An Analysis the Brain Tumor using the Hybrid Classification Approach

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Abstract - In this study, methods are presented for the early detection and diagnosis of brain cancers. We will proposed employing a Hybrid Classification (HC) method to identify & segment brain tumors. The HC method described in this study is able to identify the MRI scan of the brain that has been damaged by a tumor, a segmentation method may be employed to isolate the specific areas of the tumor. Finally, the proposed strategy for tumor detection is evaluated in light of the state-of-the-art alternatives. The proposed brain tumor detection system is tested in this chapter with NN, ANFIS and Hybrid classifier for evaluating and analyzing the performance of the proposed method in terms of classification rate.

Keywords - Brain, MRI, Hybrid Classification, ANFIS, Neural Network

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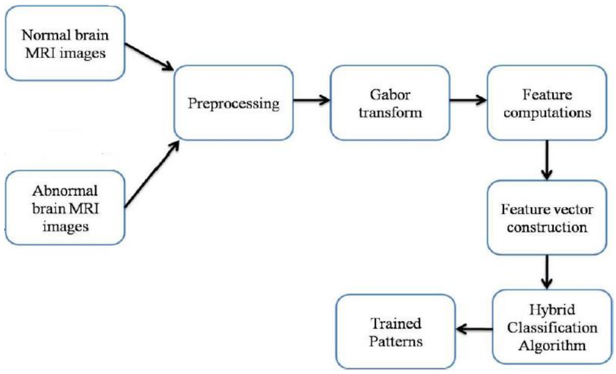
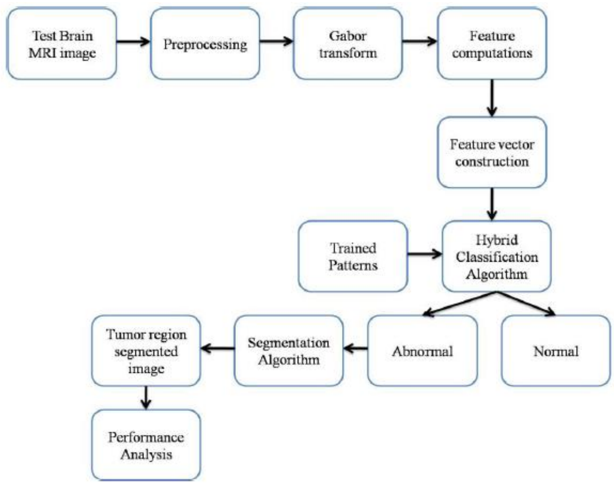
INTRODUCTION

The digital image processing can play an important role in medical side to identify the disease and tumors. A digital image can be collected of fixed number of elements known as image element or pixels, every one of which contains an intensity value and exacting position. In the medical area, the MRI can be mostly utilized for finding the idea of details in the body's inner structure. In common, it has been applied to identify the variations in the tissues of body which can be measured to be the enhanced method as contrasted to estimated tomography. Consequently, this method is used as a unique method particularly for the cancer imaging & brain tumor recognition.

In this chapter, the brain tumors are detected and segmented using HC approach. The HC approach stated in this chapter detects the tumor affected brain MRI image and then segmentation approach is applied on the detected tumor affected brain MRI image in order to segment the tumor regions. Finally, the performance of the proposed tumor detection method is associated with the other conventional methods. Figure 1(a) shows the proposed brain tumor detection system using HC approach in training mode and Figure 1(b) shows the proposed brain tumor detection system using HC approach in testing mode.



(a)



(b)

Figure 1 Proposed brain tumor detection system (a) HC approach in training mode and (b) HC approach in testing mode

Preprocessing

During medical image acquisition process, the noises are generated which affects the performance of the tumor detection and segmentation process. Hence, the noises in the source brain MRI images are detected and reduced before the tumor detection process starts in order to improve the tumor segmentation accuracy. In this chapter, Gaussian noises in the source brain MRI images are detected and reduced using bilateral filter (Yunlong He et al. 2017). Even though the conventional noise reduction filters such as Mean filter and Median filters detects and reduces the Gaussian noises. But they degrade the edge pixels during noise reduction process. In order to achieve edge preserving during noise reduction process, bilateral filter is selected in this chapter to detect and reduce the noises in source brain MRI images.

