The difference between Machine learning and Deep Learning in Classification Process for Brain Cancer MRI Images Based on Evolutionary segmentation's Algorithms

Kamel H. Rahouma[1], Rabab Hamed M. Aly[2], Hesham F.A. Hamed[1]

[1]Electrical Engineering Department, Faculty of Engineering, Minia University, Minia, Egypt

[2]The Higher Institute for Management Technology and Information, Minia, Egypt

kamel_rahouma@yahoo.com

Abstract

The medical computer vision is considered one of the important studies. Many evolutionary techniques and algorithms have been improved to extract the features of the brain MRI images and/or to classify and diagnose the different types of tumors. The evolutionary techniques are practical, especially, for deep learning based on their accuracy and speed. These techniques include preprocessing, segmentation, and classification. In this paper, we apply different evolutionary segmentation methods which recently gained much interest. These are the K-Means segmentation process and Fuzzy-c means. Furthermore, we will apply learning algorithms such as the convolution neural network and the polynomial neural network(PNN) and then we compare between them. The first scenario applies the K-means cluster for segmentation of the brain MRI images and then the Deep Neural Network (DNN)or PNN for classification. The second scenario applies the Fuzzy-c means algorithm for segmentation and then the learning technique for classification. We compare the results of the two scenarios to obtain the best solution for classification. The accuracy of classifications methods is found to range from 85% to 96.8%.

Keywords: *Deep learning, Segmentation process, K-means, Brain cancer, Neural Network (NN), Polynomial Neural, Fuzzy.*

1. Introduction

Recently, the analysis of medical big data sets plays important roles in the scientific research, especially when using the Magnetic Resonance Imaging (MRI)for diseases diagnosis. The medical computer vision based on MRI is one of the most practical techniques for diagnosis and classification of different types of cancer such as in brain tumor. Most of the research focused on the methods of classification of cancer and how to achieve the optimal solution in a minimum time. This depends on processing and detection of its features. These features are used for the classification of the type of tumors and showing the differences between tumors.

Many researchers have suggested learning techniques to analyze cancer and to diagnose its degree. These techniques utilize different tools such as the Convolution Neural Networks (CNN), the Fuzzy Logic (FL),the Optimization Techniques (OT),the Deep Learning (DL),the Linear Regression (LR), …., etc.

In this paper, we use these tools and combine them to analyze the brain tumor and determine its degree. MATLAB software is used to simulate the results and the Radiopaedia database and cancer imaging archives based on MRI images cases are used for the types of brain cancer cases [1,2].

The paper is composed of five sections. Section (1) gives an introduction and section (2) depicts a literature review. Section (3) explains the methodology and section (4) presents the results and compares them to a set of algorithms from the literature review. Section (5), gives some conclusions and some of the used references are listed at the end of the paper.

2. Literature review

The previous research of computer vision focused on the method of cancer detections and how to apply different methods of classifications. Deep learning, machine learning and computer vision play an important role in environment image analysis, especially in the detection of features of an image or a video clip. Many algorithms introduced the different measurements of how to extract the optimal features from cancer MRI images. Furthermore, researchers also tried to introduce new techniques to classify the degree of cancer tumors and to study the extracted features to help the doctors and specialists to correctly determine the degree of tumors. In the following, we will introduce some of the recent papers which focused on the detection and classification of tumors.

In [3], the author introduced Fuzzy Inference System (FIS) as a detection method. The author applied FIS to detect the features of Staphylococcus Bacteria images and also another type of bacteria based on DNA. There is a type of a neural network called the Neural Gas Network. The authors in [4] introduced this type of neural networks as a detection method for 3D images based on clustering. They characterized 2D objects with a modified Growing Neural Gas network. The method offers similar features for efficient mesh reconstruction.

In [5], authors introduced a survey about the methods of the segmentation and classifications of the computer-aided diagnosis of human brain tumor. They discussed how to improve the diagnosis of the brain tumor and they also proposed new methods of detection and classification of the brain tumor.

The authors in [6] applied discrete wavelet transform for extract features from MRI images as an automatic detection for brain tumors and they also used support vector machine as segmentation and classification methods.

Actually, Fuzzy logic is very useful in detection and classifications and some researchers introduced it. In [7], authors applied fuzzy logic to diagnose glaucoma. They introduced "Randomized Hough Transform "for feature extractions. Then, they introduced fuzzy logic to classify these features. They achieved as accuracy more than 95.8% especially in prediction. Furthermore, in [8], authors introduced a new segmentation technique to extract features of glaucoma called Ocular cup. They achieved good and satisfying results in the segmentation process.

In [9], authors introduced neural networks as classification techniques. They applied it to classify healthy tissues to highlight the presence of infiltrating tumor cells with high accuracy. Authors in [10] introduced the diffusion filter for denoising and they classified the brain tumors by evaluation if the tumors are malignant or benign to achieve high accuracy. They achieved a detection accuracy of 99.01% (for malignant) and 99.66%. (for benign)

Recently, the neural networks reused as one of the practical accurate classification methods. Gabor filter is considered one of the filters used in computer vision. So, a lot of researchers depended on Gabor filter. In [11], authors described the automation recognition of brain tumors in MRI based on Gabor wavelet features and statistical features. They compared the methods and studied it based on several classifiers.

