

## Research Article

### Probabilistic Neural Network Based Brain Tumor Detection and Classification System

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**Abstract:** Our Goal is to increase the accuracy of brain tumor detection and classification and thereby replace conventional invasive and time consuming techniques. Here a new technique is proposed to classify the brain MRI images and to detect the brain tumor using probabilistic neural network. The proposed methodology comprises of three phases. 1) Discrete wavelet transform 2) Modified region growing algorithm and 3) Probabilistic neural network. Initially, the input is subjected to discrete wavelet transform. It is used to extract the wavelet coefficients from the MRI images. Then the texture features are extracted using modified region growing algorithm from the input MRI brain images, which are obtained from the database. The texture features taken in to consideration are correlation and contrast. Soon after, the extracted features are fed as the input to the Hybrid ANN-PNN to classify the brain MRI images. Based on the features extracted the tumor will be detected and will be classified as Benign and malignant tumor. The proposed methodology will be implemented in MATLAB 7.12 with different datasets. The performance will be analyzed with existing detection methods and we will prove our efficiency in terms of accuracy.

**Keywords:** Benign tumor, discrete wavelet transform, malignant tumor, modified region growing, MRI, probabilistic neural network

## INTRODUCTION

Tumor is due to the uncontrolled growth of the tissues in any part of the body. The tumor may be primary or secondary. If the part of the tumor is spread to another place and grown as its own then it is known as secondary (Dhanalakshmi and Kanimozhi, 2013). Tumor is due to the uncontrolled growth of the tissues in any part of the body. The tumor may be primary or secondary. If it is an origin, then it is known as primary. If the part of the tumor is spread to another place and grown as its own then it is known as secondary (Kabade and Gaikwad, 2013). Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain. Tumors can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull (Logeswari and Karnan, 2010). Fully automatic normal and diseased human brain classification from Magnetic Resonance Images (MRI) is of great importance for research and clinical studies. In the recent past, the development of Computer Aided Diagnosis (CAD) systems for assisting the physicians for making better decisions have been the area of interest (Rajalakshmi and LakshmiPrabha, 2013). One

way to obtain an estimate of tumor volume is via segmentation. Such schemes implicitly acquire the tumor volume by extracting the tumor surface (Rana *et al.*, 2013).

Generally, image segmentation is defined as: “the search for homogenous regions in an image and later the classification of these regions”. It also means the partitioning of an image into meaningful regions based on homogeneity or heterogeneity criteria. Image segmentation techniques can be differentiated into the following basic concepts: pixel oriented, Contour-oriented, region-oriented, model oriented, color oriented and hybrid (Sahu and Parvathi, 2013). In image segmentation, one challenge is how to deal with the nonlinearity of real data distribution, which often makes segmentation methods need more human interactions and make unsatisfied segmentation results (Aslam *et al.*, 2013). Medical imaging in diagnostic radiology is evolving as a result of the significant contributions of a number of different disciplines from basic sciences, engineering and medicine. Therefore, computerized image reconstruction, processing and analysis methods have been developed Magnetic Resonance (MR) imaging has several advantages over other medical imaging modalities, including high contrast among different soft tissues, relatively high

spatial resolution across the entire field of view and multi-spectral characteristics (Hari Prasath *et al.*, 2012).

Diffusion Weighted Magnetic Resonance Imaging (DWMRI or DWI) is considered as the most sensitive technique in detecting acute infarction and is useful in giving details of the component of brain lesions (Mohd Saad *et al.*, 2012). In medical imaging, 3D segmentation of images plays a vital role in stages which occur before implementing object recognition. 3D image segmentation helps in automated diagnosis of brain diseases and helps in qualitative and quantitative analysis of images such as measuring accurate size and volume of detected portion (Mustaqeem and Javed, 2012). Manually segmenting brain tumors from MR imaging is generally time consuming and difficult. An automated segmentation method is desirable because it reduces the load on the operator and generates satisfactory results (Karpagam and Gowri, 2012). MRI being an advanced medical imaging technique provides valuable information about the human soft tissue anatomy. It can provide Three Dimensional (3D) data depicting a high contrast between the soft tissues (Gondal and Khan, 2013).

Actually the MRI produces a high contrast image representing each part very clearly, but sometimes due to be determined accurately so a problem of segmenting it is always there. In these cases the physiologist always need to have keen observation of the anatomical structure. But this process is too much time consuming and if the initial segmentation result is not correct then other consequent results like volume calculation also produces incorrect measurement results (Tiwari *et al.*, 2012). K-means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy (Rakesh and Ravi, 2012). Thresholding method is frequently used for image segmentation. This is simple and effective segmentation method for images with different intensities. The technique basically attempts for finding a threshold value, which enables the classification of pixels into different categories. A major weakness of this segmentation mode is that: it generates only two classes. Therefore, this method fails to deal with multichannel images (Ahmed and Mohammad, 2008).

