CLASSIFICATION AND DETECTION OF BRAIN TUMOR FROM MRI-CT IMAGE USING PNN

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***ABSTRACT* - Brain Tumor is one of the major diseases, cause death among people. So detection tumor in early stage is a best solution. There are over 120 types of brain tumors. The standard method in identifying the brain tumor is done by human inspection on the Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scan images. The scanned images contain a noise caused by operator performance which can lead to serious inaccuracies in classification. In this project from MRI or CT scan results, features like texture & colour is extracted using Discrete Wavelet Transform (DWT) & Gray Level Co-occurrence Matrix in order to detect the visually significant information. After this procedure, the feature goes through a testing phase and a training phase. In the training phase the features are jointly learned by Probabilistic Neural Network in order to classify the tumor tissue, PNN is an un-supervised learning network, which gives the target output in a minimum error rate. In the testing phase, the test vector is matched with the trained vector to classify there by identifying the type of tumor tissue with the minimal error rate.**

***Keywords* - Brain tumor MRI-CT image classification, Probabilistic Neural Networks, Discrete Wavelet Transform, Dimensionality Reduction, and Feature Extraction.**

I.INTRODUCTION

Tumor is an abnormal collection of cells or mass of tissue which is one of the major diseases which cause death among many peoples. It has been classified into many types. In order to treat tumor it must be get identified what type of tumor. Tumor is classified into two major type malignant type and benign type. Usually tumor is classified based on their shape and the colour of the tissue which appear. Detection of the brain tumor in its early stage is the key of its cure. Through some of the symptoms mentioned below we can aware to check for the presence of tumor, through various diagnosing technique. The general symptoms of brain tumor are

1) Headache in early mornings.
2) Gradually loss of movement in leg.
3) Loss of sensation in arm.
4) Loss of vision in one or both eyes.
5) Speech and hearing difficulty.

Based on the diagnosing technique the types of tumor will be got identified and treatment will be given to the patient according to the type of tumor which has been detected. Diagnosing technique like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), Biopsy etc. are there to check the presence of tumor.

But the drawback is they can identify the tumor presence alone but not their types, in order to overcome this problem we have gone for the feature extraction procedure. We are going to take the fused MRI-CT image using averaging method and minimised method and going to apply the image in the feature extraction algorithms by comparing their accuracy levels when applying in Using Discrete Wavelet Transform (DWT) which is used to extract the texture feature in the image and Gray Level Colour Matrix (GLCM) to extract the colour feature in the images, then the extracted features are the jointly learned with Probabilistic Neural Network (PNN) which is one of the unsupervised learning artificial neural network to classify and compare the tumor types.

The block diagram of the system shown in figure I.

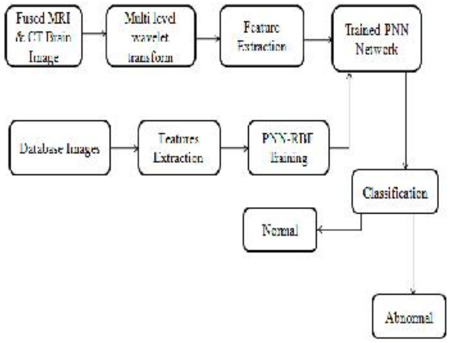

Figure I Block Diagram

II. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a transform for which the wavelets are discretely sampled. This is an implementation of wavelet transform using dyadic scales and positions. It is a mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from Mri-Ct images. Dwt uses sub band coding for image decomposition, haar transform & image pyramid for the edge detection & feature extraction.

A. 2-D Transform Hierarchy:

The 2-D transform can be computed by applying a 1-D transform to all the rows of the input, and then repeating on all of the columns with separable filters. Two Dimensional DWT feature extracted result having four sub bands at each scale. That is below LL (low low), LH (low high), HL (high low), and HH (high high).Sub band LL is the approximation component of the image, which is used for next two dimensional DWT for feature extraction. Whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis respectively. The first level of transform results in LL1, LH1, HL1, and HH1.The LL1 information is further decomposed into LL2, LH2, HL2, HH2 at the second level, and the information of LL2 is used for the third level transform. This process is continued up to fourth level transform. Based on literature study Haar wavelet is considered as the best among the other wavelet for image application. In DWT sub band coding is the process of decomposing the image pixel matrix into two levels based on the high level and low level.