The Particle Swarm technique is considered one of the most important optimization techniques. It is faster and stable than genetic algorithms [12].Some authors introduced new classification methods for environment images. In [13], authors applied deep learning for hyper spectral remote sensing images. They applied classification methods to achieve multi features learning and the accuracy is 99.7%. Furthermore, in [14], authors introduced deep learning classification for soil related to illegal tunnel activities. They proposed a new method in handling imbalance learning. This paper will introduce the deep learning as a classification method for segmented tumors datasets based on different methods of segmentations. We use, combine, and modify some of the mentioned methods to analyze the MRI images of brain cancer of any type. Then we, also, classify and predict any future complications.

3. Methodology

In this paper, our system focuses on the classification of brain tumors by using evolutionary segmentation processing. The system is composed of four main units to classify he brain tumors (eg. The preprocessing, segmentation process and learning (PNN and CNN classification) as shown in figure (1). The description of each block of the system block diagram will be discussed in the following subsections.

3.1 The preprocessing unit

The preprocessing stage is consisting of two main parts:

a) First part is filtering the cancer MRI images by using digital low pass filter using MATLAB images processing toolbox as discussed in [15].

b) The second part is Thresholding using Otsu Thresholding and binarization which is very important before segmentation and this helps in classifying the image pixels.

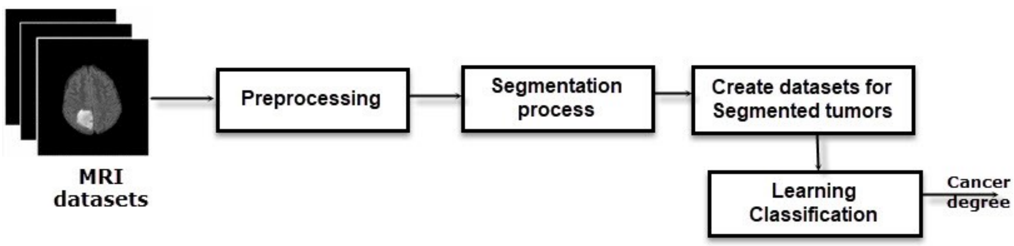

Figure 1. The system block diagram

3.2 Segmentation process

In this part, we introduce two methods of segmentations processing: -

a) K-means cluster segmentation process.

b) Fuzzy-C means segmentations.

3.2.1 K-means cluster segmentation process

The first method, for segmentation, is the K-means clusters to segment the tumor from the MRI cancer images. The segmentation helps in features extraction and the classification of the cancer degrees. The k-means algorithm divides a set of data into K-groups of a disjoint clusters as in clustering process. The method which we use to calculate the distance for centroid data is called "Euclidean distance" [16]. For example, if there is an image with a resolution (x, y) and the cluster is K-numbers, let us consider P (x, y) an input pixel in cluster and c_k is the cluster center then the algorithm of K-means will be as follows:

a) Define the number of cluster K.

b) For each pixel, the Euclidean distance" d will be calculated based on equation (1).

$$d = \|p(x,y) - c_k\| \tag{1}$$

$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x,y) \tag{2}$$

c) Based on distance "d", attribute all the pixel such as proof [16]. Recalculate the new position of the center based on equation (2).

d) Repeat the process until satisfying the minimum error.

e) Extract the segmentation from MRI images.

The K-means obtained an optimal result as shown in figure (2) and the discussion of the results will be in section (5).

The pseudo-code of the last algorithm:

```
Input K, threshold
// K is the number of clusters
// threshold is the segmentation level
For pixel = 1 to end
        d = ||p(x,y) − c_k||
                    c_k = (1/k) Σ_{y∈c_k} Σ_{x∈c_k} p(x,y)
        If d >= a threshold add p(,y) to the segmentation
Next pixel
```

