Brain Tumor Classification Using Wavelet and Texture Based Neural Network

Pauline John

Abstract— Brain tumor is one of the major causes of death among people. It is evident that the chances of survival can be increased if the tumor is detected and classified correctly at its early stage. Conventional methods involve invasive techniques such as biopsy, lumbar puncture and spinal tap method, to detect and classify brain tumors into benign (non cancerous) and malignant (cancerous). A computer aided diagnosis algorithm has been designed so as to increase the accuracy of brain tumor detection and classification, and thereby replace conventional invasive and time consuming techniques. This paper introduces an efficient method of brain tumor classification, where, the real Magnetic Resonance (MR) images are classified into normal, non cancerous (benign) brain tumor and cancerous (malignant) brain tumor. The proposed method follows three steps, (1) wavelet decomposition, (2) textural feature extraction and (3) classification. Discrete Wavelet Transform is first employed using Daubechies wavelet (db4), 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 texture statistics such as energy, contrast, correlation, homogeneity and entropy are obtained. The results of co-occurrence matrices are then fed into a probabilistic neural network for further classification and tumor detection. The proposed method has been applied on real MR images, and the accuracy of classification using probabilistic neural network is found to be nearly 100%.

Index Terms— Brain tumors, Classification, Feature extraction, Gray level co occurrence matrix, Probabilistic neural network, Texture analysis, Wavelet decomposition.

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1 INTRODUCTION

B RAIN tumor is any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Its threat level depends on a combination of factors like the type of tumor, its location, its size and its state of development. Brain tumors can be cancerous (malignant) or non cancerous (benign). Benign brain tumors are low grade, non cancerous brain tumors, which, grow slowly and push aside normal tissue but do not invade the surrounding normal tissue. They are homogeneous, demarcated, well defined and are known as non- metastatic tumors, because they do not form any secondary tumor. Whereas, malignant brain tumors are cancerous brain tumors, which grow rapidly and invade the surrounding normal tissue. They are heterogeneous, not well defined, grow in a disorganized manner and are known as metastatic tumors, because they initiate growth of similar tumors in distant organs. Malignant brain tumors (or) cancerous brain tumors can be counted among the most deadly diseases.

According to the World Health Organization, brain tumor can be classified into the following groups:
Grade I: Pilocytic or benign, slow growing, with well defined borders.

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Grade II: Astrocytoma, slow growing, rarely spreads with a well defined border.
Grade III: Anaplastic Astrocytoma, grows faster.
Grade IV: Glioblastoma Multiforme, malignant most invasive, spreads to nearby tissues and grows rapidly.

Many diagnostic imaging techniques can be performed for the early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Compared to all other imaging techniques, MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non invasive technique.

Although MRI seems to be efficient in providing information regarding the location and size of tumors, it is unable to classify tumor types, hence the application of invasive techniques such as biopsy and spinal tap method, which are painful and time consuming methods [7]. Biopsy technique is performed where, the surgeon makes a small incision in the scalp and drills a small hole, called a burr hole, into the skull and passes a needle through the burr hole and removes a sample of tissue from the brain tumor, to check for cancerous cells (Or) the spinal tap method, where the doctor may remove a sample of cerebrospinal fluid and check for the presence of cancerous cells. This inability related to invasive technique requires development of new analysis techniques that aim at improving diagnostic ability of MR images. Hence, a wavelet and texture based neural network method is proposed in order to classify the MR images into normal,

benign and malignant brain tumor images non-invasively, thereby, prevent the intervention of invasive techniques such as biopsy, spinal tap or lumbar puncture method.

According to the literature study, Mohd Fauzi Bin Othman, Noramalina Bt Abdullah [13] in 2011, performed classification of brain tumor using wavelet based feature extraction method and Support Vector Machine (SVM). Feature extraction was carried out using Daubechies (db4) wavelet and the approximation coefficients of MR brain images were used as feature vector for classification. Accuracy of only 65% was obtained, where, only 39 images were successfully classified from 60 images. It was concluded that classification using Support Vector Machine resulted in a limited precision, since it cannot work accurately for a large data due to training complexity.