The main contribution of our research is:

- We have designed an effective method for classifying the brain MRI images in to Normal and Abnormal images.
- We have designed a Novel Hybrid classification algorithm Hybrid ANN-PNN.
- We have utilized Discrete Wavelet Transform.
- We have carried out the experimentation results with different set of Brain MRI images.
- We have made a comparative analysis with an existing research and achieved better results in terms of evaluation metrics like sensitivity, specificity and accuracy.

## LITERATURE REVIEW

Gonzalez-Navarro *et al.* (2010) has applied feature selection methods and several off-the-shelf classifiers on various H-MRS modalities: long and short echo times and an ad hoc combination of both. Their experimental findings have indicated that the feature selection process enhances the classification performance compared to using the full set of features. They have also showed that the use of combined information from the different echo times is a better strategy for small numbers of spectral frequencies; however, the use of ever greater numbers of short echo time frequencies permits the obtention of many models with similar performance. The final induced models have offered very attractive solutions both in terms of prediction accuracy and number of involved spectral frequencies, which are also amenable to metabolic interpretation.

El-Dahshan *et al.* (2010) has presented a hybrid technique for the classification of the Magnetic Resonance Images (MRI). Their hybrid technique consists of three stages, namely, feature extraction, dimensionality reduction and classification. In the first stage, they have obtained the features related to MRI images using Discrete Wavelet Transformation (DWT). In the second stage, the features of magnetic resonance images have been reduced, using Principal Component Analysis (PCA), to the more essential features. In the classification stage, two classifiers have been developed. The first classifier was based on feed Forward back Propagation Artificial Neural Network (FP-ANN) and the second classifier was based on k Nearest Neighbor (k-NN). The classifiers have been used to classify subjects as normal or abnormal MRI human images. A classification with a success of 97 and 98% has been obtained by FP-ANN and k-NN, respectively. This result have showed that the proposed technique is robust and effective when compared with other recent work.

Zhan *et al.* (2011) have presented a Neural Network (NN) based method to classify a given MR brain image as normal or abnormal. They have first employed wavelet transform to extract features from images and then had applied the technique of Principle Component Analysis (PCA) for reducing the dimensions of features. The reduced features was sent to a Back Propagation (BP) NN, with which Scaled Conjugate Gradient (SCG) was adopted to find the optimal weights of the NN. They have applied their method on 66 images (18 normal, 48 abnormal). The classification accuracies on both training and test images were 100% and the computation time per image was only 0.0451 sec.

Kang *et al.* (2011) has presented a generalized automatic system for tissue classification which can be adapted to different parts of human body. In this system, a general geometric model was proposed by

them for formalizing non-structured and non-normalized medical knowledge from various medical images. An intelligent control procedure was developed for transforming the medical knowledge into several rules in order to improve the quality of the segmentation by Fuzzy C-Means. They have proposed two principles to define the priorities for these rules in order to optimize their application. They have used normalization of images before running the system.

Ze-Xuan *et al.* (2011) have proposed a framework with modified fast fuzzy c-means for brain MR images segmentation in order to take all these effects into account simultaneously and to improve the accuracy of image segmentations. Firstly, they have proposed a new automated method to determine the initial values of the centroids. Secondly, an adaptive method was proposed by them to incorporate the local spatial continuity in order to overcome the noise effectively and prevent the edge from blurring. The intensity in homogeneity was estimated by a linear combination of a set of basic functions. Meanwhile, a regularization term was added in order to reduce the iteration steps and accelerate the algorithm. The weights of the regularization terms were automatically computed in order to avoid the manually tuned parameter. Improved performance of the proposed algorithm was observed where the intensity in homogeneity, noise and PV effect are commonly encountered. The experimental results have showed that their proposed method have stronger anti-noise property and higher segmentation precision than the other reported FCM-based techniques.

Roslan *et al.* (2011) has investigated the strength and weaknesses of the two different thresholding methods on three types of MRI brain images. They have experimented on ninety samples of T1-weighted, T2-weighted and FLAIR MRI brain images. Qualitative evaluations have showed that the skull stripping using mathematical morphology outperformed region growing at an acceptance rate of 95.5%, whereas quantitative evaluation using Area Overlap, False Positive Rate and False Negative Rate was produced of 96.2, 2.2 and 1.6%, respectively.

Saha *et al.* (2012) have proposed a novel automated, fast and approximate segmentation technique. The input used was a patient study consisting of a set of MR slices and its output was a subset of the slices that include axis-parallel boxes that circumscribe the tumors. Their approach was based on an unsupervised change detection method that searches for the most dissimilar region (axis-parallel bounding boxes) between the left and the right halves of a brain in an axial view MR slice. Their change detection process have used a novel score function based on Bhattacharya coefficient computed with gray level intensity histograms. They have proved that their score function have admitted a very fast (linear in image height and width) search to locate the bounding box. The average dice coefficients for localizing brain

tumors and edemas, over ten patient studies, are 0.57 and 0.52, respectively, which have significantly exceeded the scores for two other competitive region-based bounding box techniques.

