Kurdish Studies
Jan 2024
Volume: 12, No: 1, pp. 915-924
ISSN: 2051-4883 (Print) | ISSN 2051-4891 (Online)
www.KurdishStudies.net

Received: October 2023 Accepted: December 2023
DOI: https://doi.org/10.58262/ks.v12i1.059

Presenting a New Method Based on Vector Smoothing Technique Using Image Processing and Deep Learning to Detect Brain Tumor

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Abstract

Accurate diagnosis of the size and location of the tumor plays an important role in identifying the tumor and then using the appropriate treatment course for patients with brain tumors. The innovation of the current research is the use of image processing along with machine learning algorithms to diagnose brain tumors and provide useful information about the tumor so that a suitable treatment course can be drawn for the patient according to this information. In this research, a new structure based on LVQ was presented for the detection of cancerous tumors using MRI images. The proposed method is a hybrid method based on image processing and machine learning algorithms. After applying filters and removing image noises, the images without noise were pre-processed in two categories, bright images and dark images

Keywords: *brain tumor, MRI images, vector smoothing, deep learning*

Introduction and Statement of the Problem

Each human body has more than 100 trillion cells. All the cells of the human body, except red blood cells, all have a nucleus, this nucleus has genetic or hereditary material, active genes create about 400,000 types of proteins for the body, this molecular diversity causes changes in the appearance and inside of the human body.Any abnormality in the way of growth, reproduction or stopping the production of genes affects this diversity and can have unfortunate consequences and even lead to death, cancer is one of these abnormalities [1, 2]. Cancer refers to a wide range of diseases that refer to the abnormal growth of cells.Various factors play a role in getting cancer, including genetic factors, chemicals, radiation, and the like. There are also many treatment methods for this disease, which will be different according to the type and degree of its progress. These methods either lead to treatment or slow down the progress of the disease [3, 4]. There are various methods such as surgery, chemotherapy, radiation therapy, drug therapy and so on.Usually, surgical treatment is performed in the early stages of cancer, but in some cases, it is necessary to use combined methods to treat a certain type of cancer [5 ، 6]. Today, one of the most common cancers is brain tumors, which is one of the main causes of death among children

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and adults and is considered among the deadly diseases.A brain tumor is an abnormal growth in the brain that can be benign or malignant. A tumor is an abnormal growth of a cell that is a kind of hard and dense intracranial tissue inside the brain or central spinal canal. Brain tumors include all tumors inside the skull and tumors inside the central canal of the spinal cord. These tumors are formed through uncontrolled and abnormal cell division and are usually formed in the brain itself or the cranial nerves, meninges, skull, pituitary gland, and pineal gland.Also, these tumors can be the result of the spread of malignancies that primarily involve other organs; In this case, it is called tumor metastasis.Since the diagnosis of a brain tumor in its early stages is important and can have a significant effect on the recovery of the disease; Therefore, the identification of tumors and their location is the main stage of diagnosis[7] . The only tool that can be used to identify and analyze all types of cancers and tumors is the use of medical images. The use of medical images can provide doctors with useful information about tumor size, progression rate, etc. [8, 9].Medical imaging systems have progressed rapidly in medical science and have been able to establish a suitable place for identifying all types of cancers and brain tumors in the medical industry. In general, medical imaging is a process that can be used to obtain different images of the human body or its parts and functions, and these images can be used for medical purposes in all categories of diseases, especially in the identification of cancer and tumors, as well as anatomical and physiological studies. Therefore, medical images are considered one of the most important methods to identify the location of the tumor and size of the tumor, and these images are an easy way to diagnose the tumor to provide a plan for surgery, chemotherapy and finally radiation therapy to remove the tumor [10, 11].In general, surgery, chemotherapy and radiotherapy are used as three main methods to treat tumors and different types of cancers [12, 13]. In the surgical treatment method, the brain tumor is placed in a place of the brain where the surgeon can easily remove and drain the tumor by accessing the tumor. This method of treatment for tumors that cannot be separated from the brain tissue or are located in sensitive areas of the brain is a very dangerous procedure, and surgery is not a suitable option for this category of tumors.Therefore, other methods such as chemotherapy and radiation therapy can be more useful in these patients. In the chemotherapy method, doctors use drug injections to destroy cancer and tumor cells. This method can prevent cancer cells from advancing in the body and disturb their growth process. Most of the patients who undergo chemotherapy have aggressive cancer cells, in which case doctors use radiation therapy in addition to chemotherapy.

