Detection and Classification of Brain Tumor and Breast Cancer by Using an Efficient Method Based on Image Processing and Fuzzy Inference System

Jitu Prakash Dhar [1]

[1] *Department of Electrical & Electronic Engineering, Chittagong University of Engineering & Technology, Chattogram, Bangladesh*

[1]*jitu@cuet.ac.bd*

Abstract— Brain tumor and breast cancer are considered to be the most fatal cases for the health of people in modern days. Therefore, early and precise detection of these cases can save many lives all over the world. However, detection and classification of the tumor/cancer area precisely can help the doctors for diagnosing and treatment. In this article, a method based on different noise removal and image adjustment techniques integrated with a Mamdani Fuzzy Inference System (FIS) is proposed to efficiently detect and classify both brain tumor and breast cancer. Firstly, this method is used for detection and classification of brain tumor from the standard Magnetic Resonance Imaging (MRI) dataset. Then, the same method is utilized to detect and classify breast cancer from standard Mammography image dataset with a little modification of the inputs and outputs of the FIS. The use of Otsu's Method for Global Image Thresholding of the intensity adjusted image and the Robert's Method for edge detection of the cancer/tumor area increase the efficiency of the method. Furthermore, the performance of this technique is compared with the other conventional neural network and fuzzy based techniques. Accordingly, it is found that this method is competitive with them on various performance parameters.

Keywords— Image Intensity Adjustment, Edge Detection, Global Image Thresholding, Mamdani FIS, Mammogram Image.

I. INTRODUCTION

Brain tumor means the abnormal growth of tissues in brain within which the cells divides uncontrollably. Basically there are three types of brain tumor cases. These are Benign, Malignant and Meningioma. In benign brain tumors, the cell division rate is comparatively low and the cell tends to remain in a single region. This type of tumors are considered to be non cancerous and they can be safely removed by brain surgery [1]. On the other hand, the cell division rate is higher in malignant brain tumors and spread in the areas of brain and spine. They have irregular borders and are considered to be cancerous [2]. Meningioma brain tumor grows from the membranes surrounding the brain and spinal cord just into the skull region. It has clear border but it locates near the sensitive structures of brain organs. Hence, in most cases if the classification of tumor is not done accurately it is not possible to remove the entire tumor.

Giordana et al. developed a real time classification system that uses Graphic Processing Unit (GPU) to detect brain cancer from Hyper-spectral Imaging [3]. This system can speed up the procedures of neurosurgical operation with a big dataset but power scheduling is required in the operation theatres. Seetha J et al. proposed an automatic detection method using Convolutional Neural Network (CNN) with small weight value to detect brain tumor accurately [4].

M. A. Bakr et al. proposed a brain tumor detection system based on deep convolutional neural network (DCNN) [5]. This method achieves good accuracy and F1 score for brain MRI images but it suffers from poor sensitivity. Nilesh Bhaskarrao et al. implemented berkeley wavelet transformation (BWT) to segment the brain MRI image and support vector machine to increase accuracy and sensitivity for the extracted features of the segmented images [6]. This technique can be combined with more than one classifier and feature extraction schemes to improve the performance.

Badža, Milica et al. developed a method using CNN architecture for brain tumor detection [7]. It was tested on T1-weighted contrast-enhanced MRI images and the performance was determined with three databases. Adjusting the network architecture it can detect the real time response of the tumor. T. Chithambaram et al. proposed an image filter integrated Artificial Neural Network (ANN) based brain tumor detection method which can also detect lung cancer with some changes [8]. However, this technique cannot detect the small macroscopic tumors.

Harsimranjot et al. implemented a scheme using wavelet-based decomposition on the input brain MRI image followed by fuzzy c-means clustering (FCM) and seeded region growing [9]. It gets good results compared to the other techniques that use Sobel operator but this method cannot classify the brain tumors. Neha Mathur et al. exploit different kinds of edge detectors that utilize fuzzy logic based approaches to detect the edges of the brain tumor area in the MRI images [10]. Although this method uses k-means clustering algorithm followed by Canny edge detection to improve the detection technique, it cannot classify the category of brain tumor similarly.

Yousif Ahmed et al. developed a balance contrast enhancement technique (BCET) based brain tumor diagnosis scheme that effectively detect and classify normal and tumor region [11]. Additionally, this method cannot detect small brain tumor in deep neurosurgery. P Gokila et al implemented a model based on trial and error method integrated with ANN which gains a low accuracy value [12]. Reda Shbib et al. proposed a Modified Fuzzy Logic Clustering (MFLC) segmentation method and skull-stripping algorithm to detect brain tumor which achieves better results compared to schemes that use k-means clustering [13].

Similarly, breast cancer cases are of two types: Benign and Malignant. Screening mammograms are the source of data to diagnose and treatment of breast cancer. The most difficult problem in mammogram image is to detect the blurred edges of the cancer area. Many researchers apply different kinds of computer aided techniques to visualize the blurred edges like image preprocessing, ANN, fuzzy tools, segmentation etc. Emmanuel et al. developed a modified AlexNet neural network architecture to classify the breast cancer cases from 322 mammogram image database which gains an accuracy of 95.70% for the entire system [14].

Rhaylander et al. evaluated the performance of VGG16 and XGBoost for detecting breast cancer by utilizing digital mammograms [15]. Although this method can handle the raw data, it cannot process the high resolution mammographic images. Saad Awadh et al. implemented a technique using CNN with different number of layers to improve the accuracy of the breast cancer detection system [16].Their main drawback is the use of secondary data and the use of raw dataset is not experimented.

Jose Manuel et al. developed a generalized regression neural network (GRNN) based model to categorize the breast cancer cases and they found significant development in the system performance [17]. Ali et al. used wavelet transform to extract features from mammogram images and Grey Level Co-Occurrence Matrix (GLCM) integrated with fuzzy logic to categorize breast cancer types [18]. But this method cannot handle the pixel resolution for small cancer area. M Velmurugan et al. proposed a scheme using fuzzy integrated neural networks to separate the benign and malignant cases [19]. Again, this method also suffers from low accuracy.

