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RESEARCH ARTICLE

Brain Tumor Detection using Curvelet Transform and Support Vector Machine

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Abstract— The prevalent cause of death in human being is brain tumor. A brain tumor is a mass or growth of anomalous cells in brain. The detection of brain tumor is difficult task. Image processing provides relevant techniques for efficient detection. In the proposed technique, first the features of MRI (Magnetic Resonance Imaging) images are extracted with curvelet transform, and then these features are applied to the support vector machine for successful identification. This proposed methodology gives efficient results.

Keywords— Brain Tumor; Curvelet Transform; Support Vector Machine

I. INTRODUCTION

A brain tumor is a mass of irrelevant cells growing in the brain or central spine canal. There are two basic kinds of brain tumors – primary brain tumors (benign) and metastatic (malignant) brain tumors. Primary brain tumors initiate and stay in the brain. Metastatic brain tumors begin as cancer somewhere in the body and spread to the brain [1]. MRI (magnetic resonance imaging), CT (computed tomography) are most adequate way to locate the brain tumor. The typical methods, which are present in diagnosis, are human inspection, biopsy, expert opinion and etc. These methods have some drawbacks like biopsy take so much time and human inspection is not always correct [2]. So image processing techniques are used to identify brain tumor. A number of studies have been done on brain tumor detection. Lahmiri et al. [3] designed an automated system in which it performs lobe asymmetry to distinguish the normal and abnormal brain MRI images. The proposed automated diagnosis system includes four 1). The original image is processed with a Laplacian of Gaussian (log) filter for noise filtering and edge enhancement. 2) the filtered image is split into two right and left lobe sub-images 3) the relevant features are extracted to account for asymmetry 4) the resulting feature vector feeds the input of a support vector machine (svm). Gupta et al. [4] proposed a methodology in which image processed through histogram equalization, binarization, morphological operations, region isolation, feature extraction and neuro classifier. Gray level co-occurrence matrix is used for feature extraction and neural network is used for classification. Al-badarneh et al. [5] proposed an approach which have following steps feature extraction and classification. In feature extraction main texture feature are extracted. Then neural network and k-nearest neighbour is used for classification. Gupta et al. [6] designed a system in which feature extraction is done using curvelet transform on the lung cancer CT scans. The rest of paper is organized as follows: Section II describes the proposed methodology. Section III shows experimental results. Section IV presents conclusion for the proposed method.

II. PROPOSED METHODOLOGY

The flow chart follows our proposed work:

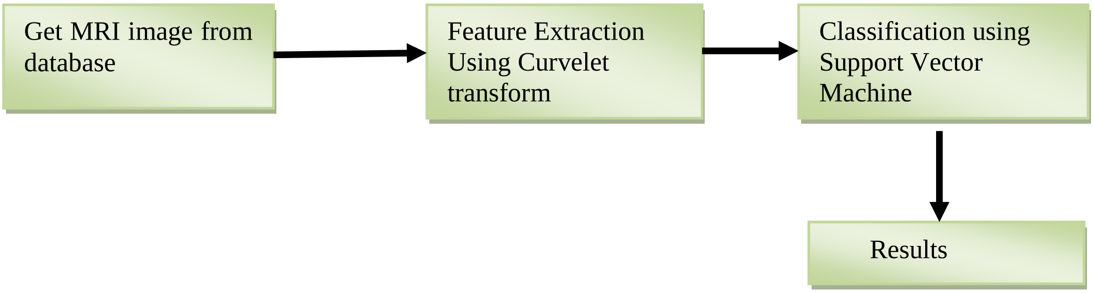


Fig 1 Flow chart of proposed work

A Feature Extraction

The quality of classification depends on the process of feature extraction. Feature extraction identifies the relevant features that are used for understanding the images. In our proposed system feature extraction is done using curvelet transform.

1) Discrete Curvelet Transform:

Candes et al. [7], developed a multiscale transform to remove the limitations of wavelet transform, is known as Curvelet transform. It provides representation of smooth objects with discontinuities along curves. In wavelet approach many wavelet coefficients are needed to account for edges, on the other hand curvelet required less coefficient to account for edges. In curvelet transform, to analyse curve singularities, the concept is taking a partition of the image, and then applies the ridgelet transform to the obtained sub-images.