Radiation therapy uses ionizing radiation such as X-ray, alpha, beta and gamma rays to destroy cancer cells. Therefore, radiation therapy can be considered one of the most important treatment methods for patients with aggressive brain tumors. But in radiation therapy, high-energy rays can damage other body cells and even cause the death of those cells.Therefore, in this method, it is very important to identify the condition of the tumor and the intensity of the radiation as well as the location of the radiation. Therefore, we need a method that can be used to process medical images with high accuracy, so that we can determine the exact location of the radiation so that it does not cause the death of other cells, and we can take the appropriate treatment process for the patient. Since the brain is completely covered by the skull,Rapid and early diagnosis of brain tumor is only possible if we can determine the condition of the intracranial cavity by accurately processing medical images so that we can choose the most appropriate treatment method with the highest accuracy along with the accurate identification of the tumor and diagnosis of its condition. According to the above-mentioned cases, a method for processing medical images based on machine learning algorithms with the aim of tumor detection is presented in the article. It can be said that brain tumor identification, mainly using CT scans, has become increasingly important. Neural networks and artificial intelligence methods dominate processing algorithms. However, new methods are expected to emerge. This research discusses brain tumor image classification by combining regionalization using learning vector quantization (LVQ). The results of the zoning matrix are used as input to the LVQ.

Suggested Method

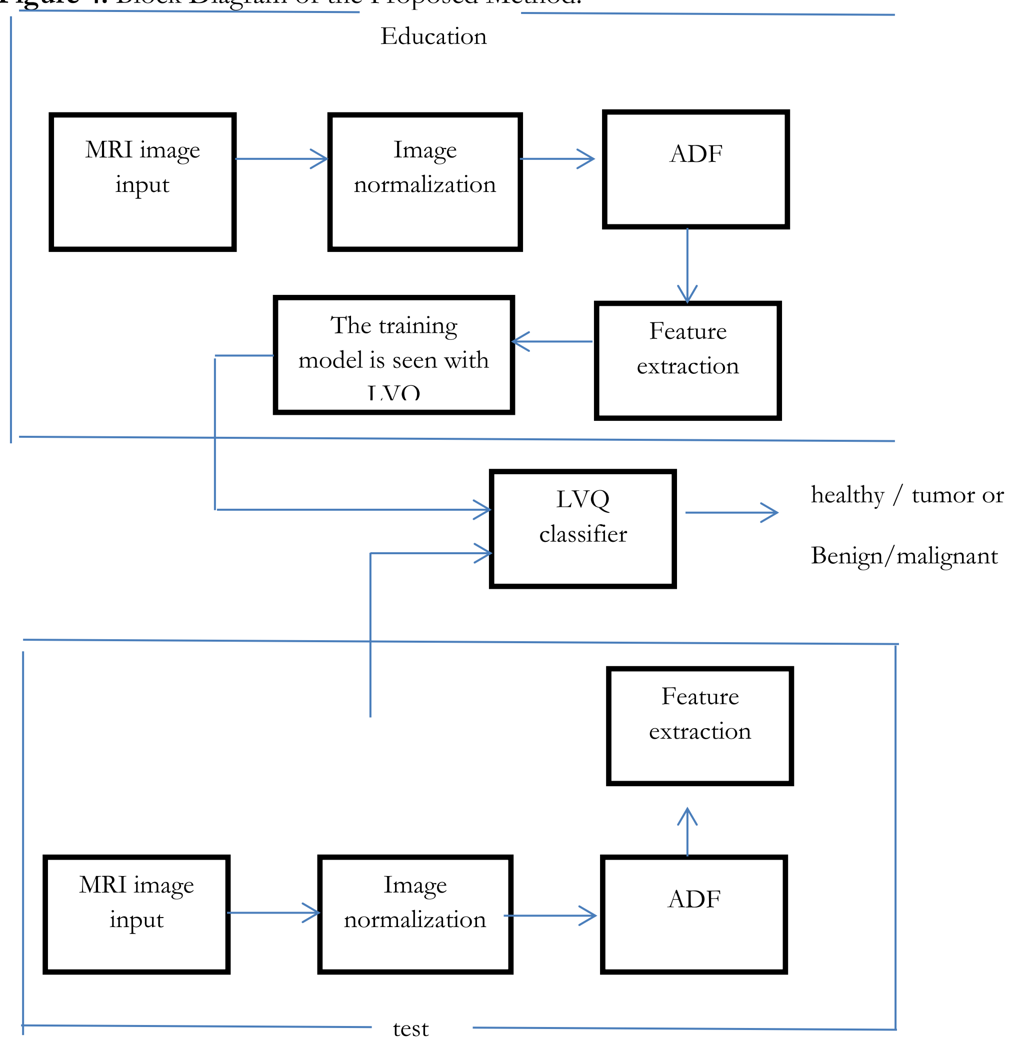
Classification of brain magnetic resonance imaging into normal and abnormal is a critical and challenging task. Given that, several medical imaging classification techniques have been devised, in which Learning Vector Quantization (LVQ) is one of these methods. The main goal of this paper is to increase the performance of the LVQ technique to achieve a higher accuracy diagnosis of brain tumors in MRI.The classic method of selecting the winning code vector in LVQ is to measure the distance between the input vector and the code vectors using the Euclidean distance function. To improve the technique of selecting the winner, the rounding function is used together with the Euclidean distance function. Moreover, in competitive learning classifiers, the fitting model is strongly dependent on the class distribution. Therefore, in this research, a multiple sampling technique is proposed for which a better class distribution can be obtained.This multiple sampling is implemented using random selection through pre-classification. The sample test data used are brain tumor magnetic resonance images collected from the UCI benchmark data set. In the proposed method, we develop an implementation of adaptive boosting using the concept of ensemble learning and machine learning algorithms in Adaboost and LVQ neural networks. In our proposed method, we organize two important steps that are useful for brain MRI image classification.