Ragab et al. implemented a method using DCNN and support vector machine (SVM) to classify the cancer cases accurately but it got low accuracy too [20]. Furthermore, Chowdhary et al. used Intuitionist Possibilistic Fuzzy C-Mean Clustering and fuzzy SVM classifier to detect breast cancer [21]. This technique shows low performance in the presence of noise and disturbances in the mammogram images.

Sun et al. utilized Image Template Matching for region of interest (ROI) detection and CNN for classification of the mammographic database [22]. They achieved better results in detection and classification compared to the ANN based methods. O. O. Soliman et al. developed a model which extracts feature from breast thermal image and Back-propagation Neural Network (BPNN) based classifier for categorizing the breast cancer cases [23]. However, they used a small database and the performance indicators are not quite promising.

So, in this study, an efficient method based on image processing techniques and fuzzy inference system is proposed for detecting and classifying the cancer/tumor area more accurately then the techniques discussed earlier. This model is developed for both brain tumor and breast cancer cases with a little modification. The remaining sections are organized as: Section II discusses the proposed methodology in details. Secondly, section III describes the performance indicators. Thirdly, section IV analyzes the system inputs. Fourthly, section V explains the data processing and system outputs. Then, section VI contains the result discussion. Finally, section VII concludes the overall model.

II. PROPOSED METHODOLOGY

The flow charts for detection and classification of brain tumor or breast cancer are shown in figure 1 and figure 2. The steps involved in both of the flow chart are similar and can be discussed as follows:

Step-1, Input image data: For brain tumor detection, the MRI scan of the brain is read from the database and for breast cancer detection, the mammogram image of the breast is read from the dataset. If the image is in RGB format it is converted into grayscale. The images are resized into a suitable matrix to preserve the image aspect ratio.

Step-2, Median Filter: The resized image is then applied to a median filter which reduces the random noises of the image and conserves the edges.

Step-3, Thresholding to Binarise: The filtered image is converted to a binary image based on a threshold value. In this model, a threshold value of 0.65 is chosen.

Step-4, Watershed Segmentation: In this step, the watershed regions of the binarised image are computed.

Step-5, Tumor/Cancer Region Detection: In this step, a flat and disk shaped structuring element is generated first from the watershed segmented image. Then the structuring element is dilated and morphologically reconstructed under the image mask to detect the cancer/tumor area.

Step-6, Edge Detection: In this step, the edges of the tumor/cancer region are calculated using Robert's Method [24]. It ignores all edges that are not stronger than threshold value.

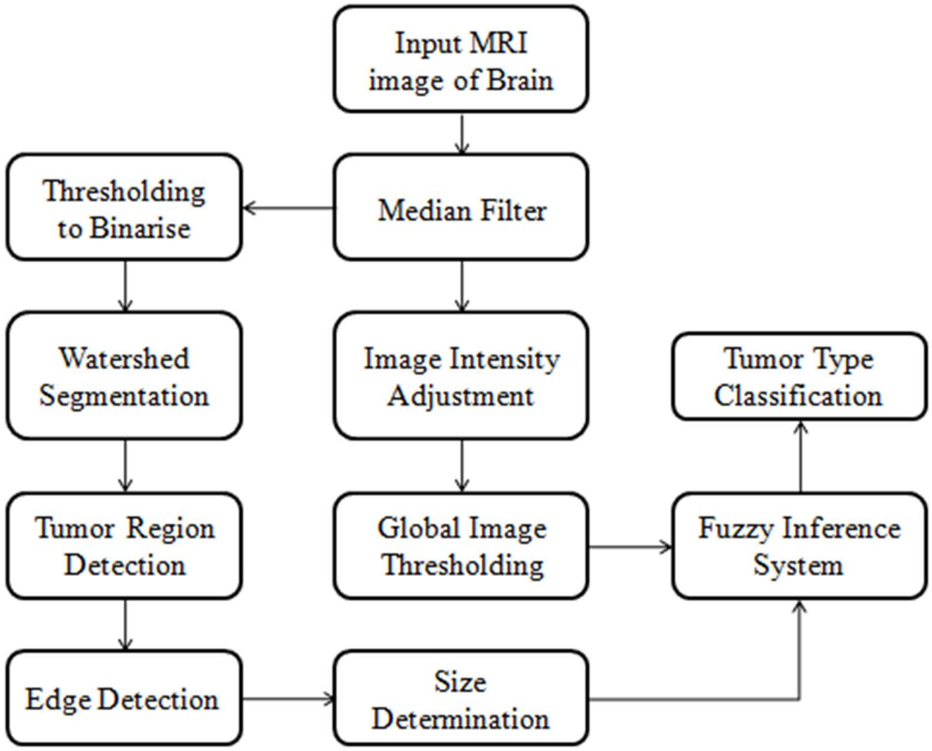


Fig. 1 Flow chart of detection and classification of brain tumor.

