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# **Brain MRI Classification Using PNN and Segmentation Using K Means Clustering**

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**ABSTRACT**: Brain tumor is one of the major causes of death among people. If the tumor is detected and classified correctly at its early stage then the chances of survival can be increased. Conventional methods uses biopsy, lumbar puncture and spinal tap method, to detect and classify brain tumors into benign and malignant. This paper replaces conventional time consuming method by introducing an efficient method of brain tumor classification and segmentation where, the real MRI is classified into normal, benign tumor and malignant brain tumor. The proposed method uses wavelet decomposition, GLCM for textural feature extraction, PNN for classification, K means clustering for image segmentation. Discrete Wavelet Transform is first applied for decomposing the MR image into different levels of approximate and detailed coefficients and then the gray level co-occurrence matrix is formed, from which the first and second order statistical features are obtained. The results of co-occurrence matrices are then given to a probabilistic neural network for classification and tumor detection. If tumor present, by k-means clustering tumor detected and its area calculated. The proposed method has been applied on real MR images, and performance of system is evaluated in terms of classification accuracy, it is checked for different spread values and found to be nearly 96% at the end Area of tumor is displayed.

KEYWORDS: Classification, DWT, GLCM, PNN, K-Means Clustering.

## I. INTRODUCTION

Brain is a soft mass of supportive tissues and nerve cells. These cells and the spinal cord together form the Central Nervous System (CNS). Now, when these cells grow old or are damaged, they are replaced by the new cells. Sometimes, this process of cell division goes wrong and abnormal multiplication of cells takes place leading to tumor within the area [1] .Brain Tumor can simply be defined as Solid Intracranial Neoplasm. Intracranial means inside the cranium (i.e. the skull bone), Neo means new and Plasma means Growth. Brain tumors have been classified in following two types: i) Benign Tumors ii) Malignant Tumors. A good classification process leads to the right decision and facilitates provision of good and appropriate treatment. Brain Tumors are diagnosed clinically by the doctor based on symptoms which are confirmed by Biopsy, Human Inspection, Expert Opinion, Nerve Test and Radiological Examination (CT scan and MRI). This process continues for long time [2]. The main problems faced by most of the medical imagery diagnosis systems are the separation of the cells and their nuclei from the rest of the image content. The process of separation i.e. segmentation is most important in the construction of effective diagnosis system. Necessity of this method is to provide CAD for fast and accurate methodology for classifying the normality and abnormality of brain and exact locating ROI of Images. The use of CAD not only assists the pathologists to reduce rate of error but in addition it helps in distribution and sharing of the digitally processed images [3].

## II. LITERATURE SURVEY

At present with the rapid growth of the Artificial Intelligence (AI) development in Biomedicine, Computer aided diagnosis is being increasingly implemented for this purpose. in proposed method Brain tumor classification and



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feature extraction is done to determine the type of brain tumor, segmentation to locate tumor. In method used by Mohd Fauzi Bin Othman, et al[6], performed classification of brain tumor using wavelet based feature extraction method and Support Vector Machine (SVM), Accuracy of only 65% was obtained. Salim Lahmiri et al [4], proposed approach shows that feature extraction from the LH (Low-High) and HL (High-Low) sub-bands using first order statistics has higher performance than features from LL (Low-low) bands. Ahmed kharrat et al [5], in this paper A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and SVM is used. This paper proposes a genetic algorithm and SVM based classification of brain tumor. It is found that, Gabor filters are poor in performance due to their lack of orthogonality that results in redundant features at different scales or channels. Bhagwat et al[1], in this paper comparison of K-means, Fuzzy C-means and Hierarchical clustering algorithms for detection of brain tumor is carried out, it observed that K-means algorithm produce more accurate result compared to Fuzzy c-means and hierarchical clustering. Pankaj Sapra, et al [11]. This proposes a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. Simulation output showed that PNN system presented and successfully handle the process of brain tumor classification in MRI image with 100% accuracy. From the literature survey, we can say that, various researchers worked on classifying MR brain images into normal and abnormal. Discrete Wavelet Transform is found to be an important tool in decomposing the images into different levels of resolution, from which the significant features can be extracted. Conventional neural networks are inferior to PNN in terms of its accuracy in classifying brain tumors. Hence a wavelet and co occurrence matrix method based texture feature extraction and Probabilistic Neural Network for classification and segmentation by k means has been used in this method.

