ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering and Technology
Vol. 6, Issue 4, April 2021

MRI Brain Image Characterization using Probabilistic Neural Network and Improved Fuzzy Segmentation Approach

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Abstract: ***Brain tumour diagnosis is a complex and challenging part in the medical field. The conventional method of Brain Magnetic Resonance Images (MRI) is of human inspection, which is not an efficient way for large amounts of data. This project presents a method for automatic classification and segmentation of Magnetic Resonance (MRI) brain tumour images using Computer Aided Design (CAD) methods. The use of Neural Networks and Fuzzy Clustering methods has shown high potential in this field. In this project, Probabilistic Neural Network using Radial Basis Function (PNN-RBF) is presented as the classification method. The classification of brain tumour stages is done as Normal, Benign or Malignant. After classification, segmentation of image is done with Spatial Fuzzy Clustering Method. The affected tumour part is extracted from the segmented abnormal images using Morphological filtering. The area of the tumour region is calculated thereafter. The stimulated results show that the proposed system performed efficiently and accurately as the classifier and segmentation algorithm provide better accuracy than the other methods. After segmentation, tumour part is extracted and the area of the tumour part is calculated quite accurately. Various alternative methods for classification and segmentation and their shortcomings are also discussed.***

1. INTRODUCTION

Different types of brain tumours are becoming a major life threat to human lives in all parts of the world. The accurate diagnosis of brain tumour is a sensitive and tedious medical task which plays a major role in the treatment of tumours. Hence the necessity of automated classification and segmentation of Brain tumour using Computer Aided Design (CAD) becomes important that can improve the accuracy of tumour detection and is more cost effective than the conventional method of tumour detection. Normally the anatomy of the brain can be viewed on the Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scan. MRI helps to diagnose brain tumour more effectively than CT scan. MRI is a procedure used to produce high resolution images of internal body organs' anatomy, including Brain. Normally an MRI machine consists of an MRI camera or scanner, where picture elements called pixels are displayed onto a computer monitor. The patient is placed inside the scanner which is made up of a movable bed structure and a hollow tube. A strong magnetic field is generated by the coils present in the tube. The change in magnetic field is noted and this information is recorded, transformed and displayed by the computer producing MR images. The information that MRI images provide about the brain has drastically improved the quality of brain pathology diagnosis and treatment [4].

The following Figure 1 shows a picture of the MRI machine normally used for diagnosing Brain tumour and the model giving the inside view[1],[2]. Figure 1(a) shows the MRI machine whereas Figure 1(b) shows the lateral view of the machine describing the main parts of the Machine.

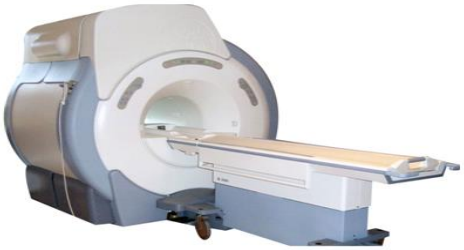

Figure 1 (a)

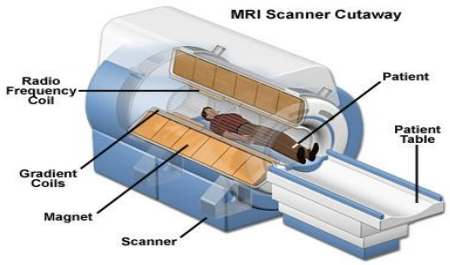

Figure 1(b)

Brain tumour can be classified as Normal, Benign or Malignant. The relatively slow growing tumours are Benign. Normally they do not spread to other parts of the body. Malignant tumours are cancerous which means they can spread into, or invade, nearby tissues and they can be life threatening. In addition, as these tumours grow, some cancer cells can break off and travel to distant places in the body through the blood or the lymph system and form new tumours far from the original tumour [3].

Different approaches have been made to classify MR images and to further segment them to different regions for further processing. The widely used method for classification and segmentation of MR images is labelling by human experts. However, this task is time consuming and challenging. Furthermore, manual methods are difficult to reproduce in a reliable and objective manner even by the same human expert. It has been proven that, double reading of the MR images could lead to better detection of Tumour. But the cost incurred in double reading is very high. Reliable methods for tumour detection using computer are of great need and interest since these methods can help in assessing the tumour growth to enhance proper treatment. The MR images normally contain complex data which makes its processing, a time consuming and complicated task. Though accurate diagnosis of MRI data is very important in medical field, in some extreme scenario, diagnosis with wrong result or the delay in making the correct diagnosis decision could make someone's life in danger. Again, the lifetime of a person with brain tumour can be increased if the tumour is detected at its early stage. Hence, there arises the need for an efficient algorithm to process the MRI complex data automatically. If an efficient medical image classification and segmentation method with minimal user interaction, fast computation and accurate segmentation results exists, then it can really help the medical practitioners in identifying tumour at its early stages and save lives.

