Semi-Automated Brain Tumor Segmentation and Detection from MRI

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Abstract - *To increases the survival rate of the brain tumor patients and to have a improved treatment technique in medical image processing, brain tumor segmentation is essential method of diagnosis. The early and correct diagnosis of brain tumors plays an important role. Magnetic Resonance Imaging (MRI) technique is the most popular non-invasive technique; in these days imaging of biological structures by MRI is a common investigating procedure. For cancer diagnosis the brain tumors segmentation can be done manually from MRI, which gives the poor level of accuracy and identification. The classification of abnormalities is not predictable and straightforward but it is a time consuming task for physician. Nowadays, the issue of automatic segmentation and analysis of brain tumours are major research area. However the detection of tumor is a challenging task since tumor possesses complex characteristics in appearance and boundaries. In order to produce a completely automated segmentation method like the KG (knowledge-guided) technique which encrypts the information of the pixel intensity and spatial relationships in the images. The k NN classifier under the learned optimal distance metrics is used to determine the possibility of each pixel belonging to the foreground (tumour) and the back ground. The paper presents semi-automatic segmentation method by using CNN (Convolutional neural networks) on the basis of individual statistical information and population, to segment brain tumours early, increase the correct rate and minimize error rate. The experimental result of proposed method demonstrates the robustness for brain tumor segmentation. It shows improved result for classification of Brain tumor from MRI of brain than k-NN Classifier.*

Key Words: *Brain Tumor, Brain Tumor Segmentation, CNN, Magnetic Resonance Imaging (MRI).*

1. INTRODUCTION

The centre of human central nervous system is Brain. Brain is a complex organ and it consists of very large network forming due to presence of 50-100 billion neurons. Brain tumor is nothing but abnormal growth of set of cells that grow inside or around the brain uncontrollably. The malignant and benign are types of brain tumors. The non-cancerous tumor is benign. It is less harmful, generally localized and it does not spread to other parts of the body and well treated due to its proper response. Benign tumor is less harmful than malignant tumor. Malignant tumors are cancerous growths. They are often resistant to treatment and it may spread to other parts of the body. Malignant tumors are classified into primary and secondary tumors. The malignant tumor spreads very fast and attacks other brain tissues and weakens the helth condition which most of the time causes even death. The detection of Brain tumor is very challenging problem for preliminary judgment on diagnosis, due to complex structure of brain [1]-[4].

The magnetic resonance imaging (MRI) images are used in medical imaging technique, to provide detailed information about the internal tissue of respective image. In the diagnosis of brain tumor, determination of the exact location is an important task which helps to find out the shape & size of tumor. In brain tumor detection techniques, image segmentation plays a energetic role. In order to extract tumor from MRI images of brain different image segmentation techniques are used. For the reason that segmentation of MRI provides the detailed information about the soft brain tissues such as gray matter (GM), white matter (WM), cerebral spinal fluid (CSF) etc. There are two types of segmentation includes a manual segmentation and automatic segmentation.

For cancer diagnosis the brain tumors segmentation is done manually from MRI images, consist of large amount of data generated in clinical routine which is a time consuming and challenging task. Subsequently the automatic brain tumor image segmentation is needed. Recently, the deep learning methods for automatic segmentation shows popular as these methods achieve the advanced results and can address the problem in improved way [5].

In general the current standard computational time is in few minutes. The actual segmentation time is too difficult to achieve but in medical routine, computation time over a few minutes is not desirable. Another essential aspect required for brain tumor segmentation methods is robustness. If an automatic segmentation technique does not work in certain situations, clinicians will not have their faith and not use such technique. Therefore, the robustness is also one of the most important assessment criteria for every new technique applied in clinical practice. Some current brain tumor segmentation methods give healthy results within a fairly good computation time [7]. The paper proposes semi-automated brain tumor detection and segmentation from MRI using convolutional neural networks has following objectives.

