_v(t)\right) \tag{8}$$

Repeat step 2 for N iterations.

Assume that t is the current iteration, v is the index of the neuron in the map, W_v is the current weight vector of neuron v, $\beta(u,v,t)$ is the neighborhood function, and $\alpha(t)$ is a learning rate.

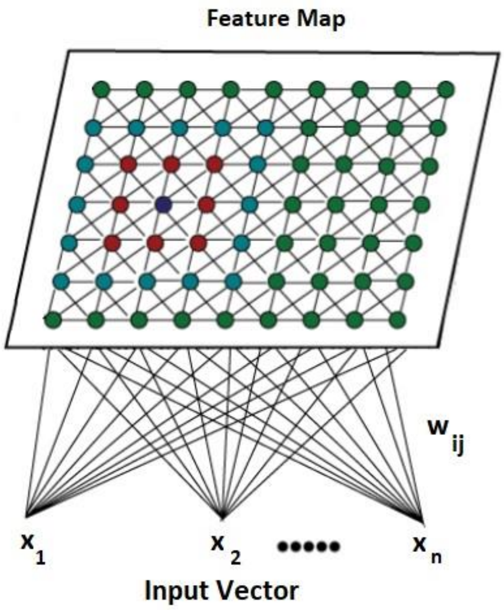

Figure 2. A diagram of Self-Organizing Map

2.4 Otsu Method

Otsu method [23]-[24] is an adaptive thresholding method for computer vision, image analysis, and processing. It is used both image segmentation and binarization by determining the input gray-scale image threshold. Namely, Otsu method separates two-class data using an optimal threshold value. The optimal threshold is detected by minimizing intra-class intensity variance.

To minimize the intra-class variance, we define a weighted sum of variances for two classes.

Inter-class variance is calculated as shown in Equation 9 and maximized to find the optimal threshold value.

$$\sigma^2(t) = w_b(t)w_f(t)\left[\mu_b(t) - \mu_f(t)\right]^2 \tag{9}$$

w_b and w_f weights are the probabilities of background and foreground classes which are distinguished with a threshold t. These probabilities can be calculated by the B bins of the histogram of the image. $\mu_b(t)$ and $\mu_f(t)$ are the background and foreground class means respectively.

$$w_b(t) = \sum_{i=0}^{t-1} p(i) \tag{10}$$

$$w_f(t) = \sum_{i=t}^{B-1} p(i) \tag{11}$$

$$\mu_b(t) = \frac{\sum_{i=0}^{t-1} i\, p(i)}{w_b(t)} \tag{12}$$

$$\mu_f(t) = \frac{\sum_{i=t}^{B-1} i\, p(i)}{w_f(t)} \tag{13}$$

Otsu's Algorithm:

1) Calculate the histogram of the gray-level image.
2) Calculate the probabilities of image intensity.
3) Initialize $w_b(0)$, $w_f(0)$, $\mu_b(0)$ and $\mu_f(0)$.
4) Apply all thresholds t=0,…, maximum intensity
5) Update w_b(t), w_f(t), μ_b(t) and μ_f(t).
6) Calculate $\sigma^2(t)$.
7) The optimal threshold is t for the maximum $\sigma^2(t)$.

3. Experimental Results and Evaluatıon of the Systems

In this study, the performances of the tumor segmentation systems are evaluated with the metrics as Accuracy, True Positive Rate (TPR) (Recall, Sensitivity), True Negative Rate (TNR) (Specificity). These metrics have been computed using TP, TN, FP, and FN as shown in Equation 14, 15, and 16.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{14}$$

$$TPR = \frac{TP}{TP + FN} \tag{15}$$

$$TNR = \frac{TN}{TN + FP} \tag{16}$$

In the above equations, TP (True Positive) is the number of the pixels which the system recognizes in the tumor area of the brain image correctly. But, TN (True Negative) denotes the number of pixels which the system recognizes in the non-tumor area correctly. In the same way, FP (False Positive) is the number of pixels which is classified wrongly in the non-tumor area. However, FN (False Negative) is the number of pixels which is classified wrongly in the tumor area.

The codes of the tumor segmentation systems have been written by MATLAB on the computer which has the features as Intel Core i7-4700HQ 2.40 GHz CPU, 16 GB RAM, 256 GB SSD Harddisk, 2 TB Harddisk, and Windows 10 Pro Operating System.

The brain tumor dataset consists of 107 images which all contain the tumor area and include gray-level (256, 256) pixels. The dataset [25] contains T1-weighted contrast-enhanced images from the patients which have three kinds of brain tumors as meningioma, glioma, and pituitary tumor. In Figure 3, the two brain MRI images in the dataset are displayed.