This project addresses this problem of automatic classification and segmentation of Brain tumour MRI and tries to find a novel and efficient solution for it making use of methods from Artificial Intelligence (AI). The project tries the hybrid combination of the Neural Network and Fuzzy Logic in classification and detection of Brain Tumours and has a significant role in medical field. The practical aim of the work described in this work is the creation of a system that performs an efficient automatic classification and segmentation technique with less user interface and further calculates the tumour area for the input Magnetic Resonance Image (MRI). The developing platform used is Matlab.

According to literature study, there are different classification and segmentation methods. Sridhar.D et al. in 2013 performed classification of brain tumour using Probabilistic Neural Networks (PNN) where feature extraction is done using Discrete Cosine Transform (DCT) [5]. The method was successful in classification with a high accuracy and provides better resistance to noise. But the visual image quality was very low at high threshold values since DCT doesn't provide many details on texture pattern and creates visual discontinuity in output images.

Matthew Turk and Alex Pentland in 1991, proposed the basic algorithm for Principal Component Analysis (PCA) which is a classical feature extraction and data representation technique [7]. Thereafter, many classification proposals have made use of PCA for feature extraction. PCA reduces multidimensional data to lower dimensions while retaining most of the information. But it doesn't consider the fundamental class structure and has poor discriminatory power. The shape and location of the original data set changes when transformed, i.e. even the simplest invariance of an image is not captured by PCA.

Arizmendi. C in 2011, proposed a classification method using Feed Forward Bayesian Artificial Neural Networks [8]. The method proposes the use of Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) to extract the features. Though this method of using Discrete Wavelet Transform together with PCA gives better compression ratio without losing much information on the image, the method suffers from lack of shift invariance and the DWT fails to provide details on curved edges on the input image. It doesn't provide optimal results for all structures of abnormal brain images.

There are different segmentation methods existing to analyse the Magnetic Resonance Imaging(MRI) of the brain after classification, including the manual analysis, Thresholding method, Region -growing, K means clustering, Fuzzy C-means clustering etc. The manual process of doing the segmentation of MRI images of brain is very time consuming and becomes a tedious task. In manual analysis, the possibility of making inaccurate results is very high. In region growing method of segmentation, images are partitioned by organizing pixels of same kind into one seed. Region growing method is time consuming. Though thresholding method of segmentation is simple it does not produce accurate results.

Segmentation using Clustering organises the objects into groups based on some characteristics. So each cluster has groups of similar objects or characteristics. K means clustering is a simplest clustering method proposed by MacQueen in 1967. In this method of K means clustering, aim is to partition n observations into k clusters, in which each observation belongs to the cluster with the nearest mean. This is a type of hard clustering as data is divided into different clusters and each data element belongs to exactly one cluster. The algorithm uses an iterative refinement technique. Though this method is very simple, the accuracy in classification is very low if the value of k is not suitably chosen. The algorithm is unable to handle noisy data [14].

Fuzzy C-means (FCM) as a soft(fuzzy) clustering method, was introduced by Dunn in 1973 and developed by Bezdek in 1981 [9]. FCM assigns membership to each data element to each cluster on the basis of distance between the cluster and the data element. Thus points on the edge of the cluster may have a less degree of membership than the points on the centre of the cluster. FCM algorithm

ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
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assigns data elements to the corresponding cluster using fuzzy membership function. The membership functions and cluster centres are updated until they converge to the minimum value. Although FCM is better than K-means clustering, computation time for the cluster centre is high and the algorithm is sensitive to the initialization of cluster centre and is noise sensitive [9].

II. METHODOLOGY

The proposed system can be outlined as shown in the Figure 2.

