Brain Tumor Detection from MRI images using Multi-level Wavelets

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***Abstract*— The death rate of humans due to the brain tumor was high some year before but due to the early diagnosis of brain tumor, this rate is significantly decreased. Due to the accurate brain tumor diagnosis on early stages, long survival chances for a patient is increased. In this paper, we proposed computationally efficient and accurate brain tumor segmentation method. The proposed method is divided into different phases. In the first phase, the image is decomposing into wavelet sub-bands and then the high energy sub-band is divided into blocks. Then, high variance features from each block are selected through discrete cosine transform and passed to neural network for classification. The classification accuracy rate of 99.7% is achieved which is good as compare to existing ones.**

***Keywords*— Brain tumor, DCT, classification, K-mean clustering.**

I. INTRODUCTION

The Brain controls the entire functionality of our body because it is more complex and principal part of human body. The body gets affected badly if any damage occurs to the brain. The protective skull hides the direct sight of the Brain. The Brain is protected from various injuries by this skull and it also prevents the functionality of the Brain. If any change has seen in normal behavior and structure, then this shows that a tumor has affected the Brain. The abnormal growth of brain cells cause by brain tumor [1]. Therefore, these cells effect on the human normal routine. In the human beings the brain tumor is the most noted cause of tumor cancer deaths. The new estimated cases are 22,070 in the US and the death cases caused by the brain tumor are 12,290 [2]. If the tumor has been diagnosed wrong, it may lead to severe results, thus the brain tumor diagnosis is one of the most critical and crucial tasks. In a complex way the cells of our brain are bounded together closely. The structure of the brain is very complicated and delicate internally. For the analysis of brain functionalities the medical imaging processes provide guidance to the doctors and researchers [3]. Recently in [4], authors presented an wavelet based approach for tumor segmentation whereas in [5], texture and DWT features are extracted for tumor classification.

A. *Major Contributions*

Brain images are accurately and efficiently classified using the proposed system. Our method is different from some existing techniques such as [5] in the form of features, and segmentation. Optimal features are utilized in classification phase which increases the classification accuracy rate and decrease the time complexity. After studying different literature, we concluded that most the researchers used different intelligent algorithms to select the optimal features for classification, which can increase the system and time complexity [6-12]. We overcome this issue by utilizing a feature extraction technique which also selects optimal features. Proposed technique results are much better in the term of accuracy rate and time complexity as compared to other techniques. Our proposed system can be deployed efficiently in the real time environment due to its significant performance

II. RELATED WORK

Lately, several brain tumor classification techniques are introduced by several researchers in the area of computer vision [13-15]. Sharif et al. [16] described a fully automated technique for brain tumor segmentation and classification and achieved an average accuracy of more than 90%. In [17], a hybrid approach is described for brain MR images. As attributes for classification the coefficients of discrete wavelet transform (DWT) are being used in this technique. Before dispensing it to the classifier, the Principal Component Analysis (PCA). The neural network is utilized for classification of reduced features which are obtained through KNN reduction method. Fresh training is being required every time when new data has arrived is the major weakness of this presented technique [17]. A classification adaptive technique for the brain MRI tissue has been suggested by Chris et.al. The pruning strategy customizes the training dataset [18].The structural changeability of brain MRI can be accommodated by the pruning strategy classification. The minimum spanning tree reduces the prior tissue probabilistic-estimated maps that are being generated by incorrect label examples. The major drawback of this technique is that it does not have the capability of classifying the malignant tissues of the brain accurately.

Ping et al. modified membership weighting of each cluster have suggested an FCM algorithm for the brain MR images segmentation and the spatial information is being integrate. For MR images of various noise types this technique provided an appropriate result as Ping et al. [19] applied this technique on different MR images. Based on image segmentation a brain tumor, detection technique has suggested by the Rajeev et al. Watershed algorithm is being used for the segmentation of brain MRI in the suggested technique. For the segmentation of the brain MRI the suggested method does not require any kind of initialization [20].

III. PROPOSED METHOD

The suggested method consists of three vital modules. Framework of the proposed system is divided into three major modules. In first module the features are extracted from brain input image using Discrete Wavelet Transform (DWT). For the selection of optimal features, the Discrete Cosine transform (DCT) is operating on Sub-band image of DWT. In second module the input image is classified as tumor or normal image. Last module is segmentation which only required tumor image to extract the tumor region. Proposed method complete architecture is shown in Figure 1. Proposed algorithm major component detail is also provided in the subsections.