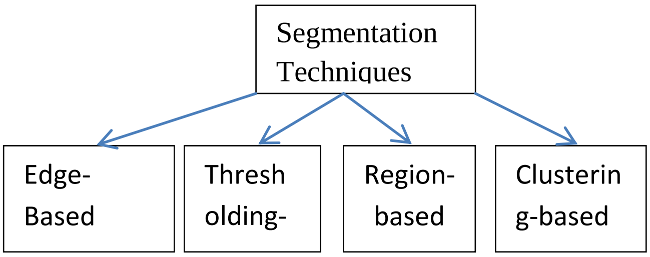
- It improves the achieved segmentation results.

- They are equivalent to the separations induced by minimum spanning forests relative to the regional minima.
- It not only shows the detailed and complete aspects of brain tumors but also improves clinical doctors to study the mechanism of brain tumors at the aim of better treatment.
- The uneven gray level distribution of the tumors is overcome by using proposed method.
- It is very competent than fully automated segmentation method.

The paper is organized as follows. The section II introduces the different automated brain tumor segmentation technique. The section III gives detailed description of convolution neural network for brain tumor segmentation. The section IV describes the experimental results and conclusion is in the section V.

2. TUMOR SEGMENTATION TECHNIQUES

In the clinic MRI is mainly used for brain tumor diagnosis and treatment. MRI offers various useful features like multiplanar capabilities, potential of tissue characterization and no bone and teeth artefacts.The different automated techniques of brain tumor segmentation using MRI images are given in Fig. 1



2.1 Edge Based Segmentation

The segmentation is achieved in edge based techniques by divide the image on the basis of sudden changes in the intensity of pixels near the edges [8]. The result of edge based technique is a binary image with edges of the objects being detected. The edges based are categorized as Gradient based and gray histogram segmentation techniques.

i). Gray Histogram Technique

In gray histogram techniques the image is converted into gray scale image and after that gray-level thresholding is applied on the histogram of that image. Since the selection of threshold (T) is important for result of the gray histogram technique.

2.2 Thresholding

The technique is used frequently for image segmentation like many other techniques [9]-[10]. In this technique the image segmentation is also done when images consist of different intensities of pixels. In this method, the image is divided directly into different regions based on these intensity values of the pixels. The algorithms for thresholding are as follow-a) Adaptive thresholding b) Local thresholding c) Global thresholding. In adaptive thresholding for different local areas different threshold values are used.

i). Global thresholding

In this technique for the whole image T is used as the single threshold value. The following condition is executed.

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) \geq T \\ 0 \;\; otherwise \end{cases} \qquad 1$$

Where T is the threshold parameter, f(x,y) is the original input image, g(x,y) is the global threshold in 2D image.

It is used for bimodal images. The image consists of uniform intensity distribution and high contrast between background and foreground. Thus globle thresholding is more rapidly in computational time and simpler. Traditional Thresholding method depends on a proper study in which the image is divides into two categories based on the intensity of gray levels in image [11]. The main advantage of Traditional/Otsu's method is simple and effective to implement but in which the larger objects is segment only from background and be unsuccessful, if the image has variable contrast distribution.

ii). Local thresholding

The threshold value for each part is calculated by taking local threshold values and then dividing an image into sub-images. A global thresholding technique, faster in computational time than the local thresholding. The result of local thresholding for image with background variations is satisfactory and it only removes smaller regions.

The limitations of thresholding as follows.

- The main drawback of thresholding techniques is that in its simplest form, it cannot be applied to multi- channel images. It generates two classes
- In Thresholding technique of image the spatial appearances is not considered. Therefore such techniques are noise sensitive and intensity inhomogeneities.

2.3. Area Based Segmentation

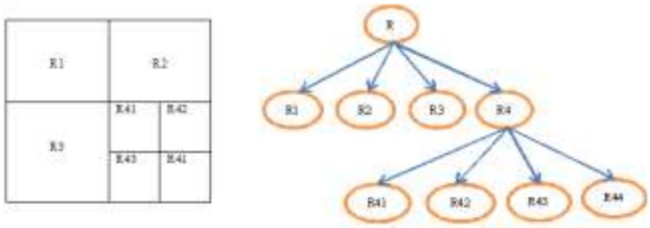
In the Region based segmentation techniques the image is divide into different regions that are similar on the basis of a set of a certain criterion [12]. The existing region segmentation techniques mainly consist of the following methods.