MRI input: In the proposed system, we use two different data for training and testing, which include abnormal and normal images.

Preprocessing: MRI normalization that includes a histogram or contrast stretch that adjusts the pixel intensity range to a desired range. In image processing, it generally sets the pixel range to (0,2).

Therefore, in this research, we are looking to be able to obtain the threshold values in this image in the best way by using new methods. In our research, these images are taken from the head and brain tumors. Therefore, the main goal of this research is to provide a new method based on image processing and the use of machine learning algorithms for tumor detection, so that we can identify the tumor with the least possible error by zoning digital images of the brain.In this research, we proposed an automatic brain tumor classification approach using a linear vector quantization (LVQ) classifier. A suitable image for the brain MRI training and testing phase is shown in Figure 2-4. The proposed system is divided into two phases. The training phase, and the testing phase, the detailed algorithm are explained as follows.

Figure 4. Block Diagram of the Proposed Method.



ADF: An adaptive smoothing technique that is usually used by the user to detect image details and properly classify the image. Noise worsens and degrades or degrades the image [11]. Such an image becomes blurred, which makes further enhancement and processing difficult [12]. This filtering technique not only preserves the image quality but also prevents the destruction of small and advanced details such as image borders. It also includes noise reduction and detail preservation, enhancing image quality with decent resolution. Adopting an isotropic filter approach, requires a balance between edge reservation and smoothing efficiency [13]. It also preserves the basic physical or standard properties with improved or developed morphological terms.

Feature extraction: The pre-processed image is the input of the feature extraction technique. Gray level co-occurrence matrix (GLCM) technique is used to extract features. In this proposed approach, 22 features were extracted. [14] GLCM is a texture feature extraction method. Features are used to distinguish different classes of an image. Table 1-4 describes the normal and abnormal brain MRI image features.

