Brain Tumor Classification using Framelet Transform based energy features and K-Nearest Neighbor Classifier

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Abstract

The tissues which are abnormal in the brain are known as brain tumor. The growth of tumor creates the more pressure in the function of the brain and cause headache, sickness and other problems. The early diagnosis is required for the brain tumor. In this study, a technique for brain tumor classification using framelet transform based energy features and K-Nearest Neighbor (KNN) classifier is presented. The normal and abnormal Magnetic Resonance Images (MRI) brain images are fed into framelet transform and the features are decomposed into subband coefficients. These framelet based decomposed features are extracted by energy features. These extracted features are given as input for KNN classifier. Results show the better classification accuracy of MRI brain classification images using framelet transform based energy features and KNN classifier.

Keywords: MRI brain images, Framelet Transform, Energy features, KNN classifier.

1 Literature Survey:

Brain tumor segmentation of Magnetic Resonance (MR) brain images using active contour model with random forest is discussed in [1]. The features of MR brain images are extracted by both local and contextual information from multimodal images for tissue segmentation by using modality specific random forests as the feature learning kernels. Different levels of the structural information are subsequently integrated into concatenated and connected random forests. Brain tumor classification using Extreme Learning Machine (ELM) and hybrid feature extraction method is discussed in [2]. Gastrointestinal Stromal Tumors (GIST) descriptor features and principal component analysis with normalized GIST a hybrid features are used to extract the MRI brain image features. ELM classifier is used for classification.

Diagnosis of brain tumor a sparse representation is discussed in [3]. The MRI brain image datasets are extracted by sparsely representing image patch set using dictionary training. The features are selected by iterative sparse representation-based feature selection. The segmentation is made by Convolutional Neural Network (CNN). The analytic Intrinsic Mode Function (IMF) representation is used for MRI brain classification using sample space density measure is discussed in [4]. The features are extracted by complete ensemble empirical mode decomposition with adaptive noise and Hilbert transformation technique. Then the IMF is used for classification.

Brain tumor segmentation in analysis of brain and level sets is discussed in [5]. The three filters anisotropic diffusion, threshold and gradient are applied for noise removal. Brain symmetry is made by bisection. Then the bounding box is detected. The slice of interest is selected for tumor segmentation. Fast bounding box algorithm is used for classification. A survey on identification of glioblastoma is discussed in [6] for multiforme and low-grade glioma brain tumor type. The input MRI brain image features are extracted by fuzzy c-means and Gray Level Co-occurrence Matrix (GLCM). The classification is made by naïve bayes classifier.

Cascaded framework for brain tumor classification using CNN and Long Short Term Memory (LSTM) is discussed in [7]. MRI brain image features are extracted by CNN. Classification is made by LSTM. CNN based MRI brain images detection and classification is discussed in [8]. The input brain image features are extracted by GLCM and fast discrete curvelet transform. The classification is made by CNN. The MRI brain image is segmented by K-means clustering.

Capsule networks for brain tumor classification based on MRI brain images is discussed in [9] for coarse tumor boundaries. The input brain images are decomposed by capsule networks and tumor boundaries are identified. CNN is used for classification. Brain tumor detection from MRI brain images using wavelet transform is discussed in [10]. MRI brain images are decomposed by discrete wavelet transform. The kernel based SVM classifier is used for classification.

Segmentation and classification of brain tumor using Deep Belief Network (DBN) is discussed in [11]. The feature extraction is made by local directional pattern for extracting the texture features. DBN classifier is used for classification. Tumor detection in brain using region proposed CNN is discussed in [12]. MRI brain images are trained and decomposed by faster region proposed CNN. The region proposal network is used for the classification.

An efficient methodology for abnormalities of brain detection using CNN deep learning network is discussed in [13]. The MRI brain images are decomposed by K-means algorithm to extract the features. The classification is deep learning network. Brain tumor detection using texture features in MR brain images is discussed in [14]. The GLCM features are used for feature extraction. Feed forward neural network is used for classification. Stationary wavelet transform, self organizing map and watershed algorithm is used for segmentation.