Arizmendi *et al.* (2012) has applied the Discrete Wavelet Transform procedure for the pre-processing of spectra corresponding to several brain tumor pathologies. This procedure does not alleviate the high dimensionality of the data by itself. For the above reason, dimensionality reduction was subsequently implemented using Moving Window with Variance Analysis for feature selection or Principal Component Analysis for feature extraction. The combined method has yielded very encouraging results in terms of diagnostic discriminatory binary classification using Bayesian Neural Networks. In most cases, the classification accuracy was improved from previously reported results.

Weizman *et al.* (2012) and Tiwari *et al.* (2012) has presented an automatic method for the segmentation, internal classification and follow-up of Optic Pathway Gliomas (OPGs) from multi-sequence MRI datasets. Their method started with the automatic localization of the OPG and its core with an anatomical atlas followed by a binary voxel classification with a probabilistic tissue model whose parameters were estimated from the MR images. Their method effectively incorporates prior location, tissue characteristics and intensity information for the delineation of the OPG boundaries in a consistent and repeatable manner. Internal classification of the segmented OPG volume was then obtained with a robust method that overcomes grey-level differences between learning and testing datasets. Experimental results on 25 datasets have yielded a mean surface distance error of 0.73 mm as compared to manual segmentation by experienced radiologists. Their method had exhibited reliable performance in OPG growth follow-up MR studies, which were crucial for monitoring disease progression.

John (2012) has introduced an efficient method of brain tumor classification, where, the real Magnetic Resonance (MR) images were classified into normal, non cancerous (benign) brain tumor and cancerous (malignant) brain tumor. Their proposed method follows three steps:

- Wavelet decomposition
- Textural feature extraction
- Classification

Discrete Wavelet Transform was first employed using Daubechies wavelet (db4), in order to decompose the MR image into different levels of approximate and detailed coefficients and then the gray level co-occurrence matrix was formed, from which the texture statistics such as energy, contrast, correlation, homogeneity and entropy were obtained. The results of co-occurrence matrices were then fed into a

probabilistic neural network for further classification and tumor detection. The proposed method has been applied on real MR images and the accuracy of classification using probabilistic neural network was found to be nearly 100%.

Nalbalwar *et al.* (2014) have developed a Brain Cancer Detection and Classification System. The system used computer based procedures to detect tumor blocks and to classify the type of tumor using Artificial Neural Network in MRI images of different patients with astrocytoma type of brain tumors. The image processing techniques such as histogram equalization, image segmentation, image enhancement and feature extraction have been developed for detection of the brain tumor in the MRI images of the cancer Detected patients. They have used ANN as a classifier for classification of brain images which provided good classification efficiency as compared to other classifiers. The sensitivity, specificity and accuracy were also improved. Their proposed approach was computationally effective and has yielded good result.

#### **Problem definition:**

- Classification of MR brain images into normal, cancerous and non cancerous brain tumors is a difficult task.
- It is found that existing methods of brain tumor diagnosis and classification involve invasive techniques such as biopsy and spinal tap method.
- It is essential to prevent and replace the invasive methods of brain tumor classification using a non invasive method.
- Discrete Wavelet Transform is found to be an important tool in decomposing the images.
- Significant features can be extracted using discrete wavelet transform.
- Probabilistic Neural Network is found to be superior over other conventional neural networks such as Support Vector Machine and Back propagation Neural Network in terms of its accuracy in classifying brain tumors.

#### **PROPOSED METHODOLOGY**

A computer aided diagnosis algorithm has been designed so as to increase the accuracy of brain tumor detection and classification and thereby replace conventional invasive and time consuming techniques. Here a new technique is proposed to classify the brain MRI images and to detect the brain tumor using probabilistic neural network. The proposed methodology comprises of three phases:

- Discrete wavelet transform
- Modified region growing algorithm
- Hybrid ANN-PNN

Initially, the input is subjected to discrete wavelet transform. It is used to extract the wavelet coefficients from the MRI images. Then the texture features are extracted using modified region growing algorithm from the input MRI brain images, which are obtained from the database. The texture features taken in to consideration are correlation and contrast. Soon after, the extracted features are fed as the input to the Hybrid ANN-PNN to classify the brain MRI images. Based on the features extracted the tumor will be detected and will be classified as Normal and tumor. The performance will be analyzed with existing detection methods and we will prove our efficiency in terms of accuracy.

**Image pre-processing:** In order to obtain better results for the purpose of feature extraction, Image Pre-processing is made. In this stage the brain MRI images were subjected to DWT based image de-noising.