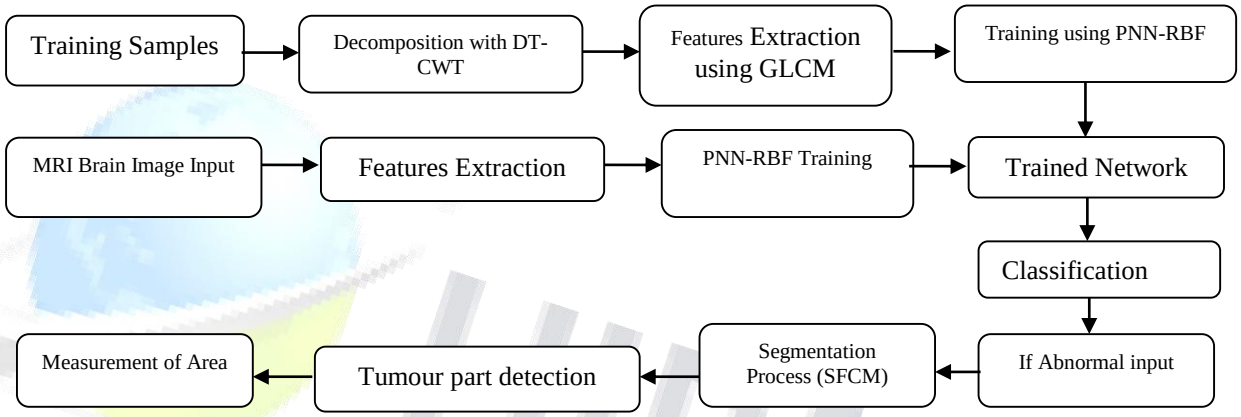

Figure 2. Block diagram of proposed work

The method used is shown in Figure 2. The various stages of the proposed method are Decomposition of the Input image with Dual Tree Complex Wavelet Transform (DT-CWT), Selective Features of the image are extracted using the Gray Level Co - occurrence Matrix (GLCM), Training the Network using Probabilistic Neural Network using Radial Basis Function (PNN-RBF). After classification, segmentation is done using SFCM and if the Input MRI image is not Normal, further extraction of the tumour area will be done using Morphological filtering and at the end, area of the affected tumour part is calculated.

A. Dual Tree Complex Wavelet Transform (DT-CWT)

The proposed method is using the classification method incorporating Probabilistic Neural Networks with Radial Basis Functions (PNN-RBF), as Probabilistic Neural Network is a fast and accurate classification method. To achieve the objective of proper classification, the texture of the input image is analysed and features are extracted with Dual Tree Complex Wavelet Transform (DT-CWT) and Gray-Level Co-occurrence Matrix (GLCM) first.

DT-CWT represents a signal with discontinuities and sharp peaks better than using traditional Fourier transform. In addition to that, it can accurately reconstruct the signal after decomposing the signal into different sub bands. DT-CWT decomposes the input signal in such a way that, the significant features can be extracted from its decomposed sub bands. Other advantages of DTCWT include good directional sensitivity to the orientation of the features, limited redundancy and it is nearly shift invariant.

DT-CWT decomposes the image in terms of a complex wavelet Ψc(t) and a complex valued scaling function ϕc(t). It provides a multiresolution representation making it possible to analyse the signal at different resolutions. A complex wavelet Ψc(t) is composed of the wavelet functions Ψr(t) representing the real part and Ψi(t) representing the imaginary part and they form a Hilbert Transform pair, means they are orthogonal i.e. shifted by π/2 in the complex plain [10].

$$\Psi c(t) = \Psi r(t) + j\Psi i(t) \qquad (1)$$

The same applies to the scaling function also such that

$$\phi_c(t) = \phi_r(t) + j\phi_j(t) \qquad (2)$$

ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
Vol. 6, Issue 4, April 2021

The scaling and wavelet functions relate to the corresponding filters through the following equations [10].

$$\Psi(t) = \sqrt{2}\sum_n h_1(n)\phi(2t-n) \quad (3)$$
$$\phi(t) = \sqrt{2}\sum_n h_0(n)\phi(2t-n) \quad (4)$$

In these equations "t" denotes the continuous time and "n" denotes the discrete time index and the filters h0 and h1 are the real valued low pass and high pass filters for the real tree and the filters g0 and g1 for the imaginary tree.

DT-CWT generates a set of complex coefficients to represent real and imaginary parts of the image signal, using two trees of real filters (Tree A and Tree B) as shown in Figure 5. The two trees correspond to the real and imaginary part of the complex wavelet transform. Wavelet transform can be implemented by cascading a pair of low and high frequency filters corresponding to the wavelets, followed by the decimation. This transform represents the edges of the images more efficiently than the other methods and give good results in image processing applications. DT-CWT produces six sidebands at each level, each of which is strongly oriented at distinct angles [10].