Whereas, in 2011, Mohd Fauzi Othman and Mohd Ariffanan Mohd Basri [14], presented their work on, Probabilistic Neural Network (PNN) for brain tumor classification. This paper introduces the brain tumor classification using Principal Component Analysis for feature extraction and PNN for classification. They concluded that PNN is a promising tool for brain tumor classification, based on its fast speed and its accuracy which ranges from 73 to 100% for spread values (smoothing factor) from 1 to 3. Hence in this research work, PNN has been used for classifying brain tumors, since it is considered to be superior over SVM and other neural networks in terms of its accuracy in classification.

Classification of brain MRI using the LH and HL wavelet transform sub-bands was performed by Salim Lahmiri and Mounir Boukadoum [18], in 2011. This 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. In 2010, Ahmed kharrat, Karim Gasmi, Mohamed Ben Messaoud [1], presented their work on A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and SVM. This paper proposes a genetic algorithm and SVM based classification of brain tumor. It is concluded that, Gabor filters are poor due to their lack of orthogonality that results in redundant features at different scales or channels. While Wavelet

Transform is capable of representing textures at the most suitable scale, by varying the spatial resolution and there is also a wide range of choices for the wavelet function.
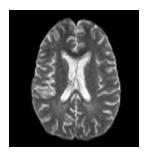
Ahmed Kharrat, Mohamed Ben Messaoud, Nacera Benamrane, Mohamed Abid [2], in 2009, proposed their work on, Detection of Brain Tumors in Medical Images. This paper proposes contrast enhancement using mathematical morphology algorithm, segmentation by wavelet transform and classification using K-means algorithm, for an efficient detection of brain tumor from cerebral MR images. Their future work is to classify brain tumors into benign and malignant brain tumors.

From the literature survey, firstly, it can be concluded that, various research works have been performed in classifying MR brain images into normal and abnormal [1], [2]. Whereas, classifying MR brain images into normal, cancerous and non cancerous brain tumors in particular, is a crucial task, which is considered in this proposed method. Secondly, it is found that existing methods of brain tumor diagnosis and classification involve invasive techniques such as biopsy and spinal tap method [7]. It is essential to prevent and replace the invasive methods of brain tumor classification using a non invasive method of brain tumor diagnosis, which has been focused in this method. Thirdly, 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 [3], [15]. Fourthly, Statistical texture analysis techniques are constantly being refined by researchers and the range of applications is increasing [17], [18], [20]. Gray level co-occurrence matrix method is considered to be one of the important texture analysis techniques used for obtaining statistical properties for further classification, which is employed in this research work. Fifthly, Probabilistic Neural Network is found to be superior over other conventional neural networks such as Support Vector Machine and Back propagation Neural Network in terms of its accuracy in classifying brain tumors [13]. Hence a wavelet and co occurrence matrix method based texture feature extraction and Probabilistic Neural Network for classification has been used in this method of brain tumor classification.

2 PROCEDURE

Proposed method of brain tumor classification is outlined in Fig. 1.

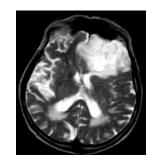Fig. 1. Brain Tumor Classification Process.

2.1 Input Data Set

For the implementation of the proposed method of brain tumor classification, normal and brain tumor (benign and malignant) T2 weighted axial plane Magnetic Resonance images in DICOM format were collected from the patients of National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore. Figure 2(a), (b) and (c), shows the T2 weighted Magnetic Resonance image database considered for the implementation of textural feature extraction and classification.

The collected T2 weighted Magnetic Resonance images are categorized into three distinct classes with each as normal, benign brain tumors and malignant brain tumors, as shown in figure 2(a), (b) and (c) respectively.

(a)   (b)

(c)

Fig. 2 (a). Normal, 2(b) Benign and 2(c) Malignant

2.2 Discrete Wavelet Decomposition

The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MR images. Discrete Wavelet Transform is an implementation of the WT using the dyadic scales and positions. The basic fundamental principle of DWT is introduced as follows:

Suppose x (t) is a square-integrable function, then the continuous WT of x (t) relative to a given wavelet Ψ (t) is defined as,

$$W_{\Psi(a,b)} = \int_{-\infty}^{\infty} x(t)\Psi_{a,b}(t)dt \qquad (1)$$

Where, the wavelet $\Psi_{a,b}(t)$ is calculated from the mother wavelet Ψ (t) by dilation and translation factor a and b respectively, which are real positive numbers.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-a}{b}\right) \qquad (2)$$