i) Region growing

One of the most frequently used segmentation method is Region growing method. The technique requires seed pixel for starts with it and increases the region by incorporating the nearby pixels based on some threshold if no edges are detected. Region growing process is iterated for each boundary pixel in the region. If adjacent regions are found, then used region-merging algorithm, in which weak edges are dissolved and strong edges are left intact. Region growing algorithms are vary depending on the criteria used to decide whether a pixel should be included in the region or not, connectivity type used to determined neighbours and the strategy used to visit neighbouring pixels.

ii). Region splitting and merging

The region splitting segmentation techniques is work on top-down approach. First the image is divided into a number of different areas depending on certain condition and after it is merged. One region is nothing but the entire image at first and after that the resemblance of the internal pixels in image is calculated by using standard deviation. The image is split into regions using some threshold value only when very large variation is occurring. This process is continual until no more further splitting of the region is possible. The algorithm used for splitting and merging is split-and-merge algorithm [13]. The Quad tree is used for splitting segmentation is a common data structure as shown in Fig. 2(a) and 2(b). Where R represent the complete image.



(a) (b)

Fig. 2 (a) Splitting of an image. (b) Representation by a quad tree.

iii). Watershed segmentation

The image has uniform contrast distribution and the intensity of the foreground and background is distinct then the Watershed segmentation algorithm is used. It is also used to find weak edges from images.

2.4. Clustering

In MRI Segmentation the Clustering segmentation technique is most frequently used, in which the pixels is divides into different parts having no prior information or training [14]. It categorizes the pixels having largest probability into the same class. The training is done by utilizing the pixel characteristics with properties of each class of classified pixels. Partitional and Hierarchical are two clustering techniques.

i). Fuzzy C-means (FCM)

For analysis of data and construction of models the Fuzzy clustering is a powerful method. It is a unsupervised method. The fuzzy clustering is more typical than hard clustering in many circumstances. Fuzzy c-means algorithm is most widely used. The membership assigned in fuzzy clustering for Objects presents on the boundaries between several classes are between 0 and 1 indicating their partial degree of membership. But not compulsory to fully belong to any one of the classes.

The Joe Dunn[15] in 1974 has first reported Fuzzy c-means clustering in the literature for a special case (m=2). The Jim Bezdek[15] has developed general case (for any m greater than 1) in his research study at Cornell University. This segmentation works on fuzzy partitioning in a way that data point can come under all groups with various membership ratings between 0 and 1.
An Algorithm of FCM is described as under:

1. Initialize U= $[u_{ij}]$ matrix, $U^{(0)}$ (2)

2. at k-step: calculate the centers vectors $C^{(k)}$= $[C_j]$ with

$$U^{(k)} \quad Ci = \frac{\sum_{j=1}^{n} U_{ij}^{m} xj}{\sum_{j=1}^{n} U_{ij}^{m}} \tag{3}$$

3. Update $U^{(k)}$, $U^{(k=1)}$

4. $d_{ij} = \sqrt{\sum_{i=1}^{n} \ (x_i - c_i\ )}$ (4)

$$U_{ij} = \frac{1}{\sum_{i=1}^{n} \ (\frac{d_{ij}}{d_{kj}})^{2/(m-1)}} \tag{5}$$

5. $if \| U(k+1) - U(k) \| < \in \ then$ STOP;
Otherwise Return to step 2.

Where - m is any real number greater than 1,
U_{ij} - is the degree of membership of x_i in the cluster j,
x_i - is the i[th] of d-dimensional measured data,
c_j - is the d-dimension center of the cluster,

The suggested algorithms has following advantages
i. Unsupervised
ii. Converges
But it has few limitations on:

- Computational time is more
- Sensitivity to the initial predict (local minima ,speed)
- Sensitivity to noise and One expects low (or even no)Membership degree for outliers (noisy points) [15].

ii). K-means

Clustering method works based on the division of set of data into a specific number of groups. It is popularly used method like many other methods. In k-means clustering, it partitions a collection of data into a k number group of data. K-means clustering algorithm is the simplest of the existing clustering algorithms that can do clustering of pixels into numerous regions based on pixel properties. The method is also called as hard clustering as the clusters must be distant enough from each other and every pixel is assigned the membership function in such a way that it belongs to one particular region only. This techniques functions properly, when the distributions extents are nearly the same but it does not function properly when the distributions come with various variances [16].