Classification

Feature images	1 self correlation	2 contrast	3 Correlation	…	20 Inverse difference homogen	21 The inverse difference was normaliz	22 Inverse difference time
1	15702.3	9.65835	0.99916	…	0.99722	0.64776	0.99494
2	13696	9.2664	0.9993	…	0.99733	0.72400	0.99588
3	9246.3	12.693	0.9988	…	0.98974	0.77760	0.99628
….	…	…	…	…	…	…	…
226	17383.1	11.078	0.9984	…	0.99918	0.60098	0.99486
227	14393	10.59	0.998	…	0.99800	0.66878	0.99508
228	11515	14.266	0.9985	…	0.99680	0.70077	0.99553

Vector quantization (VQ) is a popular supervised classifier that was first introduced by Kohonen [15]. The algorithm uses N data vectors using quantization techniques and divides the whole space into a small space of clusters with code indices as identities with an unsupervised method approach. In LVQ, the inputs of the neural network come and pass through several hidden layers to the output layer. It combines classification and clustering processes based on a feed-forward neural network. First, the input Euclidean space is divided into non-overlapping regions or clusters. Second, these areas are assigned to classes as shown in Figure 2-4.The first stage of the network implementation is done using the competitive layer [14]. The input vectors will be M-dimensional and placed in the input data space or region (subspace) to identify the cluster regions known as code indices. The linear layer maps the competitive layer neurons that are mapped to the target class. However, multiple neurons may belong to the same class in the data space. Subclass regions of the same class in the next M space need not be contiguous.

Step 1 Construction of parameter set of both layers in LQV design. Then the input data vectors should be divided into training and testing. The learning algorithm generally works as follows:

The initial phase is implemented by the competition layer using a clustering approach. It may or may not be the same size. After clustering, each cluster is defined by appropriate classes. The codebook contains input data vectors, code words and code lists. The main target for determining the class of the codebook element is defined as the target class. This is the last step performed by the linear layer. To identify the cluster, suppose we have input vectors of N directions that are placed or partitioned into small subspaces.

Each cluster is addressed by a "code index". Each cluster by itself is known as a "Warnoy region" [14] and the average of all code words is known as a "code vector". The linear layer maps the competitive layer neurons that are mapped to the target class. However, multiple neurons may belong to the same class in the data space. Sub-regions of the same class in the dimension M space need not be contiguous. To find the winning neuron: The distance between the training data and each codebook vector is known as the "Euclidean vector".

$$\boldsymbol{l} = \left\| \boldsymbol{v_j} - \boldsymbol{k_i} \right\| = \sum_i \left(\boldsymbol{v_{ji}} - \boldsymbol{k_i} \right)^2 \qquad \textbf{(1)}$$

where k is a training data vector, v is the n-dimensional codebook vector and 'l' is the Euclidean distance. The 'hc' neuron with the codebook vector is the winning neuron that has the smallest Euclidean distance to the ki data vector.

LVQ 1 is an approach that combines supervised learning and vector quantization. The random selection technique of a training vector k is used to identify the winning neuron or leading neuron. The successful codebook vector takes hc or the winning neuron and moves it to the direction or transfers this neuron to the training data vector.Apart from that, if both neurons belong to the same class or classes, the neuron is moved or advanced, while the remaining neurons remain unchanged.

$$h_c(t+1) = h_c(t) + \propto (t)(k(t) - h_c(t)) \qquad (2)$$

$$h_c{}'(t+1) = h_c(t) - \propto (t)(k(t) - h_c(t)) \qquad (3)$$

where in these relations $\propto$(t) is the learning rate, which must have a value between 0 and 1. If the location of the training vector k corresponds to the exact boundaries of two classes or vice versa, and such training vectors have the same classes. The LVQ-2 method is basically related to the idea or condition that the winning vector hc must belong to a class different from k, but the closest class hc must belong to the same class k. This algorithm or analysis relies on matching one hc or hc' with a comparable class and the other with a different class, which is followed by the LVQ-2 algorithm.

$$h_c(t+1) = h_c(t) + \propto (t)(k(t) - h_c{}'(t)) \qquad (4)$$

$$h_c{}'(t+1) = h_c(t) - \propto (t)(k(t) - h_c{}'(t)) \qquad (5)$$

If we add or combine LVQ1 and LVQ2.1 algorithms, LVQ3 is obtained. LVQ3 is reformulated into LVQ2, which combines steps where all k, hc and hc' are treated as the same or same class. For example, the LVQ3 role setting works as given by the following relationship

$$h_c(t+1) = h_c(t) + \varepsilon \propto (t)(k(t) - h_c(t)) \qquad (6)$$

$$h_c{}'(t+1) = h_c{}'(t) - \varepsilon \propto (t)(k(t) - h_c{}'(t)) \qquad (7)$$

In this regard, ε is the stabilizing factor and has a value between 0 and 1.

