A Wavelet Based Automatic Segmentation of Brain Tumor in CT Images Using Optimal Statistical Texture Features

A.Padma
Research scholar, *giri_padma2000@yahoo.com*
Thiyagarajar College of Engineering
Madurai – 625 015, India

Dr.R.Sukanesh
Prof of Electronics and Communication Engineering, *rshece@tce.edu*
Thiagarajar College of Engineering,
Madurai – 625 015, India.

Abstract

This paper presents an automated segmentation of brain tumors in computed tomography images (CT) using combination of Wavelet Statistical Texture features (WST) obtained from 2-level Discrete Wavelet Transformed (DWT) low and high frequency sub bands and Wavelet Co-occurrence Texture features (WCT) obtained from two level Discrete Wavelet Transformed (DWT) high frequency sub bands. In the proposed method, the wavelet based optimal texture features that distinguish between the brain tissue, benign tumor and malignant tumor tissue is found. Comparative studies of texture analysis is performed for the proposed combined wavelet based texture analysis method and Spatial Gray Level Dependence Method (SGLDM). Our proposed system consists of four phases i) Discrete Wavelet Decomposition (ii) Feature extraction (iii) Feature selection (iv) Classification and evaluation. The combined Wavelet Statistical Texture feature set (WST) and Wavelet Co-occurrence Texture feature (WCT) sets are derived from normal and tumor regions. Feature selection is performed by Genetic Algorithm (GA). These optimal features are given as input to the PNN classifier to segment the tumor. An Probabilistic Neural Network (PNN) classifier is employed to evaluate the performance of these features and by comparing the classification results of the PNN classifier with the Feed Forward Neural Network classifier (FFNN).The results of the Probabilistic Neural Network, FFNN classifiers for the texture analysis methods are evaluated using Receiver Operating Characteristic (ROC) analysis. The performance of the algorithm is evaluated on a series of brain tumor images. The results illustrate that the proposed method outperforms the existing methods.

Keywords: *Discrete Wavelet Transform(DWT),* Genetic Algorithm(GA), Receiver Operating Characteristic(ROC)analysis, *Spatial Gray Level Dependence Method (SGLDM), Probabilistic Neural Network (PNN).*

1. INTRODUCTION

In recent years, medical CT Images have been applied in clinical diagnosis widely. That can assist physicians to detect and locate Pathological changes with more accuracy. Computed Tomography images can be distinguished for different tissues according to their different gray levels. The images, if processed appropriately can offer a wealth of information which is significant to assist doctors in medical diagnosis. A lot of research efforts have been directed towards the field of medical image analysis with the aim to assist in diagnosis and clinical studies [1]. Pathologies are clearly identified using automated CAD system [2]. It also helps the radiologist in analyzing the digital images to bring out the possible outcomes of the diseases. The medical images are obtained from different imaging systems such as MRI scan, CT scan, Ultra sound B scan. The computerized tomography has been found to be the most reliable method for early detection of tumors because this modality is the mostly used in radio therapy planning for two main reasons. The first reason is that scanner images contain anatomical information which offers the possibility to plan the direction and the entry points of radio therapy rays which have to target only the tumor region and to avoid other organs. The second reason is that CT scan images are obtained using rays, which is same principle as radio therapy. This is very important because the intensity of radio therapy rays have been computed from the scanned image. Advantages of using CT include good detection of calcification, hemorrhage and bony detail plus lower cost, short imaging times and widespread availability. The situations include patient who are too large for MRI scanner, claustrophobic patients, patients with metallic or electrical implant and patients unable to remain motionless for the duration of the examination due to age, pain or medical condition. For these reasons, this study aims to explore methods for classifying and segmenting brain CT images. Image segmentation is the process of partitioning a digital image into set of pixels. Accurate, fast and reproducible image segmentation techniques are required in various applications. The results of the segmentation are significant for classification and analysis purposes. The limitations for CT scanning of head images are due to partial volume effects which affect the edges produce low brain tissue contrast and yield different objects within the same range of intensity. All these limitations have made the segmentation more difficult. Therefore, the challenges for automatic segmentation of the CT brain images have many different approaches. The segmentation techniques proposed by Nathali Richarda et al and Zhang et al [3][4] include statistical pattern recognition techniques. Kaiping et al [5] introduced the effective Particle Swarm optimization algorithm to segment the brain images into Cerebro spinal fluid (CSF) and suspicious abnormal regions but without the annotation of the abnormal regions. Dubravko et al and Matesin et al [6] [7] proposed the rule based approach to label the abnormal regions such as calcification, hemorrhage and stroke lesion. Ruthmann.et al [8] proposed to segment Cerebro spinal fluid from computed tomography images using local thresholding technique based on maximum entropy principle. Luncaric et al proposed [9] to segment CT images into background, skull, brain, ICH, calcifications by using a combination of K means clustering and neural networks. Tong et al proposed[10] to segment CT images into CSF,brain matter and detection of abnormal regions using unsupervised clustering of two stages. Clark et al [11] proposed to segment the brain tumor automatically using knowledge based techniques. From the above literature survey shows that intensity based statistical features are the most straight forward and have been widely used, but due to the complexity of the pathology in human brain and the high quality required by clinical diagnosis, only intensity features cannot achieve acceptable result. In such applications, segmentation based on textural feature methods gives more reliable results. Therefore texture based analysis have been presented for tumor segmentation such as SGLDM method and wavelet based texture features are used and achieve promising results.