**Image de-noising using discrete wavelet transform:** Image manipulation includes a number of operations such as transmitting, displaying, digitizing etc. Those manipulations degrade the image quality by adding many types of noise. The images with noise are de-noised using discrete wavelet transform. Wavelets are functions generated from one single function by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level. The DWT is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub bands and critically sub sampled as shown in Fig. 1. They are HL, LH, LL and HH sub bands. These four sub bands arise from separable applications of vertical and horizontal filters. Firstly the image is passed through the low pass and high pass filter separately. The low pass filtered and the high pass filtered output is down sampled separately. The down sampled outputs again low pass and high pass filtered separately in order to achieve four bands. Then the two low pass filtered and two high pass filtered outputs were down sampled again in order to attain four separate bands. After Image de-noising using discrete wavelet transform the features were extracted using modified region growing algorithm.

**Feature extraction using modified region growing algorithm:** In this phase the tumor region of the brain MRI are extracted. Grayscale images are set as input to the feature removal process. The texture features of the

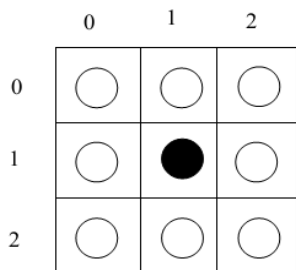


Fig. 1: Location of initial seed pixel in a 3×3 neighborhood

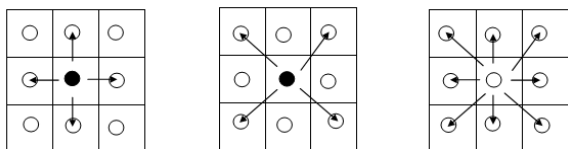


Fig. 2: Representation of neighboring pixel selection by the seed pixel

brain MRI images are removed by means of modified region growing algorithm.

**Modified region growing algorithm:** In the modified region growing algorithm the threshold of the image is not regarded instead the threshold of the direction image is taken for region rising process. The benefit of applying modified region growing is the shape of the image is fragmented competently and further data can be attained when comparing with region growing algorithm. For removing the evident part of the tumor portion modified region growing will be further efficient than region growing algorithm. The total number of pixels in the image is computed at this point. The total number of pixels in the image is equivalent to the size of the image. The Gray level of the chosen region in the image is the proportion of total of gray level for all pixels in the region to the total number of pixels in the region:

$$Graylevel = \frac{Total\ of\ graylevel\ for\ all\ pixels\ in\ the\ region}{Total\ number\ of\ pixels\ in\ the\ region} \quad (1)$$

The modified region growing is a three step process:

- Gridding
- Selection of seed point
- Applying region growing to the point

**Gridding:** A single image is partitioned into numerous smaller images by drawing an imaginary grid over it in gridding. Specifically, gridding results in exchanging the image into numerous smaller grid images. The grids are frequently square in shape and the grid number to which the unique image is dividing into is a changeable.

Gridding results in smaller grids so that study can be executed effortlessly.

**Selection of seed point:** The first step in area growing for the grid appeared is to choose a seed point for the grid. Figure 1 shows the location of initial seed pixel in 3\*3 neighborhood. The primary area starts as the precise position of the seed. Now to discover the seed point of the grid, we have executed histogram study. The histogram is found out for each pixel in the grid. When the image is a grey scale image, the values of this image is from 0 to 255. For each grid, the histogram value that approaches most common is chosen as the seed point pixel. From this, any person of the seed point pixel is occupied as the seed point for the grid.

**Applying region growing to the point:** The area is grown from it after locating out the seed point. At this juncture the adjacent pixels are compared with the seed point and if the neighbor pixel pleases constrains, subsequently the region is grown else it is not grown to that pixel. Figure 2 represents the neighboring pixel selection by the seed pixel. Constrains for our suggested adapted region growing is the “Contrast” and the “Correlation”. Figure 3 represents the architecture of our proposed methodology.

The stages in the adapted region growing algorithm are as follows:

Start

Find the gradient of the Image  $I$  in both x axis ( $I_x$ ) and y axis ( $I_y$ ).

Combine the gradient values using the formula  $g = \frac{1}{\sqrt{1+(I_x^2 + I_y^2)}}$  to get the gradient vector  $g$ .

Convert Gradient vector values into degrees to get the orientation values of the pixels of the image.

Spilt the Image  $I$  into Grids  $G_i$

Set the contrast threshold  $T_I$  and the correlation threshold  $T_o$ .

For each Grid (denoted as  $G_i$ ) do

Find the histogram (denoted as Hist) of the every pixel  $P_j$  in the grid  $G_i$

Find the most frequent histogram of the  $G_i^{th}$  grid and denote it as  $Freq_{Hist}$

Select any pixel  $P_j$  corresponding to the  $Freq_{Hist}$  and assign that pixel as the seed point  $SP$  having intensity  $I_p$  and orientation  $O_p$ .