3. CONVOLUTION NEURAL NETWORK FOR BRAIN TUMOR SEGMENTATION

The proposed method used for segmentation of brain tumors in MRI images based on convolutional neural networks. For cancer diagnosis the brain tumors segmentation is done manually, from MRI images having large amount of data generated in clinical routine which results in time consuming and challenging task. Due to the drawback, it suggests to use convolutional neural networks (CNN) method for segmentation of brain tumors in MRI images. The Fig.3 shows the block diagram of method used for brain tumors segmentation.

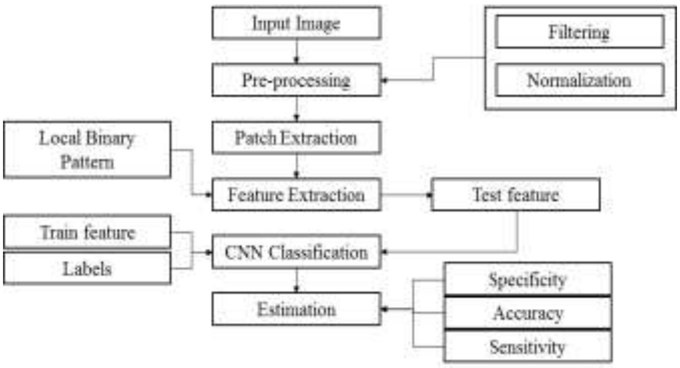


Fig. 3. The Block diagram for brain tumor segmentation

The Flow diagram of proposed method is shown in Fig. 4.

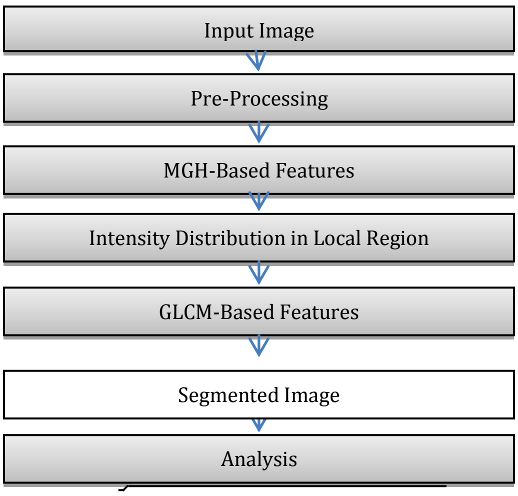


Fig. 4. Flow diagram of proposed method

The proposed method consists of mainly- pre- processing stage, Patch extraction stage, Feature extraction stage and classification stage by using CNN.

A. Pre-processing

The MRI images data need to be preprocessed to realize the segmentation purposes. The pre-processing operations consist of mainly three processes as de-noising, skull-stripping, intensity normalization. It has direct impact on the results of brain tumor segmentation. MRI requires some kind of expected preprocessing job that is Image de-noising. Due to presence of noise in MRI images makes it difficult to precisely define regions of interest between brain tumor and normal brain tissues. Therefore, it is required to preprocess MRI image for reduce noise and to enhance contrast between regions.

i. De-noising

The different de-noising techniques for MRI images have been proposed by means of Anisotropic Diffusion Filtering (ADF), Non-Local Means (NLM), wavelets and Independent Component Analysis (ICA). The current most popular method is ADF used for the de-noising of brain tumor MRI images. A serious review of the effects of de-noising algorithms on MRI brain tumor segmentation was discussed. It is concluded that, although the noise of images is reduced and also undesirable impact on the brain tumor segmentation.

ii. Skull stripping

Skull stripping is a significant preprocessing step for the analysis of MRI images. The Skull is non-cerebral tissue region and it is the process of describing and removing of skull, scalp, and meninges from the soft tissues of the brain. The accuracy of skull striping process affects the efficiency in detecting tumor, pre-surgical planning, cortical surface reconstruction and brain morphometry. Due to the removal of skull region the chances of misclassifying diseased tissues is reduces. Due to the randomness in the parameters of MR scanners, complexity of the human brain and individual physical features, the skull stripping process faced several challenges. The problems arise in segmenting the images exactly due to low contrast and poor quality of the images. Several robust skull stripping algorithms have been proposed to reduce these impacts.

iii. Intensity normalization.