B. Haar Transform

In haar wavelet, the basic idea is to transfer the image in to a matrix represents a pixel in to the image. Haar wavelet decomposes the image into approximation (A), horizontal detail (H), vertical detail (V) and diagonal detail (D). Haar wavelet that maps an integer-valued pixel onto another integer-valued pixel is suggested. Haar coefficient requires only two bytes to store each of the extracted coefficients. The cancellation of the division in subtraction results avoids the usage of decimal numbers while preserving the difference between two adjacent pixels. It is used to find the energy feature of the images.

The equation of Haar transform is,

$B_n = H_n A_n H_n^T$

Where, A_n is represented as n×n matrix and H_n is represented as n-point Haar transform

The Haar functions are,

$$h_k(z) \equiv h_{pq}(z) = \frac{1}{\sqrt{L}} \begin{cases} 2^{\frac{p}{2}} & \frac{q-1}{2^p} \le z < \frac{q-1}{2^p} \\ -2^{\frac{p}{2}} & \frac{q-1}{2^p} \le z < \frac{q}{2^p} \\ 0 & otherwise\, in\, [0,1] \end{cases}$$

$K=2^p=q-1$, $k=0, 1\ldots\ldots, L-1$, and $l=L=2^n$

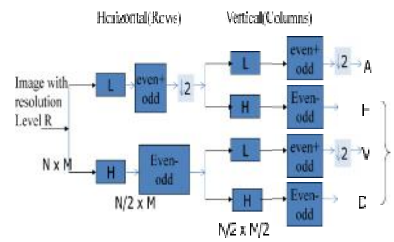

Figure II. Block diagram of DWT

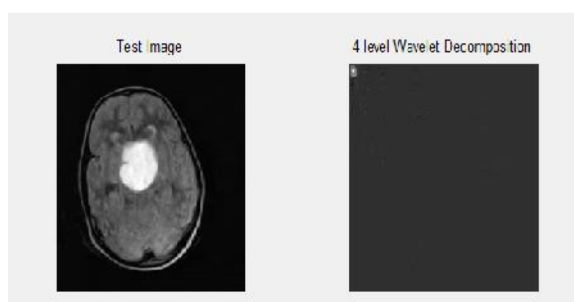

Figure III. Output Image Of The DWT

III. Gray Level Co-Occurrence Matrix

GLCM is a statistical approach it describes the spatial relationship between pixels of different gray levels. GLCM is a two dimensional histogram. The element can be represent as (i, j) where i and j is a predefined as distance and angle. Haralick produced such a texture feature based on the orientation and distance between image pixels.

GLCM is mainly used for texture analysis method. Thus texture features are: contrast, correlation, energy, homogeneity, entropy. They are obtained by LH and HL sub band coding of wavelet decomposition.

Contrast: It concentrates the main diagonal near the moment of inertia. It calculates the local variation in the GLCM matrix, it can be expressed as

$$\sum_{i,j}(i-j)^2 P_{d,\theta}(i,j)$$

It reflects the image clarity and texture of shadow depth.

Correlation: It calculates the pixel degree of correlation has to its neighbour over the entire image.

$$\sum_{i,j}\frac{(i-\mu_x)(j-\mu_y)P_{d,\theta}(i,j)}{\sigma_x\sigma_y}$$

Energy: Energy is an angular second order moment returns the sum of squared elements in the GLCM. It is a gray-scale image texture measure od changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\sum_{i,j}(P_{d,\theta}(i,j))^2$$

Homogeneity: It calculates the distribution of elements in gray level co-occurrence matrix to the gray level co-occurrence matrix diagonal

$$\sum_{i,j}\frac{P_{d,\theta}(i,j)}{1+|i-j\|}$$

Entropy: Entropy measures image texture randomness; here the space co-occurrence matrix values are equal, when it achieved minimum value

$$\sum_{i,j}P_{d,\theta}(i,j)\log_2[(P_{d,\theta}(i,j)]$$

Pixels with gray level j. μx, μy are mean values of $P_{d,\Theta}$.σ_x, σ_y are the standard deviations of $P_{d,\Theta}$. Here $P_{d,\Theta}$ (i, j) is an to be a probability of finding a pixel with gray level i at a distance d , angle Θ.

A.REGIONPROPS FUNCTIONS:

It is used measured the image properties. Some properties are measured without using the function. It computes all the shape measurements.

Area: It is the actual number of pixels in the region

Eccentricity: it specifies the eccentricity of the ellipse that has the same second moments as the region.

Perimeter: the distance around the boundary of the region. it computes the perimeter by calculating the distance between every adjoining pair of pixels among the border of the region.