The implementation of DT-CWT is done at first by decomposing the input image by separable trees, Tree A and Tree B whose filters are designed to meet Hilbert Transform Pair requirement. Then, six high pass sub bands generated at each level can be represented as HLa, HHa, LHa, LHb, HHb, HLb [10]. Every two sub bands having same pass bands are linearly combined either by averaging or differencing them, and as a result at each level the sub bands of DT-CWT are obtained as follows:

$$\frac{LH_a+LH_b}{\sqrt{2}}, \frac{LH_a-LH_b}{\sqrt{2}}, \frac{HL_a+HL_b}{\sqrt{2}}, \frac{HL_a-HL_b}{\sqrt{2}}, \frac{HH_a+HH_b}{\sqrt{2}}, \frac{HH_a-HH_b}{\sqrt{2}}$$ [10].

By applying DTCWT to the input image, the input image will be decomposed into components like textural and structural elements. The decomposed elements are of high and low frequency sub bands which contain coarse and finest details. The textural details from these feature vectors are utilized for feature extraction.

B. 3Gray-Level Co-occurrence Matrix (GLCM)

C.

The GLCM is a tabulation of how often different combinations of pixel brightness value, i.e. gray levels, occur in an image. Haralick introduced this concept of Co-occurrence matrix in 1973 [6]. It considers the relationship between the reference pixel and its neighbour pixel as how often a reference pixel with a particular gray scale intensity value i occurs either horizontally or vertically or diagonally to adjacent pixels with value j. The matrix describing these relations forms Gray Level Co-occurrence Matrix.

Considering the orientation and distance between image pixels, the GLCM is constructed and afterwards the meaningful statistical features are extracted from the matrix as the texture extraction. Haralick extracted many texture features from the GLCM [6]. For each texture feature, the corresponding co-occurrence matrix represents the spatial distribution and dependency of the gray levels. Each (i,j)th entry in the corresponding matrix represents the probability of going from one pixel with an intensity value of i to another with the value j under a defined distance d and angle Θ. The elements in the matrix are calculated as

$$P_{(i,j/d,\Theta)} = \frac{P(i,j)}{\sum_i \sum_j P(i,j)} \textit{forthe corresponding } (d,\Theta)$$

where $P_{(i,j/d,\Theta)}$ represents the probability of finding a pixel with grey level *i* at a distance *d* and angle *Θ* from a pixel with grey level index *j*.

For optimum classification, textural properties of the image are calculated using GLCM. The statistical measures calculated from these matrices are feature vectors and the feature vectors chosen here are:

Homogeneity

Homogeneity measures the closeness of the distribution of elements to the GLCM diagonal, as it measures the similarity of grey scale levels along the image. It is more sensitive to the diagonal elements in the image and has a high value when all the elements in the image are the same [11].

$$GLCM\ Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|}$$

ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
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Contrast

Contrast is a measure of the intensity contrast between a pixel and its neighbouring pixels over the whole image. If the neighbouring pixels have similar grey scale values, then contrast will be lower. High contrast values are expected for heavy textures and low for smooth textures [11].

$$GLCM\ Contrast = \sum_i \sum_j (i-j)^2 P(i,j)$$

Energy

Energy is called Uniformity or Angular Second Movement. It measures the textural uniformity. It returns the sum of squared elements in the GLCM [11].

$$GLCM\ Energy = \sum_i \sum_j P^2(i,j)$$

Correlation

Correlation returns a measure of how correlated a pixel is to its neighbours throughout the whole image measuring the grey level dependencies [11].

$$GLCM\ Correlation = \sum_{i,j} P_{(i,j)}(i-\mu_i)(i-\mu_j)/\sigma_i\sigma_j$$

μ_i, μ_j, σ_i, σj are the mean and standard deviation of $P_{(i,j)}$. These features extracted are fed into the PNN classifier for further training and testing the performance of the classifier in classifying the image.