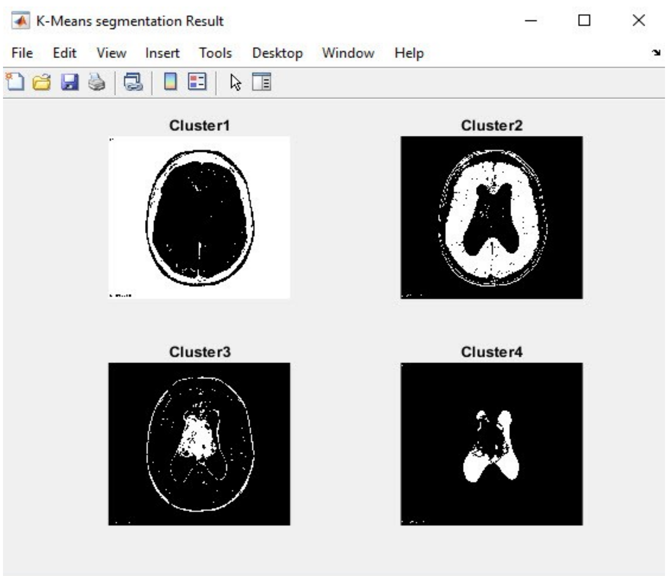

Figure 2. K-means clustering for segemantation of brain cancer

3.2.2 Fuzzy-means cluster segmentation process

Fuzzy c-means (FCM) is one of most popular clustering techniques. Some authors introduced it as one of the best methods in clustering [17].In medical images, Fuzzy C-Means converts a colored image into grey scale before the segmentation processing. In this paper, we use non-colored images. Fuzzy C-means iterates based on the number of clusters in the image. We can take the number of clusters after Fuzzy c-means finishing the segmentation. The FCM segmentation algorithm is shown in the following:

```
Start
1) Insert images into workspace MATLAB 2019 a.
2) Maximum the number of iterations =100.
Loop: 1 to number of images
3) The number clusters from 3 up to 4.
4) Choose Minimum amount of improvement
5) Get the size of the image.
6) Calculate the distance possible size using repeating structure.
7) Concatenate the given dimension for the image size.
8) Repeat the matrix to generate large data items in carrying out possibly distance calculation.
Begin Iterations 1 :100
-  identifying large component of data
-  the value of the pixel.
Stop Iteration when possible identification isreached.
Generate the time taken to segment.
Save segmented part.
End Loop
End
```

The segmentation results of the FCM are shown in Figure (3) and it will be discussed in section (5)

3.3 The storage unit

It is a very important unit and it is used before the classification unit. After the segmentation process, we collect all the segmented parts of the brain tumor images and save them in a separate file as datasets for segmentation of different cases of MRI patient images. In the next step, we will use this dataset to analyze and classify the tumors based on only segmented part.

3.4 Classification process

The classification process applies two methods:

a) The polynomial neural network.

b) The Deep neural network.

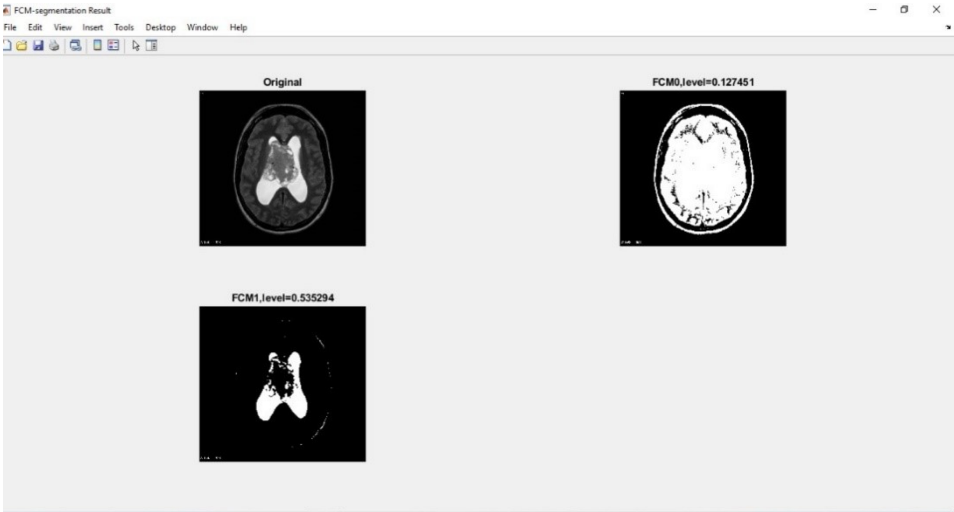

Figure 3. FCM segmentation results

3.4.1 Classification using PNN

In this method, we use the group method data handling techniques (GMDH) for classification and prediction of the next features of the MRI brain tumor databases. There are many types of ANN based on a mathematical classification equation such as PNN (Polynomial neural network) which will be discussed in the next section. The ANN is used in the classification and also to predict future data. The PNN is one of the most popular types of neural networks based on polynomial equations. It is used for classification and regression. It is practical and accurate in prediction of behavior of the system model [18]. A class of polynomials (linear, modified quadratic, cubic, etc.) is utilized. We can obtain the best description of the class by choosing the most significant input variables and polynomial according to the number of nodes and layers [19]. Layers connections are simplified and an automatic algorithm is developed to design and adjust the structure of PNN.

To obtain the characteristics of the nonlinear relationship between the inputs and outputs of the PNN, structure, a multilayer network of second order polynomials is used. Each quadratic neuron has two inputs (x_1, x_2) and the output is calculated as described in equation (3) where figure (4) shows the structure of PNN.

$$g = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1 x_2 + w_4 x_1^2 + w_5 x_2^2 \quad (3)$$

Where w_i ; $i = 0, \dots ,5$ are weights of the quadratic neuron to be learnt.