Simulation Results

To evaluate the amount of noise removal from MRI images using the proposed method, the criteria presented in Table 1-4 are used.

Table 1 Results of Noise Removal in MRI Images in the Proposed Method.

Standard deviation value	PSNR1	PSNR2	SSIM1	SSIM2	MSE1	MSE2
$\sigma = 5$	38,21	43,92	0.87	0.95	0.12	0.02
$\sigma = 10$	35,25	41,92	0.65	0.95	0.18	0.02
$\sigma = 15$	28,21	37,55	0.61	0.93	0.24	0.012

As shown in Table (1), the PSNR and SSIM benchmark results have increased after noise removal, which shows that the output image has been improved to a great extent.

Tables 2-4 to 4-4 show the calculated Dice score values for each class in different structures. These values show that the proposed LVQ network has performed well in brain tumor segmentation in MRI images compared to other methods.

Table 2 Values Related to the Dice Score of Tumor Tissues in Parallel Structure.

Tag four	Tag two	Tag one
Advanced tumor	Swollen tissue	Tumor nucleus
613.0	587.0	499.0

Table 3 Values Related to the Dice Score of Tumor Tissues in the Sequential Structure of Four Layers.

Tag four	Tag two	Tag one
Advanced tumor	Swollen tissue	Tumor nucleus
689.0	654.0	507.0

Table 4 Values Related to Dice Score of Tumor Tissues in the Consecutive Structure of Fourteen Layers.

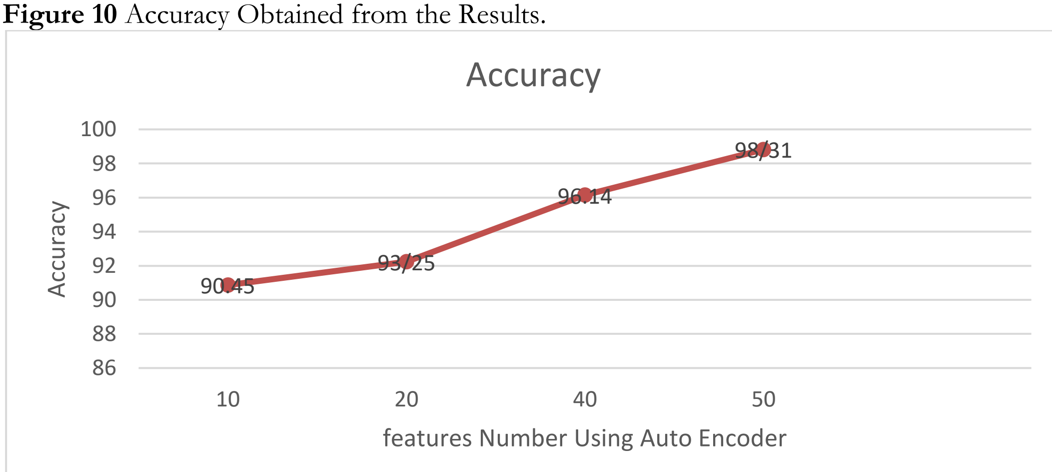
Tag four	Tag two	Tag one
Advanced tumor	Swollen tissue	Tumor nucleus
754.0	832.0	624.0

Due to the increase in types of tumors and the importance and necessity of early tumor diagnosis, various methods are used to identify tumors in medical images. While glioma is the most common brain tumor, therefore, timely diagnosis and treatment plan for this disease are of great importance. Deep learning is a subfield of machine learning. The LVQ method is one of the deep learning methods that has been very successful in image processing. The use of LVQ in the diagnosis and identification of tumors helps clinical experts and minimizes the error rate.

Feature Extraction Results

In this part, using evaluation charts, we show the accuracy and correctness of the proposed method based on LVQ in the diagnosis of brain tumors.

Figure 10 Accuracy Obtained from the Results.

