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A Comparative Study for Brain Tumor Detection Using Segmentation Based on Soft Computing and Thresholding Methods

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Abstract **– Early diagnosis of any tumor in the brain is vital because the brain is the most important organ for human life. In medical imaging, while analyzing internal structures magnetic resonance imaging (MRI) is often preferred because of making it easier to detect the desired regions. Brain tumor segmentation in MRI has become a popular area of research in image segmentation which is one of the main approaches of digital image processing in recent years. Segmentation with thresholding is a simple approach that can be used in brain tumor detection, however, for some cases, all tumors cannot be detected successfully by these techniques.**

In this study, we propose the usage of artificial neural networks (ANN) topology based on Canny edge detection (CED) and the thresholding process to detect and segment the brain tumors in early diagnosis. The comparison of ANN with traditional segmentation methods were also revealed. We performed the comparison between proposed ANN, iterative, and Otsu's thresholding segmentation methods. The results demonstrate that the proposed ANN topology with CED is a very efficient way to detect the tumors in MRI brain images and can be used instead of thresholding techniques. The performance of tumor detection is conducted with high performance (98%, 96%, 97%, and 96% for the tumor images of the brain, metastasis head scan, benign- malignant and glioma brain, respectively) by using one or two images instead of a very large database. The results confirm the observation that the ANN has better performance for processing MRI images because of its simple learning structure.

Keywords- Image segmentation; brain tumor detection; thresholding methods; artificial neural networks

I. INTRODUCTION

Since the brain is the headquarters of the central nervous system, it is responsible for performing of all activities in the human body. Therefore, human life can be significantly threatened with any tumor in the brain. The tumors in the brain, which are an undesired mass of abnormal cells, can be benign and malignant [1,2]. The growth rate of benign tumors is slow and they don't metastasize to neighbor tissues. However, since malignant tumors are aggressive and grow rapidly, they can affect the adjacent tissues and organs. Therefore, early diagnosis of the tumor and initiation of treatment increases the patient's chances of survival. Today, medical imaging methods have critical importance in diagnosing tumors in the brain and other organs at an early stage. There are techniques such as Computed tomography (CT), Magnetic resonance imaging (MRI), EEG (electroencephalography), etc. which are developed for detecting different tumors. Since the success of treatment depends on the experience and appreciation of the physician, it has critical importance to use an accurate detection system in order to help physicians to distinguish the tumors in the brain.

MR imaging is frequently preferred by clinicians to detect the tumors or determine the characteristics of tumors in the brain because of its higher resolution and quality [3]. Because magnetic resonance (MR) image includes pathology in conjunction with density and shape analysis. However, since the shape, size, location, and density of the tumor vary with every infected case, automatic detection of a brain tumor becomes a daunting task. In addition, due to being a very complex biomedical object, visualization and analysis of these images are very difficult [4].

A. Related Studies and Motivation

In recent works, a wide variety of studies have been conducted on detecting brain tumors with MR images in recent years. Segmentation [3], threshold techniques [5], feature extraction methods [2, 6], morphological reconstruction [7], optimization algorithms [8], machine learning algorithms [9] and etc. are the example of the brain tumors detection algorithms.

Among the mentioned methods, segmentation is used in many studies due to being one of the fundamental approaches to digital image processing. The constituent regions or objects of images can be divided by segmentation that is unsupervised learning [10]. In this context, the tumor can be determined by using segmentation methods for MR images. Classical algorithms based on statistical or mathematical methods, artificial intelligence are the methods that can be applied for segmentation techniques. The classical algorithms include edge/boundary detection, histogram thresholding, or region extraction approaches. The artificial neural networks model that is in the artificial intelligence field is frequently used for segmentation [11]. There have been some researches related to the comparison of segmentation with thresholding methods and machine learning in different areas of image processing [12, 13].

The image is split into smaller segments or junks by using thresholding methods. In this method, the boundary of images is defined with grayscale value or at least one color and by using segmentation, the binary images are obtained from color images. Hence the complexity of the data is reduced and the recognition process is simplified [10]. On the other hand, the thresholding can be carried out by using Otsu’s method and histogram-based techniques (HBT). All possible uniform regions in the sample image are obtained with HBT [14]. The two homogenous regions of the background and foreground of a sample image are separated with the threshold value, which is used for HBT. As for that Otsu’s method (OM), the optimal value for the threshold of global is found by using OM. By maximizing the segmented image with between-class variance, the optimal threshold value is selected automatically by OM. Moreover, in parameter-free Otsu’s method, the optimal threshold can be identified with the usage of the image histogram [15].

In literature, the numerous different methods have been proposed for the brain MR image segmentation which is based on the changes of pixels' gray level, the sudden changes in the gray level and the similarities between pixel regions. Saha et.al. proposed a bounding box method and applied it for brain MR images in order to detect the tumor [16]. Gordillo et. al have investigated the threshold-based, region-based, pixel-based, model-based segmentation methods for the detection of brain tumors and compared the advantages and limitations of these methods [17]. Tiwari et al. investigate the systematic literature for brain tumor segmentation and classification of normality and abnormality from MRI images. The application of metaheuristic techniques and deep learning techniques for MRI images are also analyzed in this study [18].

In other respects, that artificial neural networks (ANN), are used in many studies for image segmentation [19]. Artificial neural networks, which have the ability to segment like an expert and exhibit excellent performance for various data sets, are among the automatic segmentation methods. The mapped image to the neural network is trained using training samples in an ANN. After the training process, the connection between pixels (i.e., neurons) is obtained and the obtained images are segmented by using the trained image [20]. Feed-forward neural networks (FFNN), back-propagation neural networks (BPNN), Multilayer perceptron (MLP), Hopfield neural networks (HNN), Kohonen self-organizing maps (SOMs), constraint satisfaction neural networks (CSNN), and pulse-couple neural networks (PCNN) are frequently used ANN methods for image segmentation. Yasmin et al. investigate the usage of the neural networks model for image segmentation in medical imaging applications [21]. Haider et al. analyze the 3D structure of early-stage tumors based on image segmentation [22].