Based on the above literature, better classification accuracy can be achieved using wavelet based statistical texture features. In this paper, the authors would like to propose a combination of Wavelet Statistical Texture features (WST) obtained from 2-level Discrete Wavelet Transformed (DWT) low and high frequency sub bands and Wavelet Co-occurrence Texture features (WCT) obtained from two level Discrete Wavelet Transformed (DWT) high frequency sub bands. The extracted texture features are optimized by Genetic Algorithm(GA)[12] for improving the classification accuracy and reducing the overall complexity. The optimal texture features are fed to the PNN[13], FFNN[14] classifiers to classify and segment the tumor region from brain CT images.

2: MATERIALS AND METHODS

Most classification techniques offer intensity based statistical features. The proposed system is divided into 4 phases (i) Discrete Wavelet Decomposition (ii) Feature extraction (iii) Feature selection(iv) Classification and Evaluation. For feature extraction, we discovered two methods which are i) the combination of Wavelet Statistical Texture features (WST) obtained from 2-level Discrete Wavelet Transformed (DWT) low and high frequency sub bands and Wavelet Co-occurrence Texture features (WCT) obtained from two level Discrete Wavelet Transformed (DWT) high frequency sub bands ii) SGLDM method without wavelet transform. Once all the features are extracted, then for feature selection, we use Genetic Algorithm (GA) to select the optimal statistical texture features. After selecting the optimal texture features, to classify and segment the tumor region from brain CT images using PNN ,FFNN classifiers.

2.1 Discrete Wavelet Decomposition

Daubechies wavelet filter of order two is used and found to yield good results in classification and segmentation of tumor from the brain CT images. By applying 2D DWT[15], two level wavelet decomposition of region of interest(ROI) is performed which results in four sub bands. In 2D wavelet decomposition the image is represented by one approximation and three detail images ,representing the low and high frequency contents image respectively. The approximation can be further to produce one approximation and three detail images at the next level of decomposition, wavelet decomposition process is shown in Figure 1. LL1, LL2 represent the wavelet approximations at 1^{st} and 2^{nd} level respectively, and are low frequency part of the images. LH1,HL1,HH1,LH2,HL2,HH2 represent the details of horizontal, vertical and diagonal directions at 1^{st} and 2^{nd} level respectively, and are high frequency part of the images.

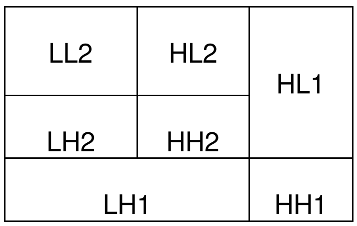

FIGURE 1: Wavelet Image decomposition at 2^{nd} level

Among the high frequency sub bands, the one whose histogram presents the maximum variance is the sub band that represents the most clear appearance of the changes between the different textures. The WST features are extracted from the 2^{rd} level of both low and high frequency sub bands and WCT features are extracted from 2^{nd} level of high frequency sub bands are useful to classify and segment the tumor region from brain CT images.

2.2 Feature Extraction

Texture analysis is a quantitative method that can be used to quantify and detect structural abnormalities in different tissues .As the tissues present in brain are difficult to classify using shape or intensity level of information, the texture feature extraction is founded to be very important for further classification. The purpose of feature extraction is to reduce original data set by measuring certain features that distinguish one region of interest from another. The analysis and characterization of textures present in the medical images can be done by using the combination of Wavelet Statistical Texture features (WST) obtained from 2-level Discrete Wavelet Transformed (DWT) low and high frequency sub bands and Wavelet Co-occurrence Texture features (WCT) obtained from two level Discrete Wavelet Transformed (DWT) high frequency sub bands .