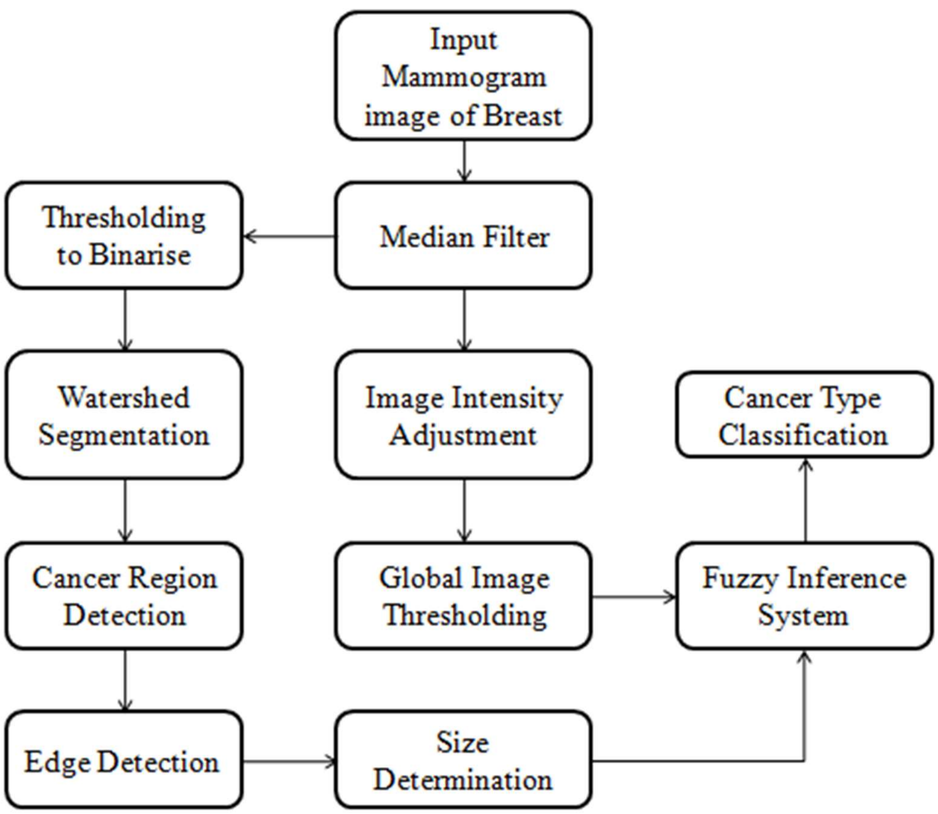


Fig. 2 Flow chart of detection & classification of breast cancer.

Step-7, Size Determination: Based on the edges of the tumor/cancer area, the shape and border are assigned first. In this method, shapes like round, oval and partial-round are considered. Also, regular and irregular border lines are found. Then, the size (small, medium, random etc) is determined from the shape and border and a membership value is assigned to the size.

Step-8, Image Intensity Adjustment: The median filtered image is adjusted such that 1% of data is saturated at the low and high intensity levels of the image. This increases the contrast value of the output adjusted image.

Step-9, Global Image Thresholding: The global image threshold value of the intensity adjusted image is calculated by using Otsu's method [25]. This method chooses an optimum threshold to reduce the intra-class variance of the black and white pixels. Mathematically, if $\Phi(t)$ and $\Psi(t)$ are the probabilities of the black and white pixels separated by a threshold t and σ_1^2 and σ_2^2 are variances of these two classes, then weighted sum of variances of the two classes is:

$$w^2(t) = \Phi(t)\sigma_1^2 + \Psi(t)\sigma_2^2 \quad \ldots\ldots(1)$$

Minimizing the intra-class variance is identical to maximizing inter-class variance for the two classes. So, the minimized intra-class variance of the two classes is:

$$w^2(t^*) = w^2 - w^2(t) \quad \ldots\ldots..(2)$$

Where, t* is the optimum or global threshold and w^2 is the total sum of variances of the two classes. To compute this global threshold, the command in MATLAB is:

G = graythresh(IA) ……….(3)

Where, IA is the intensity adjusted image and G is the Global image threshold value.

Step-10, Fuzzy Inference System: The membership value of the size for the cancer/tumor region and the global image threshold value are given as inputs to a Mamdani Fuzzy Inference System. Then, it processes them according to the fuzzification method, membership functions, fuzzy rules and defuzzification method. Benefits of using Mamdani FIS are given below:

a) It is instinctive.
b) It has universal approval.
c) It is greatly compatible with human input.

Step-11, Tumor/Cancer Type Classification: After the data processing carried out by the FIS, the system outputs the class of the tumor/cancer based on the output membership functions.

III. PERFORMANCE INDICATORS

The performance of the proposed method is evaluated by the following indicators:

a) Sensitivity = $\frac{TP}{TP+FN} X\ 100\%$ ………(4)

b) Specificity = $\frac{TN}{TN+F} X\ 100\%$ …….(5)

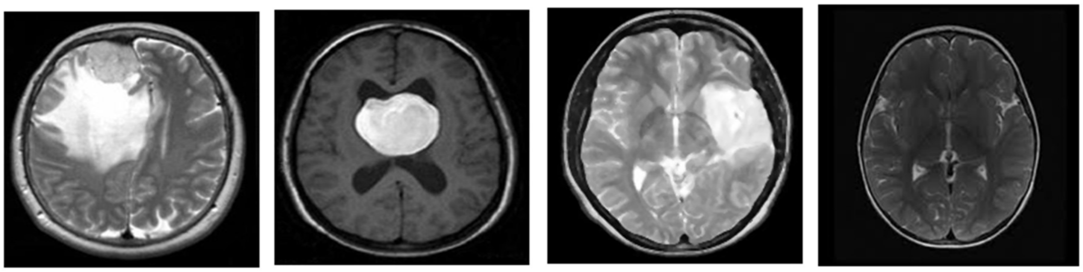
c) Accuracy = $\frac{TP+TN}{TP+TN+FP+F} X\ 100\%$ ……(6)

d) F1 score = $\frac{2TP}{2TP+FP+FN} X\ 100\%$ ……(7)

Where, TP = True and Positive detection, TN = True but Negative detection, FP = False but Positive Detection & FN = False and Negative detection respectively.