Ingole and Upasani use ANNs based on feed-forward backpropagation to detect the brain tumor in the early stage [23]. They investigate the EEG signals, which contain the human brain information. However, the detection is performed with classifiers. The thresholding and segmentation process, which are required for tumor detection with high accuracy, are not applied in this study. Although they emphasize that ANN is a good classifier for brain tumor detection, the accuracy is not given [23].

Chithambaram and Perumal used the ANN for segmentation process to detect the brain tumors obtained from MRI-scans images [24]. They also used Canny edge detection to segment the images. The achievement of this study is 82% as well [24].

Shargunam and Gopika used the Support Vector Machines (SVM) and ANN to define the benign and malignant tumors obtained from MRI images [25]. They also used Otsu Thresholding for the segmentation process. The performance of SVM and ANN are compared to detect the tumor with high accuracy. The accuracy is found at 90% with SVM and 95% with ANN [25].

Gunasekara et al. proposed the usage of Chan–Vese segmentation algorithm to contoured the concentration of the tumor boundary [26]. In addition, they classified the images to localize the tumor regions by using deep learning architecture. They achieved 92% performance for glioma and meningioma tumors segmentation [26].

Biswas and Islam used a hybrid solution to classify the Glioma, Meningioma, and Pituitary type tumors with four steps [27]. At first, the images are resized and filtered with sharpening. Thereafter, the K-means clustering algorithm is used in the second and feature extraction is performed 2-dimensional discrete wavelet transform in the third stage, respectively. To classify the Glioma, Meningioma, and Pituitary type tumors, the ANN-based on Levenberg-Marquardt network is used with 95.4% achievement. However, this method is used for classification. The segmentation process, which is important for tumor detection, has not been evaluated [27].

In all the above-mentioned studies, it has been claimed that the usage of ANN is a good tool for brain tumor detection. However, while ANN is used for classification in some methods, image segmentation methods are not used at all. Besides, in the field of image segmentation with machine learning, techniques are developing at high speed. Moreover, big data are required for the training and testing process for classification.

B. Contribution

To the best of the authors' knowledge, to detect the brain tumors in MRI images, the usage of ANN by performing with the Canny edge detection, thresholding process, and filtered with median filter is the first application in the literature.

In order to reduce the complexity of the data and simplify the recognition process, well-known segmentation methods are used and compared for brain tumor detection in this paper. In this context, three methods for image segmentation have been applied in order to detect the tumor in the brain. MRI brain images with glioblastoma multiforme tumor [28], intracranial, and calvarial metastasis tumor [29], benign and malignant tumors [30,31] and glioma tumor [32,33] have been used for the simulations.

In this paper, image segmentation is used to discriminate the foreground from the background and the goal is to cluster the pixels into parts of the tumor, natural parts of the brain, and the brain wall. This clustering enables the tumors to be detected directly or to be distinguished by investigating those that differ from natural structures in the brain. This type of image segmentation is implemented by using MATLAB software on a 2-dimensional MRI scan image with a pixel size of 211x281. A comparison between histogram thresholding, Otsu's thresholding, and ANN model has been performed and their performances for the used MR brain tumor images are evaluated. In addition, a preprocessing ANN model has been developed and implemented to extract the tumor region in the segmentation of MRI brain tumors.

The rest of the paper is as follows. The evaluated methods are detailed in Section II. Section III presents the simulation results and the performance analysis of the evaluated methods for the used MR brain images. In Section IV, the obtained results of evaluated methods for brain tumor detection are discussed and the paper is concluded.

II. METHODS FOR SEGMENTATION

A. Thresholding

Thresholding is a simple image segmentation technique that separates the pixels of different classes based on their gray levels [34]. In the thresholding method, the classes that are object and background are separated by determining a threshold value that corresponds to the intensity. Depending on the threshold value, pixels of greater value form one group, while pixels of lower value remain in the other group. The disadvantage of this method is that only two classes can be generated. The global thresholding method that holds the threshold value constant in the entire image, can be defined as given in (1),

$$g(x,y)=\begin{cases}0 & f(x,y)<T\\ 1 & f(x,y)\geq T\end{cases} \tag{1}$$

where T is the threshold value, $f(x,y)$ and $g(x,y)$ depict the image and the segmented image, respectively.

Since the different features of the image are usually distinct in its histogram, the histogram can be analyzed for the thresholding process. However, if the peaks of two features are overlapped, it could be challenging to determine the optimum threshold value. In such cases, the threshold value can be determined as the mean intensity value. The steps of the thresholding algorithm used in this study can be summarized as follows:

i. The average intensity of the image is determined as the initial threshold value.

ii. Mean gray values of the classes, μ_1 and μ_2, are calculated.

iii. Image is separated into two classes by using a threshold value.

iv. A new threshold value is selected by calculating the average of the mean gray values.

$$T=\frac{1}{2}(\mu_1+\mu_2)$$

v. The steps between (ii) and (iv) are repeated until stable mean values are obtained.

B. Otsu's Thresholding Segmentation

In Otsu's thresholding method, the gray-scaled image is converted into a binary image and the pixels of this image are leveled by the specific threshold value. In this method, the weighted sum of within-class variances that belong to the object and the background pixels are minimized and thereby an optimum threshold value is determined. This procedure is the same as maximizing the between-class variance. Since the method is based on statistical, the obtained threshold value is between 0 and 1. It is basically performed by selecting the lowest point between two classes. The total variance for Otsu's thresholding can be calculated as given in (2) where $\sigma_w^2(t)$ is the weighted within-class variance, $q_1(t)$ and $q_{2(t)}$ are the probabilities of the classes, $\mu_1(t)$ and $\mu_2(t)$ are the means of the classes, $\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variances of individual classes. The formulations for these quantities are given in (3) - (6), respectively. Additionally, in (2), the terms following addition sign correspond to the between-class variance, $\sigma_B^2(t)$. Hence, it can be clearly seen that the total variance is the sum of within-class variances and between-class variance [35].