2 Materials and Methods:

In this work, a technique for MRI brain tumor classification is discussed. Figure 1 demonstrates the workflow of MRI brain classification system. This method consists of two steps they are feature extraction and classification. MRI brain image features are extracted by framelet transform based energy features and classification is made by KNN classifier.

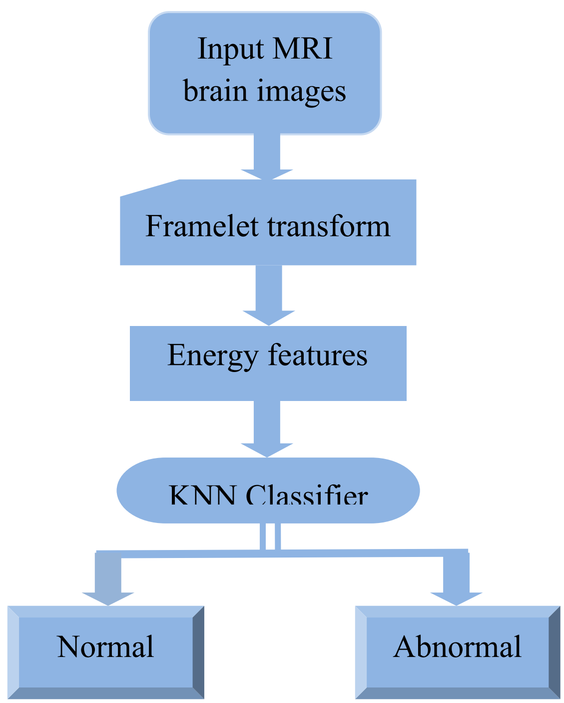

Figure 1 Workflow- MRI brain classification system

2.1 Framelet Transform

Orthogonal and biorthogonal wavelets in image processing have select wavelet frames directly. It performs fine in time and wavelet frequency analysis. Redundancy is significant property in wavelet transform and it is generally used in data denoising and identification of object. The framelet transform is defined by,

$$\sum_{j\in\delta}\left|< i, j >\right| = \left\|i\right\|^2, \forall i \in H_2(K)$$

where $\delta \subset H_2(K)$ is countable. δ is a tight frame of $H_2(K)$

This is equivalent to,

$$i = \sum_{j\in\delta} < i, j > j, \forall i \in H_2(K)$$

The basis of $H_2(K)$ is a tight frame and also a redundant orthonormal system. The characteristics of the framelet transform are stability, completeness and redundancy. The redundancy lead to the robust and framelet coefficients obtained the low accuracy and is rebuild the high accuracy. The advantage of framelet transform is denoising and fault tolerance. The tight framelet transform has a greater design freedom. The framelet transform is defined by,

$$\delta = \{\delta_1, \delta_2, ..., \delta_R, \delta\},$$

The celestial spectrum $u(p)$ is decomposed into approximate components,

$$u(p) = B_K(p) + \sum_{0<r\leq R}\sum_{k<K} E_{r,k}(p)$$

$$B_K(P) = \sum_{l\in Y} D_{K,l}(p),$$

$$E_{r,k}(p) = \sum_{l\in Y} e_{r,k,l}\delta_{r,k,l}(p),$$

where K is the level of framelet transform, B_K is the approximate component at K level, $E_{r,k}(p)$ is the detailed component of δ_r at k^{th} level.

2.2 Energy Based Framelet transform

The energy features are extracted by subband wavelet coefficients, and it is taken for classification. The gain of energy is good indication for spatial and frequency levels. The energy distribution is available for various texture patterns. The energy feature is defined by,

$$E_g = \frac{1}{AB}\sum_{k=1}^{A}\sum_{l=1}^{B} CoeffSBAND(k,l)$$

where $CoeffSBAND$ denotes the sub-bands of higher and lower frequency components with the image *A x B*. The coordinates of subband are represented by *(k,l)*.

2.3 KNN Classifier:

KNN classifier stores all available instances and based on data measurement. In particular instance of time it identifies the nearest neighbor. Known neighbor identifies the unknown instance. The rule that present in KNN classifier is it identifies the *K* neighbor. *K* indicates the any number of neighboring pixels, such as *K = 1, 2, 3, 4… n,* where *n* referred as number of cases. The KNN classifier output is measured by Euclidian distance.