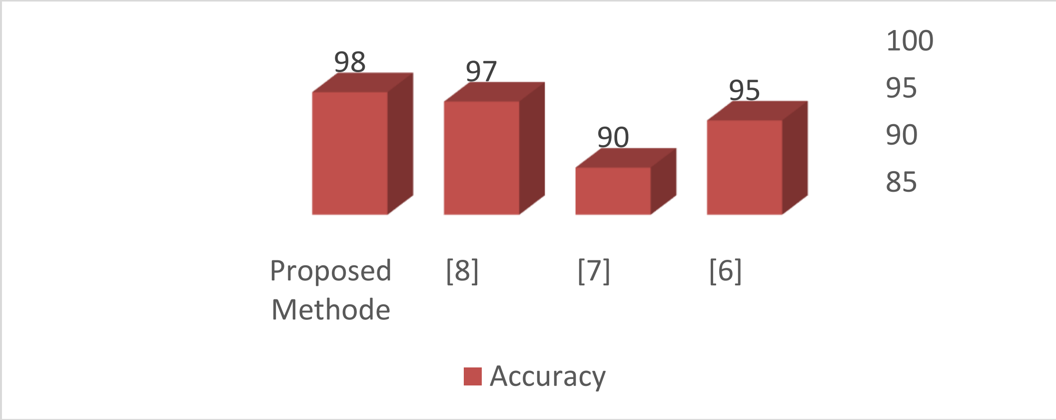


As can be seen from Figure 6, with the increase of features, the accuracy is also increasing. Here, with 50 features, the best accuracy is 98.31%, which shows the superiority of LVQ performance. Because it is possible to achieve the desired accuracy by choosing the features you like.

Comparison of the Proposed Method with Other Methods

In this section, the proposed method is compared with other methods in reference [6], [7] and [8], which is shown in Figure 7.

Figure 11 Comparison of Performance of Different Methods.



As shown in Figure 7, the superiority of the proposed method (due to the same data set in all four methods and the use of 70% of the data as training data and 30% of the data as test data) is clearly observed compared to other methods. Meanwhile, method 8 is in the second category, and method 6 and method 7 are in the next categories.

Conclusion: In this research, a new structure based on LVQ was presented for the diagnosis of cancerous tumors using MRI images. The proposed method is a hybrid method based on image processing and machine learning algorithms. In methods based on image processing, the first step is the preprocessing of input images. At this stage, the goal is to reduce the amount of noise, increase the quality of MRI images, facilitate tumor diagnosis and increase the accuracy of tumor image zoning. In general, different noises occur on medical images, and these noises can occur depending on various reasons, including the low quality and non-calibration of the imaging equipment, the movements of the patient's body during imaging, or the inappropriate environmental conditions of the equipment. According to the investigations carried out in the previous works, the most important noise that can occur in most medical images is thermal noise, which can be mentioned as salt-pepper noise and Gaussian noise.These noises occur in most digital images. Therefore, at this stage, a filter is used to improve the quality of the image and remove these noises. that we have used the median filter in the proposed method to remove salt-pepper noises. This filter is one of the main filters to remove noise and increase image quality. In this filter, we will compare the pixels of the image with their neighboring pixels and if there is a high difference in the light intensity of these pixels, we will replace that pixel with the average of the adjacent pixels. Of course, if we were faced with Gaussian noises in the input images, we would use another filter for this category of noise.In this category of noises, the most used filter is the average filter, this filter is a simple square filter and its function is as follows; First, we calculate the average of all the pixels in the square and then we replace the average value with the value of the pixel in the middle of the square. This filter is easier to implement than the filter above. After applying filters and denoising the images, the noise-free images are pre-processed in two categories, bright images and dark images, in order to determine the defining features of the tumor. In the pre-processing of dark images, by applying a rescaling operation on the gray levels of the image, the distance between the bright and dark levels increases, which determines the presence of a tumor in the image to a high extent. Preprocessing bright images is a relatively difficult task because the light intensity in these images is very similar to the light intensity of the tumor.To process this group of images, we first obtain a suitable threshold for the image using a histogram, and then select a suitable threshold to separate the tumor from the surrounding areas. This thresholding is very important. If this thresholding is done correctly, it will be very easy to separate the tumor in the image. After determining this threshold, the threshold is applied to the image and sent to the next step. Entropy-based method will be used in the proposed method for thresholding. In this method, two probability distributions are used, one for the background of the image and the other for the object (for example, the presence of a tumor). Next, according to these two distributions, a threshold value is calculated as the optimal threshold, which increases the sum of two entropies related to the background of the image and the object.In this optimal threshold, the information content of the object and the background is maximized, and the threshold found is the best threshold that keeps the maximum information in both the object and the background. By applying this threshold, we perform image zoning, in which the existence of a tumor is clear. In the next step, we extracted features. In this stage of the proposed method, the search stage is performed in the image to find the candidate areas in which there is a possibility of a tumor[16-18]. Candidate areas are areas that are extracted from the original image according to their characteristics, which can be used to limit the final search to find the tumor. After extracting image features, the obtained results are applied to a fuzzy clustering algorithm. The fuzzy clustering algorithm classifies the data to send to the proposed machine learning model for training. Using the proposed method, we showed that in addition to the significant removal of noise in MRI images, the accuracy and precision of brain tumor diagnosis increased significantly.