$$\sigma^2(t)=\sigma_w^2(t)+q_1(t)[1-q_1(t)][\mu_1(t)-\mu_2(t)]^2 \tag{2}$$

$$\sigma_w^2(t)=q_1(t)\sigma_1^2(t)+q_2(t)\sigma_2^2(t) \tag{3}$$

$$q_1(t) = \sum_{i=1}^{t} P(i),\ q_2(t) = \sum_{i=t+1}^{I} P(i) \tag{4}$$

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)},\ \mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)} \tag{5}$$

$$\sigma_1^2(t) = \sum_{t=1}^{t} [i-\mu_1(t)]^2 \frac{P(i)}{q_1(t)},$$
$$\sigma_2^2(t) = \sum_{t=1+1}^{I} [i-\mu_2(t)]^2 \frac{P(i)}{q_2(t)} \tag{6}$$

C. Artificial Neural Networks

Since neural networks are fast and do not require time-consuming calculations, they are often preferred for data clustering problems today. ANN which is consisting of three layers as the input layer, hidden layer, and output layer, executes training and learning steps similar to the brain. The input signals are received by the input layer and transmitted to the next processing. In the neural network, processing operations are carried out in hidden layers. The information is received and sent to the others by each neuron of hidden layers. The output layer produces the output for the entire network at the last stage [36]. The basic structure of the ANN is depicted in Fig. 1. Different structures and algorithms can be used in neural networks. While a basic neural network model can be used for simple and easy-to-solve problems, multi-layer structures or multiple input-output combinations may be needed if the problem complexity increases.

Different inputs of the neuron are summated as given in (7) where O_j, x_i and w_{ij} denote the output, input and weight value of the neuron, respectively.

$$O_j = \sum_{i=1}^{n} x_1 w_{ij} \tag{7}$$

The optimum output is generated by using an activation function and it is applied to the summation of the inputs. In (8), Y_j is the output of the neural network and f denotes the activation function that can be hard limit, limited ramp, sigmoid, logarithmic, tangent or linear functions [37].

$$Y_j = f\left(\sum_{t=1}^{n} x_i w_{ij}\right) \tag{8}$$

It is an important problem to make neural networks understand a pattern of different images or data sets. It can be done by using learning methods. Parameters of neural networks are adjusted in order to generate the optimum output for the given problem by the used learning algorithm. Backpropagation is the most commonly used learning algorithm because of its robust performance in determining the optimum weight values of the layers [38]. For this algorithm, the error value of the output can be calculated as given in (9);

$$E = \sum (T-Y)^2 \tag{9}$$

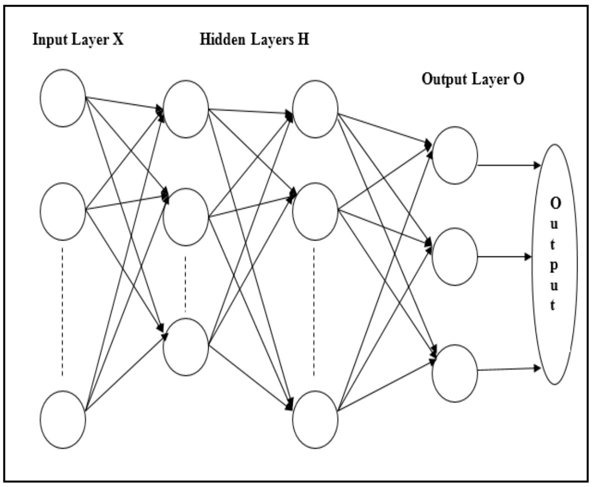

Figure 1. Basic neural network structure.

where T and Y denote the target and output of the neural network, respectively. On the other hand, ANN-based methods for segmentation are mostly preferred due to having the properties of using in real-time applications and degradation in the presence of noise. Grey level thresholding, edge detection, iterative pixel classification, surface-based segmentation are frequently used image segmentation techniques with ANN methods [11].

In the proposed ANN method, MLP with a backpropagation network is used for its simple structure. This network is created with three layers as input, hidden, and output layers. These mentioned layers consist of 100 neurons, 10 neurons, and 100 neurons respectively. With the trainscg training function, the training process is done to update the bias values. To obtain the defective image and determine the number of hidden layer neurons, the mean squared error (MSE) is calculated. We reached the best MSE, which is a performance criterion, with 10 hidden neurons. For this reason, the whole process with performed according to 10 hidden layer neurons. In addition, the ANN structure is constituted with 90 % sample for training, 5% sample for validation, and 5% sample for the test.

III. Results and Analysis

In this study, MATLAB software is used in order to detect the tumor from MRI scan images. Four different MR images that include one tumor, metastasis tumors, benign and malignant tumors together, and glioma tumor are used in order to evaluate the performances of the methods. The image I includes a glioblastoma multiforme, belongs to a 70-year-old man [28]. Image II is a metastasis MR image that consists of a tumor from a 52-year-old male patient with leptomeningeal and intracranial and calvarial metastases [29]. Image III includes benign and malignant tumors which originate from cells in the interiore and not contain cancer cell and which contain cancer cells and not have a clear border, respectively [30,31]. Finally, Image IV has a glioma brain tumor, which is a low-grade unaggressive tumor [32,33].

The purpose of using these images in our study is that they are the types of the brain tumors frequently used in the literature. For this context, the image of the glioblastoma tumor is taken from [28] performed by Castillo. This image has not been taken part in a public database. The intracranial, and calvarial metastasis tumor, which is used second MRI image in this work, is obtained by using the [29] that is in the public database on the website. The used third image is taken by using BRATS 2013 data [30,31]. The image of the glioma tumor is obtained by using the [32,33] that is accessed on the website.