IV. SYSTEM INPUTS

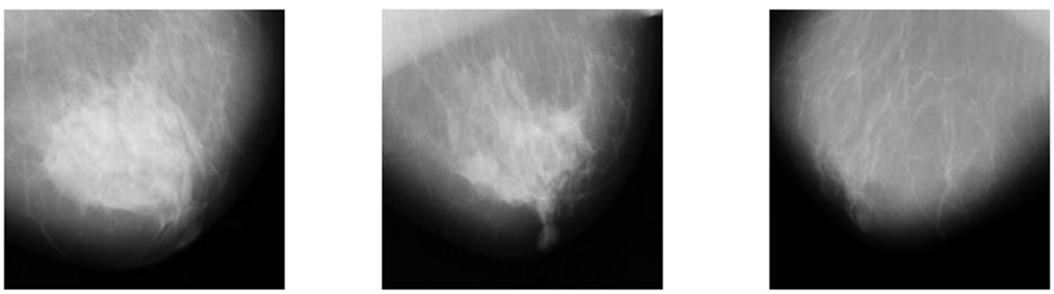
For brain tumor detection, the model is simulated with 316 MRI input images of brain from the standard database available from Ref. [26], [27] and [28]. Among them, 50 are benign cases, 65 are malignant cases, 97 are meningioma cases and 104 are normal cases. Figure 3 shows a benign, a malignant, a meningioma and a normal brain MRI scans that are used in the model.



(a) (b) (c) (d)

Fig. 3 Brain MRI scans: (a) Benign, (b) Malignant, (c) Meningioma & (d) Normal.

For breast cancer detection, again the method is experimented with 69 mammographic input images of breast from the standard dataset available from Ref. [29]. Among them, 22 are benign cases, 23 are malignant cases and 24 are normal cases. Figure 4 shows a benign, a malignant and a normal breast mammogram images that are used in the model.



(a) (b) (c)

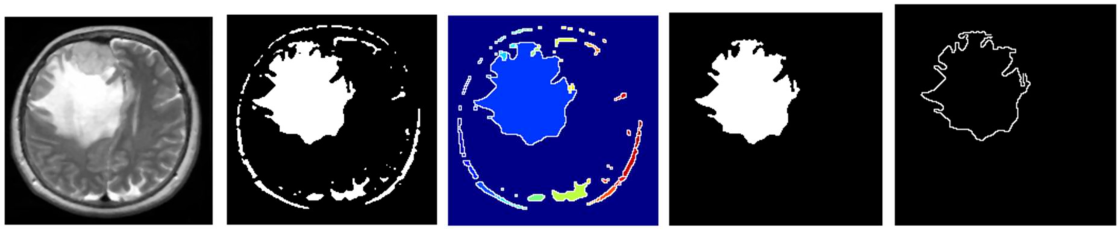
Fig. 4 Breast mammogram images: (a) Benign, (b) Malignant & (c) Normal.

V. DATA PROCESSING AND SYSTEM OUTPUTS

This section is divided into following sub-sections:

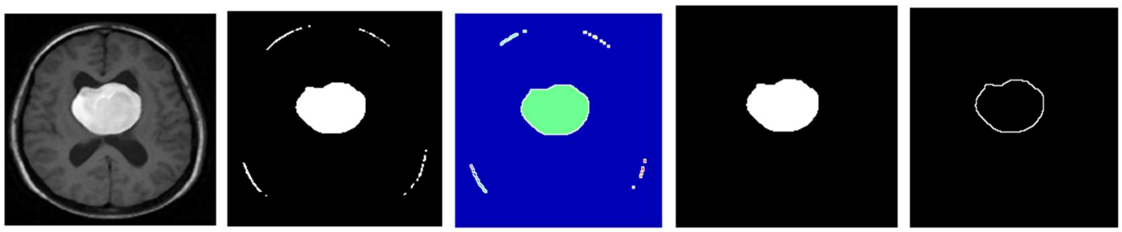
a. Data processing for brain tumor detection & classification

The brain MRI scan is first median filtered and then thresholded. After that it is watershed segmented, then the tumor region is detected and finally the edges of the tumor region are evaluated. These data processing stages for different brain tumor cases are shown in figure 5, figure 6, figure 7 and figure 8.



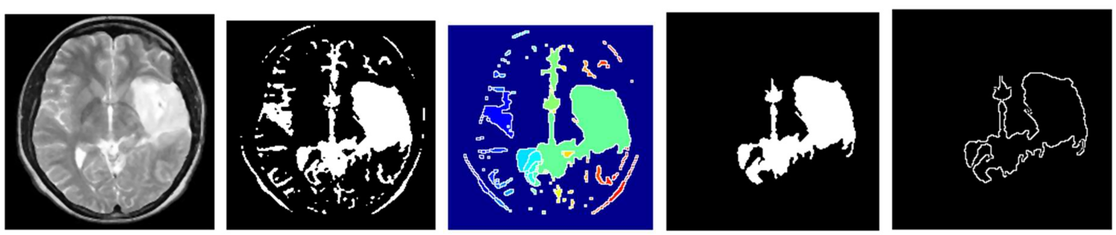
(a) (b) (c) (d) (e)

Fig. 5 Benign brain tumor detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.



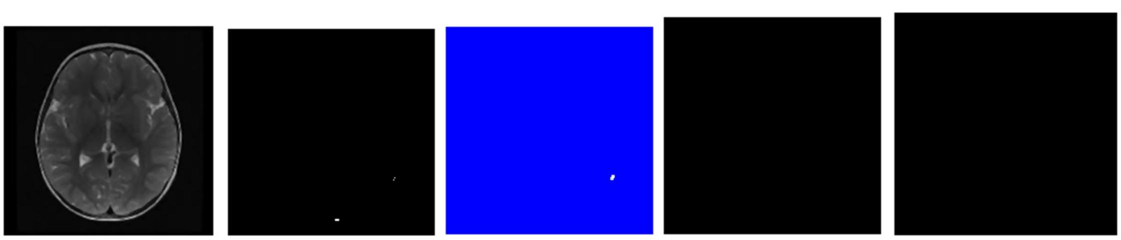
(a) (b) (c) (d) (e)

Fig. 6 Malignant brain tumor detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.