The main equations of PNN structure which is the basic of GMDH-PNN are:

$$(X_i, y_i) = x_{1i,} x_{2i}, \dots \dots, x_{Ni,} y_i \quad (4)$$

Where X_i, y_i are the data variables and $i = 1; 2; 3; \dots; n$

The input and output relationship of the PNN- structure of figure (6) is:

$$Y = F(x_1, x_2, \dots \dots \dots \dots \dots \dots x_N) \quad (5)$$

The estimated output is:

$$\grave{y} = \grave{f}(x_1, x_2, \dots \dots x_N) = c_0 + \sum_i c_i x_i + \sum_i \sum_j c_{ij} x_i x_j + \sum_i \sum_j \sum_k c_i c_j c_k x_i x_j x_k + \cdots (6)$$

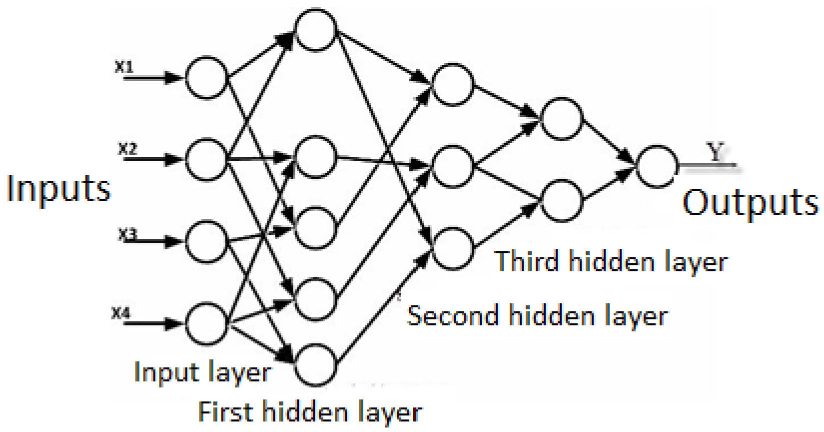

Figure 4.The polynomial network structures

The GMDH is found to give the best and a faster solution for classification and prediction [18].The main steps to apply the PNN algorithm for prediction based on polynomial equation (4) are:

a) Determine the system input variables according to equation (4).

b) Formulate the training and testing data according to equation (4), (5) [18].

c) Select GMDH as the structure of the PNN.

d) Estimate the coefficients of the polynomial of nodes to estimate the error between y_i , $\acute{y}_\imath$ then:

$$E = \frac{1}{n_{tr}} \sum_i^{n_{tr}} (y_i - \acute{y}_\imath)^2 \qquad (7)$$

Where n_{tr} is the number of training data subset, iis the node number, k is the data number, n is the number of the selected input variables, m is the maximum order and n_0 is the number of estimated coefficients.

By using the training data, the output is given by a linear equation as:

$$Y = X_i C_i \qquad (8)$$

$$C_i = (X_i^T X_i)^{-1} X_i^T Y \qquad (9)$$

Where

$$Y = [y_1, y_2, y_3, \ldots\ldots, y_{ntr}]^T, X_i = [X_{1i}, X_{2i}, X_{3i}, \ldots, X_{ntri}]^T,$$

$$X_{ki}^T = [X_{ki1}, X_{ki2}, X_{kin}, \ldots., X_{ki1}{}^m, X_{ki2}{}^m, \ldots, X_{kin}{}^m]^T$$

and $C_i = [C_{0i}, C_{1i}, \ldots., C_{n'i}]^T$, and after that, check the stopping criterion.

e) Determine the new input variables for the next layer.

3.4.2 Classification using deep neural network (DNN)

Actually, deep learning has many characteristics that make it more powerful than classical machine learning techniques. Deep learning is performed by a convolutional multilayer neural network, which has many hidden layers and free parameters. Unlike the commonly used multilayer neural network, each input image passes through some basic steps; convolution layers with filters (kernels), pooling layers, fully connected (FC) layers and Soft Max function.

3.4.2.1 Convolution Neural Network (CNN):

CNN includes assets of making decisions on hyper-parameters (Number of layers and rate of learning)[19]. The network architecture of CNN consists of sequence of layers to build the neural network (see Table 1) (see Figure.5, Figure. 6). There are four main operations in CNN (see Table. 1):

- Convolution
- Non-Linearity (ReLU)
- Pooling or Sub Sampling
- Classification (Fully Connected Layer)

These operations are the basic building blocks of every Convolutional Neural Network.

Note that:

a) The size of the feature map is controlled by three parameters:

- **Depth:** is the number of filters used for the convolution operation.
- **Stride:** is the number of pixels by which filter matrix over the input matrix. Stride specifies how much we move the convolution filter at each step.
- **Padding:** is used for input matrix with zeros around the border, matrix. We use the padding to maintain the same dimensionality.

b) On the other hand, **total**= ∑ ½ (target probability – output probability) ² and computation of the output of neurons that are connected to local regions in the input. This may result in volume such as [32x32x16] for 16 filters.