Algorithm for Feature Extraction is as Follows

- Obtain the sub-image blocks, starting from the top left corner.
- Decompose sub-image blocks using 2-D DWT.
- Derive SGLDM or Co-occurrence matrices [16] for two level high frequency sub bands of DWT with 1 for distance and **0**,45,90 and 135 degrees for θ and averaged.
- From these co-occurrence matrices, the following nine Haralick texture features [17] called wavelet Co-occurrence Texture features(WCT) are extracted .
- The Wavelet Statistical Texture features (WST) are extracted from 2 level Discrete Wavelet Transformed (DWT) low and high frequency sub bands.
- Combination of the both the WST features and WCT features are used for classification.

Then the feature values of both features are normalized by subtracting minimum value and dividing by maximum value minus minimum value. Maximum and minimum values are calculated based on the training data set. In the data set, if the feature value is less than the minimum value, it is set to minimum value. If the feature value is greater than the maximum value, it is set to maximum value. Normalized feature values are then optimized by feature selection algorithm. Table 1 shows the combination of both WST WCT features extracted using SGLDM method .

SI.No	Second order WCT features
WST FEATURES	
1	Mean(MN)
2	Standard Deviation(SD)
3	Energy(ENER)
WCT FEATURES	
1	Entropy-ENT (Measure the disorder of an image)
2	Energy- ENE (Measure the textural uniformity)
3	Contrast-CON (Measure the local contrast in an image)
4	Sum Average-SA (Measure the average of the gray level within an image)
5	Variance –VAR (Measure the heterogeneity of an image)
6	Correlation-COR (Measure a correlation of pixel pairs on gray levels)
7	Max probability-MP (Determine the most prominent pixel pair in an image)
8	Inverse Difference Moment - IDM (Measure the homogeneity of an image)
9	Cluster tendency-CT (Measure the grouping of pixels that have similar

TABLE 1: WST and WCT Features extracted using SGLDM method

2.3 Feature Selection

Feature selection is the process of choosing subset of features relevant to particular application and improves classification by searching for the best feature subset, from the fixed set of original features according to a given feature evaluation criterion(ie., classification accuracy). Optimized feature selection reduces data dimensionalities and computational time and increase the classification accuracy. The feature selection problem involves the selection of a subset of features from a total number of features, based on a given optimization criterion. T denotes the subset of selected features and V denotes the set of remaining features. So, S = T U V at any time. J(T) denotes a function evaluating the performance of T. J depends on the particular application. Here J(T) denotes the classification performance of classifying and segmenting tumor region from brain CT images using the set of features in T. In this work, genetic algorithm (GA) technique is used.

Genetic Algorithm

We consider the standard GA to begin by randomly creating its initial population. Solutions are combined via a crossover operator to produce offspring, thus expanding the current population of solutions. The individuals in the population are then evaluated via a fitness function, and the less fit individuals are eliminated to return the population to its original size. The process of crossover, evaluation, and selection is repeated for a predetermined number of generations or until a satisfactory solution has been found. A mutation operator is generally applied to each generation in order to increase variation. In the feature selection formulation of the genetic algorithm ,individuals are composed of chromosomes: a 1 in bit position indicates that feature should be selected; 0 indicates this feature should not be selected. As an example the chromosome 00101000 means the 3^{rd} and 5^{th} features are selected. That is the chromosome represents T={3,5} and V={1,2,4,6,7,8}. Fitness function for given chromosome T is defined as

$$\text{Fitness}(T) = J(T) - \text{penalty}(T) \qquad (1)$$

where T is the corresponding feature subset , and penalty(T) = w * (|T| -d) with a penalty coefficient w. The size value d is taken as a constraint and a penalty is imposed on chromosomes breaking this constraint. The chromosome selection for the next generation is done on the basis of fitness. The fitness value decide whether the chromosome is good or bad in a population. The selection mechanism should ensure that fitter chromosomes have a higher probability survival. So, the design adopts the rank-based roulette-wheel selection scheme. If the mutated chromosome is superior to both parents, it replaces the similar parent. If it is in between the two parents, it replaces the inferior parent; otherwise, the most inferior chromosome in the population is replaced. The selected optimal feature set based on the test data set is used to train the PNN, FFNN classifiers to classify and segment the tumor region from brain CT images. Table 2 shows the best features selected using Genetic Algorithm(GA) during the execution.

SI-NO	Feature set	Classification accuracy
1	IDM,ENT, ENE, VAR,CON,ENER	96%
2	IDM,CON,ENE, MP, VAR,SD	96%
3	ENT,IDM,VAR, IDM, CT,ENER	97%
4	IDM,ENT, CT, ENE,CON,ENER	97%
5	CON, IDM,VAR,ENT,ENE,MN	96%
6	ENT,SA, IDM, ENE,VAR,ENER	97%
7	VAR,ENT, ENE, SA,IDM,ENER	97%
8	ENT,CON,ENE,VAR,IDM,ENER	97%
9	IDM,ENT, CT,CON, VAR,MN	96%
10	ENE,ENT, MP,CON, COR,SD	96.5%

TABLE 2: Feature set generated by Genetic algorithm

The WCT texture features like energy (ENE), entropy (ENT), variance (VAR), inverse difference moment (IDM) and WST features like energy are present in most of the feature set generated by GA. The features such as CT,CON,SA,MP,COR,SD,MN which are least significant. The classification accuracy of 97% is obtained with five of the available 39 features using GA. Therefore this minimum number of features are possible to classify and segment the tumor region from brain CT images.