Gabor Transform

The pixels belonging to noise reduced brain MRI image are spatial or time domain. The pixel behaviour can be improved in the multi resolution domain format. In order to transform the time domain pixels in the noise reduced image into multi resolution domain format, Gabor transform is used in this chapter (Palm et al. 2002 and Kumar et al. 2018). Time-domain pixels are multiplied by the Gabor kernel to produce multi-resolution images using the Gabor transform, which is a type of Gabor filter.

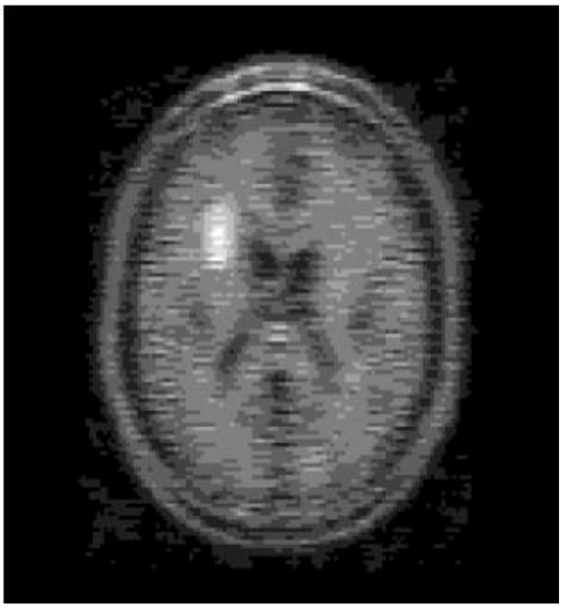


Figure 2 Multi resolution brain MRI image

Feature Computations

In this chapter, GLCM features and Pixel metric features are computed from the Gabor transformed brain MRI image for differentiating the normal image from the abnormal image.

GLCM features

When analyzing a multi-resolution brain image, GLCM features are used to calculate the texture qualities of each individual pixel. In this section, we compute these characteristics using the GLCM matrices with the pixels oriented at a ninety-degree angle.

In this chapter, 135 number of brain MRI images (70 images belonging to normal category and 65 images are belongs to abnormal category) are trained and the features are computed from all of these images. Each brain MRI image produces seven number of feature values. In this chapter, 70 normal brain images are used. Hence, the total number of features computed from the normal category is about 520 (70 normal images * 7 features). In this chapter, 65 abnormal brain images are used. Hence, the total number of features computed from the abnormal category is about 490 (65abnormal images * 7 features). Hence, the total number of features is computed by adding the total number of abnormal and normal features extracted from the brain image which is about 1015. All these computed feature values are stored in a feature vector.

DWT features

The Gabor transformed brain MRI image is decomposed into four number of sub band metrics (sub band coefficients are represented as (i,)) using DWT in this chapter. The size of each decomposed sub band metric is equals to the one by fourth of the source brain MRI image. Each brain MRI image produces four decomposed sub bands and each decomposed sub band produces three features. Hence, the total number of features computed is about 10 for a single brain MRI image. Thus the total number of features computed from the normal category is about 895 and the total number of features computed from the abnormal category is about 840. Hence, the total number of features computed is about 1690. All these computed feature values are stored in a feature vector. The feature vector size of the GLCM feature is 1010 and the feature vector size of the DWT feature is 1690. The total number of features computed in this proposed work is about 2750.

Table 1 shows the extracted GLCM and DWT feature values for both normal and abnormal case brain images. These values show the average values of the features which are computed from the brain images. These values are used by the classifier to classify the source brain images into either normal or abnormal based on these features.