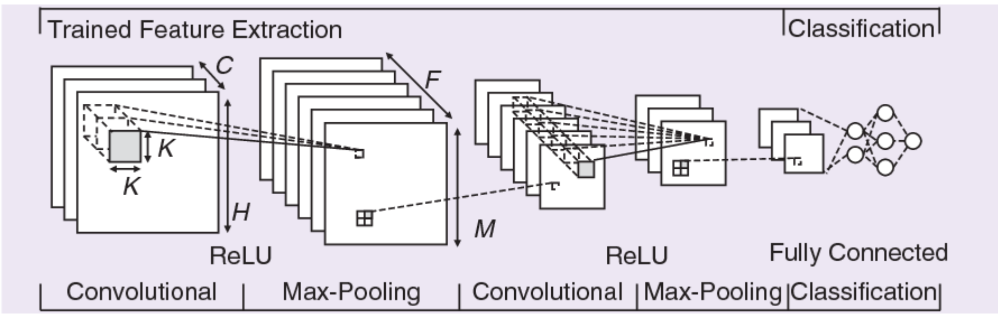

Figure 5. General architecture of CNN[20]

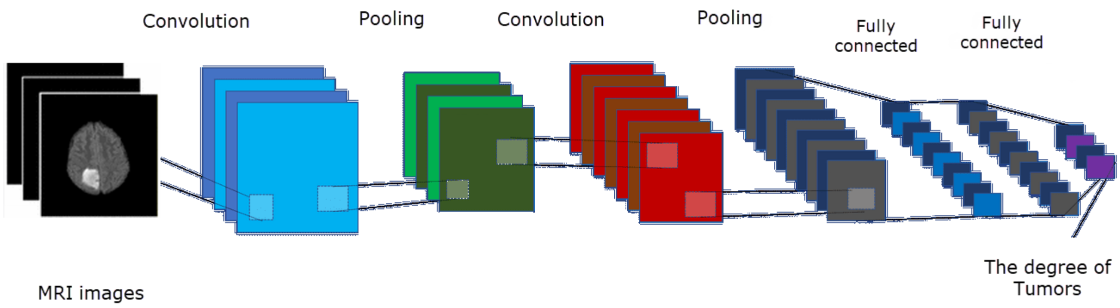

Figure 6. Architecture of CNN for brain MRI classification

A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better. We use the DNN based on basic structure of CNN classifications and it achieved very strong classifications with a high accuracy [19]. The output layer of CNN will be described in the following pseudo code based on figure (5) [20].

Table 1 Layer architecture of CNN

Type	Kernel Size	Filters	Activations
Convolution	3x3	64	ReLU
Max- Pooling	2x2	-	-
Convolution	3x3	128	ReLU
Convolution	3x3	256	RelU
Max- Pooling	2x2	-	-
Convolution	3x3	512	ReLU
Convolution	3x3	512	RelU
Full-Connected	-	100	ReLU
Full-Connected	-	1	Linear

In the following pseudo code for CNN as output for one layer as example:

```
Start
For (for (int f = 0; f < F; f++)%%Per output pixel of layer
  For (for (int mx = 0; mx < M; my++)%% Load C.K² Weights
for (int my = 0; my < M; mx++)%% Load C.K2 Inputs
for (int c = 0; c < C; c++)%%Do C.K²multiply accumulation
for (intkx = 0; kx< K; kx++)%% One Output Store
for (intky = 0; ky< K; ky++)%% Repeat F.M² Times Per Layer
o[c][mx][my] += w[f ][c][kx][ky] . i[c][mx + kx][my + ky]);
```

The accuracy of this system is calculated by using confusion matrix, the test data and the prediction data as following: -

a) Calculate True Positive (TP) and True Negative (TN).
b) Determine the False positive (FP) and False negative (FN) from segmented images of tumors.
c) Compute the accuracy = $\frac{TP+TN}{TP+TN+FN+FP}$ [21].

4. Results and discussions

In this paper, we applied our system using the image processing toolbox of MATLAB2019a.

4.1 part 1 The result of preprocessing and segmentation process:

The segmentations process applied two different methods:

a) K-means cluster: We applied the K-means clustering in steps:

1) Applying histogram for each input image as shown in Figure.7.
2) Add noise and removal using median filter as shown in Figure.8.
3)The segmentation process after 4 clusters as shown in Figure.9. The final segmentation is shown in figure (10).

b) Fuzzy-C means: The main operation in the segmentation process based of fuzzy cluster is the fuzzy logic function and the design of it which is founded in MATLAB tool boxes:

1) Fuzzy thresholding for input MRI image.
2) Find the data points with highest grade of membership for each cluster.
3) In this case, we apply two level of Fuzzy c-means clusters as shown in figure 11.