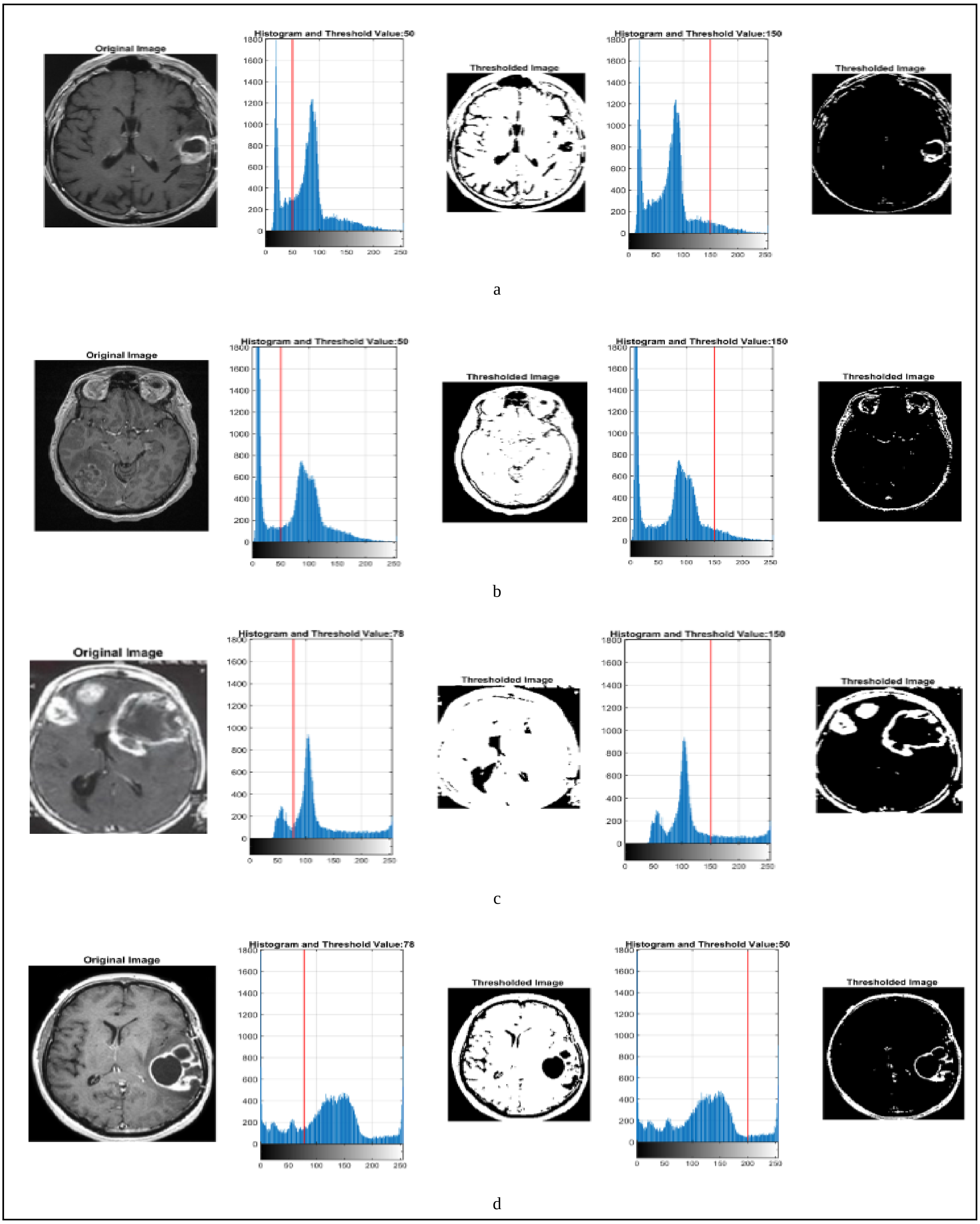

Figure 2. Original MR brain images, histograms and thresholded ones by using two different threshold values for a) Image I b) Image II c) Image III d) Image IV, respectively.

On the other hand, the images taken from the database and reference sources were used by removing the unused blank areas at the edges and adjusting them.

Since the shape of the histogram can be useful in threshold locating, histograms of figures are plotted and detection of the tumor is tried to be done by using fixed thresholding. The original MR images used in this study and the histograms obtained from these ones are shown in Fig. 2. It can be seen from Fig. 2 that peaks in the histograms correspond to different features of the original MR images. In Fig. 2, lines (a), (b), (c), and (d) belong to the original MR images that are previously specified as Image I, Image II, Image III, and Image IV, respectively and these lines will refer for these images throughout this paper. There have been apparent peaks in the histograms for the original images given in Fig.2 a, b, and c. However, for some cases such as the image shown in Fig. 2d, peaks overlap much more and the separation of these peaks is getting harder. If the threshold value is not determined appropriately, some pixels will be incorrectly classified.

Fig.2 also shows the obtained images by using two different threshold values which are chosen approximately in the middle and at the end of the peaks for each one. It can be seen easily from Fig. 2 that if the appropriate threshold value is not selected, pixels are classified incorrectly and tumors can not be determined clearly by thresholding as shown for the first chosen threshold values in the left columns of all lines.

In order to overcome this problem in the fixed thresholding method, Otsu's thresholding technique can be used to detect and segment the tumor in the brain. The obtained segmented images after applying Otsu's thresholding technique are shown in Fig. 3.