Considering, $s = (k_1, l_1)$ and $t = (k_2, l_2)$ are two points. The Euclidian distance between these two points is given as,

$$(k,l) = \sqrt{(k_1 - k_2)^2 (l_1 - l_2)^2}$$

The MRI brain image classification based on framelet transform based energy features are classified by KNN classifier.

3 Results and Discussion

A set of 50 MRI normal and affected images are selected from repository of molecular brain neoplasia database for the performance of the system. The image size is 256x256 pixels.

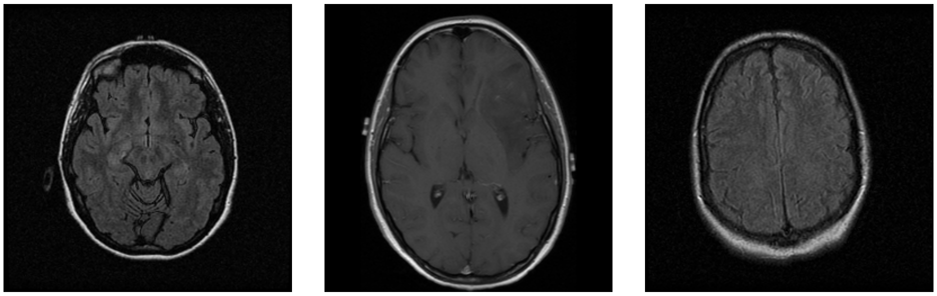

Figure 2 Normal MRI brain images for brain tumor classification

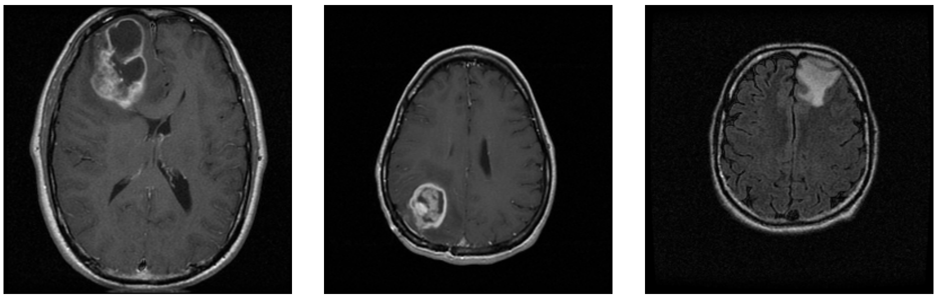

Figure 3 Abnormal MRI brain images for brain tumor classification

The system performance is measured by MRI brain images. Framelet transform is applied to set the subband coefficients and energy features are extracted and KNN classifier is used for classification. Table 1 shows the accuracy, sensitivity and specificity obtained at 1 to 4 levels.

Framlet transform Levels	KNN Classifier		
	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	68	72	70
2	80	92	86
3	84	100	92
4	80	96	88

From Table 1, it is observed that the 3rd level of framelet transform based energy features produce higher accuracy of 93% and their sensitivity and specificity are 91% and 95%. Figure 4 shows the performance MRI brain image classification using framelet based energy features and KNN classifier. Figure 4 shows the graphical representation of the MRI brain image classification system. Figure 5 shows the ROC curve for framelet based energy features at four levels.