Table 1 Extracted GLCM and DWT feature values for both normal and abnormal case brain images

Features	Feature Metrics	Normal	Abnormal
GLCM	Contrast (C)	2.28×102	4.19×102
	Energy (E)	12.72×104	75.18×104
	Homogeneity (H)	0.01837	1.7283
	Entropy (EN)	1.28	17.29
	Maximum Probability (MP)	-0.172	1.823
	Mean Metric 1	12.37	762.12
	Mean Metric 2	11.29	673.19
DWT	Energy Metric (EM)	128.87×1012	17.872×1012
	Index Metric (IM)	1.72	78.20
	Invariance Feature (IF)	-0.0928	2.182

HC Approach

In this research work, the NN is designed with single input and output layer and with 5 numbers of hidden layers. The number of neurons in input layer of this proposed design is equipped with 15 and the number of neurons in output layer of this proposed design is equipped with single neuron. Each hidden layer of this proposed NN design consists of 25 neurons. In this study, the optimal classification rate is achieved by selecting the number of hidden layers & number of neurons in each hidden layer over a series of iterations.

During training process of the hybrid classifier (NN stage), the edge pixels are detected using ‘Canny’ edge detector in both normal and abnormal category. These detected edge pixels are trained by NN classifier which produces the edge trained pattern. So that, the input of the NN classifier is edge pixels of the brain image to be tested.

During training process of the hybrid classifier (ANFIS stage), the features GLCM and DWT are computed from the both normal and abnormal category of images. These computed features along with the edge trained patterns are further trained by ANFIS classifier which produces the final trained pattern.

The architecture of the ANFIS classifier used in this proposed work is depicted in the following Figure 3. In this proposed architecture, ANFIS is designed with five numbers of layers as input layer, fuzzification layer, defuzzification layer, normalization layer and output layer. The input layer is connected with the extracted feature vector. The extracted features from the normal brain MRI images are connected with the input function X and the extracted features from the abnormal brain MRI images are connected with Y in this proposed architecture. The fuzzification layer applies fuzzy logic on each feature set and the defuzzification layer eliminates the negative values in the responses. The normalization layer performs unit normalization on the computed responses and the final output layer is connected with the normalization layer.

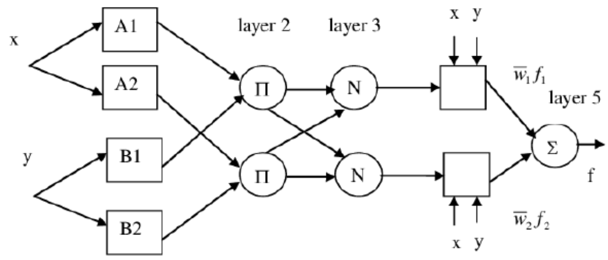


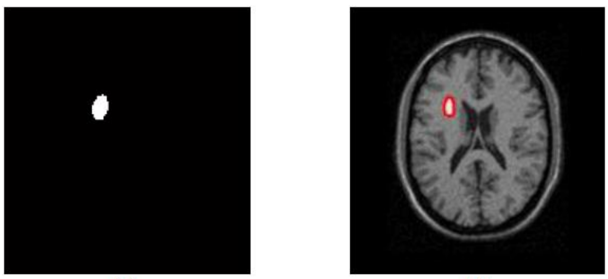
Figure 3 ANFIS architecture

During testing process of hybrid classifier (NN stage), the edge pixels are detected using ‘Canny’ edge detector in the test brain MRI image and the detected pixels are combined with the extracted features from the test brain MRI image. These computed pixels and features are classified using ANFIS classifier which produces binary values as 0 and 1.

The normal brain MRI image is identified with 0 binary response values and the abnormal brain MRI image is identified with 1 binary response value.

Segmentation

Tumor pixels in an identified abnormal MRI of the brain are the focus of the segmentation procedure. In this chapter, morphological segmentation approach (dilation followed by erosion) is used to segment the tumor pixels.



(a) (b)

Figure 4 (a) Morphologically processed image and (b) Tumor pixels segmented image

RESULTS & DISCUSSIONS

The procedure presented in this study is tested in a simulated environment utilizing MATLAB R2018 & corresponding hardware configurations of 4GB RAM & 2.4GHz processor.