2.4 PNN Classifier

Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. Probabilistic Neural Networks (PNNs) is a widely used classification methodology, because of its simplicity, robustness to noise, fast training speed, fast online speed ,no local minima issues and training samples can be added or removed without extensive retraining .Their main task is the classification of unknown feature vectors into predefined classes, where the Probability Density Function (PDF) of each class is estimated by kernel functions. PNNs are supervised neural network models, closely related to the Bayes classification rule and Parzen nonparametric probability density function estimation theory. Their training procedure consists of a single pass over all training patterns, thereby rendering PNNs faster to train, compared to the Feed forward Neural Networks (FFNNs).

The PNN architecture is composed of many interconnected processing units or neurons organized in successive layers : input layer ,pattern layer, summation layer, decision layer or output layer. The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern X from the input layer, the neuron X_{ij} of the pattern layer computes its output. The output of pattern layer is represented by

$$Y_{ij}(X) = e^{-|X-Xij|2} / \sigma^2 \quad i, j = 1,2\ldots.n \qquad (2)$$

n represents number of training sets, σ is the smoothing parameter. The summation layer neurons compute the pattern X being classified into G_i by summing and averaging the output of all neurons that belong to the same class.

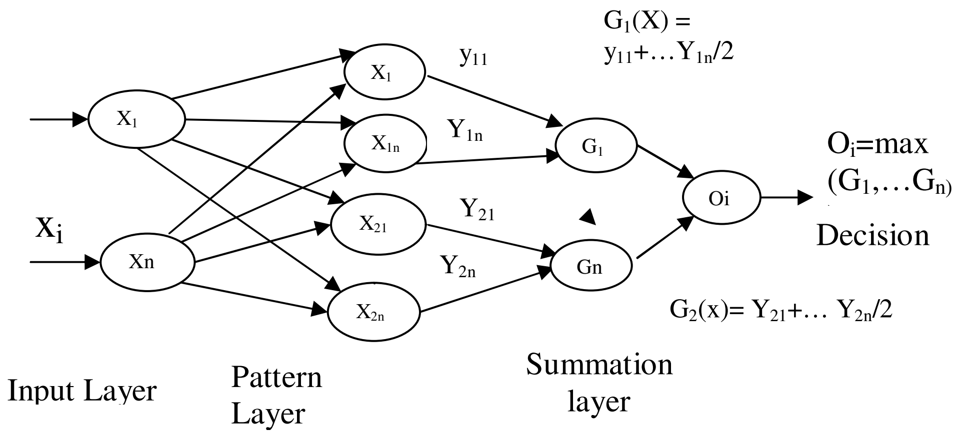

FIGURE 2: Architecture of probabilistic neural network

The output of summation layer is represented by

$$G_i(X) = 1/n_i \sum_{K=1}^{ni} e^{-\|X-Xij\|^2} / \sigma^2 \quad i= 1\ldots n\ , X = X_1,X_2,\ldots..Xn \qquad (3)$$

where n_i denotes the total number of training sets or patterns in class G_i. If the a priori probabilities for each class are the same, and the losses associated with making an incorrect decision for each class are the same, the decision layer unit classifies the pattern X in accordance with Bayes's decision rule based on the output of all the summation layer neurons:

$$O_i(X) = \max(G_i(X)), \quad i = 1\ldots.n \quad X = X_1,X_2,\ldots..Xn \qquad (4)$$

where $O_i(X)$ denotes the estimated class of the pattern X and n is the total number of classes in the training sets or patterns.

2.4.1 Segmentation of Tumor Region

Segmentation is important in selecting the sub band of the image to be decomposed. The segmentation is done by the combination of WST features are extracted from 2 level discrete wavelet transformed low and high frequency sub band and WCT features are extracted from two level discrete wavelet transformed high frequency sub bands as given in the feature extraction algorithm and the optimal texture feature set is selected by GA based on the classification performance of PNN,FFNN classifiers. From the experiments conducted for feature selection, it is found that the optimal feature set which gives good classification performance are WST features like energy and the second order WCT features like energy entropy, variance, inverse difference moment. The four WCT texture features from high frequency sub bands and one WST texture feature from low and high frequency sub bands forms the feature set. These feature set is given as input to the PNN, FFNN classifiers to segment the tumor region from brain CT images. Efficiency or accuracy of the classifiers for each texture analysis method is analyzed based on the error rate. This error rate can be described by the terms true and false positive and true and false negative as follows:

True Positive (TP) : The test result is positive in the presence of the clinical abnormality.
True Negative (TN): The test result is negative in the absence of the clinical abnormality.
False Positive (FP): The test result is positive in the absence of the clinical abnormality.
False Negative(FN): The test result is negative in the presence of the clinical abnormality. Based on the above terms, to construct the table called contingency table.