Equation (1) can be discretized by restraining a and b to a discrete lattice (a=2^b and a > 0) to give the discrete wavelet transform, which can be expressed as,

$$a_{j,k}(n) = DS\left[\sum_n x(n)g_j^*(n - 2^j k)\right] \qquad (3)$$

$$d_{j,k}(n) = DS\left[\sum_n x(n)g_j^*(n - 2^j k)\right] \qquad (4)$$

Where, the coefficients $a_{j,k}$ and $d_{j,k}$ refer to the approximate and detail components, respectively. The functions g (n) and h (n) denote the coefficients of the low-pass and high-pass filter, respectively. The subscripts j and k represent the wavelet scale and translation factors, respectively. The DS operator is used for down sampling. Two dimensional DWT results in four sub bands LL (low-low), LH (low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the

image, which is used for next two dimensional DWT. Whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis, respectively, as shown in the figure 3.
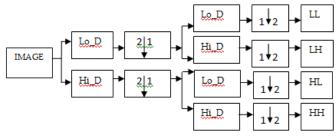

Fig. 3. 2D Discrete Wavelet Transform

Lo_D – Low Pass Filter
Ho_D – High Pass Filter

2↓1	- Down sampling columns: keeps the even indexed columns.
1↓2	- Down sampling rows: keeps the even indexed rows.

Based on the literature study, Daubechies wavelet is considered as the best among the other wavelets for image application and LH, HL sub-bands had higher performance compared to the features from LL sub band. Hence in this method, a five level decomposition using daubechies wavelet was computed and the features were extracted from LH and HL sub bands formed using DWT.

2.3 Texture Feature Extraction

Texture analysis makes differentiation of normal and abnormal tissue easy. It even provides contrast between malignant and normal tissue, which may be below the threshold of human perception. Texture analysis using computer aided diagnosis can be used to replace biopsy techniques and plays an important role in early diagnosis and tracking of diseases. In first-order statistical texture analysis, information on texture is extracted from the histogram of image intensity. This approach measures the frequency of a particular grey-level at a random image position and does not take into account correlations, or co-occurrences, between pixels. In second-order statistical texture analysis, information on texture is based on the probability of finding a pair of gray-levels at random distances and orientations over an entire image.

The statistical features from MR images are obtained using Gray Level Co-occurrence Matrix (GLCM), which is also known as Gray Level Spatial Dependence Matrix (GLSDM). GLCM, introduced by Haralick is a statistical approach that can well describe the spatial relationship between pixels of different gray levels [17], [20].

GLCM is a two dimensional histogram in which (i, j)[th] element is the frequency of event i that occurs with j. It is a function of distance d=1, angle θ (at 0° (horizontal), 45° (along the positive diagonal), 90° (vertical) and 135° (along

the negative diagonal) and gray scales i and j, thereby, calculates how often a pixel with intensity i, occurs in relation with another pixel j at a certain distance d and orientation θ. In this method, Gray level co-occurrence matrix was formed and the statistical texture features such as contrast, correlation, energy, homogeneity and entropy were obtained from the LH and HL sub bands of the first five levels of wavelet decomposition.

The statistical texture features taken into consideration are as follows:

Contrast: Measures the local variation in the gray level co-occurrence matrix, which can be calculated as,

$$\sum_{i,j}(i-j)^2 P_{d,\theta}(i,j) \tag{5}$$

Correlation: Measures the degree of correlation a pixel has to its neighbor over the whole image. Its range is [-1 1].

$$\sum_{i,j}\frac{(i-\mu_x)(j-\mu_y)P_{d,\theta}(i,j)}{\sigma_x\sigma_y} \tag{6}$$

Energy: Uniformity (or) Angular Second Moment, returns the sum of squared elements in the gray level co-occurrence matrix. Its range is [0 1].

$$\sum_{i,j}(P_{d,\theta}(i,j))^2 \tag{7}$$

Homogeneity: or the Inverse Differential Moment, returns a value that measures the closeness of the distribution of elements in gray level co-occurrence matrix to the gray level co-occurrence matrix diagonal. Its range is [0 1].

$$\sum_{i,j}\frac{P_{d,\theta}(i,j)}{1+|i-j|} \tag{8}$$

Entropy: or Disorder

$$\sum_{i,j}P_{d,\theta}(i,j)\log_2[(P_{d,\theta}(i,j)] \tag{9}$$

Where, $P_{d,\theta}$ (i, j) is the probability of finding a pixel with gray level i at a distance d and angle θ from a pixel with gray level j, and μ_x, μ_y and σ_x, σ_y are the mean and standard deviations of $P_{d,\theta}$ respectively. These statistical features can be further fed to the PNN classifier for training and testing the performance of the classifier in classifying the brain MR images into normal, benign and malignant brain tumors.