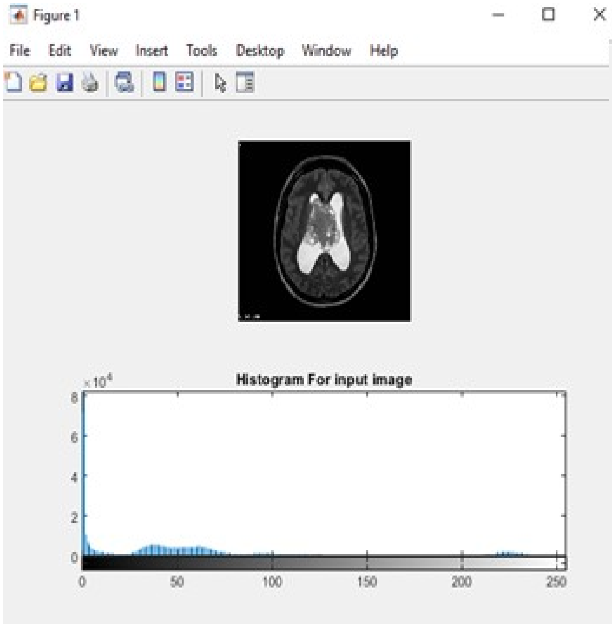

Figure 7. Histogram for any inputMRI brain image

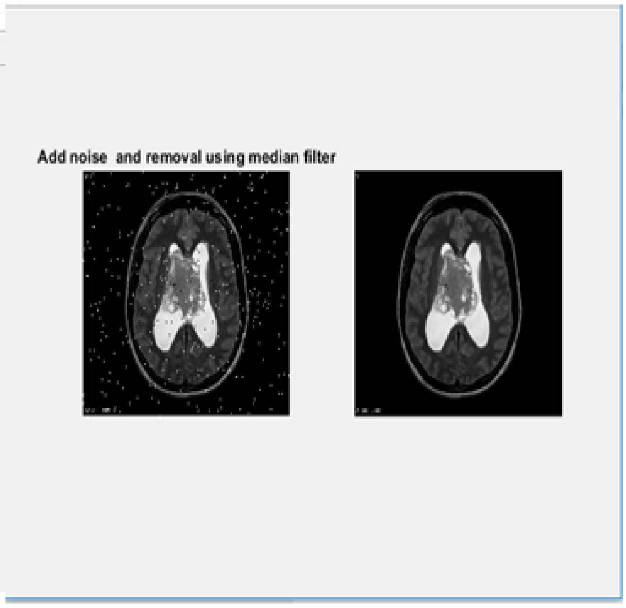

Figure 8. Add noise and then remove it using Median Filter

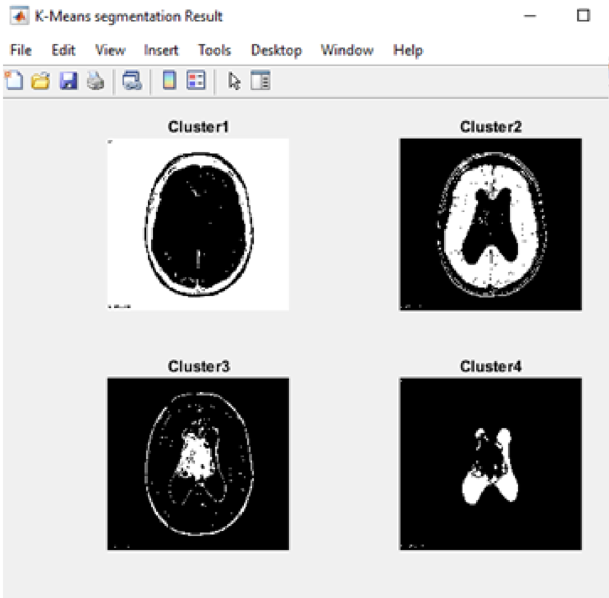

Figure 9. Result of K-means after 4 clusters

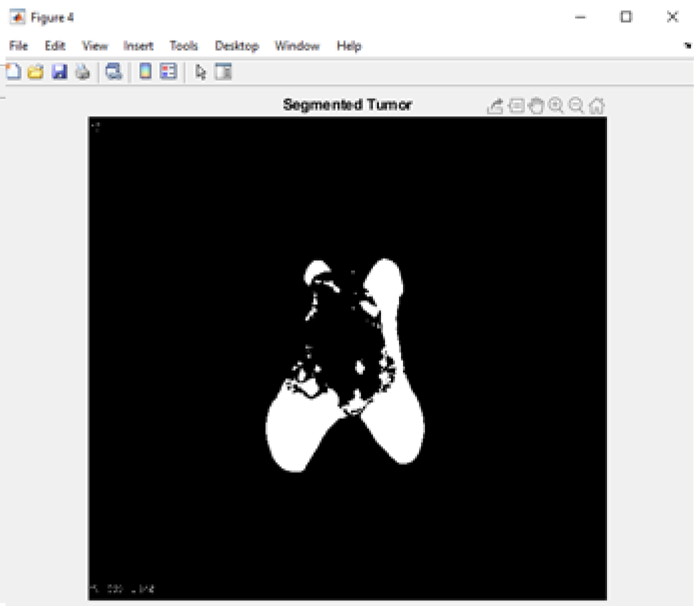

Figure 10. Segmented Tumor in the final segmentation of K-means

4.2 part 2: The result of classification process

After segmentation, all segmented parts for each image in the dataset are calculated. These segmentations are collected in one folder. This folder consists of five categories for patient cancer degree. Each category has (100 to 1000) images. The classification is different from a method to another as follows:

1) PNN classification: In this method, the images are inserted in the folder after segmentation process and the accuracy up to 98 %. It is important to notice that this is a machine learning method and thus it is slow. We divided the data into small datasets to classify it individual. On the other hand, deep learning solves the problem of high categories images.