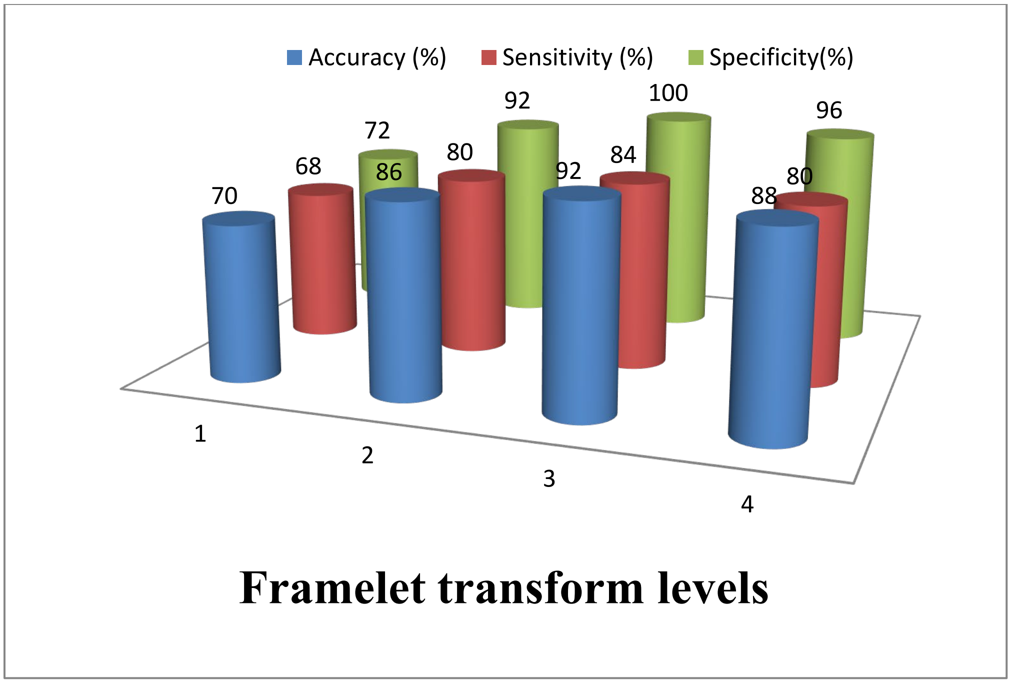

Figure 4 Graphical representation of the performance of framelet based energy features

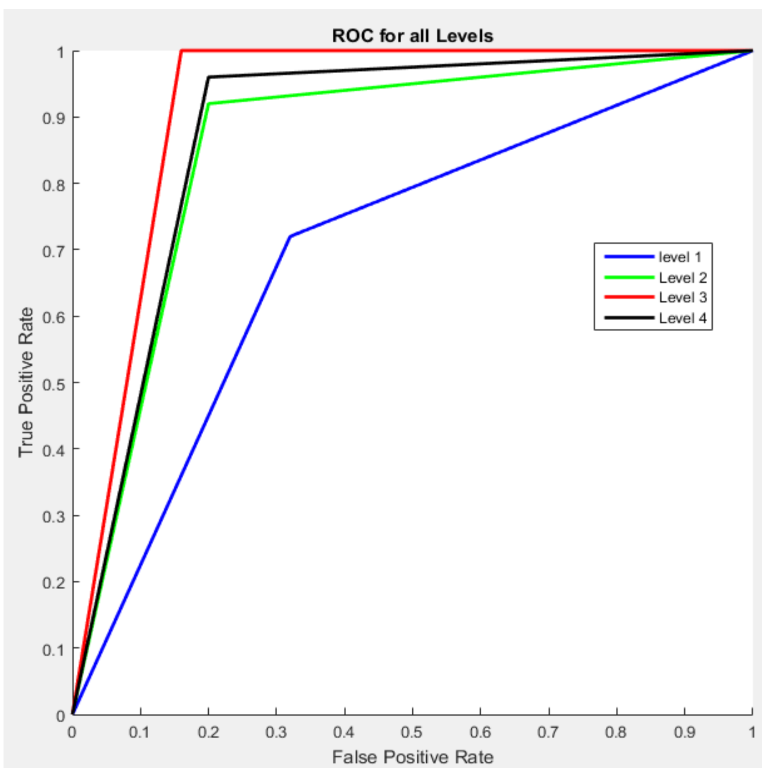

Figure 5 ROC curve for framelet transform based energy features for breast cancer image classification

4 Conclusion

An efficient method for brain image classification system using MRI brain images is discussed. The system uses framelet transform based energy features with KNN classifier. Framelet transform decomposed into subband coefficients and energy features are extracted. These extracted features are the input for the classification. KNN classifier is applied to classify the extract the features at four levels of framelet transform decomposition. Results show that the 3rd level produces better classification accuracy when compares to other levels.

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