Within the context of this chapter, the hybrid classifier system is trained using a dataset consisting of 70 normal brain MRI pictures & 65 abnormal brain MRI images (BRATS 2015 dataset). Table 3.2 also shows the results of testing the proposed hybrid classifier system with 147 examples of normal brain MRI images & 99 examples of abnormal brain MRI images. This results in a total of 222 normal brain MRIs & 169 abnormal ones.

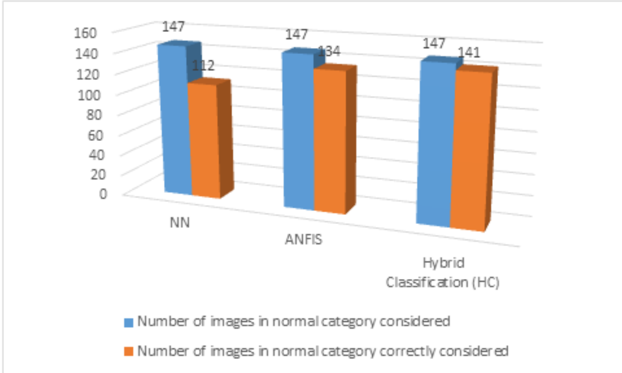
Table 2 Dataset details (BRATS 2015)

Mode	Normal	Abnormal
Training images	70	65
Testing images	147	99
Total images	222	169

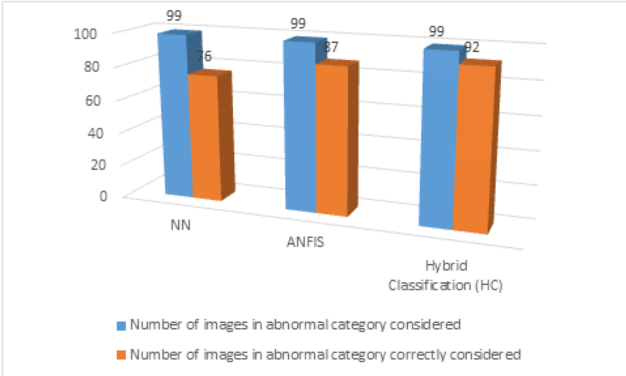
In this section, we evaluate the success of the constructed framework by looking at the classification rate, which is the percentage of correctly identified photos relative to the total number of images. The suggested system uses a NN classification strategy to label 112 out of 147 brain MRI pictures as normal. The suggested system uses a NN classification strategy to label 76 out of 99 brain MRI pictures as abnormal. Over 152 photos, the proposed system labels 134 as normal, utilizing an ANFIS classification strategy. Over a total of 99 pictures, the suggested system uses an ANFIS classification approach to label 87 as abnormal. Out of 147 brain MRIs, the suggested algorithm deems 141 to be normal. Over 99 brain MRI pictures, the proposed system correctly labels 92 as abnormal, thanks to the use of the HC method.

Table 3 Performance of proposed brain tumor detection system with respect to classification approaches

Classification methods	Number of images in normal category considered	Number of images in abnormal category considered	Number of images in normal category correctly considered	Number of images in abnormal category correctly considered
NN	147	99	112	76
ANFIS	147	99	134	87
HC	147	99	141	92



(a)



(b)

Figure 5 (a) Graphical illustrations of the proposed brain tumor detection system with respect to classification approaches (normal category) and (b) Graphical illustrations of the proposed brain tumor detection system with respect to classification approaches (abnormal category)

Table 4 Analysis of classification methods effect in proposed brain tumor detection system

Classification methods	Classification rate (%)	
	Normal category	Abnormal category
NN	73.6	73
ANNFIS	88.1	83.6
HC	92.7	88.4