D. Probabilistic Neural Network

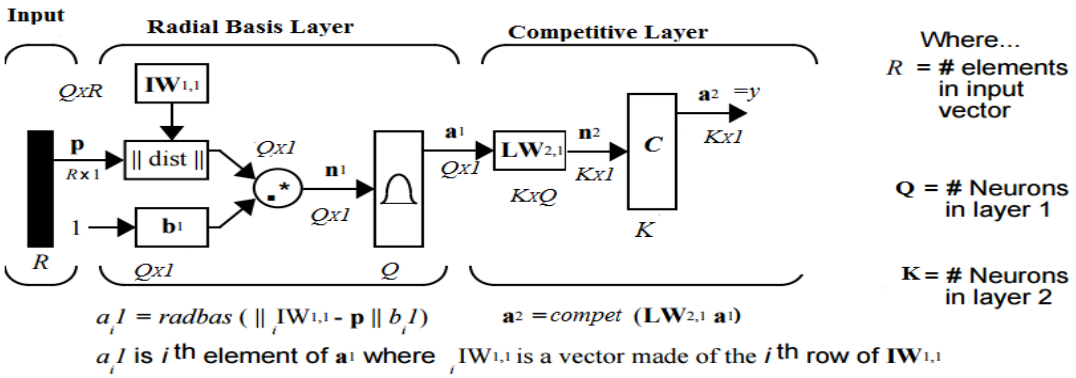
E.

The neural networks make use of artificial neurons as in the case of human brain neurons which carries information between different structures. The artificial neurons are used in training mode, where they are trained to recognize particular input patterns and using testing mode, they detect the taught input pattern.

The Probabilistic Neural Network with Radial Basis Function is a feed - forward PNN. It uses the supervised learning method for image classification. In supervised training, the neural network learns from examples of inputs with the corresponding outputs. The network learns the relationship between input and output during training and applies the learned relationship to the testing data during testing phase. The most important advantage of PNN-RBF is that, training is easy and instantaneous [15].

The PNN-RBF architecture shown in Figure 3 [12] is used in this thesis for training and classification of different MR images according to its proximity to the most relevant training vector. This model composed of radial basis function neurons and other neurons according to the structure, relations and information transmission process.

The PNN-RBF has three layers: Input Layer, Radial Basis Layer and Competitive Layer as shown.



ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
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Figure 3: PNN-RBF Architecture

When the test input is presented, the input layer computes the distances from the input vector to the training vectors and produces the vector output showing the closeness of the input to the training input. The Radial Basis Layer sums these contributions for each class of inputs to produce its net output as a vector of probabilities. These distances are scaled by a neural transfer function called Radial Basis Function (radbas). The neural transfer functions calculate a layer's output from its net input. In competitive layer, another neural transfer function called competitive function (compete) picks the maximum of these probabilities, finds the shortest distance among them and produces a 1 for maximum probability class and 0 for other classes. Thus competitive layer finds the training pattern closest to the input pattern based on their distance [12].

In figure 3, the number of elements in the input vector P is represented as RXQ that represents the number of input vector /target vector pairs which is the number of neurons in layer1. K represents the number of classes of input data or the number of neurons in layer 2. Each input vector is associated with any one of K classes. The first layer input weights are formed from the Q training pairs, P'. When an input is presented, ||W-p|| produces the distance vector whose elements indicate how close the input is to the vectors on the training set. Then the bias vector b and the distance vector ||W-p|| are combined with the Matlab operation.*, which does element by element multiplication. The result will be (||W-p||.*b). The dot product of this vector is given to the first layer neural transfer function, radbas. It calculates the layer's output from its net input. The bias function is defined by radbas transfer function, given by

radbas (n)= e^{-n^2}

i.e., the $\mathbf{i}^{th}$ element of a^1 from Radial Basis layer will be

$a_i^1 = radbas\ (\|\mathbf{W_i - p}\|.\mathbf{b_i})$

A radial basis neuron with a weight vector close to the input vector **p** will produce a value near 1 and its output weights in the competitive later will pass their values to the competitive transfer function.

The second layer weight matrix (LW_2) is set to the matrix **T** of target vectors. Each vector has a 1 only in the row associated with that particular class of input, and 0s elsewhere. There is no bias in Competitive layer. The vector $\mathbf{a^1}$ is first multiplied with **T** producing an output vector $\mathbf{n^2}$and summation of the elements due to each of the K input classes is done. $a^2 = compet\ (LW_2.a^1)$

The second layer transfer function, *compet* denoted by C produces a 1 corresponding to the largest element of $\mathbf{n^2}$ and 0's elsewhere. Thus the network classifies the input vector into a specific **K** class because that class has the maximum probability of being correct [12].

The advantages of PNN are its high training speed, robust in noise and can be easily trained. PNN can be used in real-time is also an advantage.