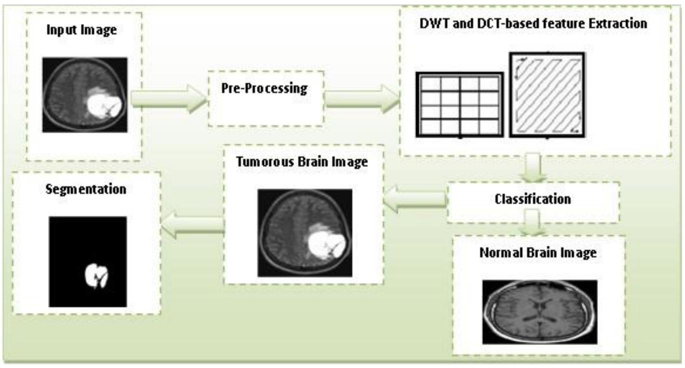

Fig. 1: Proposed flow diagram of brain tumor classification system

A. *Noise Removal*

The disturbances like Gaussian and Poisson noise mostly corrupt the MRI images [21].The additive white Gaussian noise is assumed to be the most used algorithm of de-noising. The algorithms like edge preserving bilateral filter, total variation and non-local means are being designed for the elimination of Gaussian noise.

The median filter [22] is being used in this paper. For the removal of noise throughout preserving the edges an effective non-linear method of Median filter is being used. Each value is being replace with the median value of the neighboring pixels; the filter works by moving the pixel by pixel through the image. These patterns of the neighbors are known as a "window" that sides pixel by pixel over the whole image. The median is being calculate into a numerical order by sorting all the pixel values and is then replace with the middle pixel value. For the removal of noise in the presence of edges the median filter is considered better than the linear filter as it is being claimed by the image processing researchers [23]. In preprocessing the result of this step is to eliminate noise from the MRI image.

B. *Feature Extraction*

Feature extraction is an essential step which explains that an image is being transformed into its set of features. For the classification of an image the most useful features are being extracted from the original image and several types of features are extracted in literature for classification of objects into their relevant categories [24-28]. Good feature set extraction is one of the most crucial and critical tasks for the classification of an image. In this work, DWT and DCT features [29] are extracted which are presented below.

a) Discrete Wavelet Transform (DWT)

For the image analysis and feature extraction the Haar wavelet is being proved to be effective. The Haar wavelet localizes the signal into time and frequency domains for its representation. The spatial and spectral information image registration accuracy is being improved by the wavelet and the loss of global or local information be avoided by supplying multi-resolution representation. The data of different spatial resolution is being brought to a common resolution that uses low frequency sub-bands by granting access to edge features that uses high frequency sub-bands is the supplementary advantage of using the wavelet-decomposed images.

The original N x N- pixel image created four new images. The original image size is reduced to ¼ and the new size of the image is N/2 x N/2. Filter is applying to the original image in vertical and horizontal direction, so the new image is giving the name according to high-pass and low-pass filters. The LH image is produced after applying the high-pass filter and low pass filters into vertical and horizontal directions. The four images, which generates after decomposition, are known as HH, HL, LH and LL. HH image is noisy image as it contains mostly high frequency information. Vertical edge features are represented by HL image and horizontal features by LH image. The LL sub-band contains most of the detail information and it is the reduced version of original image, so we used this image to extract the features.

b) Discrete Cosine Transform (DCT)

DCT is one of the important techniques which are widely used in image and signal processing. Due to the strong "energy compaction" property the DCT concentrated maximum information in the low-frequency component [30]. DCT computational complexity is low and accuracy rate is high. DCT produce inter-pixel redundancies after providing the natural images maximum decorrelation. The can help for dividing the image into separate part according to its importance. Frequency components of the input are known as basis function. The input of DCT is being transformed into a linear combination of weighted basis functions. DCT used fewest coefficients to represents the input image most significant features.

C. *Probabilistic Neural Network (PNN)*

In 1990, a technique for the formulation of weighted-neighbor method was suggested by Donald F. Specht [31] in the form of neural networks. Donald F. Specht named this technique as a "Probabilistic Neural Network". The PNN network is being represented diagrammatically in Figure 2.

