Classification of Brain MRI Based on LH and HL Sub-bands of Wavelet Transform

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Abstract—Automated classification of brain MRI is important for the analysis of tumor. In this paper, magnetic resonance imaging (MRI) is considered to solve the problem of automatic classification of brain images. It presents the classification system with three stages. It consists of discrete wavelet decomposition of the image, texture feature extraction from the LH and HL sub bands and final classification by probabilistic neural network (PNN). It shows that the horizontal (LH) and vertical (HL) sub bands of the wavelet transform gives higher performance compared to LL sub band. It can effectively encode the discriminating features of normal and abnormal images.

Keywords—MRI, DWT, texture feature, PNN

I. INTRODUCTION

Brain tumor is an uncharacteristic growth of cells within the brain and it is one of the major causes of death among people. Early detection and classification of brain tumor is very important in clinical practice. For the early detection of brain tumors many diagnostic imaging techniques can be performed such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [2]. Compared to all other imaging techniques MRI is efficient in the application of brain tumor detection and identification because of its high contrast of soft tissues and its high spatial resolution. [2][4] MRI does not produce any harmful radiation. Many researchers have proposed different techniques for the classification of brain tumors based on various sources of information. Brain tumor is any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Brain tumors can be cancerous or non-cancerous. [5] Benign (primary) brain tumors are low grade non-cancerous tumors which grow slowly. Malignant brain tumor is cancerous tumor. This paper proposes a classification system for brain MRIs. This paper organized in five sections, section 1 gives introduction. Section 2 describes literature review. In Section 3 Methodology of system. Section 4 gives the results. Finally, Section 5 concludes the paper.

II. LITERATURE SURVEY

Various research works have been done in classifying MR brain images into normal and abnormal. Classification of brain MRI into normal, primary and secondary brain tumors is a crucial task, which is considered in this method. Mohd Fauzi et al. [6] performed classification of brain tumor using wavelet based extraction of feature and Support Vector Machine (SVM). SVM is used to classify in two classes. It was concluded that classification result using support vector machine is in a limited correctness, since it cannot work accurately for a large data due to training complexity. It gives less accuracy about the input image. Ahmed kharrat et al. [7] presented their work on an automatic classification of brain MRI using genetic algorithm and SVM. It is concluded that, Gabor filters are poor due to their lack of orthogonally that results in redundant features at different scales or channels. Therefore wavelet transform and GLCM are capable of representing textures at the most suitable scale. In paper proposed by Alan Jose it was suggested to do clustering for segmenting tumor and to use fuzzy c-means algorithms for area calculation.
Hu et al., [8] proposed a technique to classify cancer using super unsupervised learning methods and K-means clustering methods were used. 76.50% classification rate is obtained using neural network techniques.

III. METHODOLOGY

The system consists of a) Discrete Wavelet transform b) Texture feature extraction from LH and HL sub bands c) PNN classification.

![Figure 1. Flow of system](image1)

![Figure 2.MRI images](image2)
3.1 Input Dataset
For the implementation of the proposed method both affected and non-affected type of T2-weighted brain MRI in axial plane and 256*256 in plane resolution were collected. It consists of 60 images including normal, primary and secondary type. All of these data sets images are previously in DICOM format that are converted to ‘.JPG’ format using ‘Sante DICOM editor’ software. Figure 2(a), (b) and (c) shows the T2 MRI considered for the implementation of textural feature extraction and classification.

3.2 Discrete wavelet transform
The Discrete Wavelet Transform is based on sub-band coding. The wavelet is good for feature extraction and has been used for extracting the wavelet coefficients from MR images. In this method a four level decomposition using Daubechies (db1) wavelet was computed and the features were extracted from LH and HL sub bands. The main advantage of wavelets is that they give localized frequency information about a function of a signal. It shows time-scale representation of the signal which is obtained by filtering. The basic fundamental of DWT is given as, Suppose x (t) is a square-integral function then the continuous wavelet transform of x (t) relative to a given wavelet \( \Psi(t) \) is gives as

\[
W(a,b) = \int_{-\infty}^{\infty} x(t) \Psi(a,t) dt \quad (1)
\]

It decomposes a signal into a set of basic functions. These basic functions are called wavelets. It gives as

\[
\Psi_a,b(t) = \frac{1}{\sqrt{a}} \Psi \left( \frac{t-a}{b} \right) \quad (2)
\]

Where, \( a \) is the scaling parameter and \( b \) is the shifting parameter.

3.2.1 2-D DWT
Two dimensional DWT results in four sub bands that are LL(low-low), LH(low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation which is further decomposed.

![2-D decomposition of image](image)

![input MRI image.4-level wavelet decomposition](image)

Figure 3. 2-D decomposition of image

Figure 4. (a) input MRI image. (b) 4-level wavelet decomposition.
3.3 Texture feature extraction.
Feature extraction is the process of finding higher-level information of an image such as colour, shape and texture. Its analysis makes differentiation between normal and abnormal tissue easy. The Gray-Level Co-occurrence Matrix (GLCM) is a well-known statistical technique for texture feature extraction. It consists of two steps the GLCM is computed in the first step, while the texture features from GLCM are calculated in the second step. Stats = graycoprops(glcm, properties) calculates the statistics which are specified in properties from the glcm. The GLCM is the two dimensional matrix of joint probabilities P (i, j) between pairs of pixels which are separated by a distance ‘d’ in a given direction ‘r’. It calculate how often a pixel having intensity i, occurs in relation with another pixel j at a certain distance d and direction. In this system first Gray level co-occurrence matrix(GLCM) was formed and the statistical texture features such as entropy, contrast, energy, homogeneity and correlation were obtained from the LH and HL sub bands of the fourth level of wavelet decomposition. They are as follows,