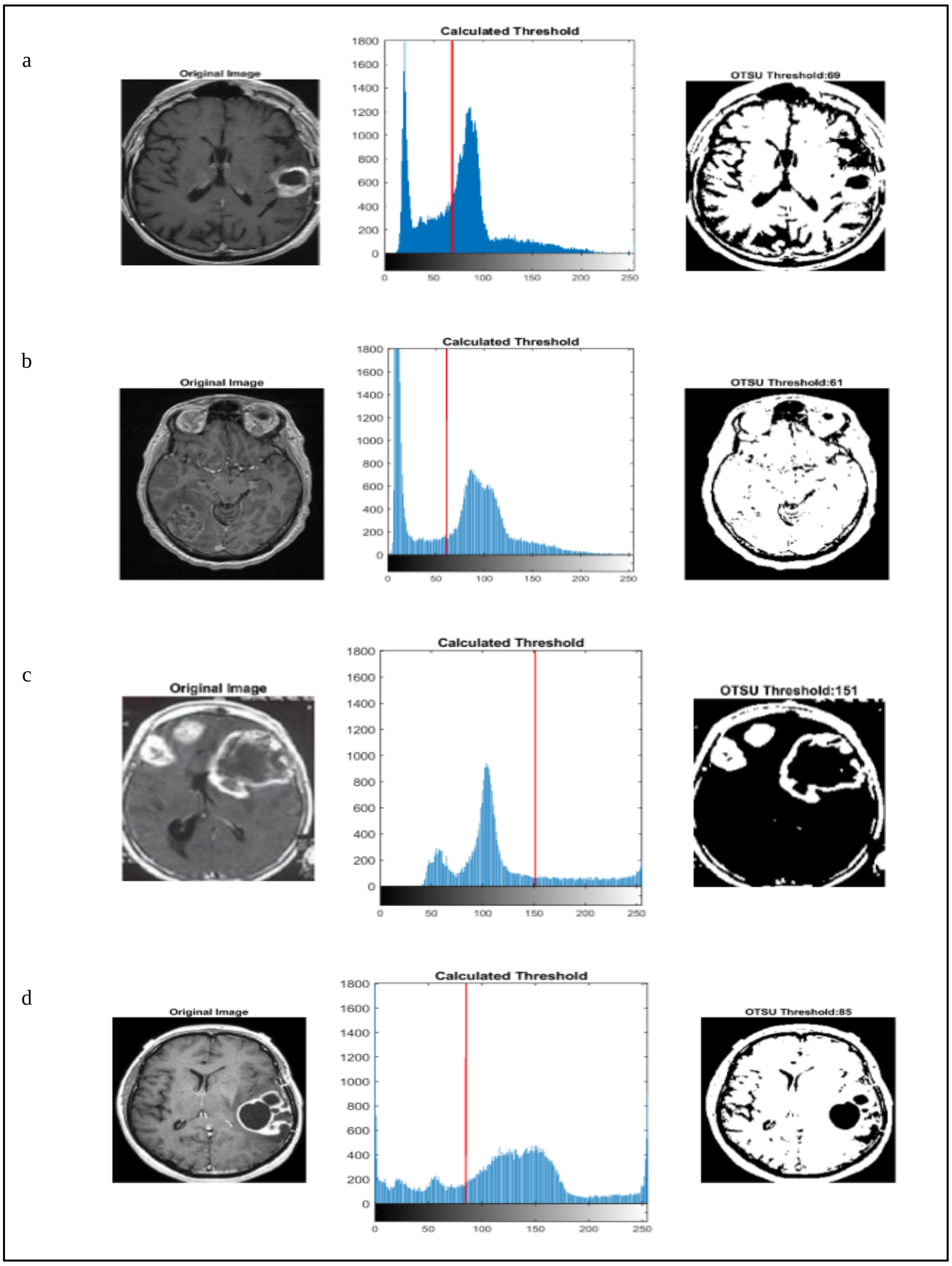

Figure 3. Original brain MR images and obtained images after applying Otsu's thresholding for a) Image I b) Image II c) Image III d) Image IV, respectively.

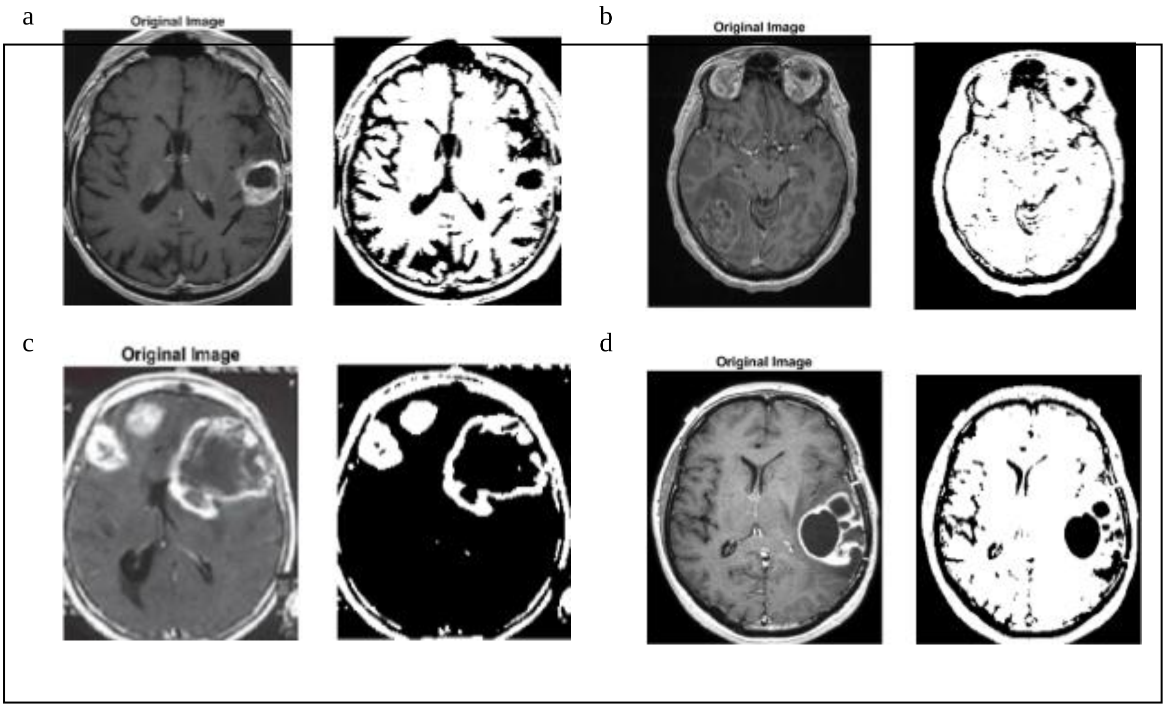

Figure 4. Original brain MR images and obtained images after applying iterative thresholding a) Image I b) Image II c) Image III d) Image IV, respectively.

Since the interclass variance of the thresholded black and white pixels is minimized by the threshold value determined in Otsu's thresholding, the lowest point between the two classes is selected. It can be seen from Fig. 3 that Otsu's thresholding method performs better if there are overlapping peaks or unclearly resolved peaks in the histogram such as benign and malignant tumors and glioma brain tumor image given in Figs. 3c and 3d, respectively. However, successful results have not been obtained for MR images given in Fig. 3 because of the uniform illumination assumption for Otsu's threshold method. In order to overcome the difficulties in fixed and Otsu's thresholding methods, an alternative iterative thresholding method which is explained with details in Section II (A) can be used. The segmented images obtained after applying iterative thresholding are shown in Fig.4.