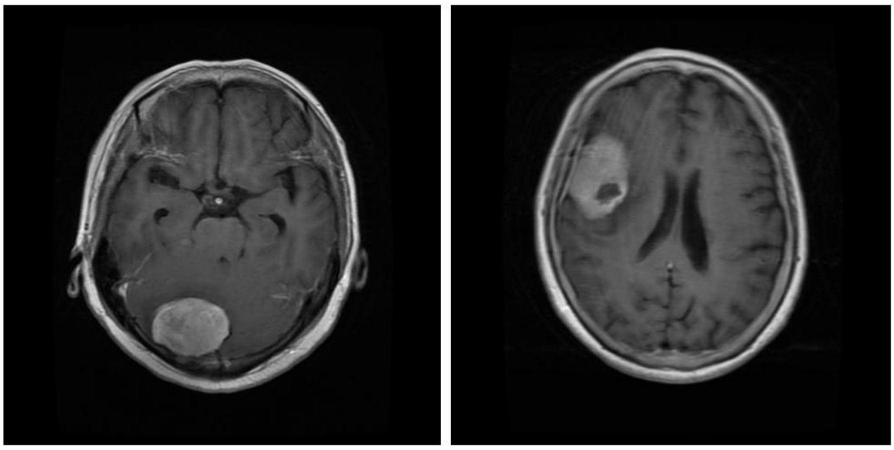

Figure 3. Two brain tumor images in the dataset

The hybrid system has been developed with the K-Means and Otsu method. The hybrid method is obtained with the intersection of the segmentation results from K-Means and Otsu methods.

In the first column of Figure 4, the MRI brain tumor images are actual images that have been obtained in the dataset. In the second column, the images in which the skull part of the brain has been removed are displayed. But, also, these gray-scaled images are filtered with the gaussian and wiener noise reduction. Namely, the images are smoothed with the convolution of these filters. The white areas of the binary images in the third column are represented as the brain tumor regions of the MRI images.

As seen in Table 1, if we evaluate the developed segmentation systems, we can say that the best segmentation method is the hybrid of K-Means and Otsu method according to Accuracy and TPR. The average success values are 94% of Accuracy and

TPR. However, the hybrid and K-Means methods have the best average results with 93% of TNR.

As shown in Table 2, the average Accuracy, TPR, and TNR scores of the systems using the hybrid method of K-Means and Otsu are 84%, 85%, and 80% respectively. According to the best Accuracy results, the methods are ordered as the hybrid method, Otsu method, K-Means, Fuzzy C-Means, and SOM. When removing the skull from the brain tumor image, the segmentation success rates increase by approximately 10%.

Table 3 shows that the fastest segmentation method is Otsu method with 11.21 seconds when doing skull stripping. Otsu method has done the fastest segmentation without skull stripping too. Because of the training operation for SOM and Fuzzy C-Means, they have the longest segmentation time.

As seen in Figure 5, The hybrid method, K-Means, Fuzzy C-Means, Otsu, and SOM methods in order are the most successful methods according to the metric Accuracy, and we can say that the unsuccessful method is SOM with the 88% of Accuracy and TNR results.

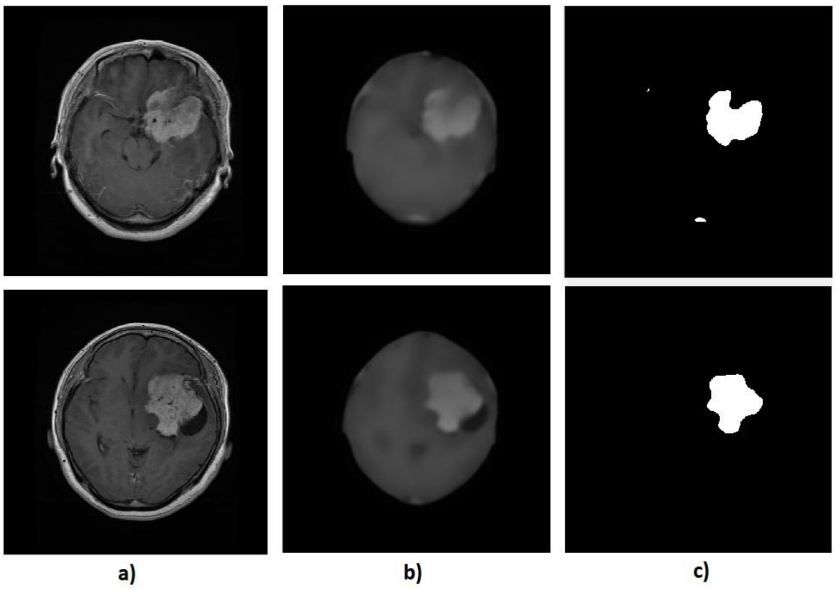

Figure 4. The images of the hybrid of K-Means and Otsu method segmentation.
a) Actual MRI image b) The brain image without skull c) Segmented brain image