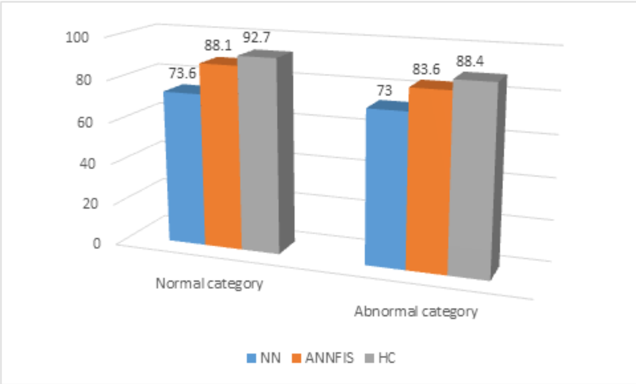


Figure 6 Pictorial representations of the classification methods effect in proposed brain tumor detection system

The proposed brain tumor detection system is tested in this chapter with NN, ANFIS and Hybrid classifier for evaluating and analyzing the performance of the proposed method in terms of classification rate (CR). The proposed brain tumor detection system using NN classifier achieves 73.6% of CR for normal category and achieves 73% of CR for abnormal category. Hence, the average CR for NN case is about 73.3%. The proposed brain tumor detection system using ANFIS classifier achieves 88.1% of CR for normal category and achieves 83.6% of CR for abnormal category. Hence, the average CR for ANFIS case is about 85.5%. The proposed brain tumor detection system using Hybrid classifier achieves 92.7% of CR for normal category and achieves 88.4% of CR for abnormal category. Hence, the average CR for Hybrid classifier case is about 90.5%.

The proposed tumor detection system is also tested with respect to the extracted features. The proposed system with GLCM feature alone achieves 67.1% of CR for normal category and achieves 69.6% of CR for abnormal category. The proposed system with DWT sub band feature alone achieves 72.7% of CR for normal category and achieves 70.5% of CR for abnormal category. The proposed system with GLCM and DWT sub band feature achieves 92.7% of CR for normal category and achieves 88.4% of CR for abnormal category, as depicted in Table 5.

Table 5 Analysis of classification methods effect in proposed brain tumor detection system

Features	**Classification Rate (%)**	
	Normal Category	**Abnormal category**
GLCM features	67.1	69.6
DWT	72.7	70.5
GLCM+ DWT	92.7	88.4

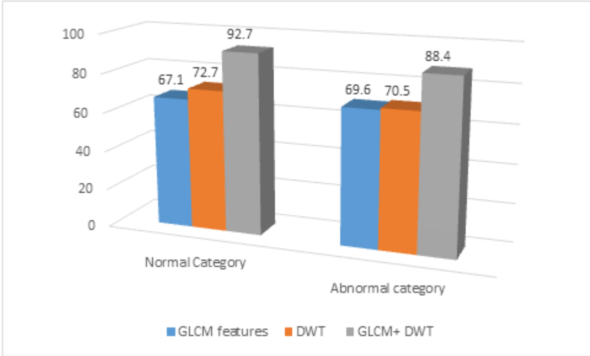


Figure 7 Pictorial analysis of classification methods effect in proposed brain tumor detection system

The evaluated characteristics & metrics of the simulation environment are then applied to the examined designed architecture or framework. Accuracy is defined as the sum of the numbers of tumor & non-tumor pixels correctly detected in the final tumor region segmented brain picture, while sensitivity & specificity determine the number of pixels that are appropriately connected with the tumor region. Well-detected non-tumor pixels are defined by precision, and the Disc Similarity Index indicates the total amount of tumor detected pixels that are comparable to ground truth images.

Table 6 Simulation results of the proposed brain tumor detection system using NN classification approach

BrainMRI image sequence	Simulation results in %					
	Sen.	Sqe.	A	Pr	FS	DSI
1	76.7	77.7	79.2	78.5	78.4	81.6
2	78.1	78.9	78.5	81.7	78.9	84.5
3	77.1	78.6	77.9	82.9	71.7	79.7
4	79.6	81.6	74.7	76.6	87.6	78.6
5	75.9	82.8	75.7	76.8	89.6	81.7
6	78.1	79.7	81.6	77.1	79.7	79.6
7	77.5	81.6	88.3	74.7	78.6	86.8
8	75.1	80.5	89.5	89.4	89.6	86.4
9	78.1	77.9	78.5	89.4	88.8	89.5
10	82.7	81.6	76.8	85.6	86.5	76.7
Average	77.89	80.9	80.07	80.29	82.94	82.51