2) DNN classification: in deep neural network is working with high accuracy and high categories. In this method, we use the folder of brain tumors categories beside to include 101 object categories from different cases, images and classes. It may contain 15000 images to improve the layers and design of convolution neural network as discussed before in pervious section.

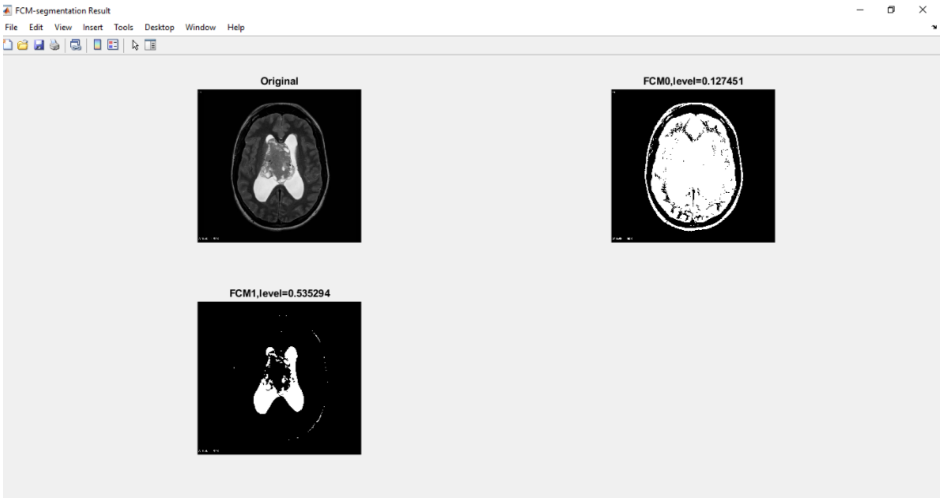

Figure 11. Fuzzy cluster C -means results for two level

The following Table compare between PNN and DNN with images:

Table 2 Results of PNN and DNN in classification

Methods	Objects Categories	Number of Images	Iterations	Time	Accuracy
PNN	1	176	100-500	Every image takes 2 minutes then total =352min	Up to 98.5 %
DNN	101	15000	500-600	332.38 hr for first time and after that any external image test take 1 second	85-Up to 95.3%

The MRI datasets contain 5 different types of categories. In DNN method, we ran a maximum number of (500 - 600) iterations. We used a system of laptop with CPU (core i3 2.5GH and 6GB Ram) and used MATLAB 2019a.

Table (3) gives a comparison between our method in classification and the accuracy with the others pervious works.

Table 3. The comparing of our work with the pervious works

Paper	Number of data sets images	Method	Epochs	Processor	Accuracy
[19]	900 categories (4096 image)	DNN	200	NVIDIA GTX 980 GPU and an Intel® CoreTM i5 CPU (3.40 GHz), running Ubuntu 14.04.	90.4%
[21]	10000 images	CNN	500	Intel i7 processor with 32 GB RAM and with two linked GPU of Titan	90.58%
[22]	10000 images	CNN-Keras	25	Two intel processors E5-2640 Xenon with 64 GB RAM and NVIDIGPU card.	82%
[23]	200 images	VGG19 + LR	Up to 100	Non limited	92.5%
This work	500 images	FCM or K-Cmeans with PNN	50	CPU (core i3 2.5GH and 6GB Ram)	Up to 98%
This work	Up to 10000	FCM- K-c Means and CNN classifier	100	CPU (core i3 2.5GH and 6GB Ram)	Up to 96%

5. Conclusions

This paper aimed to extract segmented tumor based on K-means clusters and Fuzzy c-means. Furthermore, we applied two methods of classifications; PNN and DNN. We obtained our results and compared them with the results of previous research. The previous algorithms achieved accuracy limits of (95.1% - 98.8%) while our results achieved accuracy limits of (95% - 98%) in different methods of classification. It is found that the deep learning, for big data segmented images, has achieved a good accuracy with a minimum time.

References

[1]. https://www.cancerimagingarchive.net/

[2]. https://radiopaedia.org/encyclopaedia/cases/all

[3]. A. K. Saw, G. Raj, M. Das, N. C. Talukdar, B. C. Tripathy, and S. Nandi, "Alignment-free method for DNA sequence clustering using Fuzzy integral similarity," *Sci. Rep.*, vol. 9, no. 1, p. 3753, 2019.