Actual group	Predicted group	
	Normal	Abnormal
Normal	TN	FP
Abnormal	FN	FP

TABLE 3: Contingency table of classifier performance.

Sensitivity = TP / (TP + FN)
Specificity = TN / (FP + TN)
Accuracy = (TP+TN)/(TP + TN + FN + FP)

Sensitivity measures the ability of the method to identify abnormal cases. Specificity measures the ability of the method to identify normal cases. Correct classification rate or accuracy is the proportion of correct classifications to the total number of classification tests. The PNN, FFNN classifiers were tested by using leave one out cross validation method. Leave one out cross validation can be used as a method to estimate the classifier performance in unbiased manner. Here each step, one data set is left out and the classifier is trained using the rest and the classifier is applied to the left out data set. This procedure is repeated such that each data set is left out once. In our application, to evaluate the classification accuracy of the classifiers, the 3,5, 10 fold cross validation is done on the data set collected from 100 images. Classification accuracy is calculated by taking the average number of all the correct classifications. Other statistical method known as Receiver Operating Characteristics (ROC) analysis [18] is also used to analyze the experimental results of the classifiers for each texture analysis method. In this method, the data set is divided randomly into 5 groups of 100 images with 50 benign tumor and 50 malignant tumor images. Each group consists of 10 benign and 10 malignant tumor images. Sensitivity and specificity values are recorded for each group and the ROC curve is drawn and analyzed. Depending on the training set, each group will have a different threshold value for determining true positive and true negative cases. The ROC curve is a graphical representation of sensitivity versus specificity as a threshold parameter is varied. The Area Under ROC Curve (AUC) has been calculated and that AUC value is used to determine the overall classification accuracy of a specific classifier. The larger the area (the higher AUC value) means higher the classification performance. In this research, the ROC analysis and classification accuracy are used to measure the performance of the classifiers based on the different texture analysis methods.

3. RESULTS

Our proposed method is implemented on real human brain CT dataset with the two different types of tumor images of 30 patients .We have tested our system on segmentation for two types of benign, malignant tumor images. The output of the image is compared with the ground truth (target). Ground truth was obtained from the boundary drawings of the radiologist. The segmentation results of 2 different slices from two different patients with benign and malignant tumor images are as shown in Figure 3. From the obtained results, this segmentation algorithm is effectively workable on the acquired CT images. The input data set consists of 100 images: 50 images are benign tumor images, 50 images are malignant tumor images. For each texture analysis methods, input data set is partitioned into training and test sets which are classified using PNN, FFNN classifiers. This section describes the wavelet based texture analysis method of segmenting tumor region from brain CT images.