2.4 Classification

Probabilistic Neural Network (PNN) is a Radial Basis Neural Network, which provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers. It is employed to implement an automatic MR image classification of brain tumors into normal, benign and malignant.

Probabilistic Neural Network has three layers, as shown in fig.4, the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.
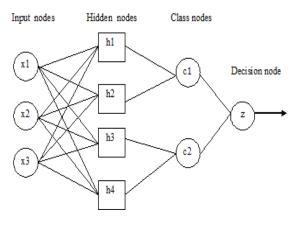

Fig 4. Architecture of a Probabilistic Neural Network

A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. The main advantages that discriminate PNN are, its fast training process, an inherently parallel structure, guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. Accordingly, a PNN learns more quickly than many neural networks model and have had success on a variety of applications [5]. Based on these facts and advantages, PNN can be viewed as a supervised neural network that is capable of using it in system classification and pattern recognition. The probability can be estimated using the formula,

$$f_q(X) = \frac{1}{(2\pi)^{P/2}\sigma^P}\frac{1}{N_q}\sum_{i=1}^{N_q}\exp\left[\frac{-(X-X_i^q)^T(X-X_i^q)}{2\sigma^2}\right] \tag{10}$$

P denotes the dimension of the pattern vector X
N_q is the samples number of category q
X_i^q is the i-th pattern sample from category q and
σ is the smoothing factor or the width of the Gaussian function. The algorithm was implemented using MATLAB software package.

3 RESULTS AND DISCUSSION

Brain cancer is most treatable and curable if caught in the earliest stages of the disease. Untreated or advanced brain cancer can only spread inward because the skull will not let the brain tumor expand outward. This puts excessive pressure on the brain, causing increased intracranial pressure and can cause permanent brain damage and eventually death. Only invasive techniques such as biopsy and spinal tap methods can determine whether the brain tumor is cancerous or non cancerous. 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 wavelet and co occurrence matrices.

Due to the fact that regularity increases with the order of the wavelet, db4 is chosen for decomposing the image.

From the literature study, it is found that the directional features extracted from LH and HL sub bands of the wavelet transform, which gives information along the horizontal and vertical directions respectively, are more efficient at characterizing changes in the biological tissue [11].

TABLE 1

STATISTICAL TEXTURE FEATURES OBTAINED FROM GLCM (GRAY LEVEL CO OCCURRENCE MATRIX) OF (1st, 2nd, 3rd, 4th & 5th LEVEL) LH & HL SUB BANDS OF A NORMAL MR IMAGE.

SUB BANDS	ENERGY	CONTRAST	CORRELATION	HOMOGENEITY	ENTROPY
LH1	0.6315	2.5288	0.4782	0.8719	1.8388
HL1	0.5190	44.7793	-0.0349	0.7825	2.5421
LH2	0.5794	128.1138	0.4429	0.7997	2.6785
HL2	0.5321	588.0337	0.0012	0.8719	2.9881
LH3	0.0005	1.6904	0.0003	0.0008	0.0029
HL3	0.0005	2.6366	0.0001	0.0007	0.0030
LH4	0.0006	2.6304	0.0003	0.0008	0.0024
HL4	0.0005	7.7530	0.0001	0.0007	0.0027
LH5	0.0004	4.0101	0.0005	0.0007	0.0031
HL5	0.0003	7.6326	0.0001	0.0006	0.0032

TABLE 2

STATISTICAL TEXTURE FEATURES OBTAINED FROM GLCM (GRAY LEVEL CO OCCURRENCE MATRIX) OF (1st, 2nd, 3rd, 4th & 5th LEVEL) LH & HL SUB BANDS OF A BENIGN MR IMAGE.