Although the iterative thresholding method provides results close to Otsu's thresholding given in Fig. 3, there have been still challenging with thresholding methods for segmentation because of inhomogeneous intensities of the images. Since special data structures can be accomplished for the desired tasks in ANN, they can be used for the detection of tumors, too. Hence, better accuracy can be provided in the segmentation process. In this study, the MLP network is used for the segmentation process. The MR images with tumors are classified as 100 input neurons, 10 hidden neurons, and 100 output neurons. The training process in the network is performed by using the trainscg training function, which updates the bias values and weights according to the scaled conjugate gradient backpropagation method. To active the neurons in the hidden and the output layers, the tansig activation function is used. The final parameters of the ANN structure are represented in Table 1.

TABLE I. TRAINED ANN FINAL PARAMETERS.

	Image I	Image II	Image III	Image IV
Input Layer Neuron Numbers	100	100	100	100
Hidden Layer Neuron Numbers	10	10	10	10
Output Layer Neuron Numbers	100	100	100	100
Maximum Iteration Numbers	1000	1000	1000	1000
Training Time	27 sec	33 sec	35 sec	129 sec
Gradient	0.0670	0.240	0.121	0.0243
Learning Rate	0.3	0.3	0.3	0.3
Momentum Rate	0.047	0.047	0.047	0.047
Activation Function	tansig	tansig	tansig	tansig

The brain images with tumors, which are defined as input for ANN structure, are enhanced for adequate identification by applying a series of image processing techniques [39]. At the first stage, the image is converted from RGB to grayscale. Secondly, the median filter -linear filter-0 is applied to a grayscale image to perform a smoothing operation and reduce the impulsive noise. After the second step, the filtered image is undergone the intensity adjustment to enhance the image quality and increase the intensity. In the fourth stage, the thresholding process is applied. The foreground and background regions are the separated regions of the adjusted image. These regions are created with a thresholding process. The foreground and the background regions contain the objects that we want to see in some needed areas such as tumors and unneeded objects, respectively. In the fifth stage, edge detection is performed by using a Canny edge detector to identify the sharp intensity contrasts of the image and to perform the segmentation process. After the segmentation process, the MLP network is constituted on MATLAB software (R2018). Thus, the ANN structure is enabled to find the thresholded image from the segmented image by learning the thresholded image. These phases are depicted with the flowchart in Fig. 5.

In Fig. 6, the thresholded images and segmented ones obtained by Canny edge detection are represented for Image I, Image II, Image III, and Image IV, respectively.

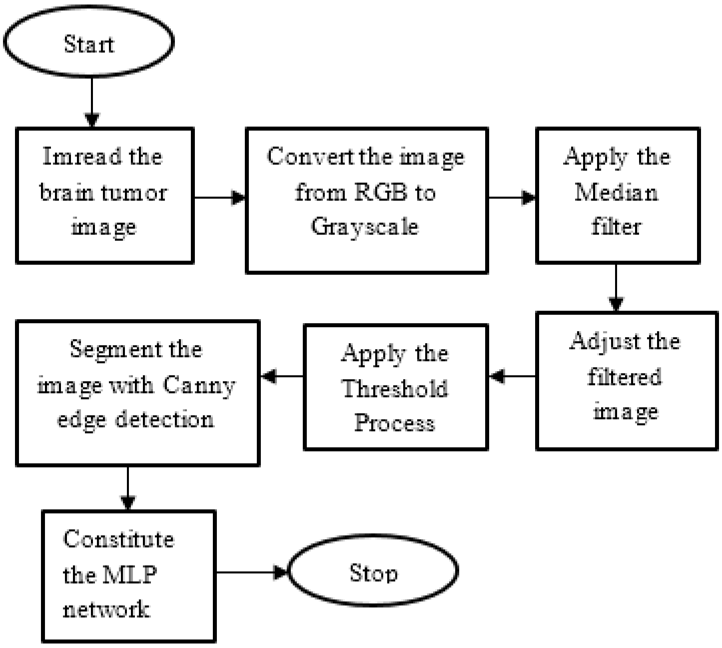

Figure 5. The flowchart of segmentation process performed with ANN.

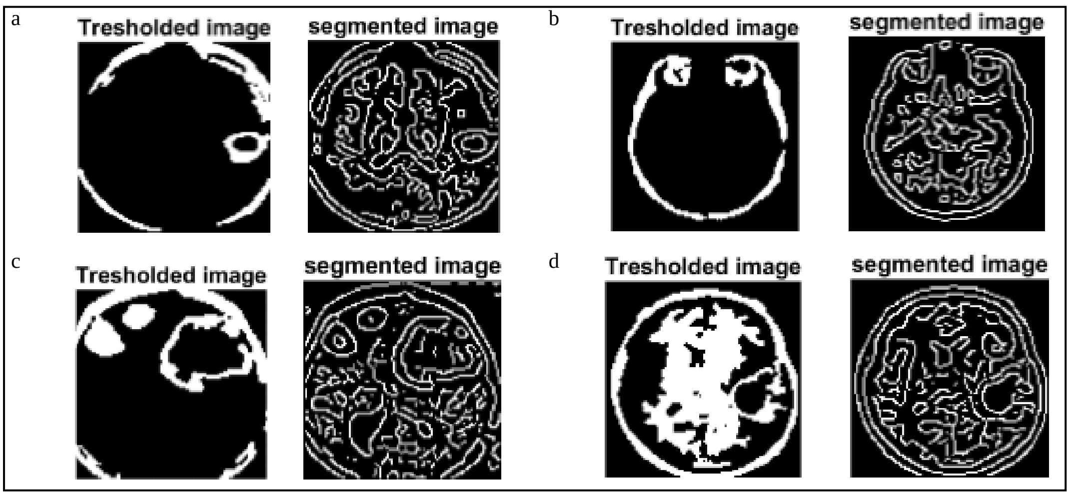

Figure 6. Thresholded and segmented images for a) Image I b) Image II c) Image III d) Image IV, respectively.