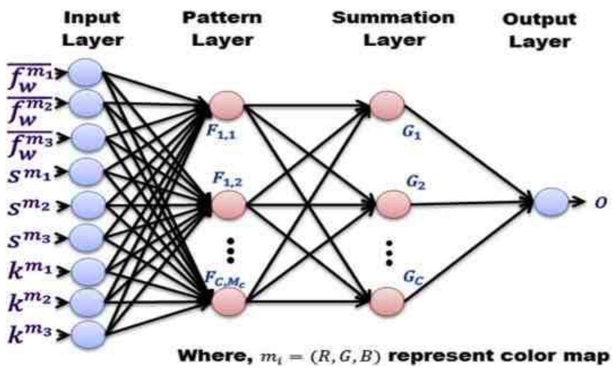

Fig. 2: Architecture of Probabilistic NN [32].

In classification problems the PNN is often used. In this work, we utilized PNN for classification of extracted DWT and DCT features.

D. Segmentation

In medical imaging, segmentation plays very important role. Segmentation can help to separate normal tissues segment from effected tumor tissues. The effected tumorous cells segment is known as tumorous region which is our desired region. Details of the segmentation phase are as follow.

E. K-Means Clustering

K-means clustering also known as unsupervised clustering used for segmentation. Data set 'n' is partition into K groups using K-mean clustering technique [18]. K-means clustering develop centroid of clusters by set center of each cluster. In this approach, maximizes the inter cluster distance whereas the intra cluster distance is minimized. Depending on the closest center value, a new instance is assigning to the cluster. Updating of each cluster center Ci is performed by its constituent instances. An objective function is minimizing by means of this algorithm. Below equation represents the K-mean objective function.

$$\text{Objective function} = \sum_{j=1}^{k}\sum_{i=1}^{n}[x_i^j - \mu_j]^2$$

A distance measure between cluster center μ_j and data point x_i^j is represented by $[x_i^j - \mu_j]^2$. This also indicates the n data points distance from cluster centers.

Based on the intensity of the pixels of an image the K-mean clustering segments the image into normal brain region and tumorous cell region. Then in the next step by means of canny edge detector method the tumor region edges are detected from the segmented brain MR image.

IV. Results and Discussions

All the experiments are performed using MATLAB 2017b environment. The standard brain images data set available at web [17] is utilized for experiments. All the images are resized to 320 x 320. In first step the noise is removed by processing the median filter on all the images. Below Figure 3 shows these facts.

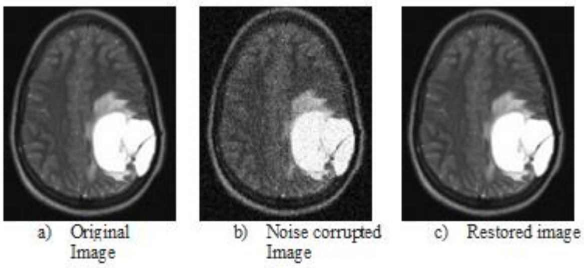

Fig.3: Image restoration from noise

In next step, Haar wavelet is used to decompose the input image into four frequency sub-band i.e. High-High (HH), High-Low (HL), Low-High (LH) and Low-Low (LL) as shown in Figure 4. As discussed earlier the LL part contains more information so which chose LL part for further processing.

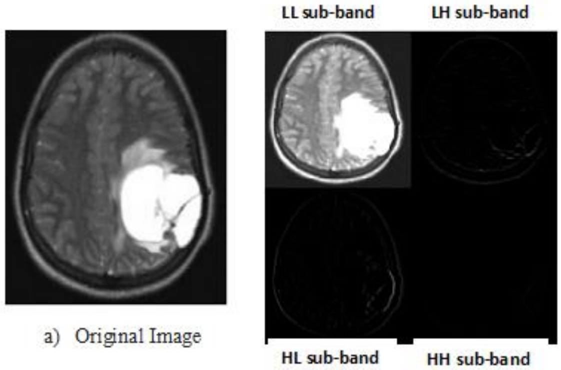

Fig.4: 1-level decomposition of brain image

The LL sub-band is then again decomposed at three different pyramid levels to achieve the multi scale analysis. In first pyramid level the image size is 320x320, whereas in the second and third, size of pyramid is 160x160 and 80x80, respectively.