Solidity: It specifying the proportion of the pixels in the convex hull that are also in the region.

These features are further given into the PNN classifier. In a PNN classifier is used for training and testing the performance of the fused MRI-CT brain images into a normal brain tumors or malignant.

IV. Probabilistic Neural Network

It is also called as feed forward neural network.PNN is a radial basis neural network, when it provides general solution to pattern classification problems by a statistics approach is called as Bayesian classifiers. It is a job to implement an automatic fused MRI-CT image classification of brain tumors into normal and abnormal. It consist of three layers, they are input layer, hidden layer (radial basis layer), output layer.

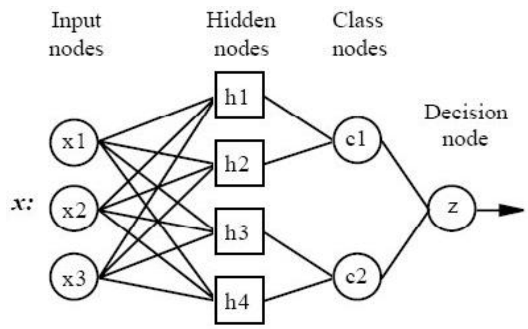

Figure IV. The Architecture Of PNN

In a PNN, hidden layer evaluates vector distances in weight matrix between input vectors and row weight vectors. Weight matrix vector distances are scaled by PNN nonlinearly. Each input vector in the training set corresponding for the pattern layer processing element. There should be an equal number of processing element in each output else a some classes may be sloped falsely leading to the poor classification results. Only once the processing elements of patter layers are trained. If there is no relationship between input layers into pattern layer, then the output cannot be generated. The PNN is much simpler then compare to feed forward back propagation network.PNN is a fast training process.it has an inherently parallel structure.PNN learns quickly then compare to other neural networks. It is a capable of using it in pattern recognition and system classification. The probability can be measured as

$$f_q(X) = \frac{1}{(2\pi)^{p}/_{2}\sigma^p}\frac{1}{N_q}\sum_{i=1}^{N_q}\exp\left[\frac{-(x-x_i^q)^T(x-x_i^q)}{2\sigma^2}\right]$$

P is the dimension of the pattern vector x

Nq is the samples number of category q

x_i^q is the i-th pattern sample from category q

σ is the smoothing factor.

The PNN algorithm was implemented using matlab

V. Result And Discussion

Brain tumor is most curable and treatable if identified in the earliest stages of the disease. Untreated or advanced brain tumor can only spread inward because the skull will not let the brain tumor expand outward. It puts excessive pressure on the brain and it can cause permanent brain damage and eventually death. But the algorithm designed in this method helps in classifying cancerous and non cancerous brain tumors automatically by the PNN classifier, using the statistical texture features extracted by DWT and GLCM. From the literature survey, it is found that the directional features extracted from LH and HL sub bands of the discrete wavelet transform, which gives information among the horizontal and vertical directions respectively, they are more efficient at characterizing changes in the tumor tissues.

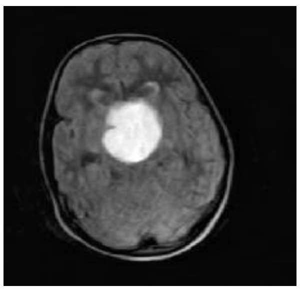

Figure V. Fused MRI-CT Benign Image

Figure VI. Fused MRI-CT malignant image

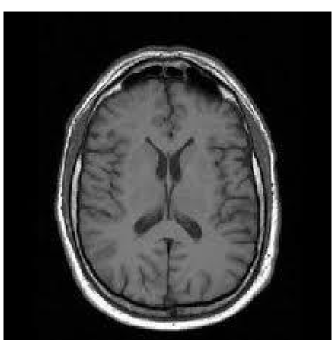

Figure VII. Fused MRI-CT normal image

Table I. Statistical Texture Features Obtained From GLCM Of LH3 And Hl3 Sub Bands Of A Normal Fused MRI-CT Images

Sub bands	Energy	Contrast	correlation	Homogeneity	Entropy
LH1	0.0000	0.0000	0.0000	0.0000	0.0000
HL1	0.9000	0.5922	1.4069	1.0163	1.1056
LH2	0.0000	0.0000	0.0000	0.0000	0.0000
HL2	0.0001	0.0001	0.0000	0.0000	0.0000
LH3	0.0004	0.0004	0.0005	0.0005	0.0006
HL3	0.0070	0.0001	0.0003	0.0002	0.0001
LH4	0.0062	0	0.0005	0.0002	0
HL4	0.0001	0.0001	0.0001	0.0001	0.0001
LH5	0.0000	0	0.0001	0.0001	0
HL5	0.0032	0.0025	0.0065	0.0049	0.0060