Check for contrast constraint  $\|I_p - I_N\| \leq T_I$  and the correlation constraint

$\|O_p - O_N\| \leq T_o$ , for the neighboring pixel having contrast  $I_N$  and correlation  $O_N$ ,

If both the constraints are satisfied and met, Region is grown to the neighboring pixel.

Else

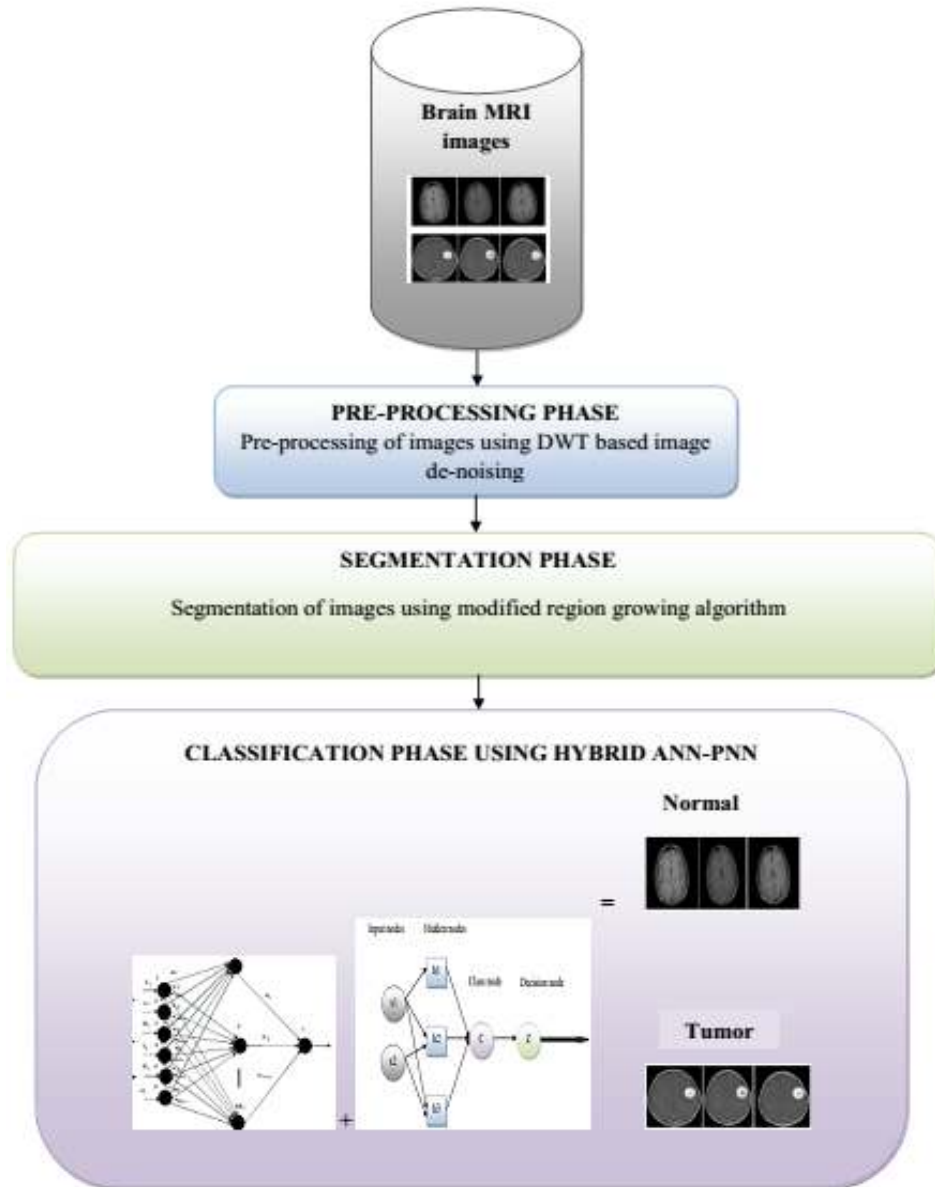


Fig. 3: Architecture of our proposed methodology

The region is not grown to the neighboring pixel.  
 End For  
 Stop

**Classification using hybrid ANN-PNN:**

**Probabilistic Neural Networks (PNN):** Probabilistic neural networks can be used for classification problems. Probabilistic Neural Network (PNN) is a Radial Basis Neural Network, which provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers. It is employed to implement an automatic MR image classification of brain tumors into normal and abnormal. Probabilistic Neural Network has three layers, the Input layer, Radial Basis Layer and the

Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them and thus finds the training pattern closest to the input pattern based on their distance. Figure 4 represents the structure of PNN classifier for proposed study.