SUB BANDS	ENERGY	CONTRAST	CORRELATION	HOMOGENEITY	ENTROPY
LH1	0.3535	19.9697	0.4559	0.7480	3.1137
HL1	0.2976	85.9331	0.0089	0.6881	3.4358
LH2	0.3008	320.2413	0.5408	0.6780	4.0389
HL2	0.0003	1.2921	0.0000	0.0007	0.0043
LH3	0.0003	1.7241	0.0003	0.0007	0.0040
HL3	0.0002	4.5909	0.0000	0.0006	0.0045
LH4	0.0002	3.8531	0.0004	0.0006	0.0044
HL4	0.0002	5.9702	0.0002	0.0006	0.0043
LH5	0.0002	7.3489	0.0003	0.0005	0.0045
HL5	0.0002	9.9897	0.0000	0.0005	0.0046

The real MR brain images have been decomposed into five levels using Daubechies wavelet of the order 4. 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. It has been observed that the texture

features of 1st, 2nd and 3rd levels were too large for training the PNN classifier. Therefore, the texture features of the 4th and 5th levels of wavelet decomposition has been taken into consideration and were used as input vectors for training and testing the performance of the PNN classifier.

TABLE 3

STATISTICAL TEXTURE FEATURES OBTAINED FROM GLCM (GRAY LEVEL CO OCCURRENCE MATRIX) OF (1st, 2nd, 3rd, 4th & 5th LEVEL) LH & HL SUB BANDS OF A MALIGNANT MR IMAGE.

SUB BANDS	ENERGY	CONTRAST	CORRELATION	HOMOGENEITY	ENTROPY
LH1	0.3078	9.6659	0.5160	0.7174	3.7161
HL1	0.2520	15.7194	-0.0816	0.6646	3.4083
LH2	0.2235	373.4352	0.4172	0.5662	5.3947
HL2	0.1436	590.2047	-0.0809	0.7174	5.4892
LH3	0.0002	3.4852	0.0003	0.0005	0.0057
HL3	0.0001	4.5499	-0.0001	0.0004	0.0062
LH4	0.0001	8.7649	0.0003	0.0005	0.0056
HL4	0.0000	1.0561	0.0000	0.0000	0.0006
LH5	0.0001	8.7637	0.0003	0.0004	0.0052
HL5	0.0000	1.5162	0.0000	0.0000	0.0005

Tables 1, 2 & 3, are the statistical texture features such as energy, contrast, correlation, homogeneity and entropy of the gray level co-occurrence matrices formed from LH and HL sub bands of all the 5 levels for a normal, benign and malignant MR image respectively.

It was observed that the entropy or the disorder of the malignant MR image is found to be more than the benign and normal image. Whereas, the homogeneity or the inverse difference moment is found to be less in malignant image compared to benign and normal image. Similarly, the energy or uniformity, 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 (energy, contrast, correlation, homogeneity and entropy) obtained from LH and HL 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 be useful in 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.

$$Specificity(\%) = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \times 100 \qquad (11)$$

$$Sensitiviy(\%) = \frac{True\ Positives}{True\ Positives + False\ Negatives} \times 100 \qquad (12)$$

$$Accuracy(\%) = \frac{Correct\ cases}{Total} \times 100 \qquad (13)$$

4 CONCLUSION

This paper presents an efficient method of classifying MR brain images into normal, benign and malignant tumor, using a probabilistic neural network. The proposed approach gives very promising results in classifying MR images. Most of the existing methods can detect and classify MR brain images only into normal and abnormal [2]. Whereas, the proposed method, with the help of the texture statistics obtained from LH and HL sub bands, is able to classify brain tumor into benign and malignant. The percentage of accuracy of classification using PNN is found to be nearly 100 %, when the spread value is set to 1. Based on the experimental results, PNN is considered to have major advantages over conventional neural networks, due to the fact that PNN learns from the training data instantaneously. This speed of learning gives the PNN the capability of adapting its learning in real time. This method of automatic early detection and classification of MR brain images into normal, benign and malignant, based on their statistical texture features, not only replaces conventional

invasive techniques, but also helps in reducing the fatality rate.

FUTURE WORK

Future work would deal with classification of brain tumors into different grades by using advanced texture analysis methods, so that the yield of brain tumor diagnosis can be increased.

ACKNOWLEDGMENT

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