For segmentation of MRI, classification and clustering methods are used. In preprocessing of MRI a very critical step is Intensity normalization. Healthy images are not so challenging as the segmentation of tumor-bearing images because the puzzling results produced by the variances in the appearance of brain tumor. Therefore pathology-robust normalization method is used to improve both global and local constraints for MRI images. In general, first a bias-field correction was employed to reduce the effect of magnetic field inhomogeneities during image acquisition and then segmentation operation is started.

B. MGH-based features

The summary of statistical information is a Gray level histogram. The method for feature extraction adopted is MGH based. The statistical properties of intensity distribution in the local region are used for feature extraction in MGH and also the efficiency for the categorizing of tissues is calculated. To compose the image features containing certain statistics, such uniformity, mean, smoothness, variance, entropy, etc., are calculated.

C. GLCM- based features

The features extraction based intensity distribution is insufficient since the information related to space is not considered for feature extraction. Therefore the GLCM (grey level co-occurrence matrix) is used for feature extraction. The GLCM uses joint probability distribution of pairs of pixels and it has been shown useful for classification texture image. The numbers of gray levels present in medical images are same as the dimension of the co-occurrence matrix in GLCM. In order to save the computational time the numbers of gray levels are reduced in medical images to M discrete levels. The W × W dimensional matrix is used in GLCM. The joint probability distribution between pair of pixels are calculated by using distance 'd' and angle 'θ'. The (i, j) th entry p (i, j) in the matrix gives the number of times that the gray level j follows the gray level i for distance'd' with an angle 'θ'.

The fundamental GLCM algorithm is as follow: Count all pairs of pixels in which the first pixel has a value i, and its matching pair displaced from the first pixel by d has a value of j.

1. This count is entered in the ith row and jth column of the matrix Pd[i,j]

2. Note that Pd[i,j] is not symmetric, since the number of pairs of pixels having gray levels[i,j]does not necessarily equal the number of pixel pairs having gray levels [j,i].

3. The elements of Pd[i,j]can be normalized by dividing each entry by the total number of pixel pairs.

4. Normalized GLCM N[i,j], defined by:

$$N(i,j) = \frac{p[i,j]}{\sum_i \sum_j p[i,j]} \tag{6}$$

D. k-NN classifier

The k-Nearest Neighbour algorithm (k-NN) is a simplest machine learning algorithm in pattern recognition and non-parametric method, where both the regression and classification is used. The input consists of the k-closest training example sets zero the MR images of the brain, in their feature spaces in classification and regression. Whether k-NN is the usage of image in the classification or not decides the output. The class membership is decided by the output. By labeling the task that whether the tumour is present or not, the MR image is categorized based on maximum vote of its neighbours. The class of first nearest neighbour set gets the article in case k = 1.

The output is the property value based, on the tumour presence in k-NN regression. This value is the average of all k –NN values. The K-NN is a type of instance-based learning, where the function is a locally estimated method and all computations are delayed up to classification is not done. A simple implementation of k-NN classification is to calculate the average of the numerical target of the K nearest neighbours and it shown with distance functions in Eqn. (7), Eqn .(8) and Eqn. (9).

Euclidean $\sqrt{\sum_{i=1}^{k} (x_i - y_i)^2}$ (7)

Manhattan $\sum_{i=1}^{k} |x_i - y_i|$ (8)

Minkowski $\left[\sum_{i=1}^{k} (|x_i - y_i|)^q \right]^{1/q}$ (9)

E. CNN Classifier

A convolutional Neural Network (CNN) is a class of deep and feed-forward artificial neural networks which successfully been applied to analyze visual images in machine learning. CNNs uses variety of multilayer perceptions designed to acquire the minimal pre-processing details. Therefore they are also known as shift invariant or space invariant artificial neural networks (SIANN).The convolutional neural networks (CNN) uses relatively little pre-processing comparing to other image classification algorithms. The simple Convolutional neural networks (CNN) is as shown Fig. 5.