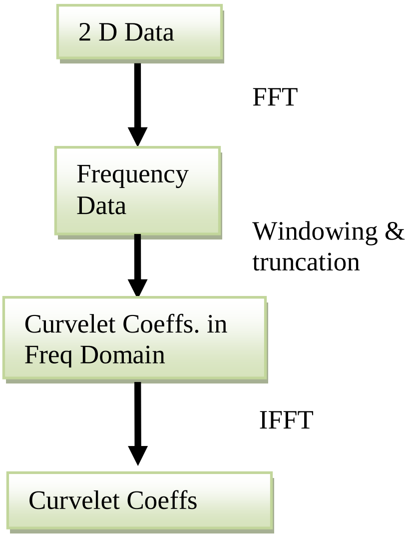
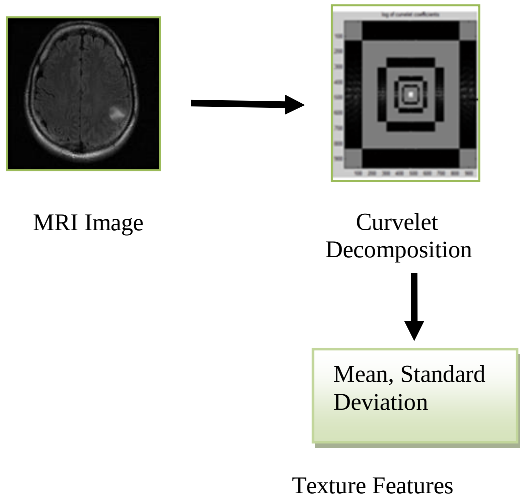


Fig 2 Data Flow Structure of Curvelet Transform

The data flow diagram of discrete curvelet transform is plotted in figure 2. The data are first converted into the frequency domain by applying Fourier transform. The transformed data are then multiplied with a set of window functions. The shapes of these windows are defined according to the requirements of the ideal curvelet transform, such as the parabolic scaling rule. By applying inverse Fourier transform on the windowing data, curvelet coefficients are obtained. Since the window functions are zero except on support regions of elongated wedges, the regions that need to be transformed by the inverse Fourier transform are much smaller than the original data. So these regions are 'wrapped' into rectangular shape before applying the inverse Fourier Transform. After applying inverse Fourier transform, curvelet coefficients are obtained [8].



Curvelet coefficients at varied angles (scale=4)

Fig 3 Schematic diagram of a proposed MRI features extraction method.

In our approach the size of image is 512x512 and it is decomposed into 4 scales. The number of directional sub band images is different in every scale. At scale 1 we will have one sub band image and eight sub band images at scale 2. Sixteen sub band images we will get at scale 3 and 4 respectively. We computed two features (Mean and Standard Deviation) of each sub band image. So we get total 82 features. At scale 4 proposed method gives efficient results.

B Classification

To classify MRI is cancerous or non cancerous, support vector machine is used. Extracted features are fed up into the support vector machine.

1) Support Vector Machine:

Support vector machines (SVMs) are a relatively new learning process in statistical learning theory and gain popularity in computer processing power in recent years. The SVM motivated from the idea of the structural risk minimization that was developed by Vapnik [9]. Support vector machines are mainly two class classifiers, linear or non-linear class boundaries. The idea behind svm is to form a hyper plane in between the data sets to express which class it belongs to. The task is to train the machine with known data and then svm find the optimal hyperplane which gives maximum distance to the nearest training data points of any class.

We consider data points of the form $\{(x_1,y_1), (x_2,y_2), (x_3,y_3) \ldots\ldots\ldots\ldots (x_i,y_i)\}$ Where y_i= 1/ -1, a constant denoting the class to which that point x_i belongs. i = number of sample. Each x_i is p-dimensional real vector. The task is to find the maximum-margin hyperplane that divides the points having $y_i = 1$from those having $y_i = -1$. Any hyperplane that satisfy the set of points x can be written as [10]

$$w.x+b=0 \qquad (1)$$

Where b is scalar and w is p-dimensional Vector. If the training data are linearly separable, svm can chose two hyperplanes that divide the data in a way that have no points between them, and also have maximum distance between both hyperplanes. The regions bounded by both hyperplanes are called "the margin". These equations for both hyperplane can be defined as

$$w.x+b=1 \qquad (2)$$

$$w.x+b=-1 \qquad (3)$$

By geometry, the distance between the hyperplane is $2 / |w|$. Now add the following constraint: for each i either