(a) (b) (c) (d) (e)

Fig. 7 Meningioma brain tumor detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.



(a) (b) (c) (d) (e)

Fig. 8 Normal brain detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.

After investigating the edges of the brain tumor images, it is found that benign cases have a round or oval shape and a regular border. Malignant cases have a partial round shape and irregular border. Meningioma cases have random shape and random border. Normal cases have no shape and border. So, these shapes and borders are organized to determine the size which is an input to the FIS. After that, each size is assigned a membership value as shown in table-1. Accordingly, the membership functions for the input variable “Size of brain tumor” in the FIS are shown in figure 9.

TABLE 1: Size determination for the brain tumor detection cases

Case	**Shape**	**Border**	**Size**	**Membership Value**
Benign	Round/Oval	Regular	Large	0.91 to 1.00
Malignant	Partial Round	Irregular	Medium	0.85 to 0.90
Malignant	Elliptical	Irregular	Small	0.78 to 0.84
Meningioma	Random	Random	Random	0.70 to 0.77
Normal	Null	Zero	Null	0.00< to 0.76

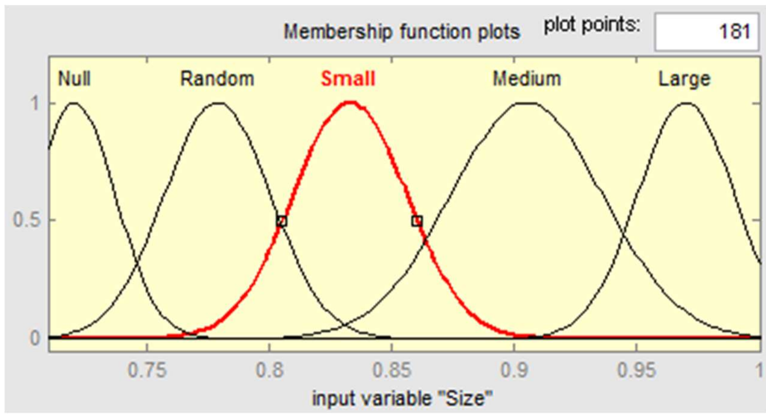


Fig. 9 Membership function plots for the input variable “Size of brain tumor”.

After determining the Global Image Threshold values of the brain tumor images, benign cases have large or medium thresholds in the scale of 1. Malignant cases have small or medium thresholds and meningioma or normal cases have random thresholds. Now, each threshold case is assigned a membership value as shown in table-2 and the membership functions for the input variable “Global threshold” in the FIS are shown in figure 10.

TABLE 2: Global Image Threshold and Their Membership Values.

Global Image Threshold	Random 1	Small	Medium	Large	Random 2
Membership Value	0.00< to 0.37	0.37 to 0.42	0.43 to 0.45	0.45 to 0.48	0.48 to <1.00

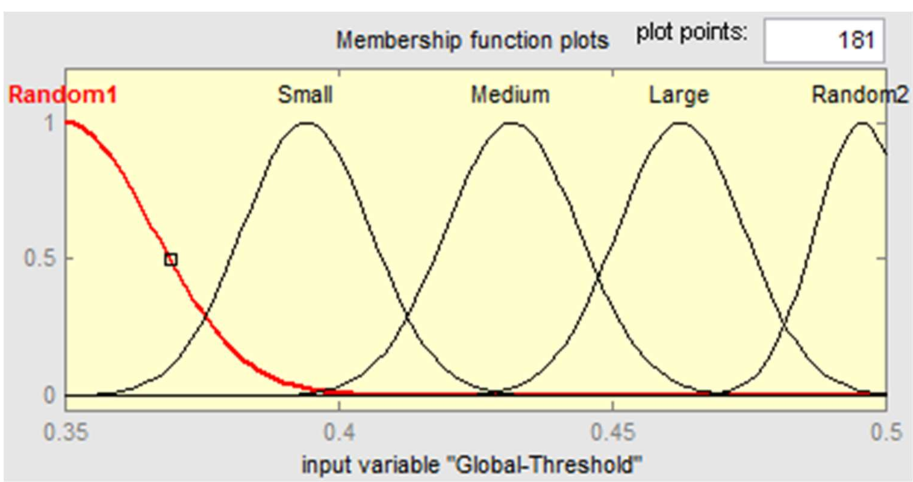


Fig. 10 Membership function plots for the input variable “Global Threshold”.

b. System outputs for brain tumor detection & classification

The FIS used for the model and its specifications are shown in figure 11 and figure 12 respectively. It takes size and global threshold as inputs and gives the type of tumor as output using centroid defuzzification method.

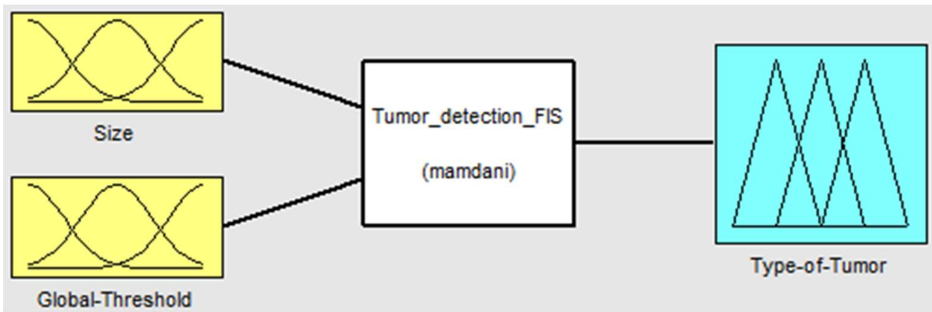


Fig. 11 Mamdani FIS.