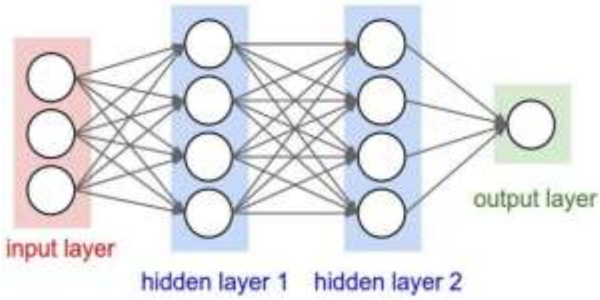


Fig. 5.Simple Convolutional Neural Networks (CNN)

The Eqn. (10) shows the calculation of the CNN Classifier in detection of the brain tumour:

$$A(x) = f * g = \int_{-\infty}^{\infty} (x-u) g(x) dx \\ -F^{-1}\left(\sqrt{2\pi F(f) F(g)}\right) \tag{10}$$

The Eqn. (11) equation is used for the mapping the features in the feature extraction process

$$\sum_{y=0}^{columns} \sum_{x=0}^{rows} input(x-p, y=q) kernel(x,y) \\ = F^{-1}\left(\sqrt{2\pi [F(input) F(kernel)]}\right) \tag{11}$$

4. EXPERIMENTAL RESULTS

The experimental result of a Semi-automatic segmentation using CNN is carried using MATLAB GUI. The experimented proposed GLCM and CNN algorithm is executed for classification with MATLAB, which prompts for the input image from data based. Test input image is tested from the selected data base for classification of tumor i.e. non-tumor and tumor image. Initially the input image is selected for segmentation and test image in GUI which shows in result of Fig. 6.

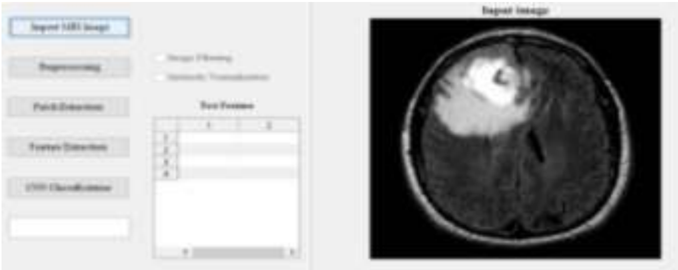


Fig. 6. Input Brain Image for Segmentation

The next step is pre-processing which includes filtered inputed image and intensity normalization which is done on filtered image and is shown in Fig. 7 and Fig. 8 respectively.

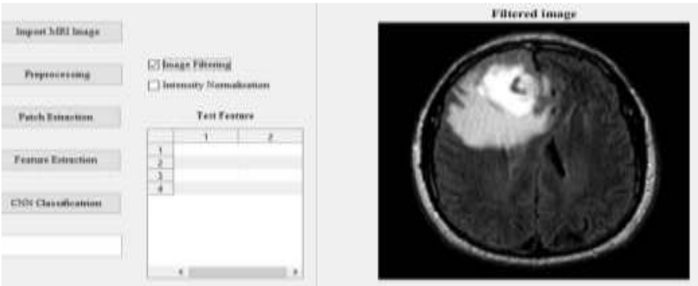


Fig. 7. Image Filtering of Input Brain Image

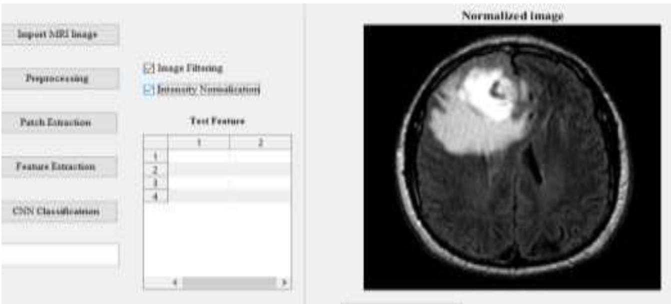


Fig. 8. Intensity Normalization of Input Brain image

The process is segmented for patch extraction and Feature Extraction is using GLCM feature extraction algorithm using MATLAB and results are shown in Fig. 9 and Fig. 10 respectively.