#### III. PROPOSED METHOD

Proposed method has four modules: preprocessing, feature extraction, classification and segmentation. Block diagram of system is shown in figure 1.

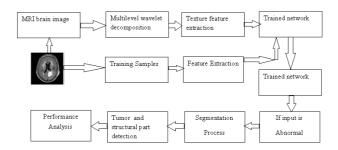


Fig. 1Block diagram of system

For implementation of proposed method of classification, normal and brain tumor T1, T2 images are collected from SAHYADRI MRI CENTER, AURANGABAD. This image dataset contains 51 brain MRI images. These 3D DICOM real images were obtained using WIPROS GE OPTIMA MR 360 1.5 T Unit. These DICOM images are converted in bmp format using DICOM to .bmp converter software.

## 3.1 Preproceesing

The raw MR images normally consist of many errors such as cranial tissues, Patient motions during imaging times, thermal noise and exist of any metal things in imaging environment and film artifacts or label on the MRI such as patient name, age and marks etc. so it reduces the overall accuracy of system. So, median filter is used. Median filter is a non-linear filtering technique used for noise removal[12]. Median filtering is used to remove salt and pepper noise from the converted gray scale image. it has advantage of it preserves edges of image [8].



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## 3.2 Discrete Wavelet Transform

Multi resolution of images that is simultaneous representation of images on different resolution levels is main feature of Wavelet transform. it uses wavelet filters for decomposition into sub images. Filter banks decompose the signal into high and low-frequency components. The low-frequency (LL) component usually consist of most of the frequency of the signal called as approximation. The high-frequency (LH, HL) component contains the details of the signal. a two-channel filter bank can be used for implementation of Wavelet decomposition. My method uses 2 level decomposition and the features are extracted from LH and HL sub bands formed by DWT.



Fig- 2: 2 level Decomposition

#### **3.3 Feature Extraction**

Texture analysis has advantage that it can differentiate normal and abnormal tissue easily. It even provides contrast between benign, malignant and normal tissue, which we cannot identified by threshold of human perception. In this method first order statistical and second order statistical features extracted from LL,HL,HL images. In first order texture information from intensity of histogram. Second order texture from gray level co oc occurrence matrix [13]. Following table shows various features extracted in this method.

| 1. | Mean Value            | $M = \sum_{i} \sum_{j} g(i, j)$                                            |
|----|-----------------------|----------------------------------------------------------------------------|
| 2. | Standard<br>Deviation | Std = $\frac{\sqrt{\sum_{i} \sum_{j} (g(i,j) - m)^2}}{\sqrt{N}}$           |
| 3. | Skewness              | $Sk = \frac{1}{N} \frac{\sum_{i} \sum_{j} (g(i,j) - m)^{3}}{std^{3}}$      |
| 4. | Kurtosis              | $\mathbf{K} == \frac{1}{N} \frac{\sum_{i} \sum_{j} (g(i,j) - m)^4}{std^4}$ |
| 5. | Contrast              | $\Sigma_{i,j}  i-j ^2 Pd, \theta(i,j)$                                     |
| 6. | Correlation           | $\sum_{ij} \frac{(i-\mu_x)(j-\mu_y)Pd, \theta(j,j)}{ x^{\sigma y} }$       |
| 7. | Homogeneity           | $\sum_{ij} \frac{Pd, \theta(j,j)}{1+ i-j }$                                |
| 8. | Entropy               | Σi,j Pd, log2 [(Pd,(i, j)]                                                 |
| 9. | Energy                | $\Sigma i, j (Pd, \theta (i, j))^2$                                        |

Table -1: first and second order features



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## 3.4 PNN Classification

Before classification, network has to be trained. In training, feature of training images are extracted and used to train network.