Table 1. Evaluation of the systems with K-Means, Fuzzy C-Means, SOM and Otsu methods after skull stripping

Methods	Accuracy	TPR	TNR
K-Means	0.93	0.91	0.93
Fuzzy C-Means	0.92	0.89	0.92
SOM	0.88	0.93	0.88
Otsu	0.91	0.93	0.91
K-Means+Otsu	0.94	0.94	0.93

Table 2. Evaluation of the systems with K-Means, Fuzzy C-Means, SOM and Otsu methods without skull stripping

Methods	Accuracy	TPR	TNR
K-Means	0.80	0.84	0.78
Fuzzy C-Means	0.79	0.82	0.79
SOM	0.77	0.90	0.76
Otsu	0.82	0.72	0.82
K-Means+Otsu	0.84	0.85	0.80

Table 3. The Duration of the systems according to the methods in seconds

Methods	With Skull Stripping	Without Skull Stripping
K-Means	11.77	4.69
Fuzzy C-Means	42.32	58.23
SOM	187.02	198.79
Otsu	11.21	4.52
K-Means+Otsu	12.44	6.25

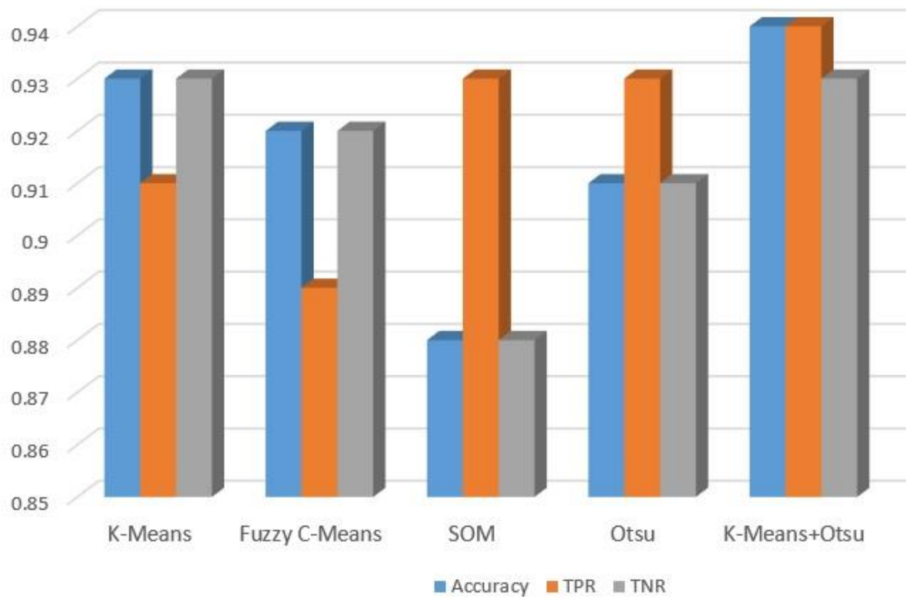

Figure 5. The successful results of segmentation methods

4. Conclusions

In this work, the hybrid of K-Means and Otsu method, K-Means, Fuzzy C-Means, SOM, and Otsu method-based systems have been designed and implemented for the segmentation of brain tumors automatically. First, the skull region of the brain tumor image is detected and removed from the brain. Then, the methods are applied to the segment and have determined the tumor area. Finally, the performances of the methods have been computed. The most successful method as the hybrid of the K-Means+Otsu method has achieved 94% Accuracy, 94% of TPR, and 93% of TNR. Besides, we can say that the success rate increases by removing the skull from the brain tumor image The developed hybrid system outperforms the other methods. The future work of this study will be extended to detect the brain region in the MRI images using other methods.

References

[1] Gooya A, Pohl KM, Bilello M, Cirillo L, Biros G. GLISTR: glioma image segmentation and registration, IEEE Trans. Med. Imaging, 2012; 31: 1941-1954.

[2] Islam A, Reza SMS, Iftekharuddin KM. Multifractal texture estimation for detection and segmentation of brain tumors, IEEE Trans Biomed Eng, 2013; 60: 3204-3215.