The following images shown in Fig. 7 and Fig. 8 are the training results of the Image I, Image II, Image III, and Image IV, respectively for the developed ANN structure. It can be seen that while the iteration number is increasing, the error is decreasing. The learning curves of the ANN for these images are depicted in Fig. 7. In the training process, as a recognition rate, the network reached a minimum error of 0.0016 at epoch 4 with 98% for a brain tumor, 0.0034 at epoch 4 with 96% for metastasis head scan, 0.0021 at epoch 5 with 97% for MR benign and malignant tumors, 0.024 at epoch 10 with 96% for the glioma brain tumor image.

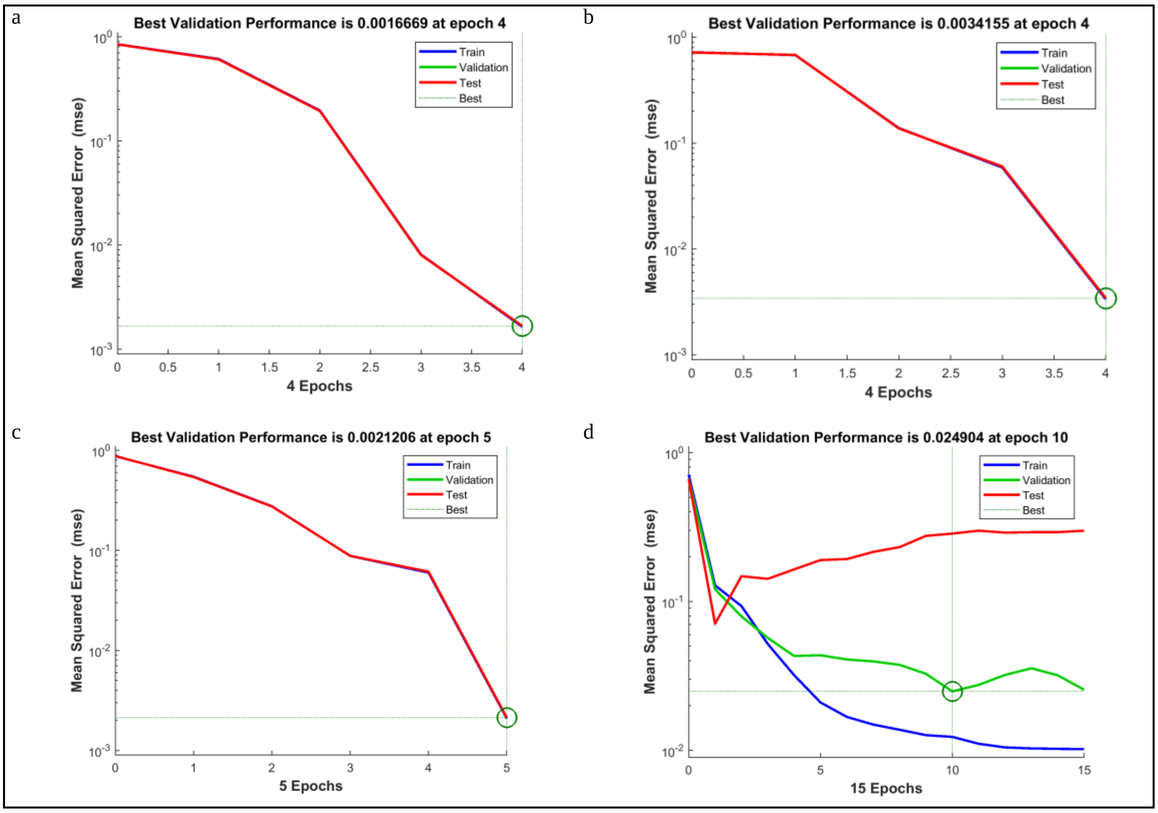

Figure 7. Learning curves for a) Image I b) Image II c) Image III d) Image IV, respectively.

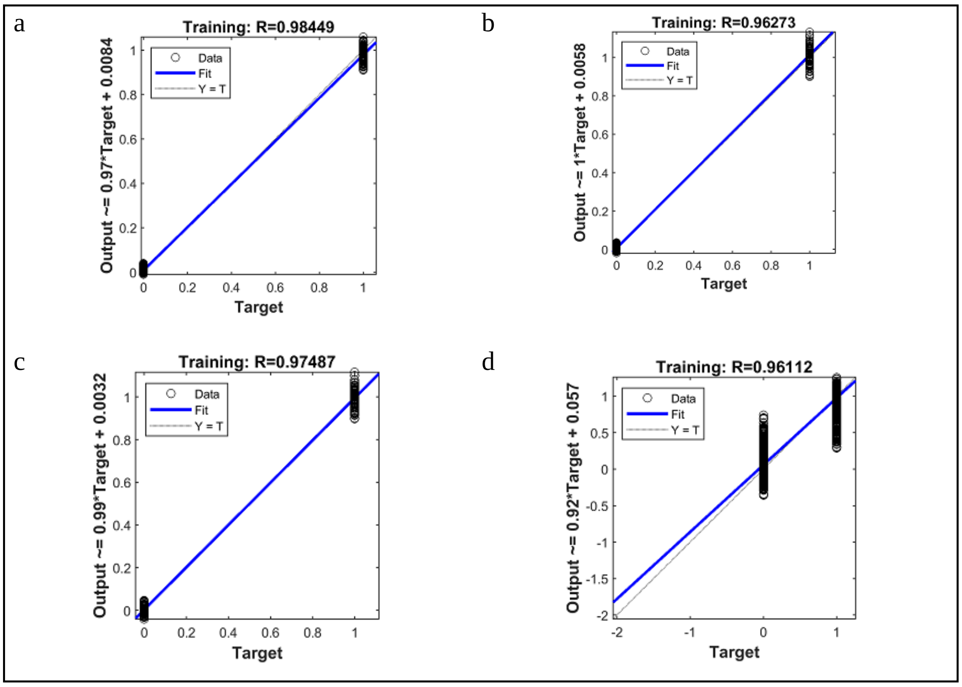

Figure 8. Training results for a) Image I b) Image II c) Image III d) Image IV, respectively.

TABLE II. SYSTEM PERFORMANCE OF THE ANN BASED ON SEGMENTATION.