In classification process, features of test image is compared with features of training and by finding the shortest distance the test image assigned to that group as normal, benign or malignant. This network provides a general solution to pattern classification problems by following an approach developed by Bayesian classifiers [9,10]. PNN is used as it has many advantages. Its training speed is many times faster than a BP network. PNN can approach a Bayes optimal result under certain easily met conditions [9]. The most important advantage of PNN is that training is easy and instantaneous [6]. Weights are not "trained" but assigned. Existing weights will not be changed but only new vectors are inserted into weight matrices when training. So it can be used in real-time.Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast[6]. The network classifies input vector into a specific class because that class has the maximum probability to be correct. The PNN has three layers:

- Input layer
- Radial Basis Layer
- Competitive Layer

Radial Basis Layer calculates 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 based on their distance it finds the training pattern closest to the input pattern. The network structure is shown below

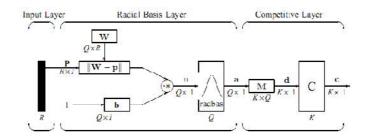


Fig- 2: Network structure.

#### 3.5 Segmentation by k-means clustering

If the output of classifier identifies tumor, segmentation locates the tumor for further analysis.

K-Means is unsupervised learning algorithm for clusters. Clustering the image means grouping the pixels according to the some characteristics. In the k-means algorithm initially we have to define the number of clusters k. Then k-cluster centre are chosen randomly [7]. The distance between the each pixel to each cluster centers are calculated. Single pixel is compared to all cluster centres using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids. The process continuous until the center converges [7].

In the approximate reasoning step the tumor area is calculated using the binarization method. That is the image having only two values either black or white (0 or 1). Here 256x256 .bmp images is a maximum image size. The binary image can be represented as a summation of total number of white and black pixels

Image (I) = 
$$\sum_{w=o}^{255} \sum_{H=o}^{255} [f(0) + f(1)]$$

pixels=Width(W)XHeight(H) = 256X256 f(0)= White pixel (digit 0) f(1)= Black pixel (digit 1)

No of white pixel  $P = \sum_{W=0}^{255} \sum_{H=0}^{255} [f(0)]$ 

Where, P = number of white pixels (width\*height)



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1 Pixel = 0.264 mm The area calculation formula is

## Size of Tumor S=[ $(\sqrt{P}) * 0.264$ ] $mm^2$

P= no-of white pixels; W=width; H=height.

By using above formula, canny edge detection, detects edge of segmented tumor which shows the no of white pixels which help us for calculating area of tumor.

## IV. RESULTS AND DISCUSSION

To evaluate the performance of the system, the data set was divided into two separate data sets – the training data set (30 images) and the testing data set (21 images). The training data set was used to train the network, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained network for the classification of brain tumors. Here MATLAB 2007b is used to implement PNN. The spread value (S.V.) of the radial basis function was used as a smoothing factor and classifier accuracy was examined when different values of S.V. are used. Clinical and performance measurements with respect to normal, benign and malignant are shown in table 2 and 3.

Table-2: Clinical measurements of PNN with respect to normal, benign and malignant

| SV | Training Sample | Testing Sample | TP | TN | FP | FN |
|----|-----------------|----------------|----|----|----|----|
| 1  | 30              | 21             | 11 | 6  | 1  | 3  |
| 2  | 30              | 21             | 13 | 6  | 1  | 1  |
| 3  | 30              | 21             | 14 | 6  | 1  | 0  |
| 4  | 30              | 21             | 11 | 6  | 1  | 3  |
| 5  | 30              | 21             | 11 | 6  | 1  | 3  |

Table- 3: Performance measurements of PNN with respect to normal, benign and malignant

| sv | Training<br>Samples | Testing<br>Samples | SENSITIVITY(%) | SPECIFICITY(%) | ACCURACY(%) |
|----|---------------------|--------------------|----------------|----------------|-------------|
| 1  | 30                  | 21                 | 92.86          | 85.71          | 80.95       |
| 2  | 30                  | 21                 | 100            | 85.71          | 90.48       |
| 3  | 30                  | 21                 | 78.57          | 85.71          | 95.24       |
| 4  | 30                  | 21                 | 78.57          | 85.71          | 80.95       |
| 5  | 30                  | 21                 | 78.57          | 85.71          | 80.95       |

The performance parameters of the proposed classification approach is identified by following formulae.