Table II. Statistical Texture Features Obtained From GLCM of LH3 And Hl3 Sub Bands Of A Benign Fused MRI-CT Images

Sub bands	Energy	Contrast	Correlation	Homogeneity	Entropy
LH1	0.0000	0.0000	0.0000	0.0000	0.0000
HL1	0.7293	0.3104	0.6043	0.9729	0.4707
LH2	0.0000	0.0001	0.0000	0.0000	0.0000
HL2	0.0000	0.0001	0.0000	0.0000	0.0000
LH3	0.0006	0.0004	0.0005	0.0005	0.0005
HL3	0.0011	0.0002	0.0115	0.0005	0.0002
LH4	0.0020	0.0002	0.0106	0.0005	0.0002
HL4	0.0001	0.0001	0.0001	0.0001	0.0001
LH5	0.0001	0.0001	0.0000	0.0001	0.0001
HL5	0.0044	0.0027	0.0040	0.0052	0.0025

Table III. Statistical Texture Features Obtained From GLCM of LH3 And Hl3 Sub Bands Of A Benign Fused MRI-CT Images

Sub bands	Energy	Contrast	Correlation	Homogeneity	Entropy
LH1	0.0000	0.0000	0.0000	0.0000	0.0000
HL1	1.6608	1.1725	1.0382	0.6565	0.5104
LH2	0.0000	0.0000	0.0000	0.0000	0.0000
HL2	0.0000	0.0000	0.0000	0.0000	0.0001
LH3	0.0005	0.0005	0.0006	0.0005	0.0004
HL3	0.0121	0.0113	0.0122	0.0099	0.0078
LH4	0.0086	0.0119	0.0100	0.0065	0.0059
HL4	0.0001	0.0001	0.0001	0.0001	0.0001
LH5	0.0000	0.0000	0.0001	0.0001	0.0001
HL5	0.0067	0.0050	0.0053	0.0031	0.0032

The fused MRI-CT brain images are decomposed into four levels using discrete wavelet transform. The detailed coefficients from LH and HL sub bands were chosen. From the sub bands obtained from wavelet decomposition, Gray Level Co occurrence Matrices have been formed and the statistical texture features such as energy, contrast, correlation, homogeneity and entropy, were extracted. When it has can be observed that the texture features to training them into the PNN classifier. Therefore, the texture features of discrete wavelet transform decomposition has been taken into consideration and were used as input vectors for training and testing the performance of the PNN classifier. Tables 1, 2 & 3, are the statistical texture features of the GLCM from LH3 and HL3 sub bands of all the above levels for a normal and abnormal fused MRI-CT image respectively.

It was observed that the entropy of the malignant fused MRI-CT image is found to be more than the benign and normal image. Here, the homogeneity is found to be less in malignant image compared to benign and normal image. Similarly, the energy also called as angular second moment is also found to be less in malignant MR image compared to benign and normal image. The proposed method, with the help of the texture statistics obtained from LH3 and HL3 sub bands, is able to classify brain tumor into benign and malignant. The differences in the statistical feature values of normal, benign and malignant brain tumors are found to calculating the performance of the PNN classifier in training and testing.

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. This method of brain tumor classification has been performed on various normal, benign and malignant real MR images and the specificity, sensitivity and accuracy of the PNN classifier has been calculated, using the equations given below.

$$\text{Specificity} = \frac{\text{true negatives}}{\text{true negatives}+\text{false positives}} \times 100$$

$$\text{Sensitivity} = \frac{true\ positives}{true\ positives+false\ negatives} \times 100$$

$$\text{Accuracy} = \frac{correct\ cases}{total} \times 100$$

VI. Conclusion

In this paper, brain tumor type is identified, based on the combination of DWT, GLCM and PNN. Based on this algorithm an effective procedure on brain tumour classification has been constructed. This pursued method will detect as well as classify the fused MRI-CT image. The ability of our method demonstrated the results obtained from Brain Tumor image database with a accuracy level of nearly 100%. If a new type is detected in the sense then it is added to the database. The result from this method is fast and with a best accuracy level than any other methods.

VII. Acknowledgment

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