When an input is presented, the first layer calculates distances from the input vector to the training input vectors and produces a vector whose elements that shows how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on

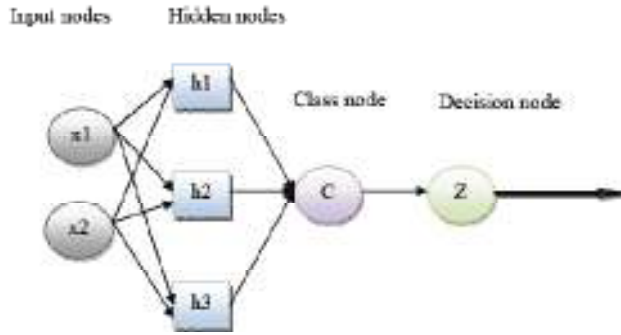


Fig. 4: Structure of PNN classifier for proposed study

the output of the second layer picks the maximum of these probabilities and produces a 1 for that class and a 0 for the other classes. Once the PNN is defined, then vectors were fed into it and then the input vectors were Read and fed in to each Gaussian function in each class. For each group of hidden nodes, all Gaussian functional values at the hidden nodes were computed. For each group of hidden nodes, all its Gaussian functional values are fed to the single output node for that group. At each class output node, the inputs are summed and multiplied by constant. The maximum value of all summed functional values was found at the output node.

**Feed Forward Back propagation Neural Network classifier (FFBNN):** One of the classification methods utilizing Feed Forward Back propagation Neural Network classifier (FFBNN) is used for classifying the images of Brain MRI. Neural network is a three-layer standard classifier with  $n$  input nodes,  $l$  hidden nodes and  $k$  output nodes. It is examined that if the two hidden layers are used then one hidden layer is to associate every pair in one important unit and second is regarded as to be the real hidden layer after classifying the input data in the first hidden layer. For our proposed work, the input layers are the three extracted features from the Brain MRI image  $\{I_N, O_N, \alpha_i\}$ ,  $HU_a$  Hidden Units and one output unit,  $f$ .

**NN function steps:**

- Set weights for every neuron's except the neurons in the input layer.
- Generate the neural network with the input units,  $HU_a$  Hidden units and age  $f$  as the output unit.
- The calculation of the proposed Bias function for the input layer is:

$$X = \beta + \sum_{n=0}^{H_{NH}-1} w_{(n)} S_1(n') + w_{(n)} S_2(n') + w_{(n)} S_3(n') + \dots + w_{(n)} S_3(n') \tag{2}$$

The activation function for the output layer is calculated as:

$$Active(X) = \frac{1}{1 + e^{-X}} \tag{3}$$

- Identify the learning error as given below:

$$LE = \frac{1}{H_{NH}} \sum_{n=0}^{N_{NH}-1} Y_n - Z_n \tag{4}$$

where,

$LE$  = Learning rate of FFBNN

$Y_n$  = Desired outputs

$Z_n$  = Actual output

**Learning algorithm-back propagation algorithm used for minimizing the error:** In Feed Forward Neural Network, Back Propagation Algorithm is utilized as the Learning Algorithm. Back Propagation Algorithm is a supervised learning technique and moreover it is an overview of delta rule. To produce the training set, it wants a dataset of the required output for various inputs. Generally, Back Propagation Algorithm is helpful for Feed-Forward Networks. This learning algorithm needs that the activation function used by the neurons be differentiable.

**Back propagation algorithm steps for FFBNN:**

- The weights for the neurons of hidden layer and the output layer are assigned by randomly choosing the weight. But the input layer has the constant weight.
- The Proposed Bias function and the activation function are calculated for the FFBNN.
- The Back Propagation Error is found for each node and then the weights are updated as follows:

$$w_{(n')} = w_{(n')} + \Delta w_{(n')} \tag{5}$$

- The weight  $\Delta w_{(n')}$  is changed as given below:

$$\Delta w_{(n)}' = \delta \cdot X_{(n)}' \cdot E^{(BP)} \quad (6)$$

where,

$\delta$  = Learning Rate, which normally ranges from 0.2 to 0.5

$E^{(BP)}$  = BP Error

- The process is repeated using (2) and (3) steps, until the BP error gets minimized. i.e.,  $E^{(BP)} < 0.1$ .
- If the minimum value is obtained, then the FFBNN is well trained for performing the testing phase.

Accordingly, FFBNN classifier is well trained with the MRI Images and saved separately. Likewise PNN classifier is trained with MRI images and saved separately. The Testing process involves the FFBNN and PNN classifier and their testing values were averaged in order to classify the images in to normal and tumor images.

## RESULTS AND DISCUSSION

The proposed Brain tumor classification technique is executed in the working stage MATLAB and it is assessed with some medical brain MRI images that are accumulated from several medical diagnosis centers. Amongst some MRI images, few images are normal and the remaining few images are abnormal. Figure 5 explains the specified input MRI brain images utilized for the brain tumor classification.