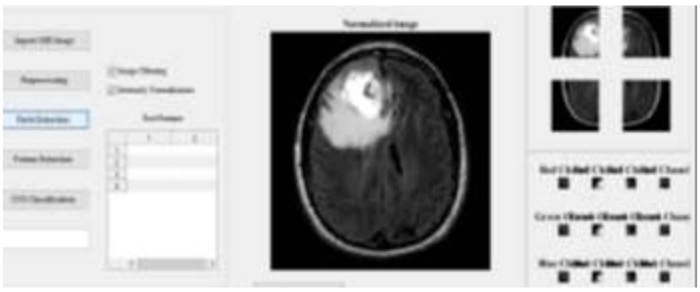


Fig. 9. Patch Extraction

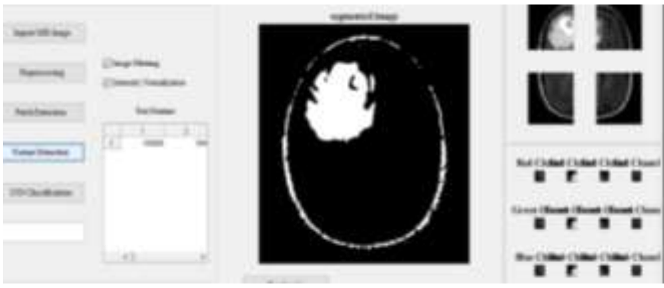


Fig. 10. Feature Extraction

The test image is process for the classification under CNN classifier using MATLAB. The test MRI brain image result using CNN classification is as shown in Fig.11. The measured parameters of test MRI brain image as Correct rate, Error rate, Sensitivity and Specificity are shown in Fig. 12. and results are highlighted in Table I.

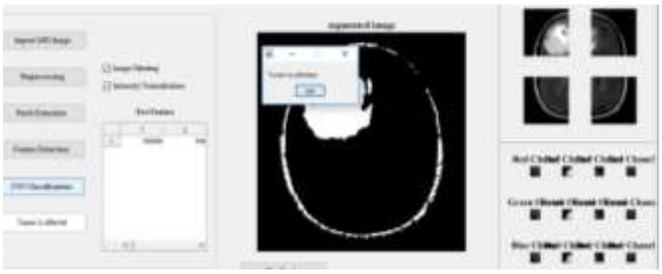


Fig. 11. Result of CNN classification


ommand Window
New to MATLAB? See resources for Getting Started.
CountingMatrix: [15x14 double]
CorrectRate: 0.9286
ErrorRate: 0.0714
LastCorrectRate: 0.9286
LastErrorRate: 0.0714
InconclusiveRate: 0
ClassifiedRate: 1
Sensitivity: 1
Specificity: 1
PositivePredictiveValue: 1
NegativePredictiveValue: 1

Fig. 12. Parameters displayed in command window of MATLAB

The result parameters and their corresponding values obtained are shown in TABLE-I

TABLE - I

Parameters values

Sr. No.	*Parameters Measured*	*Values Obtained in %*
1	Correct Rate	92.86
2	Error Rate	7.14
3	Sensitivity	100

5. CONCLUSIONS

The purpose of proposed CNN method is to provide an early preliminary judgment on diagnosis, tumor monitoring, and treatment planning for the physician. For cancer diagnosis brain tumors segmentation is done generally manually, from MRI created in clinical routine but it is a time consuming and challenging investigation. The fully automatic segmentation technique fails in number of cases and then clinicians will lose their trust and not adopt such technique. Therefore, the robustness is also one of the main assessment criteria for every new technique applied in clinical investigation.

The computation time is also important parameter for development of accuracy and validity for result. The proposed CNN method required less computational time as of other methods which is in few minutes. The real-time segmentation is difficult to achieve. But the current standard computation time over a few minutes is also unacceptable in clinical routine.

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