[4]. A. Angelopoulou, J. G. Rodriguez, S. Orts-Escolano, G. Gupta, and A. Psarrou, "Fast 2D/3D object representation with growing neural gas," *Neural Comput. Appl.*, vol. 29, no. 10, pp. 903–919, 2018.

[5]. E.-S. A. El-Dahshan, H. M. Mohsen, K. Revett, and A.-B. M. Salem, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," Expert Syst. Appl., vol. 41, no. 11, pp. 5526–5545, 2014.

[6]. A. R. Mathew and P. B. Anto, "Tumor detection and classification of MRI brain image using wavelet transform and SVM," in 2017 International Conference on Signal Processing and Communication (ICSPC), 2017, pp. 75–78.

[7]. A. Soltani, T. Battikh, I. Jabri, and N. Lakhoua, "A new expert system based on fuzzy logic and image processing algorithms for early glaucoma diagnosis," Biomed. Signal Process. Control, vol. 40, pp. 366–377, 2018.

[8]. F. Bokhari, T. Syedia, M. Sharif, M. Yasmin, and S. L. Fernandes, "Fundus image segmentation and feature extraction for the detection of glaucoma: A new approach," Curr. Med. Imaging Rev., vol. 14, no. 1, pp. 77–87, 2018.

[9]. E. Minelli et al., "Neural Network Approach for the Analysis of AFM Force-Distance Curves for Brain Cancer Diagnosis," Biophys. J., vol. 114, no. 3, p. 353a, 2018.

[10]. A. Chowdhury, I. Das, A. R. Chowdhury, and A. Halder, "DETECTION AND CLASSIFICATION OF BRAIN TUMOR USING ML," Int. J. Adv. Res. Comput. Sci., vol. 9, no. 2, p. 585, 2018.

[11]. N. Nabizadeh and M. Kubat, "Brain tumors detection and segmentation in MR images: Gabor wavelet vs. statistical features," Comput. Electr. Eng., vol. 45, pp. 286–301, 2015.

[12]. M. R. Bonyadi and Z. Michalewicz, "Particle swarm optimization for single objective continuous space problems: a review." MIT Press, 2017.

[13]. S. Lahmiri, "Glioma detection based on multi-fractal features of segmented brain MRI by particle swarm optimization techniques," Biomed. Signal Process. Control, vol. 31, pp. 148–155, 2017.

[14]. L. Wang, J. Zhang, P. Liu, K.-K. R. Choo, and F. Huang, "Spectral–spatial multi-feature-based deep learning for hyperspectral remote sensing image classification," Soft Comput., vol. 21, no. 1, pp. 213–221, 2017.

[15]. X. Meng, "Digital Image Processing Technology Based on MATLAB," in Proceedings of the 4th International Conference on Virtual Reality, 2018, pp. 79–82.

[16]. S. M. A. Burney and H. Tariq, "K-means cluster analysis for image segmentation," Int. J. Comput. Appl., vol. 96, no. 4, 2014.

[17]. A. AjalaFunmilola, O. A. Oke, T. O. Adedeji, O. M. Alade, and E. A. Adewusi, “Fuzzy kc-means clustering algorithm for medical image segmentation,” J. Inf. Eng. Appl. ISSN, vol. 22245782, pp. 506–2225, 2012.

[18]. RAHOUMA, Kamel H.; ALY, Rabab Hamed M. Applying Polynomial Learning for Soil Detection Based on Gabor Wavelet and Teager Kaiser Energy Operator. In: International Conference on Advanced Machine Learning Technologies and Applications. Springer, Cham, 2019. p. 771-783.

[19]. J. Manit, A. Schweikard, and F. Ernst, “Deep convolutional neural network approach for forehead tissue thickness estimation,” Curr. Dir. Biomed. Eng., vol. 3, no. 2, pp. 103–107, 2017.

[20]. M. Verhelst and B. Moons, “Embedded deep neural network processing: Algorithmic and processor techniques bring deep learning to iot and edge devices,” IEEE Solid-State Circuits Mag., vol. 9, no. 4, pp. 55–65, 2017.

[21]. S. Mukherjee, A. Adhikari, and M. Roy, “Malignant Melanoma Classification Using Cross-Platform Dataset with Deep Learning CNN Architecture,” in Recent Trends in Signal and Image Processing, Springer, 2019, pp. 31–41.

[22]. E. Ayan and H. M. Ünver, “Data augmentation importance for classification of skin lesions via deep learning,” in 2018 Electric Electronics, Computer Science, Biomedical Engineerings’ Meeting (EBBT), 2018, pp. 1–4.

[23]. L. B. Maia, A. Lima, R. M. P. Pereira, G. B. Junior, J. D. S. de Almeida, and A. C. de Paiva, “Evaluation of melanoma diagnosis using deep features,” in 2018 25th International Conference on Systems, Signals and Image Processing (IWSSIP), 2018, pp. 1–4.