$$w.x_i+b=1 \qquad (4)$$

$$w.x_i+b=-1 \qquad (5)$$

It is equivalent to

$$y_i\,(w.x+b) >= 1 \qquad (6)$$

The classifier written as

$$f(x) = \text{sign}(w.x+b) \tag{7}$$

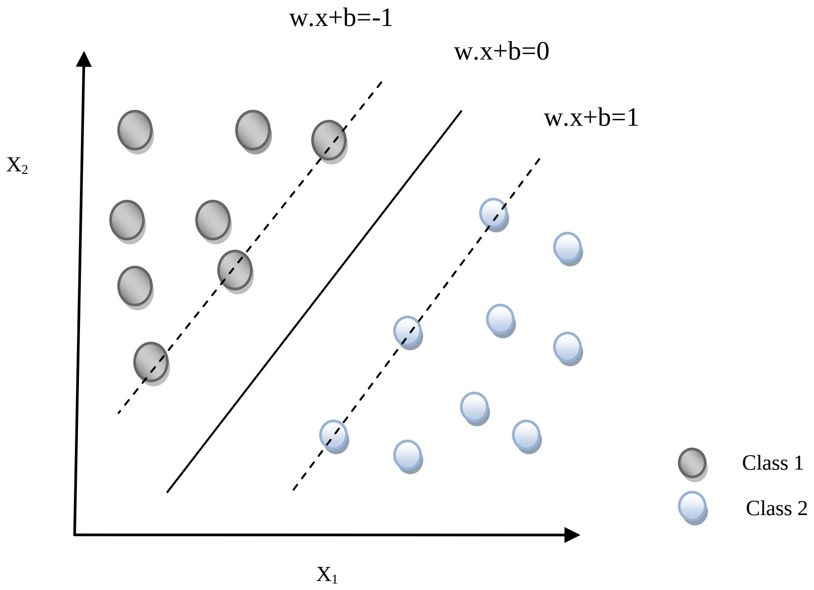


Fig 4 SVM classification

Maximum margin hyperplanes for a SVM trained with samples from two classes shows in figure 4. Samples that on the margin are called support vectors.

III. RESULTS

I have selected 50 MRI images from the TCIA database [11]. Out of 30 MRI images, 15 images are cancerous and 15 images are non cancerous. We have used all the images for training & testing of classification framework. Out of 50 images, 30 images are used for training and 25 images are used for testing. To estimate the performance of proposed method we used some metric. They are precision (P), recall (R) and accuracy (AC) and the respective definition are as follows:

$$AC= (TP+TN)/ (TP+TN+FP+FN)*100 \tag{8}$$

$$P = TP/TP+FP*100 \tag{9}$$

$$R= TP/TP+FN*100 \tag{10}$$

Where TP is the number of true positives, TN is the number of true negatives, FN is the number of false negatives, and FP is the number of false positives, are defined as:
TP: Predicts cancerous as cancerous.
TN: Predicts noncancerous as noncancerous.
FN: Predicts cancerous as noncancerous.
FP: Predicts noncancerous as cancerous.
Accuracy measure how many instances that are correctly classified. Precision is the percentage of the instances which actually have class label A with all those which were classified as class label A. Recall is the percentage of the instances which were classified as class A, with all instances which truly have class A.

Table I
Results after testing the classifier

No of Images	Precision	Recall	Accuracy
25	76.92%	100%	85.00%

Table 1 gives results after testing the approach and it found that proposed method gives satisfactory results.

A ROC Curve

Receiver Operating Characteristics (ROC) graphs is visualizing the performance of the classifier. ROC curve draw between the true positive rate (TPR) and false positive rate (FPR). The TPR represent how many correct positive results come from all positive samples which are available during test. FPR on the other hand, represent how many incorrect positive results come from all negative samples which are available during test. In ROC curve the diagonal line shows random classification, if curve is draw above the diagonal line it shows better classification. Figure 5 shows the ROC curve for proposed classifier. The following ROC curve shows the good performance for the identification of brain tumor.

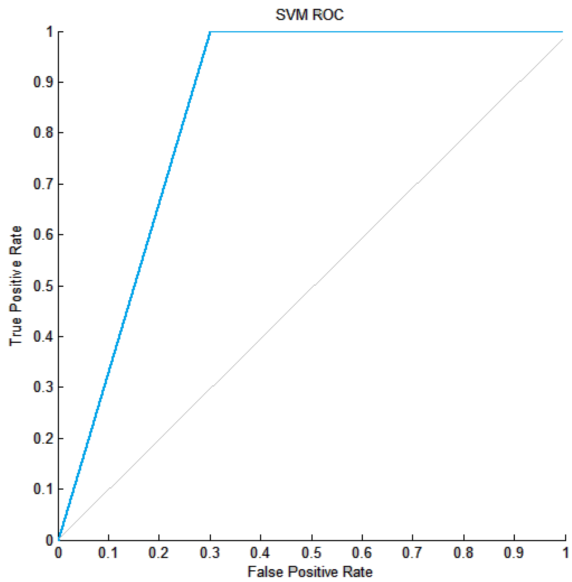


Fig 5 ROC Curve

IV. CONCLUSION

Brain Tumor is a major cause of death. Many techniques are used to detect the tumor as early as possible because early detection is cure of this disease. Medical Imaging provides many techniques for the identification of tumor. The proposed system follows an approach in which feature extraction is done using curvelet transform, then support vector machine has been utilized using these extracted features for identification. From the results, it is found that proposed system gives satisfactory performance.

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