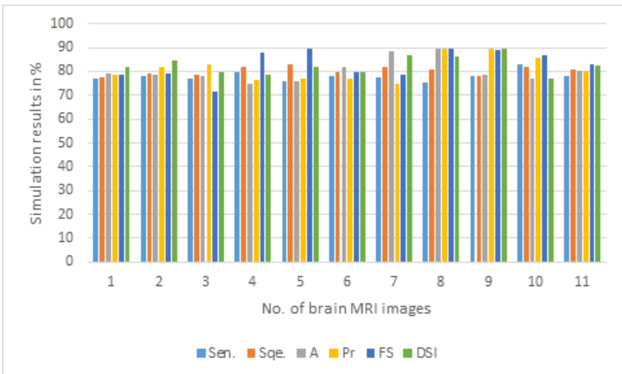


Figure 8 Graphical illustrations of the proposed brain tumor detection system using NN classification approach

Table 7 Simulation results of the proposed brain tumor detection system using ANFIS classification approach

Brain MRI image sequence	Simulation results in %					
	Sen.	Sqe.	A	Pr	FS	DSI
1	76.7	79.6	81.8	81.7	81.6	85.8
2	81.5	79.1	79.6	82.6	80.6	85.9
3	76.6	79.7	78.6	83.8	76.9	80.6
4	78.5	81.9	77.9	77.1	88.5	79.6
5	77.5	84.5	77.6	77.9	90.6	80.6
6	79	81.6	82.5	78.6	81.5	81.7
7	78.1	83.8	89.7	80.5	80.6	87.4
8	77.6	81.6	90.1	75.8	90.5	88.5
9	78.1	80.7	79.5	90.5	91.6	89.7
10	86.7	82.5	77.6	87.9	90.4	81.5
Average	79.03	81.5	81.49	81.64	85.28	84.13

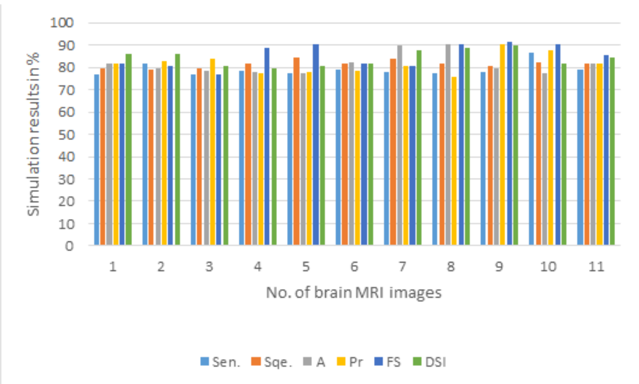


Figure 9 Graphical illustrations of the proposed brain tumor detection system using ANFIS classification approach

Table 8 is the simulation results of the proposed brain tumor detection system using HC approach. The proposed system using HC approach obtains 91.54% Sen, 96.2% Spe, 98.4% A, 88.5% Pre, 94.8% FS and 93.2% DSI. In addition, all of the brain MRI pictures in the open dataset are used to evaluate the proposed method and produces the similar simulation results on the entire number of brain MRI images in the dataset.

Table 8 Simulation results of the proposed brain tumor detection system using Hybrid Classification approach

BrainMRI image sequence	Simulation results in %					
	Sen.	Sqe.	A	Pr	FS	DSI
1	90.7	90.9	98.2	83.5	95.6	90.1
2	91.7	95.8	91.4	85.7	97.6	91.2
3	92.7	97.8	97.5	92.1	91.3	93.5
4	90.6	92.5	92.7	95.4	92.6	92.6
5	89.7	95.1	95.2	96.8	.95.6	98.4
6	90.5	92.3	91.5	97.3	94.6	95.8
7	91.8	94.1	93.5	88.5	93.5	96.6
8	98.6	98.5	96.6	84.6	98.5	97.7
9	94.5	97.4	93.8	93.6	91.0	95.2
10	93.5	91.5	91.2	96.8	92.4	93.8
Average	91.54	96.2	98.4	88.5	94.8	93.2