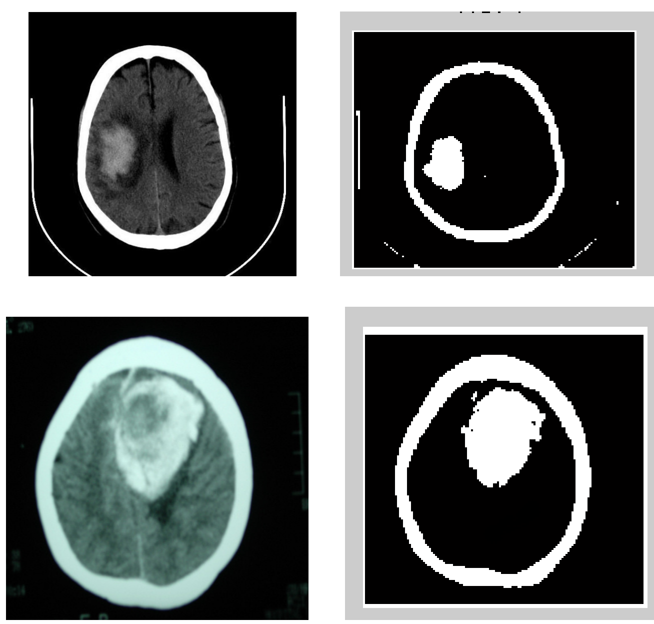

FIGURE: 3 Segmentation of tumor for sample images

There is an outstanding issue associated with the PNN concerning network structure determination (i.e) determining the network size, the number of pattern layer neurons as well as the value of the smoothing parameter. The PNN (trained on 16 extracted features) implemented for classification of the brain CT images had 16 neurons in the input layer for giving 16 extracted features (WST features 1*4 and WCT feature 4*3=12, i.e 4+12=16) as inputs ,50 pattern layer neurons as training set contains 50 feature vectors and one summation layer neuron corresponding to one segmented tumor region, and one decision layer neuron to make a one class Bayesian decision. The objective is to select representative pattern layer neurons from the training samples. The output of a summation layer neuron becomes a linear combination of the outputs of pattern layer neurons. Subsequently, an orthogonal algorithm was used to select pattern layer neurons. The smoothing parameter sigma was determined based on the minimum misclassification rate computed from the partial evaluation data set. The minimum misclassification rate was attained at sigma equal to 0.04.

Feature selection is carried out using GA. There are 9 WCT features are extracted from two level discrete wavelet high frequency sub bands and 3 WST features are extracted from 2 level wavelet transformed low and high frequency sub bands. So totally 9*3+3*4= 39 features are extracted. The next step is to determine the relevance of each selected feature to the process

Parameter used	Wavelet domain	Gray level domain
TP	49	47
FN	48	47
TP	2	4
FN	1	2
Sensitivity in %	98%	95.9%
Specificity in %	96%	92.15%
Accuracy in %	97%	94%

TABLE 4: Classification performances of the PNN classifier for 100 images

of segmenting the tumor region. During the evaluation process by using GA, some features may be selected many times as the number of generation increases. If the feature was selected more times in the feature set that feature was given as more important in the feature selection. The number of times the WCT features selected were energy, entropy, variance and inverse difference moment and WST feature was energy. The parameter set for the GA algorithm is as follows: Population size is 30; Cross Over probability is 1.0; Mutation rate is 0.1; Penalty coefficient is 0.5 and stopping condition is 100 generations.

Parameter used	Wavelet domain	Gray level domain
TP	48	47
FN	47	46
TP	3	4
FN	2	3
Sensitivity in %	96%	94%
Specificity in %	94%	92%
Accuracy in %	95%	93%

TABLE 5: Classification performances of FFNN classifier for 100 images

A comparative study of the classification accuracy was performed for both combined wavelet based texture analysis method and Spatial Gray Level Dependence Matrix method. To justify the choice of using wavelet domain for the same data set, without applying wavelet transform in the gray level domain, the performance of the PNN classifier is as shown in Table 4 and the performance of the FFNN classifier is as shown in Table 5. The accuracy of the PNN, FFNN classifiers in the wavelet domain are 97%,95% and in the gray level domain are 94%, 93% respectively. From the statistical analysis, PNN and FFNN classifiers in wavelet domain have better accuracy compared to the classifiers in gray level domain.

Cross validation method	Classification accuracy of PNN classifier	Classification accuracy of FFNN classifier
3 fold	96%	94%
5 fold	96.6%	94.6%
10 fold	97%	95%

TABLE 6: Classification results of classifiers with different cross validation methods

Table 6 shows the classification performances of the classifiers with different cross validation methods. The accuracy of PNN with 3,5,10 fold cross validation methods are 96%,96.6%,97% and the accuracy of FFNN with 3,5,10 fold cross validation methods are 94%,94.6%,,95% respectively for the same training and testing data sets. Results show that, we get good classification accuracy for the 10 fold cross validation method in both PNN, FFNN classifiers. A comparison is made between the PNN and FFNN classifiers with different texture analysis methods using the performance criteria as the area under the Roc value for detecting and segmenting the tumor region. The results of comparisons are represented using Roc analysis graph as shown in Figure 4 and Figure 5. The AUC values of PNN, FFNN classifier in wavelet domain are 0.974,0.938 and in gray level domain are 0.936,0.928 respectively. From the results, it is observed that the performance of the classifiers in wavelet method is better both quantitatively and qualitatively compared to the classifiers in SGLDM method.