D. Spatial Fuzzy Clustering

Image segmentation has a significant role in bio medical applications where the radiologists use the image segmentation techniques to segment the input image into meaningful regions. The abnormal regions can be segmented from the input MRI images using these techniques. Clustering is the widely used segmentation technique, where it partitions an input image into different homogenous regions called classes or clusters, so that meaningful information about the image can be obtained and analysis can be performed onto these segmented images. Clustering helps to classify patterns in such a way that samples of same group are more similar to one another than samples of different groups. In fuzzy clustering, data elements belong partially to many classes with a degree of membership associated with it. Bezdek in 1981 formulated the Fuzzy c-means clustering for image segmentation [13]. Fuzzy c-means Clustering is an iterative algorithm, in which the data may belong to more than one cluster with a degree of membership associated with it. The data points closer to the cluster centre will have a higher degree of membership than the points away from the centre.

In any image, the pixels in the immediate neighbourhood possess almost the same features, i.e. the pixels in an image are highly correlated. In image segmentation, this spatial relationship with neighbouring pixels can be utilised to produce accurate segmentation. However, the conventional FCM method for segmentation does not fully utilise the spatial information of the image [16]. The initialization conditions of the cluster number and cluster centre initialization has real impact on FCM method of segmentation. Pedrycz and Waletzky modified the FCM algorithm including the spatial information for image segmentation [16]. The modified algorithm results in Spatial Fuzzy Clustering Method (SFCM) and has improved the results of conventional Fuzzy clustering methods.

IJIRMET ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
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The neighbouring pixels have similar feature values and the probability that they belong to the same cluster is more. Therefore, the spatial information is very much important in clustering and in conventional FCM it is not utilised. In Spatial FCM, a spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} U_{ik} \quad \text{.....(4)}$$

where NB(xj) represents a square window centred at the pixel xj at the spatial domain. The spatial function hij represents the probability of pixel xi belonging to ithcluster.

The spatial function of a pixel for a cluster is large, if majority of its neighbouring pixels belong to the same clusters. The spatial function incorporated into the membership function as shown in equation (5).

$$U_{ij}^{*} = \frac{U_{ij}^{p} * h_{ij}^{q}}{\sum_{k=1}^{c} U_{kj}^{p} * h_{kj}^{q}} \quad for \;\; i = 1,2,\ldots,c \;\; and \;\; j = 1,2,\ldots,n \quad \text{.....(5)}$$

where p and q are parameters to control the relative importance of both functions. In a homogenous region, the clustering result remains unchanged whereas in a noisy pixel, the membership reduces its weights of the noisy cluster by the labels of its neighbouring pixels. Thus, misclassified pixels can be easily removed.

In SFCM, clustering is a two pass process. In the first pass, membership function is calculated as in the conventional FCM, whereas in the second pass the membership function of each pixel is mapped into the spatial domain and the spatial function is computed from that. The iteration proceeds with the new membership function associated with the spatial information and the iteration stops when the maximum distance between two cluster centres at successive iterations is less than the threshold value.

The advantages of using SFCM include the elimination of noise, low sensitivity to noise and homogenous regions can be obtained more clearly.

E. Morphological Filtering and Calculation of the tumour Area

The segmented cluster image containing the tumour region is given as the input to Morphological filtering. Morphological filtering is a technique used for image enhancement. Image enhancement techniques are normally used for improving the visibility of the given image by making the picture details more obvious, to highlight and detect certain features of the image and for smoothening of image boundaries. Morphological filtering is a powerful methodology used in the field of image processing and is based on the concepts of Mathematical Morphology [17]. Morphological operations can be performed on binary image or greyscale images. A binary image has only two values for each pixel in the image, either 1 representing white pixel or 0 representing black pixel, while on the other hand a grey scale image pixels carries intensity information. In this dissertation, the image is converted to a binary image and is given as the input to Morphological operations.

Morphological operations process the images based on the shapes or morphology of the features in an image, e.g. as boundaries, basic frames etc. This is done with the help of small shape or template called Structuring Element (SE). The input image is probed with the SE to define the Regions of interest or neighbourhood around each pixel in the image, i.e. morphological operations can be defined between two sets: the input image, which may be binary, or greyscale and the Structuring Element. The SE is placed at all locations in the image and is compared with the corresponding neighbourhood.

The basic morphological operations are Dilation and Erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels from object boundaries. For morphological operations, the structuring element will place over a section of the input. Dilation process is performed by laying the Structuring Element onto the image and sliding it across the image. The dilation of an image, A by a structuring element, SE produces a new binary image with ones in all locations of the image A covered by the structuring element if the origin of SE hits with the image. If the origin of SE doesn't hit with image A, no change is made to A and SE moves onto the next pixel. With dilation operation, boundaries of the image are expanded and small holes will be filled, i.e. dilation adds a layer of pixels to inner and outer boundaries of regions.