Accuracy(%)= (TP+TN)/(TP+TN+FP+FN)\*100

Specificity (%) = 
$$TN/(TN+FP)*100$$

Sensitivity (%) = TP/(TP+FN)\*100

True Positive (TP): Correctly classified positive cases.

True Negative (TN): Correctly classified negative cases.

False Positive (FP): Incorrectly classified negative cases.

False Negative (FN): Incorrectly classified positive cases.



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For this system 30 training samples and 21 testing samples have been used. The classifier accuracy varies from 80.95% to 95.24%.

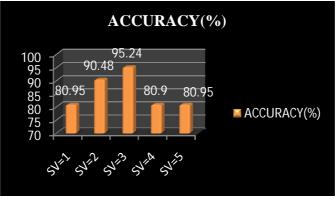
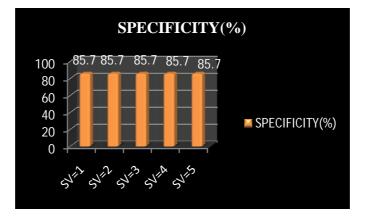
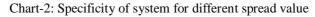


Chart-1: Accuracy of system for different spread value





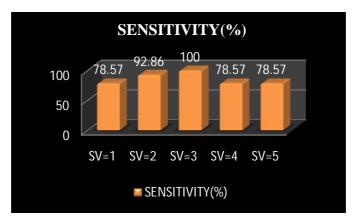


Chart-3: Sensitivity of system for different spread value

From above discussion, maximum accuracy is obtained for sv=3. To evaluate performance of system, accuracy is compared with various systems,



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Table-4: Accuracy comparison with various system

| Classification Result | ACCURACY(%) |
|-----------------------|-------------|
| BPN                   | 88.3%       |
| RBNN                  | 84 %        |
| PNN(THIS SYSTEM)      | 95.24%      |
| Sahar, G. (2012)      | 90.11%      |
| Amasaven, V. (2013)   | 89.9%       |

In abnormality analysis if the output of classifier is benign or malignant then next task is to locate ROI & find its area.

| I/P MRI                   | SEGMENTED IMAGE      | TYPE OF TUMOR |
|---------------------------|----------------------|---------------|
|                           | No Segmentation      | Normal        |
|                           | No Segmentation      | Normal        |
|                           |                      | Benign        |
| Contraction of the second | Corry expension      | Malignant     |
| 01                        |                      | Benign        |
|                           | Carry expension<br>S | Malignant     |

Table-5: Input MRI and Segmented output

Area and segmentation time of sample images of my system is shown in below table



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#### Table-6: Area of tumor and segmentation time

| MRI i/p | TUMOR AREA | SEGMENTATION TIME |
|---------|------------|-------------------|
| Image 1 | Nil        | Nil               |
| Image 2 | Nil        | Nil               |
| Image 3 | 2.2710     | 7.005232          |
| Image 4 | 4.4880     | 6.932843          |
| Image 5 | 4.1575     | 7.203296          |
| Image 6 | 4.2569     | 8.484655          |

#### V. CONCLUSION

The proposed approach gives very promising results in classifying MR images. Texture statistics obtained from LH and HL sub bands system is able to classify brain tumor into benign and malignant. The developed classifier was examined under different spread values as a smoothing factor. Experimental result indicates that PNN classifier is workable with an accuracy ranged from 80% to 95.24% according to the spread value ranged from 1to5. From experimental result maximum accuracy of 95.24% obtained for SV=3. It also helps to find the area of tumor from which we can find stage of tumor. This work will act as supportive tool for radiologists and will help doctor for fast diagnosis based on which the treatment plan can be decided.

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