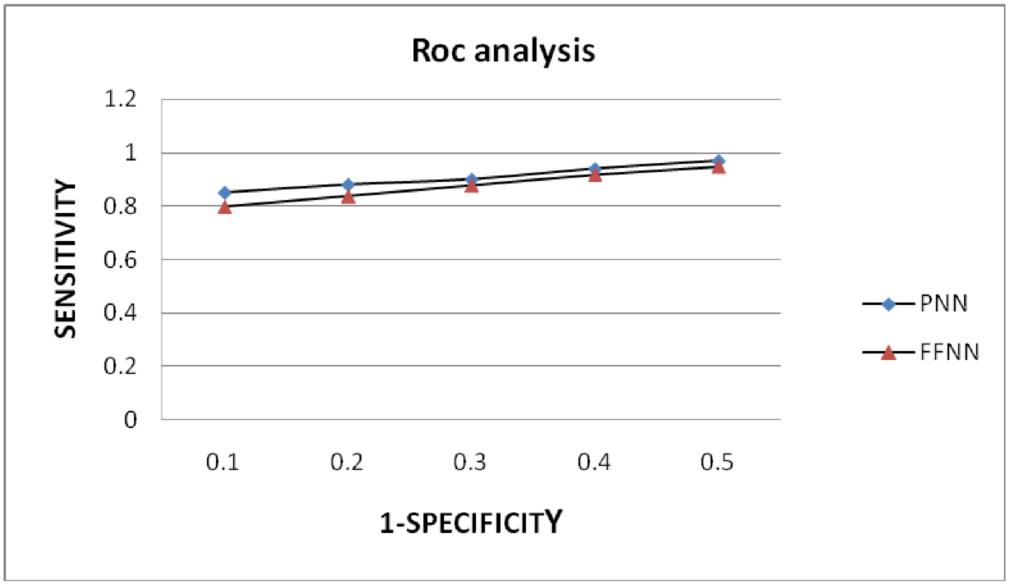

FIGURE 4 : Roc analysis curve of classifiers in wavelet domain

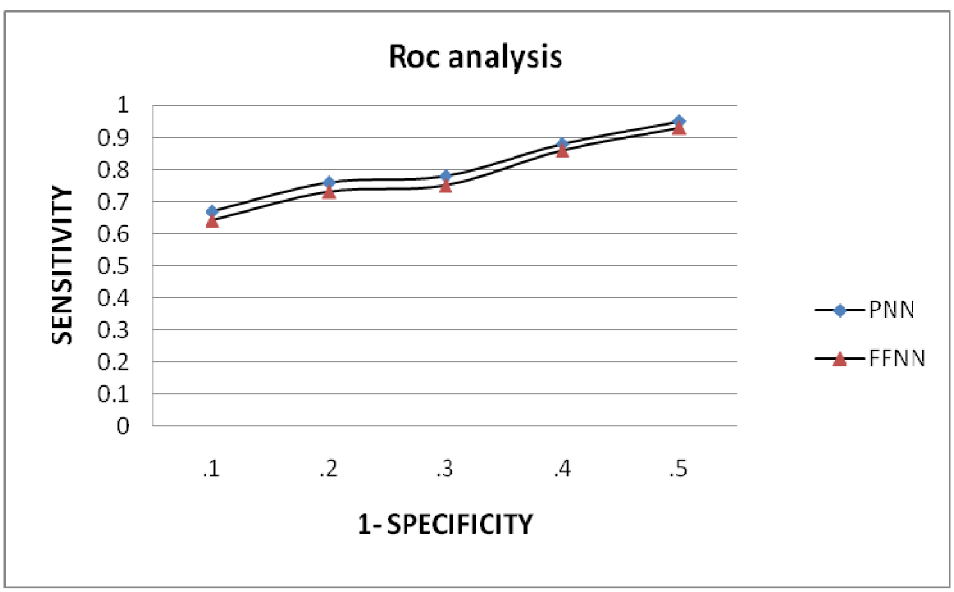

FIGURE 5: ROC analysis curve of classifiers in gray level domain

Table 7 shows the classification performances of our proposed combined technique and SGLDM method. The classification accuracy of our proposed method is 97% is high while compared with the SGLDM method. The proposed system which may be valuable especially in cases of small region of benign, malignant brain tumor images.

SI-NO	Technique	Classification accuracy
1	WT+SGLDM+GA+ PNN	97%
2	SGLDM+GA+PNN	94%
3	WT+SGLDM+GA+FFNN	95%
4	SGLDM+GA+FFNN	93%

TABLE 7: Classification accuracy of the proposed technique

4. DISCUSSION AND CONCLUSION

As a conclusion, we have presented a method for combined WST and WCT based texture feature extraction method and selecting the optimal texture features using GA , and evaluated the PNN, FFNN classifiers to segment the tumor region. The algorithm have been designed based on the concept of different types of brain soft tissues have different textural features. This method effectively works well for segmentation of tumor region with high sensitivity, specificity and accuracy. The results show that the segmentation by the combined feature extraction method yields better results compared to the SGLDM method without using wavelet transform based on the PNN, FFNN classifiers. It is found that this method gives favorable result with accuracy percentage of above 97% for the images that are being considered. This would be highly useful as a diagnostic tool for radiologists in the automated segmentation of tumor region from brain CT images.