	Image Numbers	Image I	Image II	Image III	Image IV
Training Set	90	98%	96%	97%	96%
Testing Set	10	96%	92%	95%	61%
Whole Set	100	98%	96%	97%	91%

The errors between the input image and target outputs are shown in Fig. 7 by giving the neural network training recognition rate. When the input image and target output are overlapped, a good local minimum is achieved with the trained network.

In this study, the ability of the ANN system to detect the tumor region with the segmentation process is investigated. After the training process, the testing phase performs and the performance of the system is evaluated. In Table 2, the performance of the testing and training process results are presented for four images, respectively.

CONCLUSION

Since the brain is the most important organ for human life if the detection and intervention of any tumor in the brain can be performed rapidly, the success of the treatment increases. Moreover, having sufficient and detailed information about the location, size, and spreading scheme of the tumor in the brain ensures performing more successful operations with minimum risk. To detect brain tumors, numerous researches are performed. The existing applications in the literature given in Table III are detailed to compare with our current study.

In this study, the tumors in the brain MR images are detected by using thresholding methods and artificial neural networks. Segmentation of images allows detecting the tumor and getting more information about it. Also, from studying the paper we can conclude that determining an appropriate threshold value for MRI images that have separable peaks in their histogram is proved to be most successful for the detection of the brain tumor and type of it. However, there have been difficulties with fixed thresholding and other thresholding methods mentioned in this study. Therefore, the use of artificial neural networks can be beneficial in the classification of the tumor part and the detection of the tumor from MRI images can be implemented by the generated network topology.

In order to prove that the usage of artificial neural networks is a correct approach, our current study is compared with the studies in the literature. For instance, Chithambaram and Perumal classify the brain tumor tissues on MRI images into two classes. One of them is normal and the other is abnormal tumors in the brain. They apply the Canny edge detection and segmentation process with ANN to detect the tumors. The 82% accuracy is obtained in their study [24]. However, we achieved 98% accuracy to detect the brain tumors in the performed study by using Canny edge detection with ANN-based on MLP network.

The Glioma, Meningioma, and Pituitary tumors are detected with 95% accuracy by Biswas and Islam. [27]. They achieved this performance by classifying the type of tumors by using an artificial neural network based on the Levenberg-Marquardt network. However, in our study, a metastasis MR image with leptomeningeal is detected with 96% accuracy by using the MLP network after applying the segmentation process performed with Canny Edge Detection.

On the other hand, benign and malignant tumors are segmented by using Otsu Thresholding and identified by using SVM and ANN by Shargunam and Gopika. The achievement of this study is 90% for SVM and 95% for ANN [25]. Moreover, the MRI images included benign and malignant tumors are enhanced by applying the threshold segmentation process and classified by using Pulse Coupled Neural Network (PCNN) and backpropagation network (BPN) in ANN [25]. However, the accuracy is not mentioned in this study. The benign and malignant tumors are detected with 97% accuracy in our performed study.

Furthermore, the glioma and meningioma tumors are segmented with Chan–Vese segmentation algorithm classified with deep convolutional neural network (CNN), region-based convolutional neural network (R-CNN) by Gunasekara et al. [26]. The obtained accuracy is 92% for this study. However, we detect the glioma brain tumor by using Canny Edge Detection in the segmentation process and with ANN based on the MLP network. Our performance of the whole set is 91%, 61% for the testing set, and 96% for the training set. The reason for the 61% success in the test set is that the training number is selected the same for each image when training with ANN. In other words, regardless of the type of brain tumor, it is obtained with high detection by subjecting to the same training conditions. When the number of training is increased for this image, the success is around 95%.

In this study, we illustrate the effective results for detecting the MR brain images by comparing the ANN topology and other segmentation methods. The best results are achieved by using the ANN method. The ANN performance is obtained as 98%, 96%, 97%, and 96% for brain tumor (Image I), metastasis head scan (Image II), MR benign and malignant tumors (Image III), and glioma brain tumor image (Image IV), respectively.

TABLE III. RELEVANT STUDIES DEALING WITH DETECTING THE BRAIN TUMOR

Authors	Simulated tissue/ purpose of the study	Used image	Used method for Segmentation	Accuracy
Subashini and Sahoo, 2013 [38]	To enhance the MRI images by using segmentation and classification process based on backpropagation networks in ANN.	benign or malignant tumors	Threshold Segmentation, Pulse Coupled Neural Network (PCNN) and back propagation network (BPN)	-
Ingole and Upasani, 2014 [23]	To detect the brain tumor obtained from EEG signals by using ANNs based on feed forward backpropagation.	brain tumor obtained from EEG signals	feed forward back propagation neural network	-
Chithambaram and Perumal 2017 [24]	To classify the brain tumor tissues on MRI images into two classes of normal and abnormal by applying the edge detection and segmentation process with ANN.	Normal and abnormal brain tumors	Canny Edge Detection with ANN	82%
Shargunam and Gopika,2020 [25]	To identify the tumor on MRI images by using SVM and ANN.	benign tumor and malignant tumor	Otsu Thresholding , SVM and ANN	90% for SVM and 95% for ANN
Gunasekara et al. 2021 [26]	To segment the boundaries of the tumors correctly and to classify the images by using deep learning architecture by localizing the tumor regions.	The glioma and meningioma tumors	deep convolutional neural network (CNN), region-based convolutional neural network (R-CNN), Chan–Vese segmentation algorith	92 %
Biswas and Islam, 2021 [27]	To classify the type of tumors by using an artificial neural network based on the Levenberg-Marquardt network	The Glioma, Meningioma and Pituitary tumors	Artificial neural network based on Levenberg-Marquardt network	95.4%

This paper provides an ANN topology based on the edge detected and thresholded target brain MR images. We have shown that using ANN methods for segmentation provides early diagnosis and more accurate treatment of brain tumors by supporting doctors. In addition, it can also be concluded that high resolution may affect the performance of traditional thresholding methods. Because by increasing the contrast, the contour information of the tumor may be lost. It is thought that this situation can be avoided by applying some other adaptive thresholding methods. In further studies, it is aimed to develop the method by combining adaptive thresholding and machine learning algorithms.

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