I. **Contrast:** It is the amount of local variation present in an image. High contrast values are expected for heavy textures and low for smooth, soft textures
$$\sum_{i,j} (i-j)^2 P_{d,\theta}(i,j)$$………………………………………(3)

II. **Correlation:** This feature measures how correlated a pixel is to its neighbourhood pixel.
$$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P_{d,\theta}(i,j)}{\sigma_x \sigma_y}$$………………………………………(4)

III. **Homogeneity:** Homogeneity measures the similarity of pixels.
$$\sum_{i,j} \frac{P_{d,\theta}(i,j)}{1+|i-j|}$$………………………………………(5)

IV. **Entropy:** Entropy is a measure of randomness of intensity image.
$$\sum_{i,j} P_{d,\theta} \log_2 [(P_{d,\theta}(i,j))]$$………………………………………(6)

V. **Energy:** It returns the sum of squared elements in the gray level co-occurrence matrix
$$\sum_{i,j} (P_{d,\theta}(i,j))^2$$………………………………………(7)

These statistical features are given as input to PNN classifier.

3.4 PNN Classification
Probabilistic Neural Network (PNN) is a radial basis neural network. It is used for classify gives input image into normal, primary or secondary. It is multi layered feed forward network with four layers Input, Patter, Summation and output.
When an input is present, the first layer computes the distance from the input features vector to the training input features vectors [2]. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

In this system there are three classes [2]. The probability can be estimated using the formula,

\[ f_q(X) = \frac{1}{(2\pi p)^{P/2}} \frac{1}{\sigma^p N_q} \exp \left( -\frac{(X - X_P)^T(X - X_q)}{2\sigma^2} \right) \]  

(8)

\( P \) denotes the dimension of the pattern vector
\( N_q \) is the samples number of category \( q \)
\( x_i^q \) is i-th pattern sample from category \( q \)
\( \sigma \) is the smoothing factor or the width of the Gaussian function.

IV.RESULTS
Statistical texture features obtained from LH3 (band 1) & HL3 (band 2) sub bands of 4-level decomposition of given normal, primary and secondary MRI are given as follow. These feature values are average value of all dataset images features. Table 1 shows the energy feature. It measures the local uniformity of the gray levels. Its range is [0 1].Table 2 shows correlation features. It measures correlation of pixel to its neighborhood pixel. Its range is [-1 1]. Table 3 shows the contrast feature, it measures the local variations in GLCM. Its range is [0, (size (GLCM, 1) - 1)^2]. Table 4 shows homogeneity feature, it measures the similarity of pixels. Its range is [0 1].

<table>
<thead>
<tr>
<th>Energy</th>
<th>Normal</th>
<th>Primary</th>
<th>Secondary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1</td>
<td>0.12</td>
<td>0.29</td>
<td>0.32</td>
</tr>
<tr>
<td>Band 2</td>
<td>0.09</td>
<td>0.25</td>
<td>0.27</td>
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Table 1

<table>
<thead>
<tr>
<th>Contrast</th>
<th>Normal</th>
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<th>Secondary</th>
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<tbody>
<tr>
<td>Band 1</td>
<td>2288.02</td>
<td>7259.42</td>
<td>6996.74</td>
</tr>
<tr>
<td>Band 2</td>
<td>5660.4</td>
<td>10850.7</td>
<td>10463.86</td>
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Table 3

<table>
<thead>
<tr>
<th>Correlation</th>
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<th>Primary</th>
<th>Secondary</th>
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<tbody>
<tr>
<td>Band 1</td>
<td>0.307</td>
<td>0.247</td>
<td>0.313</td>
</tr>
<tr>
<td>Band 2</td>
<td>-0.019</td>
<td>0.094</td>
<td>0.156</td>
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Table 2

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<thead>
<tr>
<th>Homogeneity</th>
<th>Normal</th>
<th>Primary</th>
<th>Secondary</th>
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<tbody>
<tr>
<td>Band 1</td>
<td>0.427</td>
<td>0.568</td>
<td>0.591</td>
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<tr>
<td>Band 2</td>
<td>0.346</td>
<td>0.509</td>
<td>0.547</td>
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Table 4

<table>
<thead>
<tr>
<th>Entropy</th>
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<th>Primary</th>
<th>Secondary</th>
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<tbody>
<tr>
<td>Band1</td>
<td>5.257</td>
<td>4.57</td>
<td>3.41</td>
</tr>
<tr>
<td>Band2</td>
<td>5.544</td>
<td>4.205</td>
<td>3.89</td>
</tr>
</tbody>
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Table 5

Table 5 shows entropy feature. Entropy in any system represents disorder. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.
In this system, the texture statistics are acquired from LH and HL sub bands. The differences in the statistical feature values of normal, primary and secondary brain tumor images are shown in following figures. It is found to be useful in calculating the performance of the PNN classifier in testing and training.

V. CONCLUSION
Based on the experimental results statistical features extracted from LH (horizontal) and HL (vertical) sub bands are more efficient at characterizing changes in the biological tissue and help distinguish normal and abnormal image textures. This paper presents an effective method of classifying MR brain images into normal, primary and secondary tumor using a discrete wavelet transform and probabilistic neural network.

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