[3] Kwon, D., 2014, Combining generative models for multifocal glioma segmentation and registration, Medical Image Computing and ComputerAssisted Intervention, Heidelberg, Springer, 763-770.

[4] Sing JK, Adhikari SK, Basu DK. A modified fuzzy C-means algorithm using scale control spatial information for MRI image segmentation in the presence of noise, Int J Imag Syst Technol, 2015; 29: 492-505.

[5] Rao, V., Sharifi, M., Jaiswal, A., 2015, Brain tumor segmentation with deep learning", MICCAI Multimodal Brain Tumor Segmentation Challenge, 56-59.

[6] Pereira S, Pinto A, Alves V, Silva CA, Brain tumor segmentation using convolutional neural networks in MRI images, IEEE Trans Med Imag, 2016; 35: 1240-1251.

[7] Prakash RM, Kumari RSS. Fuzzy C means integrated with spatial information and contrast enhancement for segmentation of MR brain images, Int J Imag Sys Techol., 2016; 26: 116-123.

[8] Ali SM, Abood LK, Abdoon RS. Brain tumor extraction in MRI images using clustering and morphological operations techniques, Int J Geograph Inform Syst Appl Remote Sens, 2013; 4(1): 12-25.

[9] Sharma, M., Mukharjee, S., 2013, Brain Tumor Segmentation using Genetic Algorithm and Artificial Neural Network Fuzzy Inference System ANFIS, Advances in Intelligent Systems and Computing, Springer, Berlin, Heidelberg, vol. 177, 329-339.

[10] Kathirvel R, Batri K. Detection and diagnosis of meningioma brain tumor using ANFIS classifier, Imaging Syst Technol, 2017; 27: 187-192.

[11] Zhang, J., Ma, K., Er, M., Chong, V ., 2004, Tumor segmentation from magnetic resonance imaging by learning via one-class support vector machine, Workshop on Advanced Image Technology, 207-211.

[12] Ayachi, R., Amor, N., 2009, Brain tumor segmentation using support vector machines", European Conference on Symbolic and Quantitative Approaches to Reasoning with Uncertainty, 736-747.

[13] Tustison N, Shrinidhi KL, Wintermark M, Durst CR, et al. Optimal symmetric multimodal templates and concatenated random forests for supervised brain tumor segmentation (simplified) with ANTsr, Neuroinformatics, 2015; 13(2): 209-225.

[14] Corso, J., Sharon, E., Yuille, A., 2006, Multilevel segmentation and integrated Bayesian model classification with an application to brain tumor segmentation, Medical Image Computing and Computer Assisted Intervention, 790-798.

[15] Iftekharuddin K, Zheng J, Islam M, Ogg R. Fractal-based brain tumor detection in multimodal MRI, Appl. Math. Comput, 2009; 207: 23-41.

[16] Prastawa M, Bullitt E, Sean H, Gerig G. A brain tumor segmentation framework based on outlier detection, Med. Image Anal., 2004; 8(3): 275-283.

[17] Held K, Kops E, Krause B, Wells W, Kikinis R. Markov random field segmentation of brain MR images, IEEE Trans. Med. Imaging, 1997; 16(6): 878-886.

[18] Batista, J., Kitney, R., 1995, Extraction of tumors from MR images of the brain by texture and clustering, Conference on Image Analysis and Processing, 235-240.

[19] Wu, M., Lin, C., Chang, C., 2007, Brain tumor detection using color-based k-means clustering segmentation, Conference on Intelligent Information Hiding and Multimedia Signal Processing, 245-250.

[20] Juang L, Wu M. MRI brain lesion image detection based on color-converted k-means clustering segmentation, Measurement, 2010; 43(7): 941-949.

[21] Dharshini, R., Hemanandhini, S., 2016, Brain tumor segmentation based on Self Organising Map and Discrete Wavelet Transform, International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India.

[22] Saraswathi, D., Priya, B.L., Lakshmi, R.P., 2019, Brain Tumor Segmentation and Classification using Self Organizing Map, International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India.

[23] Karaddi, S., Babu, P., Reddy, R., 2018, Detection of Brain Tumor Using Otsu-Region Based Method of Segmentation, International Conference on Computing Methodologies and Communication (ICCMC), 128-134.

[24] AlAzawee WS. Computer-Aided Brain Tumor Edge Extraction Using Morphological Operations, MSc. Thesis, Western Michigan University, Kalamazoo, USA, 2015.

[25] Cheng, J., 2017, Brain Tumor Dataset, figshare, Dataset. [Online]. https://figshare.com/articles/brain_tumor_dataset /1512427 [Access Date: 11 .05. 2020].