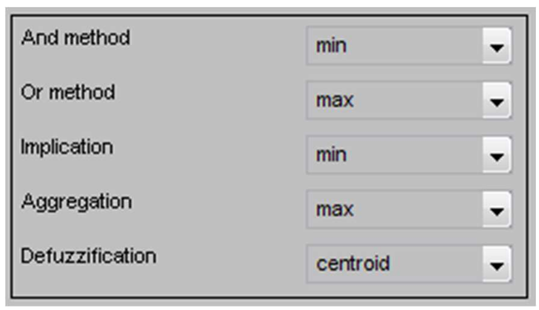


Fig.12 Specifications of the FIS.

For begin brain tumor, the output membership value is from 0.00< to 0.20. For malignant it is from 0.21 to 0.48. For meningioma it is from 0.49 to 0.76 and for normal cases it is from 0.77 to <1.00. Membership functions for the output variable "Type of Tumor" are shown in figure 13.

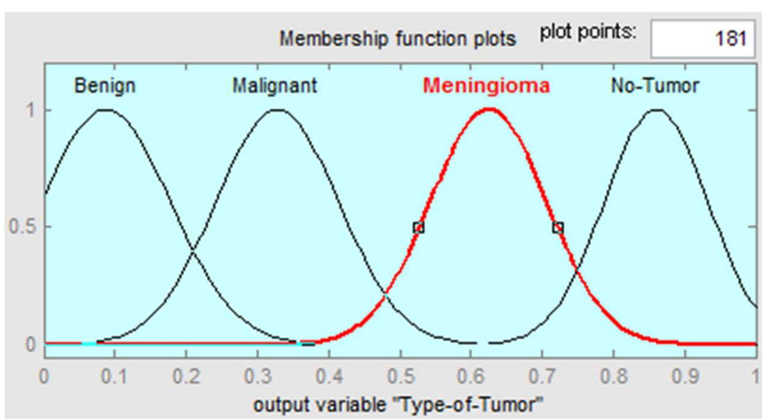


Fig. 13 Membership function plots for the output variable "Type of Tumor".

The fuzzy rules for brain tumor detection are shown in table-3. The 3D rule viewer surface is also shown in figure 14.

TABLE 3: Fuzzy Rules for Brain Tumor detection.

Fuzzy Rule No.	Size	Global Threshold	Type of Tumor
1	Random	Random 1	Meningioma
2	Random	Random 2	Meningioma
3	Null	Random 1	No Tumor
4	Small	Small	Malignant
5	Small	Medium	Malignant
6	Medium	Small	Malignant
7	Medium	Medium	Malignant
8	Large	Medium	Benign
9	Large	Large	Benign

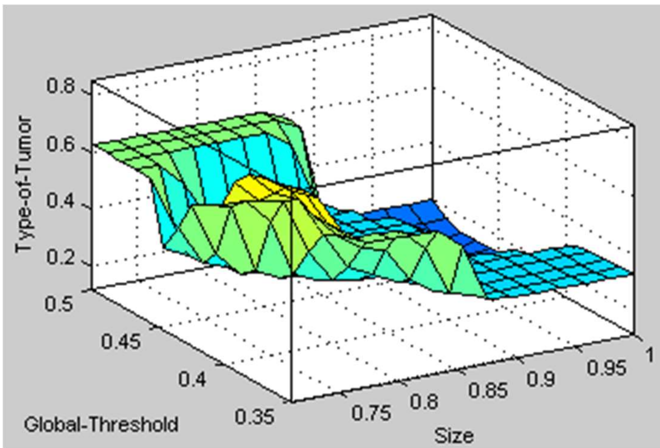
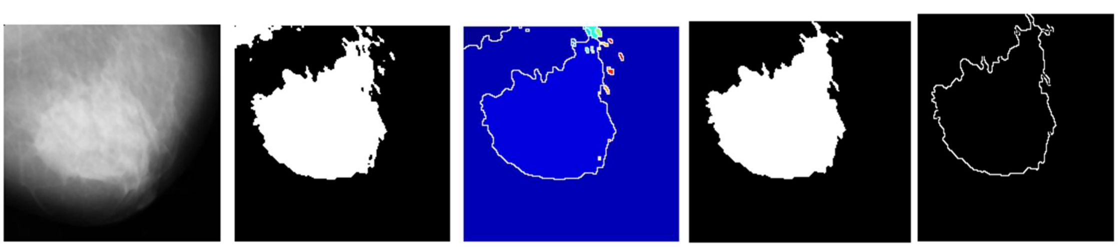


Fig. 14 3D rule viewer surface.

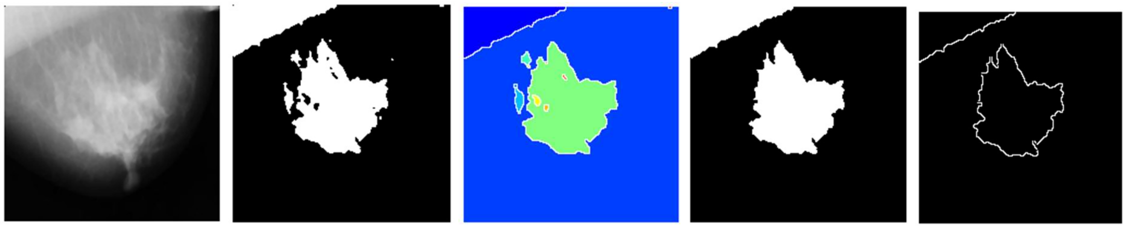
c. Data processing for breast cancer detection & classification

Similarly, the breast mammogram image is first median filtered and then thresholded. After that it is watershed segmented, then the cancer area is detected and finally the edges of the cancer area are evaluated. These data processing stages for different breast cancer cases are shown in figure 15, figure 16 and figure 17.