**Experimental results:** Initially, the brain MRI images are collected for our work and then these images are subjected to pre-processing step using DWT based denoising. The brain MRI images that get pre-processed are shown in the following Fig. 6.

After getting pre-processed, the images are segmented. The outputs from the pre-processing step are segmented using Modified region growing algorithm. The results of the segmentation process from brain MRI images are shown in the Fig. 7.

**Performance evaluation of our proposed work with various evaluation metrics:** We need various assessment metric values to be calculated in order to analyze our proposed technique for the Brain tumor detection and classification system. The metric values are found based on True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The usefulness of our proposed work is analyzed by five metrics namely False Positive Rate (FPR), False Negative Rate (FNR), Sensitivity, Specificity and Accuracy. The demonstration of these assessment metrics are specified in equations that given below.

### Evaluation results of brain tumor classification:

**False Positive Rate (FPR):** The percentage of cases where an image was segmented to tumor part, but in fact it did not:

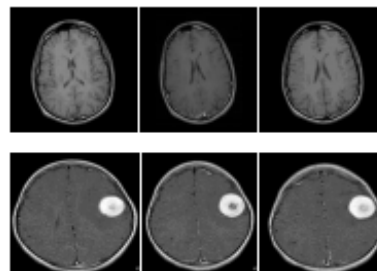


Fig. 5: Sample of brain MRI images input

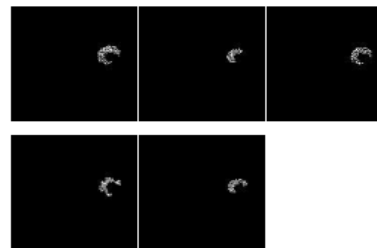
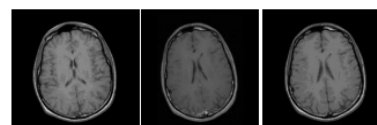
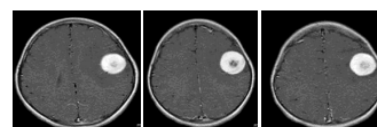


Fig. 6: Segmented brain MRI images



(a)



(b)

Fig. 7: Classification results for the sample MRI brain tumor; (a): Normal images; (b): Abnormal images

$$FPR = \frac{FP}{FP + TN} \quad (7)$$

**False Negative Rate (FNR):** The percentage of cases where an image was segmented to non-tumor part, but in fact it did:

$$FNR = \frac{FN}{FN + TP} \quad (8)$$

**Sensitivity:** The measure of the sensitivity is the proportion of actual positives which are properly recognized. It relates to the capacity of test to recognize positive results:

$$Sensitivity = \frac{\text{Number of true positives}}{\text{Number of true positives} + \text{Number of false negatives}} \times 100 \quad (9)$$



Table 1: Brain tumor classification results obtained for our proposed study based on the evaluation metrics

Images	TP	TN	FN	FP	FPR	FNR	Sensitivity (%)	Specificity (%)	Accuracy (%)
Img1	1	2	0	0	0	0	100	100	100
Img2	0	4	1	0	0	1	0	100	80
Img3	0	8	2	0	0	1	0	100	80
Img4	1	2	0	0	0	0	100	100	100