References

1. Ari, A. and D. Hanbay, *Deep learning based brain tumor classification and detection system.* Turkish Journal of Electrical Engineering & Computer Sciences, 2018. 26(5): p. 2275-2286.
2. Khan, M.A., et al., *Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection.* Microscopy research and technique, 2019. 82(6): p. 909-922.
3. Ismael, S.A.A., A. Mohammed, and H. Hefny, *An enhanced deep learning approach for brain cancer MRI images classification using residual networks.* Artificial intelligence in medicine, 2020. 102: p. 101779.
4. Nadeem, M.W., et al., *Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges.* Brain sciences, 2020. 10(2): p. 118.
5. Tomaszewski, W., et al., *Brain tumor microenvironment and host state: implications for immunotherapy.* Clinical Cancer Research, 2019. 25(14): p. 4202-4210.
6. Khan, H.A., et al., *Brain tumor classification in MRI image using convolutional neural network.* Math. Biosci. Eng, 2020. 17: p. 6203.
7. Abiwinanda, N., et al. *Brain tumor classification using convolutional neural network*. in *World congress on medical physics and biomedical engineering 2018*. 2019. Springer.
8. Muhammad, K., et al., *Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey.* IEEE Transactions on Neural Networks and Learning Systems, 2020. 32(2): p. 507-522.
9. Gumaei, A., et al., *A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification.* IEEE Access, 2019. 7: p. 36266-36273.

10. Saravanan, S., R. Karthigaivel, and V. Magudeeswaran, *A brain tumor image segmentation technique in image processing using ICA-LDA algorithm with ARHE model*. Journal of Ambient Intelligence and Humanized Computing, 2021. 12(5): p. 4727-4735.
11. Shree, N.V. and T. Kumar, *Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network*. Brain informatics, 2018. 5(1): p. 23-30.
12. Mendes, M., et al., *Targeted theranostic nanoparticles for brain tumor treatment*. Pharmaceutics, 2018. 10(4): p. 181.
13. Saeed, M., et al., *An application of neutrosophic hypersoft mapping to diagnose brain tumor and propose appropriate treatment*. Journal of Intelligent & Fuzzy Systems, 2021(Preprint): p. 1-23.
14. Angove, M.S.C., et al., *Machine-Learning Approach Based Gamma Distribution for Brain Abnormalities Detection and Data Sample Imbalance Analysis*.
15. Sultan, H.H ,.N.M. Salem, and W. Al-Atabany, *Multi-classification of brain tumor images using deep neural network*. IEEE Access, 2019. 7: p. 69215-69225.
16. Abbasian S, Kargar Moghaddam M, Nazari B. The Effect of High-Intensity Treadmill Training on Motor Function in Patients with a Stroke. sjmshm 2022; 4 (1) :1-3
17. Mirfasihi S P, Ghazali S, Baradaran Shokouhi S. Designing and Implementing of Real-Time Intelligent System with the Ability to Identify and Classify Different Topics in Autonomous Vehicle. sjis 2022; 4 (4) :1-7
18. Samadi H, Farrokh E. Utilization of Rock Mass Parameters for Performance Prediction of Rock TBMs Using Machine Learning Algorithms. sjfst 2021; 3 (3) :1-9