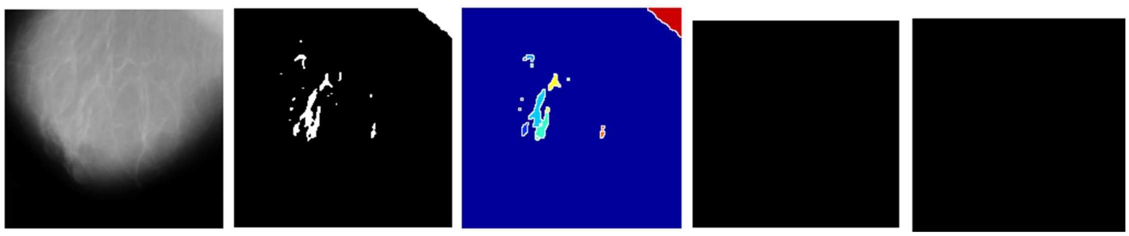
(a) (b) (c) (d) (e)

Fig. 15 Benign breast cancer detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.



(a) (b) (c) (d) (e)

Fig. 16 Malignant breast cancer detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.



(a) (b) (c) (d) (e)

Fig. 17 Normal breast detection: (a) Median filtered image, (b) Thresholded image, (c) Watershed segmented image, (d) Tumor Region, (e) Edge detection.

After investigating the edges of the breast cancer images, it is found that benign cases have a round or oval shape and a regular border. Malignant cases have a partial round or random shape and irregular border. Normal cases have no shape and border. So, these shapes and borders are organized to determine the size which is an input to the FIS. After that, each size is assigned a membership value as shown in table-4. Accordingly, the membership functions for the input variable "Size of breast cancer" in the FIS are shown in figure 18.

TABLE 4: Size determination for the breast cancer detection cases

Case	**Shape**	**Border**	**Size**	**Membership Value**
Benign	Round/Oval	Regular	Large	0.93 to 1.00
Malignant	Partial Round	Irregular	Medium	0.84 to 0.92
Malignant	Random	Irregular	Random	0.76 to 0.83
Normal	Null	Zero	Null	0.00< to 0.75

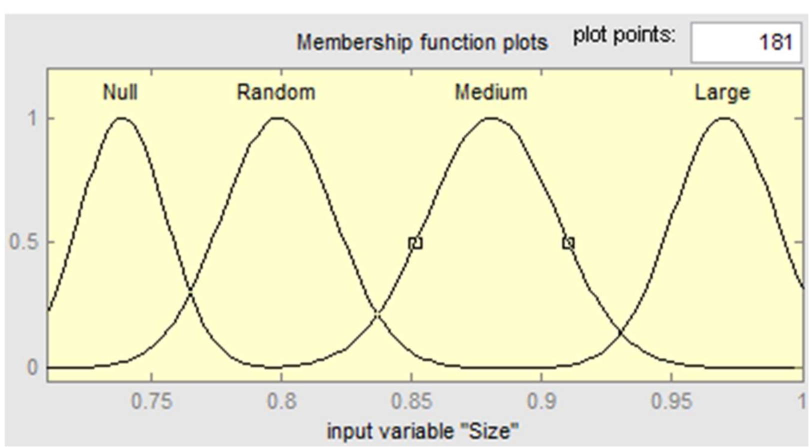


Fig. 18 Membership function plots for the input variable "Size of breast cancer".

The same global image threshold values evaluated in brain tumor cases can be used in breast cancer too. So, this input variable remains unchanged.

d. System outputs for breast cancer detection & classification

The same FIS discussed earlier takes size from figure 18 and global threshold from figure 10 as inputs and gives the type of cancer as output. For benign breast cancer, the output membership value is from 0.00< to 0.20. For malignant it is from 0.21 to 0.40 and for normal cases it is from 0.41 to 1.00. Membership functions for the output variable "Type of Cancer" are shown in figure 19.

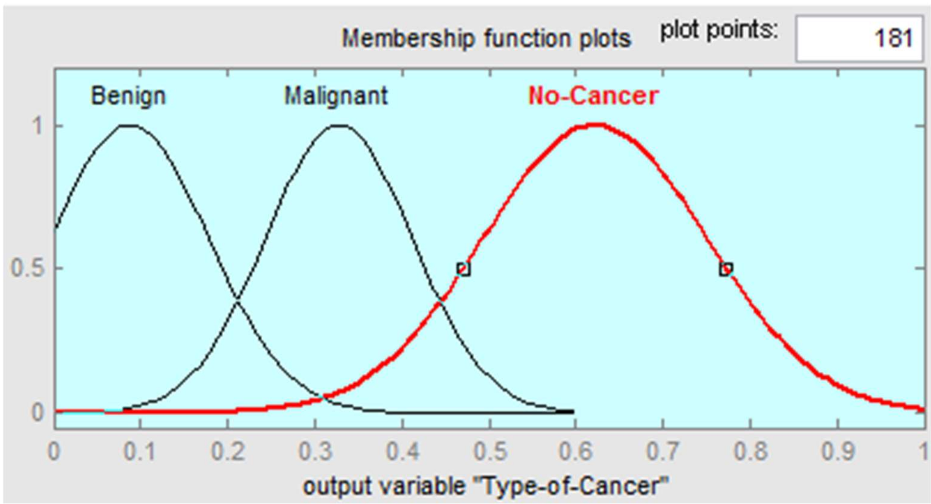


Fig. 19 Membership function plots for the output variable "Type of Cancer".

The fuzzy rules for breast cancer detection are shown in table-5.

TABLE 5: Fuzzy Rules for Breast Cancer detection.