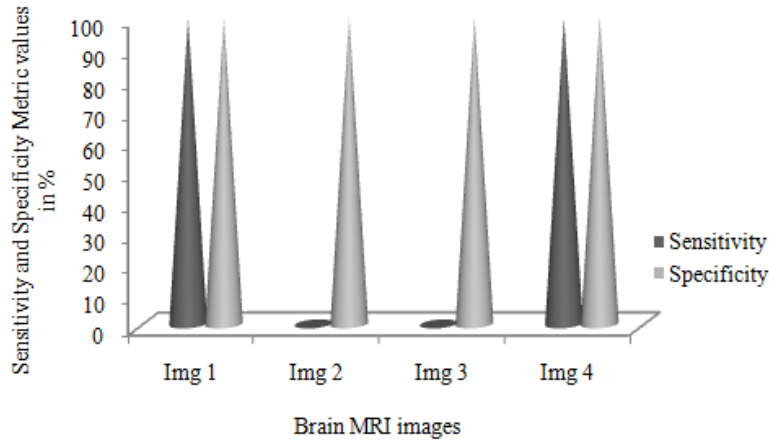


Fig. 8: Sensitivity and specificity values for our proposed study

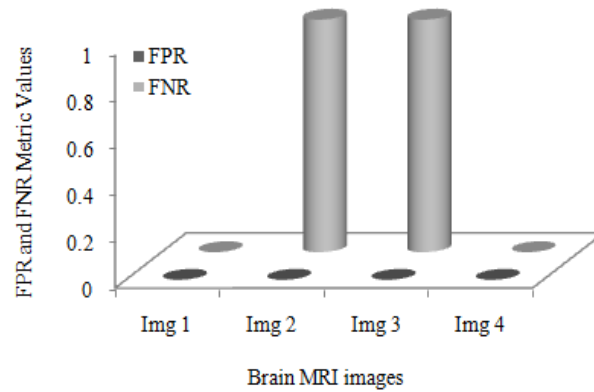


Fig. 9: FPR and FNR values for our proposed study

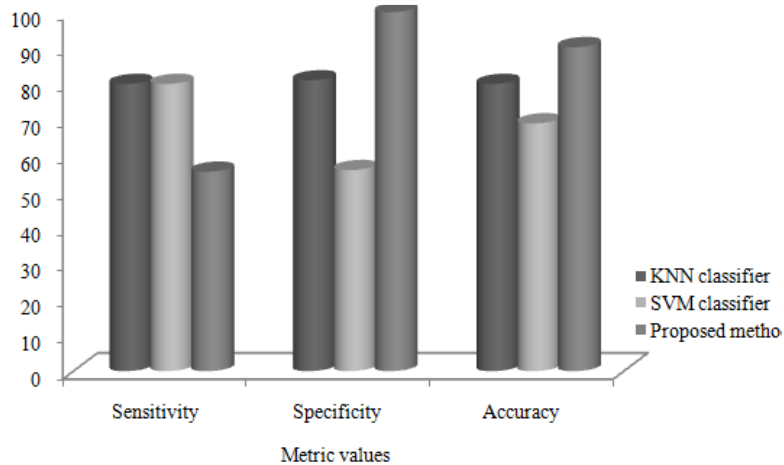


Fig. 10: Comparison of our proposed study with existing techniques

**Specificity:** The measure of the specificity is the proportion of negatives which are properly recognized. It relates to the capacity of test to recognize negative results:

$$\text{Specificity} = \frac{\text{Number of true negatives}}{\text{Number of true negatives} + \text{Number of false positives}} \times 100 \quad (10)$$

**Accuracy:** The weighted percentage of tumor parts in images is correctly segmented by the measurement accuracy. It is represented as:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100 \quad (11)$$

For examining the segmentation usefulness our proposed technique is assessed with these above explained assessment metrics False Positive Rate, False Negative Rate, Sensitivity, Specificity and Accuracy. The metrics values are estimated for the classification of brain tumor from the MRI brain images, which are specified in Table 1.

The graph for the metric values FPR and FNR with dissimilar MRI brain images is designed in the below specified Fig. 8. According to the figure, the classification efficiency is examined based on the FNR and FPR values. The false positive and false negative rate values for every five images are established from the Fig. 9. False Positive Rate measures the count of segmentation of tumor part which is in fact not segmented. False Negative Rate determines the count of segmentation of non-tumor parts which are really segmented. In comparison with the FPR values, FNR is high. It slightly lessens the accuracy value and it does not make high alteration in accuracy values on average. A positive thing for our classification outcome is that the low value in FPR provides better development for our segmentation of tumor. One more graph in Fig. 8 is designed for the metric values sensitivity and specificity with dissimilar MRI brain images.

The accuracy results reached 96.5% value. Thus, we can understand that our proposed study gives very good normal and abnormal brain MRI image classification accuracy results by extracting the features of brain MRI images effectively. The proposed method results are also compared to the existing methods. Our proposed method is compared with brain tumor detection using KNN classifier and brain tumor detection using SVM classifier.

In all cases, we compare the values to the KNN and SVM classifier and it is found that the proposed technique performs better as shown in Fig. 10. All cases irrespective of segmentation problems, obtained a high accuracy which clearly indicates the effectiveness and stability of the proposed technique.

## CONCLUSION

In this study, we have proposed brain tumor classification system with the aid of modified region growing algorithm and Hybrid ANN-PNN. The proposed system was implemented and a set of test images were utilized to analyze the outcomes of the proposed brain tumor classification system. Thus the proposed brain tumor classification system offers a significant tempo of accuracy, sensitivity and specificity. We can say that proposed method more precisely classified the brain tumor from the given test images by seeing the elevated rate of measurements. The comparison result shows that our proposed brain tumor classification system based on modified region growing algorithm and Hybrid ANN-PNN has given high exactness than the previous methods. Therefore by utilizing the modified region growing algorithm and Hybrid ANN-PNN techniques, our proposed brain tumor classification system proficiently classified the images as normal and tumor. The segmentation and classification results were analyzed based on FAR, FRR, Sensitivity, Specificity and Accuracy. Our proposed work has provided 96.5% of accuracy by using modified region growing algorithm and hybrid ANN-PNN. The classification of normal and tumor images using Hybrid ANN-PNN has gained 96.5% of accuracy.

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