The goal of this work is to compare the classification performance of the PNN classifier using combined wavelet feature extraction method and SGLDM method. Hence it is concluded that the neural network supported by conventional image processing operations can be effectively used for segmentation of tumor region from CT images. Use of large data bases is expected to improve the system robustness and ensure the repeatability of the resulted performance. The automation procedure proposed in this work using a PNN enables proper abnormal tumor region detection and segmentation there by saving time and reducing the complexity involved. The proposed system may be particularly useful in small tumor regions, where segmentation of tumor in these two types of brain tumor images is radio logically difficult. The work can be extended to get 100% segmentation accuracy by using other classifiers such as Radial basis function neural network with Particle Swarm Optimization as a future work. The developed segmentation system is expected to provide valuable diagnosis for the physicians.

5. REFERENCES

[1] Duncan J.S.,Ayache N, “Medical Image Analysis Progress Over two decade and challenges ahead”, *IEEE Trans on PAMI* ,Vol 22,pp. 85 – 106,2000.

[2] Tourassi G D, “Journey towards computer aided Diagnosis – Role of Image Texture Analysis*”, Radiology* , Vol 213,pp.317 – 320,1999.

[3] Nathalii Richards, Michael Dujata, Catherine Garbay, ”Distributed Markovian segmentation : Application to MR brain scans”, *Journal of Pattern Recognition* , Vol 40,pp. 3467 – 3478,2007.

[4] Zhang Y, Brady M, Smith S, “Segmentation of Brain MR images through Hidden Markov Random field Model and the expectation maximization algorithm*”, IEEE Transactions on Medical Imaging* , Vol 20,pp. 45-57,2001.

[5] Kaiping Wei, Bin He, Tao Zhang, Xianjun Zhen, "A Novel Method for Segmentation of CT Head Images", *1st International conference on Bioinformatics and Biomedical Engineering; Wuhan: IEEE Explore*; p 717 – 720, 2007 July 6-8.

[6] Dubravko Cosic ,Sven Loncaric, "Rule based labeling of CT head image"; *6th conference on Artificial Intelligence in Medicine, Europe: Springer* ; p.453 – 456, 1997 March 23-26.

[7] Matesn Milan, Loncaric Sven, Petravic Damir, " Rule based approach to stroke lesion analysis from CT brain Images", *2nd International Symposium on Image and Signal Processing and Analysis; Pula, Crotia : IEEE Explore* ; p.219 – 2231, , 2001 June 19-21.

[8] Ruthmann,V.E, Jayce E.M, Reo D.E, Eckardit M.J, "Fully Automated segmentation of cerebrospinal fluid in computed tomography ", *Psychiatry Research : Neuro Imaging* , Vol 50 ,pp. 101 – 119,1993.

[9] Loncaric S and Kova Cevic D, "A Method for segmentation of CT head images", *Lecture Notes on Computer Science* ,Vol 1311,pp.1388 – 305,1997.

[10] Tong Hau Lee, Mohammad Faizal, Ahmad Fauzi and Ryoichi Komiya, " Segmentation of CT brain images using unsupervised clusterings", *Journal of Visualization*, Vol 12,pp.131-138,2009.

[11] Clark M C., Hall L O., Goldgof D B., Velthuzien R., Murtagh F R., and Silbiger M S., "Automatic tumor segmentation using knowledge based techniques", *IEEE Transactions on Medical Imaging*, Vol 17,pp.187-192,1998.

[12] Frank Z. Brill., Donald E. Brown., and Worthy N. Martin, "Fast Genetic Selection of features for Neural Network Classifiers", *IEEE Trans. Neural Networks,* Vol 3,pp. 324-328,1993.

[13] Xiukun Yang., Finger print Smear Detection based on sub band Feature representation. *Eurasip Journal on Advances in Signal processing* , Vol 5,pp. 325-339,2011.

[14] Fausett L, "Fundamentals of Neural Networks: Architectures Algorithms and Applications*", Englewood cliffs, NJ: Prentice Hall* International, p. 289-293,1994.

[15] Van G., Wouver P.,Scheunders and D.Van Dyck, "Statistical texture characterization from discrete wavelet representation*", IEEE Trans. Image processing*,Vol 8,pp.592-598,1999.

[16] Haddon J F, Boyce J F, "Co-occurrence Matrices for Image analysis", *IEE Electronic and Communications Engineering Journa*l , Vol 5,pp. 71 – 83,1993.

[17] Haralick R M, Shanmugam K and Dinstein I, "Texture features for Image classification", *IEEE Transaction on System, Man, Cybernetics* ,Vol 3,pp. 610 – 621,1973.

[18] Tom Fawcett ,"An introduction to ROC analysis", *Pattern Recognition Letters* , Vol 27,pp. 861-874,2006.