Fuzzy Rule No.	Size	Global Threshold	Type of Cancer
1	Null	Random 1	No Cancer
2	Null	Random 2	No Cancer
3	Random	Random 1	Malignant
4	Random	Random 2	Malignant
5	Medium	Small	Malignant
6	Medium	Medium	Malignant
7	Large	Medium	Benign
8	Large	Large	Benign
9	Large	Small	Benign

VI. RESULT DISCUSSION

For a typical brain tumor classification, if the evaluated size is 0.855 and global threshold is 0.425, then the designed FIS processes the values and gives output as type of tumor = 0.328 which means it is a malignant case. This process is shown in figure 20.

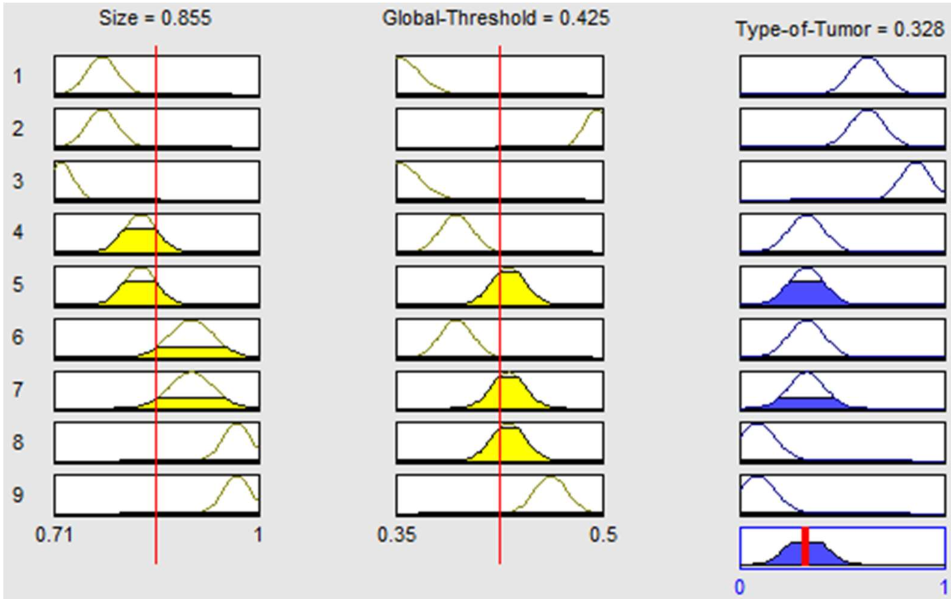


Fig. 20 A typical brain tumor classification with size = 0.855 and global threshold = 0.425.

Now, the system is simulated in fuzzy toolbox of MATLAB with all the brain MRI images discussed in the system input section and the performance indicators for each tumor cases are calculated using equations (4), (5), (6) and (7). The results are shown in table-6.

TABLE 6: Brain Tumor Classification Results.

Case	Classification				Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 score (%)
	TP	TN	FP	FN				
Benign	46	1	1	2	95.83	50.00	94.00	96.84
Malignant	58	3	1	3	95.08	75.00	93.85	96.67
Meningioma	88	4	1	4	95.65	80.00	94.85	97.24
No Tumor	93	5	2	4	95.88	71.43	94.23	96.88

The average values of sensitivity, specificity, accuracy and F1 score for brain tumor classification are 95.61%, 69.11%, 94.23% and 96.91% respectively. These results are compared with the performance of some conventional brain tumor classifiers as shown in table-7. It can be seen that, the proposed model have good sensitivity, accuracy and F1 score which are quite competitive with the other techniques. Effective use of image processing techniques and accurate selection of the fuzzy membership functions with fuzzy rules boost these performances.

TABLE 7: Comparison of results of the proposed model with some related methods

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 score (%)
Ref. [1]	87.83	97.83	94.20	91.40
Ref. [5]	87.89	93.00	96.00	97.00
Ref. [6]	97.72	94.20	96.51	97.36
Ref. [7]	94.81	95.07	95.40	94.94
Proposed Model	95.61	69.11	94.23	96.91

Again, the model is tested with all the breast mammogram images discussed in the system input section and the performance indicators for each breast cancer cases are determined using equations (4), (5), (6) and (7). The results are shown in table-8.

TABLE 8: Breast Cancer Classification Results.

Case	Classification				Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 score (%)
	TP	TN	FP	FN				
Benign	17	3	1	1	94.44	75.00	90.91	94.44
Malignant	18	2	2	1	94.74	50.00	86.96	92.31
No Cancer	20	1	1	2	90.91	50.00	87.50	93.02

The average values of sensitivity, specificity, accuracy and F1 score for breast cancer classification are 93.36%, 58.33%, 88.46% and 93.26% respectively. Consequently, these results are compared with the performance of some traditional breast cancer classifiers as shown in table-9. It can be observed that, the proposed model have better F1 score than the other breast cancer classifiers. In addition, it has promising accuracy and sensitivity values.

TABLE 9: Comparison of results of the proposed method with some related models

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 score (%)
Ref. [15]	64.11	64.09	68.29	64.10
Ref. [16]	92.00	86.00	87.00	91.00
Ref. [20]	86.20	87.70	87.20	87.10
Ref. [21]	99.00	25.00	98.00	61.00
Ref. [22]	95.38	50.81	85.82	66.31
Proposed Model	93.36	58.33	88.46	93.26

III. CONCLUSION

In this research, the noise removal technique (Median filter) effectively removes the image noises from the MRI and mammogram scans which support the following stages of detection and classification. Furthermore, the Otsu's Method for Global Image Thresholding and the Robert's Method for edge detection serve effectively to extract the image features like global threshold and size of the cancer or tumor area. In the end, the Mamdani FIS classifier operates as a well organized tool to categorize the brain tumor or breast cancer cases. However, the designed method comparatively has a low specificity value for both of the classification cases. So, in future work, the use of large database and other types of fuzzy classifiers with more fuzzy rules can be investigated to decrease the false-positive classification can be investigated. In result, the suggested future modifications might improve the specificity and other performance indicators.

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