Erosion and Dilation are dual operation operations with opposite effects. To compute the erosion of an image by the structuring element, for each pixel in the input image SE is superimposed on top of the input image. Erosion produces a new binary image, with ones in all locations of the input image covered by SE if the origin of SE fits the input image, otherwise 0. This repeats for all pixels in

the input image. Erosions shrinks an image by removing layer of pixels from input and output boundaries.

By using morphological operations, the tumour part of the image is enhanced from the segmented cluster. The number of white pixels corresponding to the tumour part are calculated and area of the tumour is calculated using the following equation,[18] where P represents the number of white pixels inside the tumour region.

SizeoftheTumor=(√P)*0.264mm2

Each pixel equals 0.264mm, i.e. 1 Pixel =0.264mm.

III. RESULTS AND ANALYSIS

The proposed method has been implemented using Matlab 8.4 as the development platform. For the performance analysis the MRI images are collected from internet [19], [20].The dataset was divided into two separate sets, a database of 15 images is used for training and another dataset of 10 test images is used to validate the test results. The following Table 3.1 shows the test input image, the class assigned after classification and the output image after segmentation of 3 test images. The texture features extracted for each test image is also included.

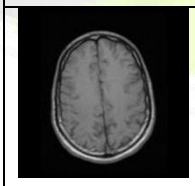
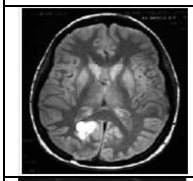
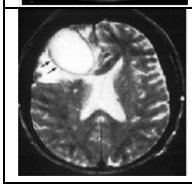
Input Test Image	Output Segmented Image	Contrast	Correlation	Energy	Homogeneity	Class Assigned
		1.7251	0.0017491	0.61292	0.86606	**Normal**
		7.4582	-0.14236	0.20295	0.61377	**Benign**
		10.354	-0.23291	0.13827	0.53502	**Malignant**

Table3.1. Results of classification and segmentation

While analysing the results, it is observed that Energy, measuring textural uniformity, is found to be less in Malignant MR Images compared to Benign and Normal images, and Energy has high values for Normal MRI. Similarly, Homogeneity, representing homogeneity of image textures that measures the closeness of distribution of elements is also found to be less for Malignant MRI. The value of Contrast, measuring the intensity contrast between pixels, is found to have increasing values from Normal MRI to Benign and Malignant MRI has higher values. Correlation values are also found to be less for Malignant MRI.

Performance of the developed system for classifier can be evaluated through Sensitivity, Specificity and Accuracy. Sensitivity can be defined as the measure which determines the probability of the results that are True Positive (TP), such that the corresponding image contains Tumour. It is also called True Positive Rate. Sensitivity measures the proportion of actual Positives which are correctly measured, i.e. it gives the percentage of patients correctly detected with tumour.

Sensitivity is calculated using the equation Sensitivity = TP. / (TP + FN)..... (1)

where, TP = True Positive shows the abnormality correctly classified as abnormal.

FN = False Negative represents the abnormality incorrectly classified as normal.

Specificity measures the probability of results that are True Negative (TN), such that the corresponding MRI does not have Tumour. It is a measure of True Negative Rate. Specificity measures the proportion of actual Negatives which are correctly identified, i.e. it gives the percentage of patients that could be correctly identified without tumour.

ISSN (Online): 2456-0448
International Journal of Innovative Research in Management, Engineering, and Technology
Vol. 6, Issue 4, April 2021

Specificity is calculated using the equation Specificity = TN. / (FP + TN)..... (2)
where, FP = False Positive shows the Normal image classifies as Abnormal.
TN = True Negative shows the Normal image correctly classified as Normal.

Accuracy is a measure which determines the probability that shows how many results are accurately classified. Accuracy determines the percentage of predictions that are correct.

Accuracy can be calculated using the equation Accuracy = (TP+ TN) ./ (TP + TN + FP + FN)
where, TP - True Positive - The result is Positive in the presence of Abnormality in MR Image
TN -True Negative - The result is Negative in the absence of Abnormality in MR Image
FP - False Positive- The result is Positive in the absence of Abnormality in MR Image
FN -False Negative - The result is Negative in the presence of Abnormality in MR Image

With the given data, the classifier results can be validated. For this, the Accuracy, Specificity and Sensitivity are calculated and the results are verified. The classifier is found to be working accurately with high precision. The classifier performance is analysed with test data set of 10. The training data set was used to train the Network and the testing data set was used to verify the accuracy and effectiveness of the trained PNN- RBF network for detection of Brain Tumours. The classifier was able to identify normal and abnormal MRI accurately. Results show that the classifier performs classification with a very high accuracy of 90%. Sensitivity and Specificity of the classifier is shown to be very high percentage of 85.71 and 100% respectively.
The classifier performance can again be validated using a Chart diagram. The following chart diagram in Figure 4 shows the Classifier Performance in Test Phase and validates the results from the classifier.