In next step, the image is being splitting into 8x8 blocks and Discrete Cosine transform is applied to extract the high-level features from LL sub-band at different levels. Figure 5 depict the DCT convolution process in Zig-Zag manner on LL sub-band image.

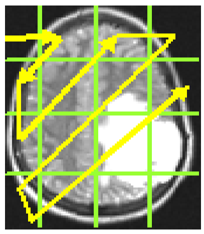

Fig. 5: DCT coefficient zig-zag scan

High variance coefficients are located at the top left corner, so only the first 2 coefficients from each block at different pyramid levels are selected and combined to generate feature vector. The feature vectors are train and test the neural network algorithm for classification. Figure 6 shows the performance comparison of the clustering algorithm of single pyramid level features with combined three level pyramid features.

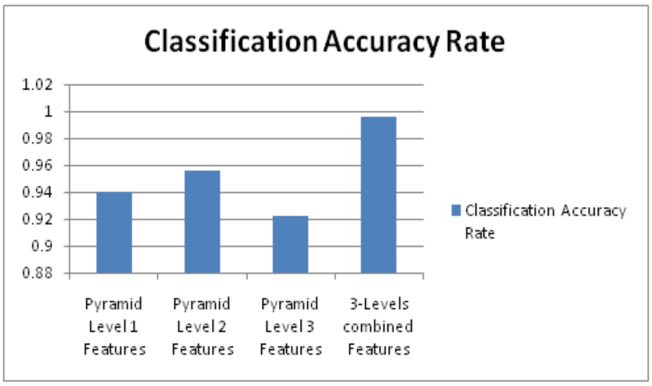

Fig. 6: Classification accuracy rate comparison with different pyramid levels

In Figure 6, the results on Harvard dataset are presented and achieved maximum accuracy of 99.7% on 3-level combined features. The accuracy on 3-level features combination is better as compare to individual 1, 2, and 3 levels features pyramids. We have not only capture micro texture of the image but also macro texture by using different pyramid levels due to which our proposed Multi-scale DWT is more robust. We have also compared the proposed technique performance with accuracy rate of DCT-based extracted features along with neural network (NN) classifier and DCT features along with support vector machine classification (SVM). We examine that DCT+NN produce accuracy rate of 94.5% and DCT+SVM accuracy rate 95%. Below Figure 7, shows these facts.

TABLE 1: COMPARISON WITH EXISTING TECHNIQUES

Technique	Accuracy Rate (%)
DWT+SVM [19]	97.25
DWT+PCA+KNN [19]	98.2
DWT+SOM [19]	95.13
DWT+PCA+ANN [19]	95.4
Proposed	**99.7**

It has been also observed that all the other technique are greatly affected by reduction in image size however the proposed technique outer-perform even if the size of the image is changed. Images are categories as malignant image or normal image in the classification phase. In Last phase the malignant images are passed to segmentation phase where the tumor region is extracted using K-mean clustering algorithm.

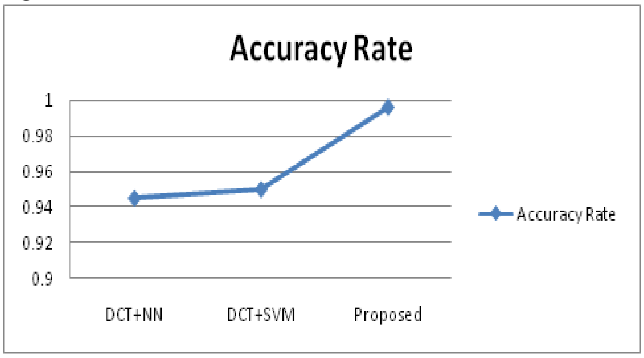

Fig. 7: Proposed technique accuracy rate comparison with DCT+NN and SVM

V. CONCLUSION

In this paper, an efficient brain tumor algorithm framework is proposed. Low computational complexity and accurate segmentation of tumor region demonstrate the efficiency of proposed algorithm. Another advantage is that it also works correctly on multi resolution images as the features are extracted in block-based manner from different wavelet levels. Additionally, other methods used intelligent algorithms to select the optimal features after extraction of large number due to which the computational time is increased. We resolve this issue by applying DCT which select the high variance features in zigzag manner. Classification accuracy rate is also compared with current techniques, found that the proposed technique is more accurate, and can be used in practical medical applications.

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