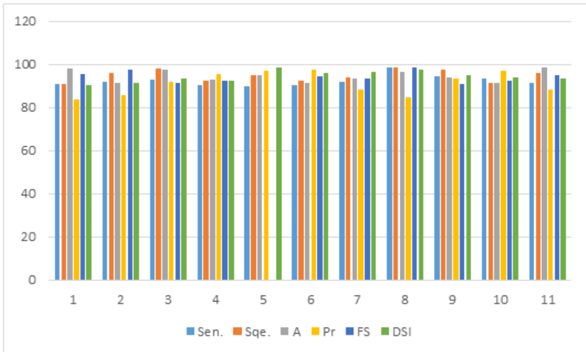


Figure 10 Graphical illustrations of the proposed brain tumor detection system using Hybrid classification approach

Table 9 is the comparison analysis of proposed method with respect to classification approaches. Based on the simulation findings, the proposed brain tumor detection system employing the HC technique achieves impressive tumor segmentation results in comparison to existing classification approaches.

Table 9 Comparison analysis of proposed method with respect to classification approaches

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Performance estimation parameters (%)	Classification methods		
	NN	ANFIS	Hybrid (HC) approach
Sen.	90.7	94.6	90.3
Spe.	93.1	92.1	92.6
A	90.4	93.9	93.1
Pr	94.6	91.4	94.7
FS	83.6	97.9	96.8
DSI	91.1	93.5	98.8

Simulation results are compared to those of more traditional approaches in Table 10. Milica M Badža et al. (2020) and Tripathi et al. (2019) on same dataset images.Milica M Badža et al. (2020) obtained 96.5% Sen, 96.1% Spe and 92.1%. Tripathi et al. (2019) obtained 92.8% Sen, 94.5% Spe and 94.1% A. The conventional methods for brain tumor detection used single classification process to classify the brain images into either normal or abnormal. In this chapter, the integration of two classifiers is used to improve the tumor image detection accuracy. Comparisons with other traditional approaches on the same dataset of brain MRI images suggest that the suggested system employing the HC approach produces high simulation values.

Table 10 Conventional approaches are compared to the proposed simulation findings.

Study	Methodology	Preprocessing	Number of classes	Sen (%)	Spe (%)	A (%)
Proposed work	Hybrid classifier (HC)	Yes	2	97.3	96.7	95.8
Milica M Badza et al. (2020)	CNN	Yes	2	96.5	96.1	92.1
Tripathi et al. (2019)	Decision Tree	Yes	2	92.8	94.5	94.1

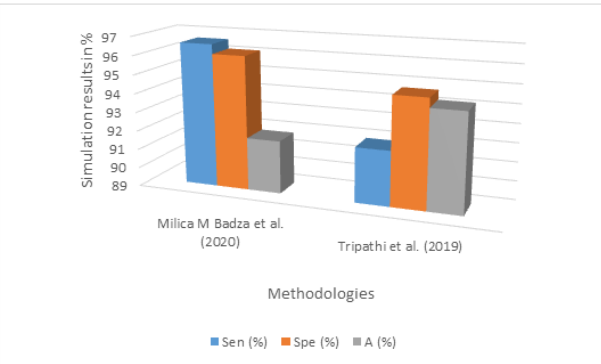

Figure 11 Illustrations comparing the results of the proposed simulation with those of more conventional approaches

CONCLUSION

Brain tumor detection in MRI head scans is a difficult task for clinical applications. This thesis develops brain tumor detection and diagnosis system using machine and deep learning algorithms. The approach detects and segments the brain tumors using machine learning based Hybrid Classification method. Finally, the performance of the proposed tumor detection method is compared with the other conventional methods. The proposed brain tumor detection system is tested in this chapter with NN, ANFIS and Hybrid classifier for evaluating and analyzing the performance of the proposed method in terms of classification rate.

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