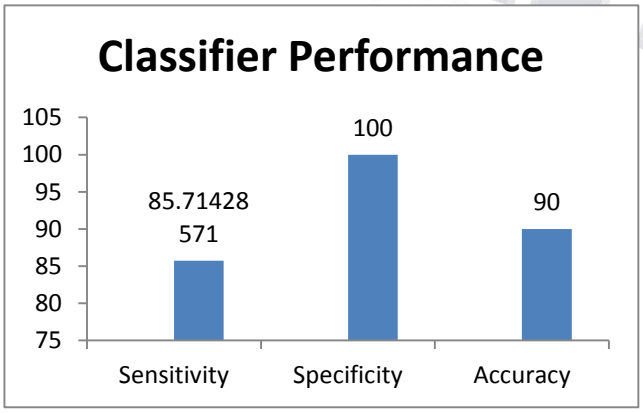


Figure 4: Classifier Performance

Thus as per the results, it is shown that the PNN- RBF classifier works very efficiently and accurately. Classification Phase provides the images which are Abnormal, either Malignant or Benign, to the Segmentation Phase as Input. In Segmentation Phase, the segmentation is done preserving the Spatial Features so that the accuracy of segmentation is high. Segmentation of the proposed system quite accurately extracted the Tumour regions from the MR images. The Malignant or Benign MR images are given for segmentation and clusters are generated from them. The results show that the tumour region which is high in contrast is quite accurately segmented and extracted by the proposed system as shown in Table 3.1. The proposed algorithm works very well in segmentation phase. The segmentation is done very effectively and managed to extract tumours from images very efficiently. The segmentation method provides thus produces accurate results. The area of the tumour region is also calculated and is found to be accurate.

IV. CONCLUSIONS AND FUTURE WORK

The importance of image classification and segmentation is increasing day by day. The automatic image classification and segmentation has many forms and uses. Unfortunately, there is no current strategy for automatic classification and segmentation which is able to accommodate all its applications. In this thesis, the possibility of developing an efficient algorithm for Classification and Segmentation of Magnetic Resonance Image (MRI) has been explored and in addition to that, the area of the tumour is also calculated effectively. A system has been developed to automatically classify and segment the MR images properly. The thesis proposes the combination of most efficient methods in classification and segmentation. The neural network model PNN is used as the classifier with Radial Basis function for Network activation function. The proposed system shows a very high accuracy in classification. The developed system

has 85.71% Sensitivity, 90% Accuracy and 100%Specificity. The results show that the developed system has exceptionally good results. In the developed System, after classification, Segmentation of the input image occurs and for Segmentation, a new and improved Fuzzy Logic known as Spatial Fuzzy Clustering method (SFCM) is used. By using SFCM the spatial function to modify the membership function is also taken into account. This provides accurate results compared to other methods. With the use of Morphological filtering, the tumour region is extracted properly from the Brain MRI after Segmentation. The area of the Tumour extracted region is also calculated which can improve the Diagnosis procedure for Brain Tumour.

The System proposed here has shown a very encouraging level of performance for Brain tumour classification and Segmentation. However, the accuracy of the system can be increased, given that MR images training database is broadened with large number of different classes of tumour images. After simulating the System developed, it has been proven that an efficient method for Brain Tumour MRI classification and Segmentation is proposed in this thesis. The System developed is very accurately classifying the Brain MRI and the tumour is efficiently extracted with the area of the tumour region. The developed approach is worth serious consideration for the development of an automatic tool in image classification and segmentation in Medical field.

The developed System in this project is dealing with Two- Dimensional images and has a training data set of 15samples. As of now, there is no database of MR images for classification of tumours. It would be better, if the medical laboratories work together to make a universal database of MRI Brain tumour Images. If a database with a large capacity can be obtained for training, the proposed method can be validated for its effectiveness and further improvement. Again, instead of using 2D images, it would be better if 3D image is developed in future work. 3D provides more real visualization than the 2D and can be employed in further studies.

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